Essays on Corporate Finance

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Essays on Corporate Finance

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Abstract of Dissertation

Corporations and financial institutions are both key players in the financial markets, making strategic decisions to maximize the value of their business operations. On one hand, managers of firms make strategic decisions to maximize the wealth of existing shareholders at the expense of new shareholders. Alternatively, managers execute business decisions to enhance their long-term profitability, with these corporate decisions depending on various factors such as future expectations, information asymmetry, and firm characteristics. Financial institutions, particularly lenders, respond differently in their lending relationships with corporate borrowers. They carefully evaluate and monitor various risks of borrowers and offer stricter loan contracts when borrowers face higher risks. However, lenders do not systematically respond to every risk posed by borrowers; instead, they become more lenient or stringent towards certain groups of borrowers, considering the same factors in their assessment of borrowers' risks. In this dissertation, I examine the strategic decisions of corporations and lenders in their business operations. Understanding these decisions enables managers to improve their decision-making, competitive advantages, risk management, and ultimately contributing to their long-term growth and sustainability.

The first chapter examines the propagation of corporate borrowers' natural disaster risks to their lenders. Using covenant violations caused by natural disasters as a channel that transmits borrowers' natural disaster risks to lenders, we investigate how lenders respond to these violations. We first find that disaster impacted firms are more likely to violate covenants and experience decreases in financing activities. This leads lenders to impose stricter loan and covenant terms to disaster impacted firms, reflecting their heightened concerns about the natural disaster risks of borrowers. More importantly, we

observe different responses from lenders to covenant violations caused by natural disasters depending on firms' capabilities to access funds. We find that, when firms have higher capabilities, lenders show leniency toward these violations by mitigating loan margin increments after disaster impacts. On the contrary, they restrict funding to firms that do not meet these criteria. These lenders' heterogeneous responses to the natural disaster risks of borrowers align with the subsequent business performances of the affected borrowers, indicating that lenders accurately assess natural disaster risks and covenant violations of firms. Overall, our findings suggest that lenders do not systematically penalize every climate change risk of borrowers but consider other factors affecting firm recovery.

The second chapter examines strategic behaviors of overvalued firms. We find that a firm is more likely to engage in acquisitions when its private information, measured by changes in purchase obligations, predicts that future profitability will fall and thus that its shares are overvalued in the current stock market. Overvalued acquirers are as likely to pay with stock as non-overvalued acquirers, suggesting that these firms do not necessarily take advantage of overvalued stock. Such acquisitions are followed by increases in profitability and generate positive announcement returns that are similar in magnitude to those generated by non-overvalued acquirers. In addition, bidding-period returns on overvalued acquirers are higher than those on similarly overvalued non-acquirers. Being an overvalued acquirer is not associated with executive compensation structure or ownership, suggesting that these acquisitions are less likely to be driven by managers' private incentives. The results suggest overall that managers engage in acquisitions to boost profitability when their private information predicts diminishing profitability rather than to take advantage of overvaluation and that such acquisitions benefit shareholders.

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Chapter 1.

Natural Disasters, Covenant Violations, and Bank Loans

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Abstract:
We examine the propagation of corporate borrowers' natural disaster risks to their lenders. Using covenant violations caused by natural disasters as a channel that transmits borrowers' natural disaster risks to lenders, we investigate how lenders respond to these violations. We first find that disaster impacted firms are more likely to violate covenants and experience decreases in financing activities. This leads lenders to impose stricter loan and covenant terms to disaster impacted firms, reflecting their heightened concerns about the natural disaster risks of borrowers. More importantly, we observe different responses from lenders to covenant violations caused by natural disasters depending on firms' capabilities to access funds. We find that, when firms have higher capabilities, lenders show leniency toward these violations by mitigating loan margin increments after disaster impacts. On the contrary, they restrict funding to firms that do not meet these criteria. These lenders' heterogeneous responses to the natural disaster risks of borrowers align with the subsequent business performances of the affected borrowers, indicating that lenders accurately assess natural disaster risks and covenant violations of firms. Overall, our findings suggest that lenders do not systematically penalize every climate change risk of borrowers but consider other factors affecting firm recovery.

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1. Introduction

Natural disasters are becoming more frequent, creating adverse shocks for firms' business activities. These events cause not only direct damage to their operations but also indirect effects through shareholders' concerns, regulatory issues, supply-chain impacts, and lenders' attention to climate change risks. As a result, firms affected by disasters may experience a detrimental impact on their financial capabilities, making it challenging for them to secure new funds, repay their debts, or maintain their debt covenants. Numerous firms report covenant violations caused by natural disaster impacts in their 10K filings. For example, Gaylord Entertainment Co. requested a conditional waiver on covenant violations to Bank of America because of the cessation of operations due to flood damage in 2010. ATN International, Inc. also filed in 2017 that their violations of the net leverage ratio covenant, due to the damage to operations from hurricanes, was waived by their lenders. These examples illustrate that lenders face heightened climate change risks from their borrowers through covenant violations caused by exogeneous events of natural disasters. It becomes increasingly crucial for lenders to strategically address these risks. Lenders may find it advantageous to assist their borrowers capable of recovery from these impacts to maximize their long-term benefits. Alternatively, they might exercise their rights to take control of such firms to minimize losses from disaster impacted borrowers. This raises our question about how lenders evaluate and manage these covenant violations caused by disasters, as penalizing every one of them may not always be beneficial for lenders either. In this context, we consider covenant violations caused by natural disasters as a channel that transmits natural disaster risks of borrowers to their lenders. We aim to investigate whether lenders exhibit distinct responses to these covenant violations or, more broadly, to

climate change risks of borrowers.

Recent literature highlights the impact of natural disasters on corporate policies and debt contracts, as firms face more climate change risks (Dessaint and Matray, 2017; Addoum, Ng, and Ortiz-Bobea, 2020; Painter, 2020; Ouazad and Kahn, 2022)[1]. Especially, Schuwer, Lambert, and Noth (2019) and Correa, He, Herpfer, and Lel (2022) explore banks' reaction to natural disaster events in loan pricings by showing that spreads on loans are amplified when attention to climate change is high. This provides indirect evidence that firms would violate covenants more after natural disaster impacts, leading lenders to increase their monitoring on borrowers' climate change risk. We have limited knowledge, however, on whether natural disasters critically affect borrowers' covenant violations and lenders consider such natural disaster-driven covenant violations seriously. Literature also examines the importance of debt covenants and violations, highlighting their role as an important tool for monitoring borrowers' performance and preventing decisions harmful to creditors. [2] After covenant violations, lenders frequently use their bargaining power to renegotiate loan terms to increase the likelihood and the amounts of repayments of their investments rather than forcing them to bankruptcy (Griffin, Nini, and Smith, 2021). On the other hand, lenders may unconditionally accept borrowers' waiver requests if covenant violations are temporary and do not severely harm borrowers' financial conditions. Yet, it remains unclear which factors lenders would rely on and drive them to respond differently

[1] They examine that the impacts of climate change and natural disasters on corporate cash holdings, establishment sales, and bond and mortgage pricing.

[2] Debt covenant violations act as a signal for the transfer of control rights from managers to creditors, leading a firm to reduce its financial activities and prepare for interest and principal repayments (Roberts and Sufi, 2009, Nini, Smith, and Sufi, 2009; 2012; Chava and Roberts, 2008). While the literature suggests that creditors may require higher loan pricing based on the probability of a covenant violation (Murfin, 2012; Freudenberg, Imbierowicz, Saunders, and Steffend, 2017), these decisions may be influenced differently depending on the reason for the violations.

to these violations. Lastly, lenders would view covenant violations caused by disasters as a harmful signal, but natural disasters are uncontrollable and unavoidable external factors that result in covenant violations. Lenders may weigh these differently compared to other violations stemming from firms' idiosyncratic risks. Putting these together, we employ various firm characteristics, associated with their capabilities to access funds, to examine whether lenders become more lenient towards certain groups of borrowers even though they have experienced covenant violations caused by natural disasters.

In this research, we examine lenders' responses to corporate borrowers' climate change risks, specifically through covenant violations caused by natural disasters. To address this question, we conduct comprehensive analyses of changes in bank loan contracts following natural disasters and covenant violations. Furthermore, we explore whether lenders would respond more favorably to affected firms that have better capabilities to access funds, as proxied by financial constraints, ESG engagements, and banking relationships. We first examine the impact of natural disasters on borrowers' covenant violations, financing activities, and loan terms. We find that disaster impacted firms are more likely to violate debt covenants and that their financing activities deteriorate in the contemporaneous years. This leads lenders to impose stricter loan and covenant terms in the following years after disaster impacts. Our finding supports the notion that when firms violate debt covenants, it is considered a negative signal for their creditors and as a rationale for stricter loan contracts in the following years. Yet, we find that covenant violations during disaster impacts are not significantly associated with covenant and loan terms. This suggests that lenders may not penalize covenant violations when they are linked to natural disasters.

Next, we examine whether lenders treat all covenant violations as horrifying signals or assess them independently when certain violations result from natural disasters. In this regard, we examine lenders' response to covenant violations caused by natural disaster in relation to three firm characteristics associated with their capabilities to secure new funds: financial constraints, ESG engagements, and banking relationships of borrowers. We divide our sample into high and low groups based on these factors and find strong and consistent evidence that lenders provide additional funds exclusively to high groups after natural disasters, albeit with stricter loan terms. More importantly, our results suggest that lenders refrain from penalizing every covenant violation caused by disasters, showing forbearance when firms are financially non-constrained, highly ESG-rated, and have strong existing banking relationships. We find that lenders require higher loan margins to these groups when they experience natural disasters. However, lenders also alleviate such loan margin increments if these borrowers suffer from covenant violations caused by natural disasters. These findings support our claim that lenders do not respond uniformly to these covenant violations but become more lenient to firms with better capabilities to access funds.

Then, we evaluate whether lenders correctly distinguish firms with strong recovery capabilities by examining the business performances of borrowers after disasters and violations. We find consistent results with the literature, indicating that both natural disasters and covenant violations have a negative impact on business performance.[3] Moreover, we observe that groups with high financial constraints, low ESG ratings, and

[3] Barrot and Sauvagnat (2016) find that suppliers hit by natural disasters impose significant output losses on their customers and Dessaint and Matray (2017) claim that hurricanes can trigger liquidity shocks because of the heavy damage they inflict. Nini, Smith, and Sufi (2012) examine that covenant violations are followed immediately by a decline in investment and operating behaviors.

lacking banking relationships experience additional declines in business performance when violating covenants after disaster impacts. This suggests that covenant violations caused by natural disasters are more significantly associated with a severe impact on the business activities of low groups, whereas high groups remain relatively unaffected. These findings align with lenders' heterogeneous responses to covenant violations caused by natural disasters.

We perform a set of robustness tests to support our findings. First, we perform separate estimations for each type of disaster, consistently obtaining results in line with our main findings. Then, we employ difference-in-differences analysis to mitigate potential influences from local economic conditions. Specifically, we match firms in counties directly impacted by natural disasters with those in similarly risky, non-affected counties and compare changes in loan terms for each group. We find that loan terms for directly impacted firms become stricter after disaster impacts, consistent with the results presented earlier.

This research contributes to the literature in several dimensions. First, this study supports the literature on creditors' responses to climate change risks. While Huynh, Nguyen, and Truong (2020) establish a positive relationship between drought risk and the cost of equity and Correa, He, Herpfer, and Lel (2022) discuss that higher loan pricings for adjacent disaster unaffected borrowers, our study uniquely reveals that covenant violations caused by natural disasters serve as a channel that propagates natural disaster risks from borrowers to lenders. This clearly illustrates that lenders also face realized risks from their disaster impacted borrowers, leading them to provide stricter loan terms, thus supporting the findings of existing literature. Second, this research highlights the lenders' responses to

covenant violations, particularly, those arising from external factors. We demonstrate how lenders assess covenant violations caused by natural disasters differently based on intrinsic firm characteristics such as financial constraints, ESG engagements, and banking relationships. Our work contributes to the literature on debt covenant by emphasizing the influence of external factors, which lead to covenant violations, on lenders' future lending decisions. This builds upon previous studies such as Nini, Smith, and Sufi (2009; 2012) and Chava and Roberts (2008), which emphasized covenant violations as a monitoring tool for borrowers' repayment capabilities. Furthermore, this study advances the understanding of covenant violations and creditors' behavior by addressing the nuanced reasons behind lenders' non-uniform penalties for such violations. Lastly, we provide more generalized analyses of natural disaster impacts. In contrast to the literature, we use an aggregate measure of disasters, rather than specific types, to address potential geographical and seasonal variations that could distort our findings. We also define disaster impacted firms by their facility locations instead of their headquarters, enabling us to more accurately identify business disruptions caused by natural disasters.

The rest of the article proceeds as follows. Section 2 describes our data and variables. Section 3 examines the impacts of natural disasters on borrowers' covenant violations and financing activities. Section 4 explores lenders' heterogeneous responses to borrowers' natural disaster risks based on firms' capabilities to access funds. Section 5 provides empirical evidence that these non-uniform responses of lenders are aligned with the business performance of firms after covenant violations caused by natural disasters. Section 6 performs robustness tests and Section 7 makes the conclusions of this study.

2. Data and Variables

2.1. Natural Disasters

We rely on the database from the Federal Emergency Management Agency (FEMA) to define natural disaster variables. FEMA reports natural disaster events by type, state, county, and their approved assistance amounts declared by the federal government. This enables us to define natural disasters and their magnitudes that affect individual firms and their facilities located in disaster impacted counties. We focus on four major and frequent natural disaster events related to climate change (hurricanes, severe storms, winter storms, and wildfires) and define *Disaster* as an indicator variable of natural disaster occurrence in each county-year. Additionally, *DS_amt* is defined as the aggregate amount of assistance on natural disasters for each county-year approved by FEMA. This serves as an alternative disaster variable that can also reflect the magnitudes of natural disaster impacts. Then, we use the facility registry data from the United States Environmental Protection Agency (EPA) and integrate it with the FEMA data to determine firms' facilities within the counties affected by the disaster. Finally, we match Compustat firms with FEMA-EPA disaster impacted facilities by company names to identify firms that are affected by natural disasters. Figure 1 presents the spatial map of natural disaster impacts across the U.S. mainland between 2000 and 2021. Panel A and B display the number of natural disaster events by counties for each type of disaster and the number of facilities impacted by disasters, respectively. The distributions of facilities impacted by each disaster closely mirror those of affected counties, indicating a well-defined scope for our identified disaster-affected

facilities.[4] However, Figure 1 illustrates the substantial influence of geographical factors on disaster-affected areas. To address both geographical and seasonal variations, we aggregate data from all four types of disasters. Nevertheless, facilities in California, Florida, and New York show a higher number of disaster-impacted facilities, attributed to the greater concentration of business establishments in these states.

Figure 1. About Here

2.2. Covenant Violations and Loan Characteristics

Following Nini, Smith, and Sufi (2012), we use keyword searching algorithm to collect covenant violations reported in 10-K filings issued between 2000 and 2021. In addition to their original methods, we employ additional steps to sort out paragraphs not associated with actual covenant violations by excluding any paragraphs that include violation keywords but are related to retirements, compensations, or general descriptions of covenant terms. We define *Violation* as an indicator variable that equals one when a firm reports covenant violations during a firm-year in its 10-K filing.[5] 11% of violation frequency from our sample is close to those of Griffin, Nini, and Smith (2019) (12%) and Chava and Roberts (2008) (15%). Then, we use DealScan to define firm-level covenant and loan characteristic variables. DealScan collects thirteen financial covenant types for each loan-level entry, but there are three challenges in converting loan-level covenants into

[4] Some counties in California exhibit higher hurricane impacted facilities while few hurricanes affect. This is due to 'Hurricane Katrina Evacuation' reported in the FEMA disaster database. The results remain similar after excluding this event from our sample.

[5] We utilize an indicator variable, consistent with Nini, Smith, and Sufi (2012). Information on covenant violations is only available through MD&A, footnotes, or supplementary data, making it extremely difficult to trace the history of individual loan contracts that violates covenants. Therefore, the indicator may be the best estimate of firms' covenant violations or defaults of loan contracts.

firm-level. First, not all loan entries have every covenant variable observed. Debt-to-cash flow ratio is the most frequently reported covenant variable (73%), while only 12% of loan entries have non-missing tangible net worth ratio covenants. Moreover, each loan entry has different sets of covenant variables, making it difficult to understand how firm-level covenants change by year. Therefore, we calculate the maximum (minimum) value of each financial covenant variable based on all outstanding loans within a given firm-year to define firm-level covenant characteristics. Maximum (minimum) covenant values represent the most lenient and optimistic views of lenders toward their borrowers, and these views are likely to change quickly to reflect any realized risks associated with borrowers.[6] Second, DealScan records initial levels of covenant terms and their subsequent changes, but it is unclear when such changes take effect. Therefore, we only use the initial values of these covenants and exclude the following amended values. Third, since not all firms initiate new loans every year, many firm-year level observations would be dropped from the sample if we only considered firms with new loans each year. Thus, we match each loan until its maturity across all firm-years and define aggregate firm-level loan characteristics based on all outstanding loans that have not yet matured in our analyses. Additionally, we conduct our analyses using change values in loan terms, as they provide a better measure of how lenders respond to borrowers' natural disaster risks. The change values can also mitigate the base-level differences in loan characteristics among various firms in our sample.

DebtCF represents the maximum debt-to-cash flow ratio covenant among all outstanding loans within each firm-year. *DebtCF* reflects the firms' ability to repay debt

[6] In unreported analyses, we test averages of each financial covenant and find similar but less significant results compared to the maximum (minimum).

given cash flows, and lenders require borrowers to maintain target *DebtCF* levels until maturity. Higher debt-to-cash flow covenants indicate that borrowers are allowed to carry heavier debt loads, thereby reducing lenders' control rights. We focus on the maximum debt-to-cash flow covenants because they represent the least stringent covenant values, and lenders tend to adjust them quickly when firms face increased risks. We also calculate the minimum fixed charge coverage ratio covenants (*FixCost*) across all outstanding loans, which measure the borrowers' ability to generate sufficient cash flow to meet their principal and interest payments. The higher the *FixCost* covenants, the more secure lenders are, as they offer higher ratios for stricter covenants. Additionally, we define a leverage-related covenant as the maximum tangible net worth amount covenants (*TanNW*).[7] Tangible net worth refers to equities but excluding intangible assets. Lenders use this metric to assess borrowers' actual net worth and their abilities to repay debts. A higher *TanNW* indicates stricter covenants. For loan characteristics, we compute *LoanAmt* as the sum of outstanding loan amounts and *Margin* as the weighted average of loan margins over LIBOR base rates. *BankDebt* represents the bank debt ratio over total assets. These metrics serve to capture both the scale and cost aspects of risk exposure for borrowers.

Figure 2 exhibits the time trends of covenant violations (*Violation*), debt-to-cash flow ratio covenants (*DebtCF*), and loan margins (*Margin)* between firms impacted by disasters and non-impacted firms over the sample periods. From all three plots, we do not observe significant differential time trends between two groups. This tells us that macroeconomic factors do not affect differently to firms' covenant violations and loan terms regardless of

[7] We also tested other covenant and loan term variables including senior debt-to-cash flow ratio, interest cost coverage ratio, net worth, number of loans, number of lenders, and maturity. These variables are not significant as their values mostly remain stable. Number of lenders decrease when firms have disaster impacts while other loan terms are not affected by disaster impacts.

their disaster impacts. $DebtCF_{t+1}$ continuously increases during the sample periods, suggesting that lenders are providing less strict covenants over the years. This aligns with the findings of Griffin, Nini, and Smith (2019) that argue decline in loan covenant restrictions in recent years.[8] Loan margin levels are influenced by macro-financial events such as the 2008 global financial crisis or the Federal Reserve's interest rate policies. Interestingly, Figure 2 shows that, on average, non-disaster impacted firms receive stricter loan terms than disaster impacted firms. Since base-level loan terms highly depend on firms' idiosyncratic factors, we use change values of loan terms in the main analyses to address this issue.

Figure 2. About Here

2.3. Firms' Capabilities to Access Funds

We employ three firm characteristics that are associated with firms' capabilities to access funds. First, following Farre-Mensa and Ljungqvist (2016), we define *KZ*, *WW*, *HP*, *Payout* as our financial constraint measures and set firms with indexes below medians as non-constrained (high group) and financially constrained (low group) otherwise. Campello, Graham, and Harvey (2010) find that constrained firms burned through more cash and drew more heavily on lines of credit and Dahiya, Saunders, and Srinivashan (2003) claim that banks with higher exposure to distressed firms have larger negative returns on borrowers' default or bankruptcy announcements. Therefore, financially constrained firms may find it

[8] Griffin, Nini, and Smith (2019) find that lenders have eased the restrictiveness of covenants over the last 20 years in ways that greatly reduce the ratio of false positive relative to false negatives, including by switching to covenant packages with higher signal-to-noise ratios.

more challenging to secure additional funds from banks when they experience disaster impacts, reflecting heightened attention from lenders on borrowers' climate change risks. In contrast, non-constrained firms may obtain new loans, benefiting from their better recovery capabilities.

Next, we categorize our sample by firms' ESG engagements. There is a growing trend among lenders to consider borrowers' ESG engagements in their lending policies. Flammer (2021) finds that investors respond positively to green bonds and Houston and Shan (2022) show that banks are more likely to grant loans to borrowers with strong ESG activities. While the literature presents mixed results regarding the effects of ESG engagements on firm values or corporate policies, it is evident that managers are increasingly compelled to consider ESG activities due to rising regulatory and stakeholder risks (Stroebel and Wurgler, 2021; Flammer, Toffel, and Viswanathan, 2021; Huang, Li, Lin, and McBrayer, 2022). As both creditors and firms benefit from participating in ESG activities, creditors may prefer to lend only to firms with higher ESG engagements when those firms are impacted by disasters. We use overall MSCI ESG ratings (*MSCI*) to divide the sample into groups with high and no ESG ratings. High groups have overall ESG ratings, following Lins, Servaes, and Tamayo (2017), greater than zero and no groups do not have ESG ratings reported in MSCI ESG database. Alternatively, we define environmental only MSCI ratings (*MSCI_env*), overall and environmental only ratings of Refinitiv ASSET4 (*ASSET4* and *ASSET4_env*) for robustness tests.

Lastly, we investigate whether firms' existing banking relationship also performs as a channel for lenders to assess firms after natural disaster impacts. Bharath, Dahiya, Saunders, and Srinivasan (2011) and Prilmeier (2017) find that covenant tightness is

relaxed as the banking relationships become stronger and Rosenfeld (2014) claim that relationship-backed loan significantly increases the probability of future firm emergence from distress. Furthermore, close relationships enable lenders to have better monitoring of their borrowers and minimize the information asymmetry between lenders and borrowers. Therefore, if firms have strong banking relationships, it is possible for them to have less penalized loan terms after disasters impacts. Following Bharath, Dahiya, Saunders, and Srinivasan (2011) and Prilmeier (2017), we divide the sample into firms with existing banking relationships and no relationships by *Banking_amt*, the maximum of the percentage of previously borrowed amounts arranged by the same lender. We also use the banking relationship measures of *Banking_num*, the maximum of the number of loans by each lender, and *Banking_dum*, an intensity indicator for the existence of prior lending by the same lender, to support this association.

2.4. Empirical Model

To examine lenders responses on natural disaster risks and covenant violations of borrowers, we estimate the following OLS regression model:

$$\Delta Loan_{i,t+1} = \alpha + \beta_1 Disaster_{i,t} + \beta_2 Disaster_{i,t} \times Violation_{i,t} + \beta_3 Violation_{i,t} + \boldsymbol{\Gamma}' \boldsymbol{X}_{i,t} + \text{Year FE} + \varepsilon_{i,t}. \quad (1)$$

where, for firm i and year t, $X_{i,t}$ represents a vector of firm-level control variables. In Equation (1), we employ changes in loan characteristics after natural disaster impacts as dependent variables and include only year fixed effect. Covenant terms tend to remain stable over time, and the incorporation of firm fixed effects eliminates all subtle variations in loan term changes. The variables of interest in this study are *Disaster* and *Disaster* x

Violation, which represent impacts of disasters and covenant violations caused by disasters, respectively. As control variables, we include profitability (*Profit*), leverage (*Leverage*), interest expense (*IntExp*), net worth (*NetWorth*), current ratio (*CurrentRatio*), market-to-book ratio (*MtB*), size (*Size*), and tangibility (*PPE*), following the approach outlined by Nini, Smith, and Sufi (2012). We also incorporate variables that proxy for the financing activities, investment activities, and operating performance of firms. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level to account for serial correlation of the error term within firms. We also conduct difference-in-differences tests based on propensity score matching to check robustness of our tests.

2.5. Summary Statistics

For our sample construction, we begin with all Compustat firms between 2000 and 2021, excluding those in the financial and utility industries (SIC codes 4900-4999 and 6000-6999), and then merge it with firm-level loan characteristics data from DealScan. We focus on firm-year observations that have at least one outstanding loan to investigate changes in loan characteristics. Subsequently, we incorporate FEMA disaster data and information on covenant violations extracted from 10-K text analyses, which results in a dataset comprising 22,789 firm-year observations. To further analyze our sample, we also use variables from Capital IQ, MSCI ESG ratings, and Refinitiv ASSET4 database to create subgroups within the sample. Table 1 shows the summary statistics. Panel A reports the variables of interest of natural disasters and covenant violations. On average, 59% of firm-

year observations are directly affected by natural disasters (*Disaster*).[9] As *Disaster* is an aggregate measure of different disaster types of hurricanes, severe storms, winter storms, and wildfires, it can alleviate concerns that the associations between bank loans and natural disasters are driven by seasonal and geographical factors. Although firms are widely impacted by natural disasters, only 7% of firm-year observations are severely affected, with facilities in counties where annual assistance amounts from natural disasters exceeding 1 billion U.S. dollars. 11% of the sample firms report covenant violations (*Violation*), which is close to those of Griffin, Nini, and Smith (2019) (12%) and Chava and Roberts (2008) (15%). Panel B shows loan characteristics. New loan initiations (*NewLoan*) are prevalent across firm-years as 39% firm-year exhibit new loans each firm-year. Mean (median) of debt-to-cash flow ratio covenants (*DebtCF*) is 3.37:1 (3.25:1). Importantly, 73% of the sample reports *DebtCF* but other covenant conditions are not as frequently observed as *DebtCF*, thus we focus more on *DebtCF* in our analyses. As covenants get stricter, *DebtCF* decreases, and borrowers are unable to increase debts relative to their cash-flows. *FixCost* is fixed cost coverage ratio covenants and increases as the covenants get stricter. This covenant is less volatile than *DebtCF* and has a mean (median) ratio of 1.41:1 (1.25:1). *TanNW* is the tangible net worth amount and rises as the covenants become stricter. Griffin, Nini, and Smith (2019) claims that lenders rely more on EBITDA related covenants than leverage-based ones, and we also find small numbers of *TanNW* observed in our sample. Compared to covenant characteristics, other loan terms are well-collected from DealScan. On average, firms have 1.24 billion dollars of outstanding loan amounts (*LoanAmt*)[10].

[9] We also tested alternate disaster measures to intensify disaster impacts including define disaster impacted firms if more than 30% of their facilities are affected by disasters. The results are similar to presented.
[10] This may overstate bank loan exposures as DealScan does not report the actual remaining balances of loan amounts. We also test bank debt amounts from Capital IQ to mitigate this issue.

Margin is the most important loan term variable reflecting the price that lenders appraise borrowers' risk and has a mean (median) of 1.91% (1.75%). The sample firms finance 15% of their total assets through bank loans. Panel C shows the summary statistics of firms' capabilities to access funds factors that may affect the lenders' assessments on natural disaster impacts and covenant violations of borrowers. Summary statistics of firms' capabilities to access funds factors resemble those in the reference studies. Panel D shows the summary statistics of firm characteristics used as control variables and business performance proxies. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions.

Table 1. About Here

Then, we further examine loan characteristics of high and low groups of firms based on financial constraints, ESG engagements, and banking relationships, particularly focusing on firms with covenant violations after natural disaster impacts. If our prior assumptions hold that lenders become more lenient to firms with high capabilities to access funds, we expect to observe lower loan characteristics in the high groups. We first categorize our sample into high (H) and low (L) groups using *KZ*, *MSCI*, and *Banking_amt*. We then selectively choose firms with both disaster impacts and covenant violations to examine whether lenders discriminate among these firms considering their capabilities to access additional funds. Table 2 presents the univariate t-tests for $Margin_{t+1}$ between each pair of subgroups, along with $\Delta Margin_{t+1}$, representing the log differences of $Margin_{t+1}$. $\Delta Margin_{t+1}$ offers a more comprehensive insight into lenders' responses to borrowers'

natural disaster risks. In Column (1)-(3), we find that firms with higher capabilities to access funds (H) have significantly lower $Margin_{t+1}$ compared to low groups (L) when these firms experience disaster impacts and covenant violations. This clearly indicates that lenders perceive firms with lower financial constraints, high ESG engagements, and existing banking relationships as less risky, especially during borrowers' distressed periods. Furthermore, in Column (5), we note positive and significant means of $\Delta Margin_{t+1}$ only in low groups.[11] This suggests that lenders penalize borrowers' natural disaster risks if firms have relatively lower capabilities to access funds, while not significantly requiring higher loan terms from higher groups. Overall, Table 2 supports our claim that lenders respond differently to natural disaster risks of borrowers, becoming more lenient toward firms with better recovery capabilities.

Table 2. About Here

3. Natural Disasters, Covenant Violations, and Bank Loans

Grand streams of literature examine that natural disasters and climate changes seriously affect economy and business operations. Dessaint and Mattray (2017) point out that hurricanes can trigger liquidity shocks because of the heavy damage they inflict. Massa and Zhang (2021) also find the spillover effects of Hurricane Katrina that firms shift from bond financing to bank-based borrowings. Therefore, it is natural to question whether disaster impacted borrowers are considered riskier to their lenders. Table 3 provides

[11] In unreported analyses, we repeat the same t-tests for $DebtCF_{t+1}$ and $\Delta DebtCF_{t+1}$ but the results are mixed as the levels of covenant terms are less volatile and heavily dependent on firm or industry characteristics. We also find decreasing changes in covenants, aligned with the findings of Griffin, Nini, and Smith (2019).

statistical evidence that disaster impacted firms are more likely to report covenant violations in their 10-K filings, supporting our claim that covenant violations caused by natural disasters serve as a channel that transmits borrowers' natural disaster risks to their lenders. Column (1) of Panel A shows that coefficient of *Disaster* on *Violation* is 0.015, which can be interpreted as being a disaster impacted firms would increase 13.6% (0.015/0.11) of covenant violation probability. In column (2) and (3), we run the same model with industry-year and state-year fixed effects to control for industrial and geographical factors, and the relationships still hold. We also find the strong and positive coefficients of *DS_amt* on *Violation*. Therefore, Panel A of Table 3 implies that climate change risks of borrowers can be transferred to their lenders through increasing covenant violations after natural disasters. In Table A1 in the Appendix, we also conduct panel logistic regressions of covenant violations on natural disaster impacts, as *Violation* is a binary dependent variable, and our results remain consistent. Then, we examine how firms' financial activities are being affected once they face natural disasters as disaster damages and recovery expenses are directly related to their financial health. Panel B shows that firms with disaster impacts are more likely to have decrease in changes in cash holdings (Δ*Cash*), net debt issuances (Δ*NewDebt*), and bank debt over total asset ratios (Δ*BankDebt*). This is consistent with the findings of Dessaint and Mattray (2017) and Massa and Zhang (2021), which suggest that natural disasters can lead to liquidity shocks, and this can be a reason why firms call for more covenant violations after natural disasters.[12] Overall, Table 3 suggests that natural disaster impacts deteriorate firms' financing activities, leading to an

[12] In Table A2 in the Appendix, we also find that additional debt financing activities are all adversely affected by disaster impacts. However, we do not observe a significant association with equity financing or payout policies. One possible explanation is that managers of disaster impacted firms may avoid providing a negative signal to their shareholders and the market.

increase in covenant violations caused by natural disasters. Creditors may consider these violations as horrifying signals, as they propagate corporate borrowers' climate change risks to them.

Table 3. About Here

Next, we examine how lenders respond to borrowers that are affected by natural disasters. Given that disaster impacts increase the probability of covenant violations by firms, it can be inferred that lenders may demand stricter monitoring or lending terms on their new loans to disaster impacted borrowers. Table 4 shows how covenant and loan terms change in the following years after disaster impacts. The dependent variables in Panel A include changes in debt-to-cash flow ratio ($\Delta DebtCF$), fixed cost coverage ratio ($\Delta FixCost$), and log differences in tangible net worth amount ($\Delta TanNW$). From Column (1) of Panel A, *Disaster* is negatively and highly significantly correlated with $\Delta DebtCF_{t+1}$, which implies that having natural disaster impacts increases debt-to-cash flow ratio covenants in the following years by 23% (0.007/0.031). Coefficients of $\Delta FixCost_{t+1}$ and $\Delta TanNW_{t+1}$ also support that covenants are getting stronger after natural disasters. Column (4)-(6) of Panel A replicate the same regressions with *DS_amt*, and their coefficients are also positive and significant. This indicates that bank loan conditions are also affected by the magnitude of disaster impacts. Our finding in Panel A tells us that lenders require much stricter monitoring tools to disaster impacted firms once they provide new loans or amend existing loan terms.

Panel B shows the impact of natural disasters on loan characteristics in the following

years. In Column (1), we examine whether the amount of outstanding loans changes (Δ*LoanAmt*) after disasters and find that loan amounts significantly decrease after disaster impacts. This can be interpreted as lenders still providing loans to disaster impacted borrowers but managing their exposure to borrowers' climate change risks by reducing loan amounts per new loans by 32% (0.018/0.057). Moreover, lenders demand higher loan margins (Δ*Margin)*, and there is a decrease in bank loan ratios (Δ*BankDebt*), aligning with the findings of Correa, He, Herpfer, and Lel (2022). Column (4)-(6) also consistently present the same results from *DS_amt*. Therefore, Panel B indicates that lenders reduce their exposures to disaster impacted borrowers and charge higher risk prices on their loans.[13] Overall, Panel A and B provide strong evidence that lenders change their lending behaviors following borrowers' natural disaster impacts by imposing stronger covenant and loan terms to enhance their monitoring on borrowers' climate risks.

Then, we address how lenders view covenant violations caused by natural disasters. Although disasters are expected to seriously damage corporate business and cause covenant violations, it is also possible that firms have strong fundamentals to get through these impacts shortly. When lenders consider this and allow firms to have time for recovering, they may accept firms' waiver requests on covenant violations and not impose stricter loan conditions. This is consistent with Griffin, Nini, and Smith (2019), which argue that lenders do not prefer to take control over their covenant violating borrowers as it is not always beneficial for lenders to take further steps to rehabilitate or sell down borrowers' assets. On the contrary, lenders may perceive such covenant violations as harmful and horrifying signals, leading them to offer much less favorable loan terms to firms experiencing both

[13] Unreported results find that loan initiations and number of loans are not affected after natural disasters, which can be interpreted as lenders still provide loans to disaster impacted firms but with stricter monitoring.

disaster impacts and covenant violations. Panel C examines the question of how lenders respond to covenant violations caused by natural disasters. In Panel C, we extend our analyses by incorporating *Violation* and *Disaster* x *Violation* to investigate whether lenders impose additional penalties on disaster impacted borrowers when they also violate covenants. While the main effects of *Disaster* still survive, we find no significant correlations from *Violation* and *Disaster* x *Violation* across all our covenant and loan characteristic variables. This corresponds to the possibility that lenders may not consistently view borrowers' covenant violations seriously but consider other factors before implementing stricter actions. In the next chapter, we delve into the potential factors that influence lenders' assessments of firms experiencing both natural disaster impacts and covenant violations.

Table 4. About Here

4. Disasters, Violations, and Capabilities to Access Funds

Literature widely examines factors that affect bank loan conditions including macroeconomic components (Bae and Goyal, 2009), financial industries and institutions (Lim, Minton, and Weisbach, 2014, Schwert, 2018), credit cycle or shocks (Carvalho, Gao, and Ma, 2023), Ivashina and Scharfstein, 2010), and corporate policies and firm characteristics (Erel, 2011, Chava, Livdan, and Purnanandam, 2009, Saunders and Steffen, 2011). In our study, we specifically concentrate on firms' capabilities to access funds as key factors that influence lenders' assessments of firms' covenant violations caused by natural disasters. This allows us to narrow the scope of this research to borrower-side

variations. We explore three possible channels that can explain lenders' different responses to natural disasters and covenant violations: financial constraints, ESG engagements, and banking relationships of borrowers.

First, the literature finds that lending to financially constrained firms negatively affect banks share price reactions (Dahiya, Saunders, and Srinivashan, 2003), and therefore, lenders may apply even more stricter loan conditions when constrained borrowers get disaster impacted and violate covenants. Following Farre-Mensa and Ljungqvist (2016), we define *KZ*, *WW*, *HP*, and *Payout* financial constraint measures, and set firms with indexes above medians as financially constrained and non-constrained otherwise. In Panel A of Table 5, we examine the differential impact of covenant violations caused by natural disasters on the financing activities of non-constrained and financially constrained groups. In Column (1) and (5), we find that *Disaster* is positively associated with *Violation* only in financially constrained groups, which seems obvious that constrained groups are more vulnerable to disaster impacts. While Δ*Cash* decreases in both non-constrained and financially constrained groups, Δ*NewDebt* and Δ*BankDebt* drops only in constrained groups. This implies that natural disaster impacts result in further deterioration of the financial health of constrained groups. Coefficients of *Violation* and *Disaster* x *Violation* are not significant in non-constrained groups as disaster-driven covenant violations are less likely to harm these firms' fundamental. Overall, the results in Panel A clearly demonstrate that financially constrained borrowers become much riskier to lenders than non-constrained groups when facing disaster impacts. This implies that lenders will require stronger risk management over constrained firms after natural disasters. In Panel B, we investigate how firms' financial constraints influence loan and covenant conditions after

natural disasters and covenant violations. In Column (1)-(4), we observe positive and significant coefficients of *Disaster* and *DS_amt* on both $\Delta DebtCF_{t+1}$ and $\Delta Margin_{t+1}$, but only in non-constrained groups, reflecting their heightened attention to borrowers' natural disaster risks. More interestingly, in Column (3) and (4) coefficients of *Disaster* x *Violation* and *DS_amt* x *Violation* are negative and significant on $\Delta Margin_{t+1}$, which can be interpreted as lenders do not penalize non-constrained groups when they suffer from disaster-driven covenant violations. Instead, coefficient of *Disaster* x *Violation* on $\Delta Margin_{t+1}$ is positive in constrained groups in Column (7), supporting the notion that lenders express more concerns about the climate change risks of constrained groups. These suggest the possibility that lenders only provide additional loans to non-constrained groups but with stricter loan terms, while restricting new credit supplies to financially constrained groups,[14] reflecting their enhanced management on borrowers' climate change risks. In Panel C, we employ alternative measures to validate the association between financial constraints and disaster impacts. Panel C shows that our findings hold similarly with WW index and dividend payout ratios constraint measures.[15] Coefficients of *Disaster* and *Disaster* x *Violations* only consistently significant among non-constrained groups that again supports our claims that lenders respond differently to natural disaster risks of corporate borrowers by their financial constraints. In sum, Table 5 tells us that creditors use firms' financial constraints as a channel to assess their natural disaster impacts and covenant violations.

[14] Unreported results find that new loan amounts decrease significantly in constrained group and that constrained groups also exhibit stricter loan terms once they have new loans in the following years.
[15] Results of constrained groups also show similar with these alternative financial constraint measures.

Table 5. About Here

Next, we explore whether ESG engagements influence lenders' evaluations of borrowers experiencing covenant violations caused by disasters. As ESG becomes more important in business activities and capital markets also emphasize green financing, firms with active ESG engagements have better access to these funds. Houston and Shan (2022) investigate creditors' preference for high ESG-rated borrowers and find that banks are more likely to grant loans to borrowers with ESG profiles. Therefore, it is reasonable to assume that lenders punish highly ESG-rated firms less. Table 6 explores whether firms' ESG engagements can be a channel that distinguishes firms after natural disasters and covenant violations. We use MSCI ESG ratings to divide the sample into groups with high and no ESG ratings. High groups have *MSCI*, following Lins, Servaes, and Tamayo (2017), greater than zero and no groups do not have ESG ratings reported in MSCI ESG database. Panel A shows how ESG engagements are associated with natural disasters, covenant violations, and financing activities. Both high and no ESG-rated groups exhibit no significant effects of *Disaster* on *Violation*. However, in Column (6)-(8), we find that no ESG-rated groups experience significant declines in all financing activities when they are impacted by natural disasters. This implies that no ESG-rated firms may have limited external funding access to recover from disaster impacts, compared to high rated groups. *Violation* and *Disaster* x *Violation* show no statistical significance on financing activities in both groups as covenant violations are less associated with ESG ratings. In Panel B, we examine the impacts of natural disasters and covenant violations on loan characteristics by firms' ESG engagements, and our results align with those with a financial constraint channel. In

Column (1)-(4), high ESG-rated firms exhibit significant effects of *Disaster* and *DS_amt* on both $\Delta DebtCF_{t+1}$ and $\Delta Margin_{t+1}$, indicating that lenders concern natural disaster risks of borrowers. However, coefficient of *Disaster* x *Violation* and *DS_amt* x *Violation* are again negative and significant, mitigating loan margin increase from *Disaster* and *Violation*. This provides strong evidence that lenders favor high ESG-rated firms by alleviating their penalties on disaster impacts and covenant violations. Instead, there is no statistically significant evidence that lenders provide either stricter or less monitoring on no ESG-rated groups. In Panel C, we use *MSCI_env* and *ASSET4* as alternative ESG measures, consistently finding that lenders utilize ESG engagements as a channel to evaluate firms after natural disaster impacts and covenant violations. Overall, our results in Table 6 suggest that lenders only provide additional loans to high ESG-rated firms after disasters and violations but with stricter monitoring enforced.

Table 6. About Here

Lastly, we test whether firms' banking relationship can be used in evaluating firms after covenant violations caused by disasters. Literature reveals the positive relationship between banking relationships and loan contracts. Blackwell and Winters (1997) find an inverse relation between the closeness of banking relationships and interest rates and Gopalan, Udell, and Yerramilli (2011) suggest that firms form new banking relationships to expand their access to credit. In this context, lenders might show greater leniency towards disaster impacted borrowers with established strong relationship. Table 7 examines the effectiveness of banking relationships as a channel for assessing firms affected by

disasters and covenant violations. Following Bharath, Dahiya, Saunders, and Srinivasan (2011) and Prilmeier (2017), we divide the sample into firms with existing banking relationship and no relationships by *Banking_amt*, *Banking_num*, and *Banking_dum*.[16] Panel A of Table 7 studies whether banking relationship affect the associations among disaster impacts, covenant violations, and financing activities. In Column (1) and (5), we find that only no relationship groups experience more covenant violations after natural disasters, whereas high banking relationship groups do not exhibit a significant coefficient. Additionally, no relationship groups suffer from more significant adverse effects on financing activities after disaster impacts in Column (6)-(8). This outcome could be attributed to the absence of established banking relationships, depriving them of potential benefits in raising additional funds. In Panel B, we investigate the significance of banking relationships in loan characteristics following covenant violations caused by disasters, and we find similar results to those with financial constraints and ESG engagements. We first observe that both high and no banking relationship groups experience stricter loan terms after natural disasters. As existing banking relationships are less tied to firms' intrinsic values, lenders may extend new funds for business recovery to no banking relationship groups, even though these firms experience damages from disasters. We still find negative and significant coefficients of the interaction terms of *Disaster*, *DS_amt*, and *Violation* on $\Delta Margin_{t+1}$ exclusively in high relationship groups. This provides evidence that lenders are more lenient towards covenant violations caused by disasters when their borrowers have better capabilities to access funds, consistent with Rosenfeld (2014). In Panel C, we repeat the same regressions of $\Delta Margin_{t+1}$ on disaster impacts and covenant violations using

[16] Alternatively, we define bank loan amounts over total assets or total debts to measure bank loan relationships (dependence). These measures also provide strong results.

alternate banking relationship measures (*Banking_num*, and *Banking_dum*), and the results remain consistent. Overall, Table 7 supports that banking relationships can be a channel to explain how lenders evaluate firms after covenant violations caused by natural disasters.

Table 7. About Here

5. Disasters, Violations, and Business Activities

If lenders accurately assess the effects of natural disasters on borrowers, their reactions to covenant violations caused by disasters will differ. Therefore, we investigate whether lenders' evaluations of firms after disaster impacts and covenant violations are precise. In Table 8, we examine the effects of natural disasters and covenant violations on firms' business activities. If lenders correctly differentiate firms by three capabilities to access fund factors, high groups of firms would be less affected by natural disasters and covenant violations, while low groups would experience more deterioration of their business activities. In Panel A of Table 8, we analyze changes in investment activities and operating performances after disasters and covenant violations. Overall, *Disaster* is negatively and highly significantly associated with investment activities and operating performances. In Column (1)-(3), we observe negative and significant coefficients of *Disaster* on Δ*Size*, Δ*PPE*, and Δ*CAPEX*, indicating that firms significantly reduce their investment activities after disaster impacts. Coefficients of *Disaster* x *Violation* also show negative associations with investment activities, suggesting that lenders strictly restrict borrowers' new investment decisions once covenants are violated. In Column (5)-(8), we observe that operating performances also decrease after disaster impacts. However,

Violation and *Disaster* x *Violation* have no significant effects on operating performance since covenant violations are less related to operational activities. More interesting results come in Panel B. We conduct the same regression of Δ*PPE* on disasters and violations for both high and low groups based on our three capabilities to access fund factors. We observe that both high and low groups experience decreasing in Δ*PPE* after disaster impacts. However, only low groups exhibit negative and significant coefficients of *Disaster* x *Violation*. This indicates that investment activities of low groups suffer even more when they violate covenants even though they are caused by disaster impacts. These findings are aligned with our main analyses that lenders respond heterogeneously to covenant violations caused by disasters based on firms' recovery capabilities.[17] We find non-significant interaction coefficients for low ESG-rated groups as controversies exist in the ESG literature regarding the effects of ESG engagements on firm values and business performances. In separate analyses not included here, we find weak evidence that operating performances are also affected by natural disasters, covenant violations, and firms' capabilities to access funds. Overall, Table 8 show the differential effects of disasters and violations on borrowers' business activities and supports that lenders correctly evaluate and favor (penalize) firms by their recovery capabilities after covenant violations caused by natural disasters.

Table 8. About Here

6. Robustness Tests

[17] In unreported results, we also find consistent results from other investment activity proxies.

We perform two robustness tests to support our claims that lenders do not always penalize borrowers' covenant violations caused by natural disasters. First, we investigate whether our findings still hold for each natural disaster type. We use an aggregate measure of *Disaster* to accommodate geographical and seasonal differences of disaster types. Nonetheless, there is a possibility that lenders consider them differently when evaluating the climate change risks of borrowers, given that the frequency, persistence, severity, seasonality, and geography of natural disasters vary by each type. Therefore, we extend our examinations by focusing on individual disaster types to address such concerns. In Table 9, we define *Hurricane*, an indicator variable if a firm has facilities in hurricane affected counties. Similarly, we define *SevereStorm*, *WinterStorm*, and *Wildfire*, respectively. We explore the impacts of covenant violations caused by disasters on $\Delta DebtCF_{t+1}$ and $\Delta Margin_{t+1}$ within high groups based on financial constraints, ESG engagements, and banking relationships. In Panel A, we find that coefficients of individual disaster types on both $\Delta DebtCF_{t+1}$ and $\Delta Margin_{t+1}$ are positive and significant, indicating that lenders provide stricter loan terms to non-constrained groups after disaster impacts. Additionally, we find negative and significant coefficients of *Disaster* x Violation, which is again consistent with the results observed with *Disaster*. In Panel A, the results demonstrate that loan margins of non-constrained firms increase after each type of disasters impact. However, lenders somehow alleviate such loan margin increments when these firms also violate covenants caused by disasters.[18] Panel B and C replicate the same analyses for high ESG-rated and high banking relationship groups, yielding comparable results. Overall, Table 9 supports our claims that lenders refrain from penalizing every covenant violation

[18] We find consistent results with the main findings when analyzing lower groups (financially constrained, no ESG-rated, and no banking relationship).

caused by disasters, showing forbearance when firms are financially non-constrained, highly ESG-rated, and have strong existing banking relationships is still valid with individual natural disaster measures.

Table 9. About Here

Next, we proceed with our second set of robustness tests to investigate whether this effect is exclusive to firms with direct disaster impacts. If lenders also consider non-affected but adjacent firms to disaster-hit areas as highly risky and provide stricter loan contracts, it becomes challenging to assert that lenders can distinguish firms after disasters and violations. Therefore, we conduct difference-in-differences tests to examine whether borrowers directly impacted by natural disasters experience more covenant violations and receive stricter loan contracts in the following years. We focus on the three most disastrous hurricanes that affected the U.S. mainland after 2000: Katrina (2005), Sandy (2012), and Harvey (2017). We define firms with facilities in the disaster affected counties as treatment groups and set firms with similar hurricane risks but not affected by these hurricanes as control groups. Control firms are located either in the same states but not in the disaster impacted counties (adjacent counties) or in the Gulf Coast states with no hurricane impacts. Then, we apply the propensity score matching on size, market-to-book, industry, and year to find at most three closest matched firms within control groups. We perform difference-in-difference tests and examine parallel trend assumptions of covenant violations, debt-to-cash flow ratio covenants, and loan margins in the following years. Figure 3 presents the linear-trend model graphs of *Violation*, *DebtCF* and *Margin* between treatment and control

groups. We find that parallel trend assumptions are held in all three plots before the hurricanes. After the events we find that time-trends of *Violation*, *DebtCF*, and *Margin* fluctuate together between treatment and control groups, but gaps become wider in all three plots after disaster events.[19] As the probability of covenant violations of treated groups increases after disasters, *DebtCF* and *Margin* also remain higher for them compared to control firms. This tells us that lenders respond differently to the directly impacted firms right after hurricane impacts. Even though such differential effect survives in only a few years, parallel trends after hurricanes imply that lenders consider natural disaster risk of firms in the same areas similarly. In sum, Figure 3 supports our claim that lenders respond differently to natural disaster risks of borrowers.

Figure 3. About Here

Additionally, we explore the potential for endogenous treatment effects of natural disaster occurrences. While we address geographical and seasonal variations in natural disasters by utilizing our aggregate measure of *Disaster*, there may be alternative factors driving lenders' responses to the natural disaster risks of borrowers and their covenant violations. In the Appendix, we examine survivorship bias in our sample selection, confounding and latent variables that may influence our findings, conduct placebo tests, and employ Heckman correction and endogenous treatment regressions to correct bias stemming from non-randomly selected disaster affected samples. All our results remain consistent, indicating that *Disaster* effectively mitigates concerns regarding the

[19] Unreported parallel-trend tests and the average treatment effect on the treated (ATET) estimates support parallel-trend assumptions and significant disaster impacts on treated groups after hurricanes.

endogenous treatment effect of natural disasters.

7. Conclusion

This study investigates the propagation of borrowers' climate change risks to their lenders and lenders' non-uniform responses to these risks. Specifically, we use covenant violations caused by natural disasters as a channel that transmit borrowers' natural disaster risks to lenders. We provide empirical evidence about why lenders do not always exercise their step-in rights after borrowers' covenant violations but allow certain groups of firms to cure themselves by exploiting the impacts of natural disasters on covenant violations and loan contracts. We find that natural disaster impacts result in more covenant violations and stricter loan terms in the following years. However, such relationships are held differently by borrowers' financial constraints, ESG engagements, and banking relationships. We find that lenders continue to provide additional funds only to firms with higher capabilities to access funds after disasters but with stricter monitoring, reflecting their heightened concerns on borrowers' natural disaster risks. More importantly, however, lenders do not penalize these firms with covenant violations caused by natural disasters. We observe that lenders provide higher loan margins to firms that are not financially constrained, have high ESG ratings, and possess existing banking relationships. Instead, they alleviate such punishment by reducing loan margins if they also violate covenants due to disaster impacts. This supports the idea that lenders do not systematically penalize every natural disaster risk of borrowers but become lenient to firms with better recovery capabilities. We also examine business activities of borrowers after natural disasters and covenant violations to investigate if these different assessments of lenders to borrowers'

natural disaster risks are accurate, and we find supporting results. This study contributes to the grand stream of literature in debt contracts and covenant violations. Our findings are consistent with Freudenberg, Imbierowicz, Saunders, and Steffen (2017) and Roberts and Sufi (2009) that loan terms get worse after covenant violations and further explain that such relationships do not hold if covenant violations are driven by external or unexpected events. This can answer questions why creditors consider not all covenant violations as horrifying signals and sometimes support borrowers by providing additional loans but with stricter loan terms. This research also supports the literature in climate change risks and natural disasters in corporate finance. The literature examines how creditors react to climate changes or natural disasters (Huynh, Nguyen, and Truong, 2020, Correa, He, Herpfer, and Lel, 2022), yet it mainly focuses loan pricings to study disaster impacts. We reveal that covenant violations caused by natural disasters serve as a channel that propagates natural disaster risks from borrowers to lenders. This research further explains how loan contracts are affected by borrowers' disaster impacts by investigating various loan and covenant characteristics and incorporating covenant violations. Lastly, we provide more generalized analyses of the impacts of natural disasters by employing an aggregate measure of these events, addressing geographical and seasonal variations. Our analyses also offer a more accurate identification of business disruptions caused by natural disasters by defining firms impacted by disasters based on their facility locations.

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Appendix. Variable Definitions

Variable	Description
Disaster	Natural disaster impact indicator that is equal to one if a firm has facilities in disaster affected areas, declared by FEMA, and zero otherwise. We use the FEMA database to define natural disaster events by counties including hurricanes, severe storms, winter storms, and wildfires, and combine them by counties with the facility registry data from the EPA database. Finally, we merge them with the Compustat samples based on the company names.
DS_amt	Sum of the total amounts of individual, household, housing, and public assistance for natural disaster impacts by counties, approved by FEMA (Bil$).
Violation	Covenant violation indicator that is equal to one if a firm reports covenant violations in 10-Ks and zero otherwise. Following Nini, Smith, and Sufi (2012), we use keyword searching algorithm to collect covenant violations from 10-Ks and employ further steps to sort out paragraphs that are associated with retirements, compensations, or general descriptions of covenant terms.
Hurricane	Hurricane impact indicator that is equal to one if a firm is affected by hurricanes, declared by FEMA, and zero otherwise. Similarly, we define SevereStorm, WinterStorm, and Wildfire.
NewLoan	New loan initiations indicator that is equal to one if a firm has new loans and zero otherwise. We use the Roberts DealScan-Compustat Liniking Database.
DebtCF	Max debt to cash flow ratio among all outstanding loans given a firm-year. We first reshape package- or facility-level loans from DealScan into firm-year level by expanding them from start to maturity dates. Then, we find maximum, minimum, or weighted average of covenant and loan characteristics from all outstanding loans given firm-years to define firm-year level characteristics.
FixCost	Min fixed cost coverage ratio among all outstanding loans
TanNW	Tangible net worth amounts among all outstanding loans
LoanAmt	Sum of all outstanding loan amounts (bil$)
Margin	Weighted average of loan margins from all outstanding loans (%)
BankDebt	Bank debt ratios (from CapitalIQ). bdbt / at

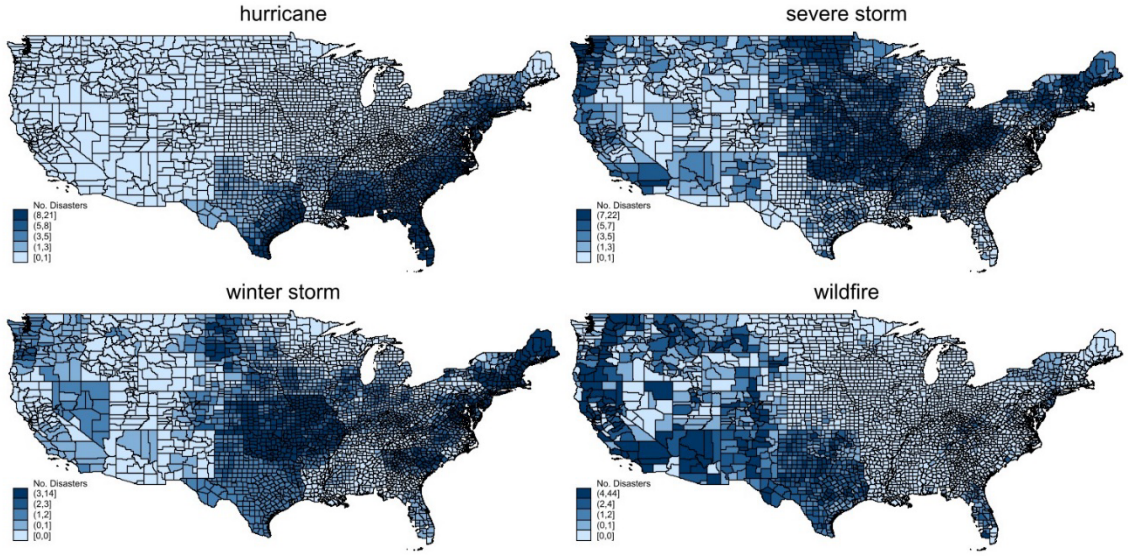
KZ	KZ index from Kaplan and Zingales (1997)
WW	WW index from Whited and Wu (2006)
HP	HP index from Hadlock and Pierce (2010)
Payout	Dividends and share repurchases. (dvp+dvc+prstkc) / oibdp
MSCI	Overall ESG scores following Lins, Servaes, and Tamayo (2017)
MSCI_env	Environmental ESG scores following Lins, Servaes, and Tamayo (2017)
ASSET4	Overall ESG scores from Refinitiv ASSET4
ASSET4_env	Environmental ESG scores from Refinitiv ASSET4
Banking_amt	Maximum of the percentage of previously borrowed amounts arranged by the same lender from Bharath, Dahiya, Saunders, Srinivasan (2011)
Banking_num	Maximum of the number of loans by each lender from Bharath, Dahiya, Saunders, Srinivasan (2011)
Banking_dum	Banking relationship intensity dummy for the existence of prior lending by the same lender from Bharath, Dahiya, Saunders, Srinivasan (2011)
Cash	Cash holdings. che / at
NewDebt	Net debt issuance. (dltis-dltr) / at
CAPEX	Capital expenditure. capx / at
Acquisi	Acquisition expense. aqc / at
Sale	Natural log of sales. ln(sale+1)
Opcost	Operating costs. (sale-oibdp) / at
ROE	Return on equities. oibdp / ceq
Profit	Profitability (return on assets). oibdp / at
Leverage	Market leverage. (dlc+dltt) / (prcc_f*csho - (at-lt+txditc) + at)
IntExp	Interest expense scaled by total asset. xint / at
NetWorth	Net worth ratio. seq / at
CurrentRatio	Current ratio. act / lct

MtB	Market-to-book ratio. (prcc_f*csho - (at-lt+txditc) + at) / at
Size	Natural log of total assets. ln(at+1)
PPE	Tangibility. ppent / at

Figure 1. Natural Disaster Impacts across the U.S. counties

This figure presents the spatial maps of natural disaster impacts across the U.S. mainland between 2000 and 2021. Panel A shows the frequency of disaster impacts by counties for each type of disaster, declared by the FEMA. Counties with more frequent disaster impacts during the sample period are represented by darker colors. Panel B shows the frequency of disasters impacted facilities by counties for each type of disaster.

Panel A: Frequency of disaster impacts by counties



Panel B: Frequency of disaster impacted facilities by counties

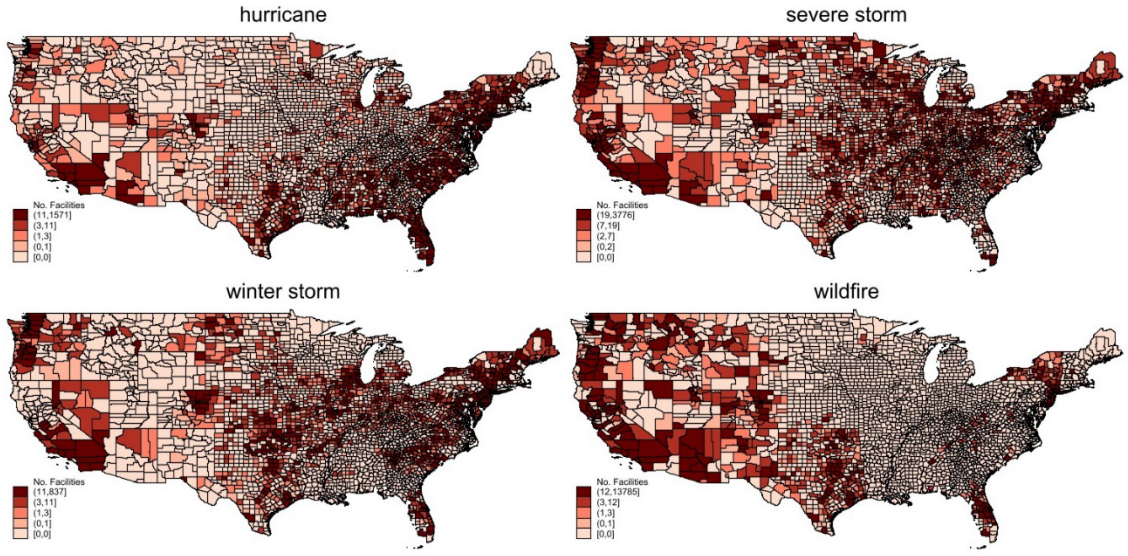


Figure 2. Time Trends of Covenant Violations and Loan Terms

This figure presents the time trends of covenant violations (*Violation*), debt-to-cash flow ratios (*DebtCF*) and the weighted average of outstanding loan margins (*Margin*) between disaster impacted firms (solid red lines) and non-impacted firms (dashed blue lines). Disaster impacted firms are defined as firms that have facilities in disaster affected counties (hurricanes, severe storms, winter storms, and wildfires) declared by FEMA.

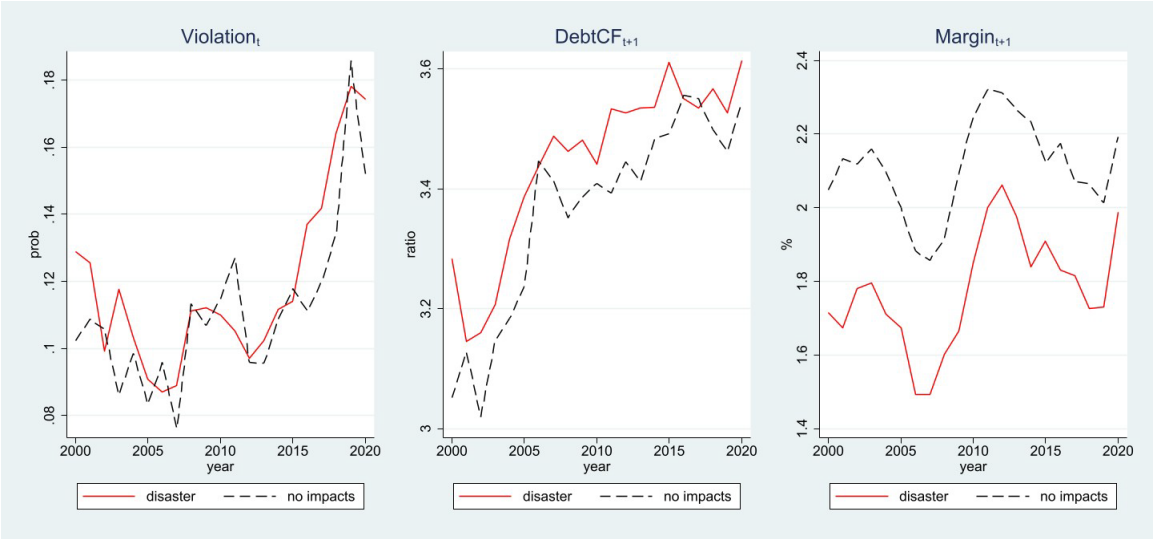


Figure 3. Hurricane Impacts on Loan Contracts of Similarly Risky Firms

This figure presents the time trends of covenant violations (*Violation*), debt-to-cash flows ratios (*DebtCF*), and loan margins (*Margin*) of firms affected by the three most disastrous hurricanes landed on the U.S. mainland (Katrina 2005, Sandy 2012, and Harvey 2017). We first determine the disaster impacted counties by these hurricanes and define firms with facilities in these areas as treatment groups (solid red lines). We set firms with facilities in adjacent counties but not directly affected by these hurricanes as control groups (dashed blue lines). Then, we apply the propensity score matching on size, market-to-book, industry, and year to find three closest matching firms.

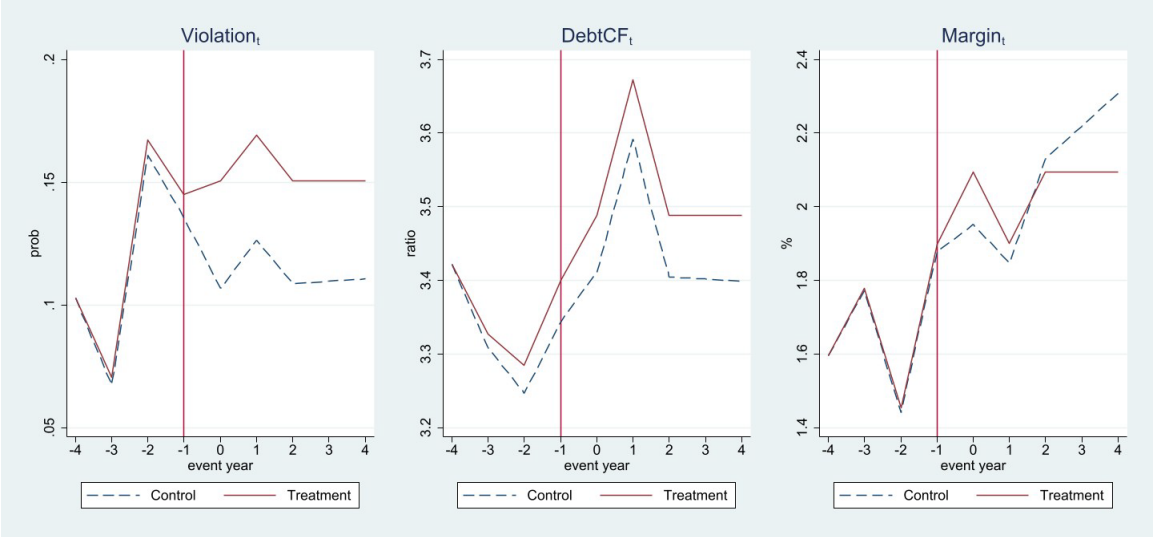


Table 1. Summary Statistics

This table presents the summary statistics of variables used in this research. Panel A and B exhibit the variables of interest and loan characteristics. Panel C shows the summary statistics of financial constraint, ESG engagement, and banking relationship measures, and Panel D for firm characteristics. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions.

Panel A. Natural Disaster and Covenant Violation

	Count	Mean	SD	P1	P25	P50	P75	P99
Disaster	22789	0.59	0.49	0.00	0.00	1.00	1.00	1.00
DS_amt (bil$)	22789	0.30	0.91	0.00	0.00	0.01	0.17	5.03
Violation	22789	0.11	0.31	0.00	0.00	0.00	0.00	1.00

Panel B. Loan Characteristics

	Count	Mean	SD	P1	P25	P50	P75	P99
NewLoan	22789	0.39	0.49	0.00	0.00	0.00	1.00	1.00
DebtCF	16667	3.37	1.03	1.25	2.75	3.25	4.00	6.50
FixCost	9947	1.41	0.53	0.75	1.10	1.25	1.50	3.50
TanNW	2728	0.25	0.65	0.00	0.03	0.09	0.22	2.40
LoanAmt (bil$)	22789	1.24	2.07	0.01	0.15	0.50	1.40	11.36
Margin (%)	22788	1.91	1.05	0.19	1.12	1.75	2.50	5.12
BankDebt	16947	0.15	0.17	0.00	0.02	0.10	0.22	0.74

Panel C. Financial Constraints, ESG Engagements, and Banking Relationships

	Count	Mean	SD	P1	P25	P50	P75	P99
KZ	22701	0.04	30.90	-8.74	-0.43	0.42	1.22	6.70
WW	22722	-0.40	2.85	-0.98	-0.47	-0.39	-0.31	0.32
Payout	16395	0.53	0.50	0.00	0.00	1.00	1.00	1.00
MSCI	12220	-0.03	0.83	-1.59	-0.50	-0.05	0.29	2.77
MSCI_env	12220	0.05	0.18	-0.33	0.00	0.00	0.00	0.69
ASSET4	6455	0.28	0.25	0.00	0.00	0.27	0.48	0.82
Banking_amt	3882	0.18	0.23	0.00	0.04	0.09	0.21	1.00
Banking_num	3882	0.27	0.24	0.05	0.12	0.17	0.33	1.00
Banking_dum	22789	0.08	0.28	0.00	0.00	0.00	0.00	1.00

Panel D. Firm Characteristics

	Count	Mean	SD	P1	P25	P50	P75	P99
Cash	22787	0.10	0.11	0.00	0.02	0.06	0.14	0.52
NewDebt	21441	0.01	0.11	-0.26	-0.03	-0.00	0.04	0.39
Capex	22748	0.06	0.06	0.00	0.02	0.03	0.06	0.36
Acquisi	21810	0.04	0.08	-0.00	0.00	0.00	0.03	0.36
Sale	22789	7.04	1.58	3.46	6.00	7.02	8.08	10.70
Opcost	22789	1.06	0.87	0.08	0.49	0.85	1.37	4.23
ROE	22768	0.32	1.17	-3.50	0.17	0.28	0.43	5.39
Profit	22789	0.12	0.11	-0.18	0.08	0.12	0.17	0.39
Leverage	22789	0.22	0.18	0.00	0.08	0.18	0.32	0.76
IntExp	22789	0.02	0.03	0.00	0.01	0.01	0.03	0.11
NetWorth	22789	0.39	0.31	-0.55	0.28	0.43	0.56	0.86
CurrentRatio	22789	2.00	1.29	0.33	1.21	1.71	2.43	6.88
MtB	22789	1.70	1.22	0.64	1.09	1.41	1.94	5.97
Size	22789	7.11	1.64	3.32	6.01	7.10	8.19	10.82
PPE	22789	0.30	0.24	0.02	0.11	0.22	0.44	0.90

Table 2. Univariate Tests of Loan Margins after Disasters and Violations

This table presents the t-tests for differences in means of loan margins between subgroups of firms with disaster impacts and covenant violations. The sample is divided into high and low groups by financial constraint (*KZ*), ESG rating (*MSCI*), and banking relationship (*Banking_amt*) measures. *Margin* is the weighted average of outstanding loan margins and Δ*Margin* is the log differences of *Margin*. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Margin_{t+1}$			$\Delta Margin_{t+1}$		
	Disaster & Violation sample					
	High (H)	Low (L)	Diff	High (H)	Low (L)	Diff
Fin Const (H: non vs L: const)	1.384***	2.073***	-0.689***	0.013	0.026***	-0.013
	43.27	54.60	-13.75	1.45	3.57	-1.09
ESG (H: high vs L: no)	1.521***	1.644***	-0.123**	0.003	0.016	-0.012
	33.63	40.38	-1.99	0.38	1.51	-0.86
Banking (H: high vs L: no)	1.600***	1.776***	-0.176**	0.008	0.022***	-0.014
	24.20	61.16	-2.57	0.75	3.38	-0.93

Table 3. Natural Disasters and Covenant Violations

This table presents the impact of natural disasters on covenant violations. Panel A shows the regression of covenant violations on natural disaster variables. The dependent variable is *Violation*, an indicator variable that is equal to one if a firm reports covenant violations in its 10-K filings. The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires) and *DS_amt*, the log of disaster assistance amounts approved by the FEMA. The dependent variables in Panel B are changes in cash holdings (Δ*Cash*), net debt issuances (Δ*NewDebt*), and bank debt ratios (Δ*BankDebt*) that are proxies of firms' financing activities. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Natural Disasters and Covenant Violations

	(1)	(2)	(3)	(4)	(5)	(6)
				$Violation_t$		
$Disaster_t$	0.015**	0.016**	0.013**			
	(2.38)	(2.57)	(2.01)			
DS_amt_t				0.003**	0.003**	0.003**
				(2.56)	(2.45)	(2.47)
$Profit_t$	-0.061**	-0.059**	-0.069***	-0.061**	-0.059**	-0.069***
	(-2.44)	(-2.16)	(-2.68)	(-2.44)	(-2.16)	(-2.68)
$Leverage_t$	0.127***	0.131***	0.124***	0.126***	0.131***	0.124***
	(4.73)	(4.65)	(4.44)	(4.72)	(4.64)	(4.43)
$IntExp_t$	0.048	0.112	0.092	0.045	0.110	0.091
	(0.40)	(0.87)	(0.73)	(0.37)	(0.86)	(0.72)
$NetWorth_t$	-0.017	-0.020	-0.014	-0.017	-0.020	-0.014
	(-1.36)	(-1.53)	(-1.06)	(-1.37)	(-1.53)	(-1.08)
$CurrentRatio_t$	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(-1.50)	(-1.42)	(-1.59)	(-1.49)	(-1.41)	(-1.58)
MtB_t	-0.006*	-0.005*	-0.005	-0.006*	-0.005*	-0.005
	(-1.73)	(-1.76)	(-1.60)	(-1.71)	(-1.75)	(-1.59)
$Size_t$	0.002	0.007	0.005	0.002	0.007	0.005
	(0.32)	(0.99)	(0.82)	(0.30)	(0.97)	(0.81)
PPE_t	-0.046	-0.016	-0.044	-0.045	-0.015	-0.043
	(-1.29)	(-0.43)	(-1.22)	(-1.27)	(-0.42)	(-1.19)
R-squared	0.400	0.435	0.424	0.400	0.435	0.424
N	22565	22474	22411	22565	22474	22411
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Year	Industry x Year	State x Year	Year	Industry x Year	State x Year

Panel B. Natural Disasters and Financing Activities

	(1) $\Delta Cash_t$	(2) $\Delta NewDebt_t$	(3) $\Delta BankDebt_t$	(4) $\Delta Cash_t$	(5) $\Delta NewDebt_t$	(6) $\Delta BankDebt_t$
$Disaster_t$	-0.005***	-0.007***	-0.005**			
	(-3.91)	(-2.83)	(-2.16)			
DS_amt_t				-0.001***	-0.001**	-0.001**
				(-2.81)	(-2.50)	(-2.17)
$Profit_t$	-0.004	-0.049***	-0.044**	-0.004	-0.049***	-0.044**
	(-0.36)	(-2.62)	(-2.44)	(-0.38)	(-2.62)	(-2.44)
$Leverage_t$	0.006	0.203***	0.164***	0.006	0.203***	0.164***
	(0.69)	(8.36)	(7.29)	(0.69)	(8.35)	(7.27)
$IntExp_t$	-0.114**	-2.449***	-1.548***	-0.113**	-2.447***	-1.548***
	(-2.08)	(-6.97)	(-5.36)	(-2.06)	(-6.97)	(-5.36)
$NetWorth_t$	-0.004	-0.122***	-0.077***	-0.004	-0.122***	-0.077***
	(-0.59)	(-5.29)	(-4.70)	(-0.58)	(-5.29)	(-4.71)
$CurrentRatio_t$	0.017***	0.007***	0.001	0.017***	0.007***	0.001
	(10.41)	(3.98)	(0.69)	(10.38)	(3.94)	(0.67)
MtB_t	0.011***	0.007***	0.006	0.011***	0.007***	0.006
	(4.86)	(3.22)	(1.53)	(4.85)	(3.19)	(1.51)
$Size_t$	0.002***	-0.005***	-0.003***	0.002***	-0.005***	-0.003***
	(5.12)	(-5.07)	(-3.19)	(4.89)	(-4.99)	(-3.12)
PPE_t	0.000	0.005	-0.004	-0.000	0.004	-0.004
	(0.02)	(0.69)	(-0.70)	(-0.06)	(0.67)	(-0.70)
R-squared	0.072	0.056	0.078	0.072	0.056	0.078
N	22748	20595	14024	22748	20595	14024
FE			Year			

Table 4. Natural Disasters, Covenant Violations, and Bank Loans

This table presents the impact of natural disasters on covenant and loan characteristics. Panel A shows the regression of changes in covenant conditions in the following years of disaster impacts. The dependent variables are changes in debt-to-cash flow ratios (Δ*DebtCF*), fixed cost coverage ratios (Δ*FixCost*), and log differences in tangible net worth ratios (Δ*TanNW*). To facilitate coefficient interpretation, Δ*DebtCF* is multiplied by (-1). The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires) and *DS_amt*, log of disaster assistance amounts approved by the FEMA. The dependent variables in Panel B are log differences in sum of outstanding loan amounts (Δ*LoanAmt*), weighted average of outstanding loan margins (Δ*Margin*), and changes in bank debt ratios (Δ*BankDebt*). Panel C exhibits the interaction effects of *Disaster* and *Violation* on covenant and loan characteristics. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Natural Disasters and Covenant Terms

	(1) $\Delta DebtCF_{t+1}$	(2) $\Delta FixCost_{t+1}$	(3) $\Delta TanNW_{t+1}$	(4) $\Delta DebtCF_{t+1}$	(5) $\Delta FixCost_{t+1}$	(6) $\Delta TanNW_{t+1}$
$Disaster_t$	0.007**	0.004**	0.009*			
	(2.01)	(2.28)	(1.77)			
DS_amt_t				0.001	0.001**	0.002*
				(1.58)	(2.50)	(1.92)
$Profit_t$	-0.002	0.020**	0.081***	-0.002	0.019**	0.081***
	(-0.11)	(2.53)	(3.85)	(-0.12)	(2.51)	(3.89)
$Leverage_t$	-0.045***	-0.004	-0.032	-0.045***	-0.004	-0.031
	(-2.78)	(-0.72)	(-1.42)	(-2.76)	(-0.66)	(-1.37)
$IntExp_t$	-0.111	0.044	0.029	-0.112	0.045	0.030
	(-0.88)	(0.87)	(0.15)	(-0.88)	(0.88)	(0.15)
$NetWorth_t$	-0.032***	-0.005	0.006	-0.032***	-0.005	0.006
	(-3.44)	(-1.11)	(0.32)	(-3.43)	(-1.09)	(0.38)
$CurrentRatio_t$	0.004***	0.000	-0.003*	0.004***	0.000	-0.003*
	(2.97)	(0.51)	(-1.85)	(3.02)	(0.56)	(-1.86)
MtB_t	-0.006***	0.001*	0.000	-0.006***	0.001*	0.000
	(-2.82)	(1.85)	(0.01)	(-2.79)	(1.89)	(0.03)
$Size_t$	-0.003**	-0.000	-0.001	-0.003**	-0.000	-0.001
	(-2.56)	(-0.26)	(-0.40)	(-2.47)	(-0.42)	(-0.54)
PPE_t	0.010	0.001	0.009	0.011	0.001	0.009
	(1.36)	(0.35)	(0.88)	(1.41)	(0.36)	(0.85)
R-squared	0.025	0.015	0.023	0.025	0.015	0.024
N	14394	8374	2133	14394	8374	2133
FE	Year					

Panel B. Natural Disasters and Loan Terms

	(1) $\Delta LoanAmt_{t+1}$	(2) $\Delta Margin_{t+1}$	(3) $\Delta BankDebt_{t+1}$	(4) $\Delta LoanAmt_{t+1}$	(5) $\Delta Margin_{t+1}$	(6) $\Delta BankDebt_{t+1}$
$Disaster_t$	-0.018***	0.008***	-0.005**			
	(-2.99)	(2.91)	(-2.24)			
DS_amt_t				-0.002**	0.001***	-0.001*
				(-2.00)	(2.60)	(-1.93)
$Profit_t$	0.173***	-0.079***	0.036*	0.173***	-0.079***	0.036*
	(4.18)	(-4.97)	(1.88)	(4.17)	(-4.98)	(1.88)
$Leverage_t$	-0.075**	0.001	-0.093***	-0.075**	0.001	-0.094***
	(-2.55)	(0.05)	(-6.82)	(-2.55)	(0.09)	(-6.84)
$IntExp_t$	-0.004	-0.463***	0.449***	-0.000	-0.464***	0.449***
	(-0.02)	(-4.01)	(3.22)	(-0.00)	(-4.02)	(3.22)
$NetWorth_t$	0.051***	-0.040***	0.031***	0.051***	-0.040***	0.031***
	(2.93)	(-4.66)	(3.24)	(2.93)	(-4.65)	(3.23)
$CurrentRatio_t$	-0.005*	-0.000	-0.001	-0.005**	0.000	-0.001
	(-1.91)	(-0.04)	(-0.85)	(-1.98)	(0.01)	(-0.88)
MtB_t	0.007	-0.001	0.002	0.007	-0.001	0.002
	(1.10)	(-0.47)	(0.76)	(1.09)	(-0.45)	(0.74)
$Size_t$	0.004**	0.006***	-0.002***	0.004*	0.006***	-0.002***
	(1.96)	(6.11)	(-2.79)	(1.82)	(5.97)	(-2.74)
PPE_t	0.039***	0.006	0.020***	0.038***	0.006	0.020***
	(3.28)	(1.15)	(3.97)	(3.21)	(1.18)	(3.94)
R-squared	0.059	0.069	0.051	0.058	0.069	0.050
N	20327	20324	13905	20327	20324	13905
FE			Year			

Panel C. Natural Disasters, Covenant Violations, and Bank Loans

	(1) $\Delta LoanAmt_{t+1}$	(2) $\Delta DebtCF_{t+1}$	(3) $\Delta Margin_{t+1}$	(4) $\Delta LoanAmt_{t+1}$	(5) $\Delta DebtCF_{t+1}$	(6) $\Delta Margin_{t+1}$
$Disaster_t$	-0.019***	0.009**	0.008***			
	(-2.99)	(2.34)	(2.97)			
$Disaster_t$ x $Violation_t$	0.010	-0.014	-0.005			
	(0.49)	(-1.25)	(-0.58)			
DS_amt_t				-0.002**	0.001*	0.001***
				(-2.04)	(1.74)	(2.74)
DS_amt_t x $Violation_t$				0.002	-0.001	-0.001
				(0.45)	(-0.63)	(-0.79)
$Violation_t$	-0.005	-0.001	0.004	-0.004	-0.006	0.004
	(-0.32)	(-0.13)	(0.54)	(-0.27)	(-0.78)	(0.68)
R-squared	0.059	0.025	0.069	0.058	0.025	0.069
N	20327	14394	20324	20327	14394	20324
Control			Yes			
FE			Year			

Table 5. Disasters, Violations, and Financial Constraints

This table divides the sample into non-constrained and financially constrained groups, based on *KZ*, *WW*, and *Payout*, and presents the impact of covenant violations caused by natural disasters on loan characteristics of each group. The dependent variables in Panel A are covenant violations (*Violation*), changes in cash holdings (Δ*Cash*), net debt issuances (Δ*NewDebt*), and bank debt ratios (Δ*BankDebt*) that are proxies of firms' financing activities. Changes in debt-to-cash flow ratios (Δ*DebtCF*) and log differences in weighted average of outstanding loan margins (Δ*Margin*) are used in Panel B and C. To facilitate coefficient interpretation, Δ*DebtCF* is multiplied by (-1). The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires), *DS_amt*, log of disaster assistance amounts approved by the FEMA, and the interaction effects of *Disaster*, *DS_amt*, and *Violation*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Disasters, Violations, Financing Activities, and Financial Constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$
	Non-constrained				Financially constrained			
$Disaster_t$	0.007	-0.005**	-0.003	-0.003	0.020**	-0.005***	-0.009**	-0.007*
	(0.79)	(-2.25)	(-0.87)	(-1.01)	(2.36)	(-3.05)	(-2.06)	(-1.79)
$Disaster_t$ x $Violation_t$		-0.004	-0.005	0.003		0.012**	-0.011	-0.002
		(-0.42)	(-0.46)	(0.40)		(2.06)	(-0.68)	(-0.14)
$Violation_t$		0.002	0.004	0.001		-0.011**	0.016	0.021**
		(0.30)	(0.47)	(0.21)		(-2.35)	(1.31)	(2.12)
$Profit_t$	-0.017	-0.082**	-0.075**	-0.143***	-0.055**	0.008	-0.042*	-0.029*
	(-0.24)	(-2.52)	(-2.17)	(-2.87)	(-1.97)	(0.73)	(-1.83)	(-1.77)
$Leverage_t$	0.045	0.004	0.484***	0.373***	0.077**	0.011	0.158***	0.117***
	(0.67)	(0.21)	(9.69)	(7.44)	(2.36)	(1.43)	(6.05)	(5.21)
$IntExp_t$	-0.274	-0.128	-4.305***	-2.828***	0.151	-0.089*	-2.135***	-1.380***
	(-0.38)	(-0.75)	(-8.79)	(-3.85)	(1.24)	(-1.67)	(-5.69)	(-4.71)
$NetWorth_t$	-0.078	-0.006	-0.117***	-0.065***	-0.006	-0.008	-0.120***	-0.081***
	(-1.59)	(-0.52)	(-4.78)	(-3.79)	(-0.51)	(-1.04)	(-4.08)	(-4.42)
$CurrentRatio_t$	-0.004	0.017***	0.005***	0.001	-0.005	0.016***	0.008**	-0.001
	(-0.83)	(7.16)	(2.87)	(0.48)	(-0.88)	(7.80)	(2.32)	(-0.30)
MtB_t	-0.012**	0.018***	0.014***	0.021***	-0.005	0.007***	0.006**	0.001
	(-1.97)	(4.85)	(4.69)	(4.16)	(-1.31)	(3.52)	(2.02)	(0.43)
$Size_t$	-0.014	0.001*	-0.009***	-0.005***	0.017*	0.003***	-0.004***	-0.002
	(-1.29)	(1.72)	(-7.05)	(-4.29)	(1.84)	(5.31)	(-2.61)	(-1.61)
PPE_t	-0.068	-0.010**	0.002	0.000	-0.047	0.012***	0.013	-0.007
	(-1.00)	(-2.16)	(0.28)	(0.02)	(-0.98)	(3.55)	(1.26)	(-0.95)
R-squared	0.377	0.086	0.088	0.115	0.505	0.064	0.058	0.080
N	10953	11356	10134	6494	10920	11344	10414	7502
Measure				KZ				
FE	Firm/Yr	Year	Year	Year	Firm/Yr	Year	Year	Year

Panel B. Disasters, Violations, Bank Loans, and Financial Constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$		$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$	
	Non-constrained				Financially constrained			
$Disaster_t$	0.013**		0.014***		0.005		0.002	
	(2.50)		(3.16)		(0.86)		(0.68)	
$Disaster_t$ x $Violation_t$	-0.018		-0.028**		-0.011		0.019*	
	(-1.03)		(-2.10)		(-0.65)		(1.73)	
DS_amt_t		0.002**		0.002***		0.000		0.001
		(2.37)		(2.78)		(0.16)		(0.78)
DS_amt_t x $Violation_t$		-0.001		-0.005**		-0.002		0.003
		(-0.28)		(-2.35)		(-0.51)		(1.54)
$Violation_t$	-0.002	-0.010	0.017	0.015	-0.002	-0.003	-0.010	-0.008
	(-0.22)	(-0.98)	(1.64)	(1.62)	(-0.12)	(-0.29)	(-1.29)	(-1.04)
R-squared	0.026	0.025	0.080	0.080	0.029	0.028	0.063	0.063
N	7088	7088	10220	10220	7243	7243	10029	10029
Measure	KZ							
Control	Yes							
FE	Year							

Panel C. Alternative Financial Constraint Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Margin_{t+1}$							
	Non-constrained				Financially constrained			
$Disaster_t$	0.015***		0.019***		-0.001		0.008*	
	(3.53)		(3.62)		(-0.24)		(1.79)	
$Disaster_t$ x $Violation_t$	-0.024*		-0.046***		0.019*		0.013	
	(-1.81)		(-2.75)		(1.76)		(0.90)	
DS_amt_t		0.003***		0.003***		-0.000		0.001
		(3.36)		(3.25)		(-0.46)		(0.76)
DS_amt_t x $Violation_t$		-0.004*		-0.008***		0.004*		0.003
		(-1.86)		(-2.68)		(1.94)		(1.04)
$Violation_t$	0.017	0.014	0.021	0.015	-0.009	-0.008	0.009	0.009
	(1.49)	(1.43)	(1.59)	(1.31)	(-1.15)	(-1.16)	(0.84)	(0.96)
R-squared	0.092	0.092	0.104	0.104	0.052	0.052	0.064	0.064
N	10522	10522	7021	7021	9743	9743	7747	7747
Measure	WW		Payout		WW		Payout	
Control	Yes							
FE	Year							

Table 6. Disasters, Violations, and ESG Engagements

This table divides the sample into high ESG-rated and no ESG-rated groups, based on *MSCI*, *MSCI_env*, and *ASSET4*, and presents the impact of covenant violations caused by natural disasters on loan characteristics of each group. The dependent variables in Panel A are covenant violations (*Violation*), changes in cash holdings (Δ*Cash*), net debt issuances (Δ*NewDebt*), and bank debt ratios (Δ*BankDebt*) that are proxies of firms' financing activities. Changes in debt-to-cash flow ratios (Δ*DebtCF*) and log differences in weighted average of outstanding loan margins (Δ*Margin*) are used in Panel B and C. To facilitate coefficient interpretation, Δ*DebtCF* is multiplied by (-1). The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires), *DS_amt*, log of disaster assistance amounts approved by the FEMA, and the interaction effects of *Disaster*, *DS_amt*, and *Violation*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Disasters, Violations, Financing Activities, and ESG Engagements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$
	High ESG-rated				No ESG-rated			
$Disaster_t$	0.013	-0.008***	-0.001	0.002	0.010	-0.005**	-0.010**	-0.011***
	(0.82)	(-2.77)	(-0.21)	(0.47)	(0.90)	(-2.00)	(-2.26)	(-2.74)
$Disaster_t$ x $Violation_t$		0.009	-0.006	-0.016		0.001	-0.010	0.014
		(0.90)	(-0.27)	(-1.13)		(0.10)	(-0.68)	(1.11)
$Violation_t$		-0.009	0.005	0.020		0.000	0.014	0.003
		(-1.12)	(0.25)	(1.56)		(0.07)	(1.22)	(0.37)
$Profit_t$	0.039	-0.037	-0.118***	-0.098***	-0.195**	0.006	-0.046	-0.071**
	(0.37)	(-1.26)	(-3.08)	(-2.85)	(-2.34)	(0.29)	(-1.42)	(-2.26)
$Leverage_t$	0.239*	0.022	0.376***	0.341***	0.065	0.006	0.293***	0.287***
	(1.67)	(1.32)	(5.83)	(6.70)	(0.91)	(0.52)	(8.65)	(9.64)
$IntExp_t$	0.799	-0.717***	-6.036***	-3.728***	0.621	-0.312**	-4.143***	-2.527***
	(0.64)	(-3.03)	(-8.12)	(-6.98)	(1.39)	(-2.48)	(-8.89)	(-6.56)
$NetWorth_t$	-0.096	-0.042**	-0.212***	-0.088***	-0.047	-0.030***	-0.187***	-0.075***
	(-1.06)	(-2.35)	(-5.18)	(-5.26)	(-0.91)	(-2.60)	(-6.59)	(-3.78)
$CurrentRatio_t$	-0.020	0.017***	0.011***	0.002	-0.004	0.019***	0.009***	-0.001
	(-1.61)	(6.16)	(3.43)	(1.04)	(-0.55)	(6.31)	(2.68)	(-0.81)
MtB_t	-0.009	0.006***	0.011***	0.013***	-0.013	0.012***	0.012***	0.015***
	(-1.21)	(3.12)	(3.16)	(4.38)	(-1.27)	(5.24)	(4.48)	(4.56)
$Size_t$	-0.030	0.002*	-0.009***	-0.008***	0.001	0.003***	-0.010***	-0.007***
	(-1.17)	(1.83)	(-3.69)	(-4.69)	(0.08)	(3.83)	(-6.14)	(-4.13)
PPE_t	-0.154	-0.003	-0.005	-0.016	0.025	0.002	0.004	-0.012
	(-1.29)	(-0.70)	(-0.41)	(-1.58)	(0.28)	(0.39)	(0.43)	(-1.34)
R-squared	0.488	0.075	0.095	0.127	0.416	0.086	0.077	0.107
N	3872	4139	3863	2923	7769	8072	7267	5243
Measure				MSCI				
FE	Firm/Yr	Year	Year	Year	Firm/Yr	Year	Year	Year

Panel B. Disasters, Violations, Bank Loans, and ESG Engagements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$		$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$	
	High ESG-rated				No ESG-rated			
$Disaster_t$	0.014**		0.014**		0.004		0.011**	
	(2.20)		(2.32)		(0.65)		(2.11)	
$Disaster_t$ x $Violation_t$	0.003		-0.041***		-0.018		0.002	
	(0.17)		(-2.75)		(-0.90)		(0.11)	
DS_amt_t		0.002*		0.002*		0.000		0.001
		(1.72)		(1.90)		(0.37)		(1.08)
DS_amt_t x $Violation_t$		0.002		-0.006**		0.001		0.000
		(0.52)		(-2.25)		(0.19)		(0.16)
$Violation_t$	-0.006	-0.009	0.031***	0.020*	-0.008	-0.020	-0.008	-0.008
	(-0.37)	(-0.64)	(2.61)	(1.90)	(-0.56)	(-1.62)	(-0.59)	(-0.68)
R-squared	0.029	0.028	0.123	0.123	0.022	0.022	0.084	0.084
N	2574	2574	3859	3859	5500	5500	7485	7485
Measure	MSCI							
Control	Yes							
FE	Year							

Panel C. Alternative ESG Engagement Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Margin_{t+1}$							
	High ESG-rated				No ESG-rated			
$Disaster_t$	0.016		0.016***		0.010**		0.004	
	(1.58)		(3.04)		(2.29)		(1.27)	
$Disaster_t$ x $Violation_t$	-0.047*		-0.032**		-0.004		0.006	
	(-1.75)		(-2.27)		(-0.28)		(0.54)	
DS_amt_t		0.003*		0.002*		0.001		0.001*
		(1.83)		(1.84)		(0.83)		(1.74)
DS_amt_t x $Violation_t$		-0.007*		-0.005*		-0.000		0.000
		(-1.77)		(-1.88)		(-0.07)		(0.10)
$Violation_t$	0.023	0.013	0.012	0.006	0.003	0.001	0.001	0.004
	(1.04)	(0.74)	(1.05)	(0.56)	(0.24)	(0.08)	(0.14)	(0.57)
R-squared	0.137	0.137	0.094	0.093	0.078	0.078	0.064	0.064
N	2340	2340	6007	6007	9004	9004	14317	14317
Measure	MSCI_env		ASSET4		MSCI_env		ASSET4	
Control	Yes							
FE	Year							

Table 7. Disasters, Violations, and Banking Relationships

This table divides the sample into high banking relationship and no relationship groups, based on *Banking_amt*, *Banking_num*, and *Banking_dum*, and presents the impact of covenant violations caused by natural disasters on loan characteristics of each group. The dependent variables in Panel A are covenant violations (*Violation*), changes in cash holdings (Δ*Cash*), net debt issuances (Δ*NewDebt*), and bank debt ratios (Δ*BankDebt*) that are proxies of firms' financing activities. Changes in debt-to-cash flow ratios (Δ*DebtCF*) and log differences in weighted average of outstanding loan margins (Δ*Margin*) are used in Panel B and C. To facilitate coefficient interpretation, Δ*DebtCF* is multiplied by (-1). The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires), *DS_amt*, log of disaster assistance amounts approved by the FEMA, and the interaction effects of *Disaster*, *DS_amt*, and *Violation*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Disasters, Violations, Financing Activities, and Banking Relationships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$	$Violation_t$	$\Delta Cash_t$	$\Delta NewDebt_t$	$\Delta BankDebt_t$
	High banking relationship				No relationship			
$Disaster_t$	0.017	-0.006	-0.003	-0.008	0.013*	-0.006***	-0.008***	-0.005**
	(0.77)	(-1.45)	(-0.40)	(-0.91)	(1.95)	(-3.76)	(-2.71)	(-2.00)
$Disaster_t$ x $Violation_t$		-0.006	0.003	0.015		0.006	-0.009	-0.000
		(-0.26)	(0.11)	(0.59)		(1.18)	(-0.86)	(-0.02)
$Violation_t$		0.004	-0.007	0.009		-0.005	0.011	0.010*
		(0.19)	(-0.34)	(0.44)		(-1.28)	(1.43)	(1.71)
$Profit_t$	-0.098*	-0.068*	-0.094**	-0.058	-0.075***	0.009	-0.038*	-0.041**
	(-1.65)	(-1.90)	(-2.57)	(-1.41)	(-2.71)	(0.83)	(-1.84)	(-2.23)
$Leverage_t$	0.135	0.051*	0.336***	0.362***	0.131***	-0.001	0.179***	0.142***
	(1.59)	(1.96)	(6.82)	(6.98)	(4.50)	(-0.13)	(7.13)	(6.49)
$IntExp_t$	0.265	-0.266*	-3.985***	-3.524***	0.015	-0.102*	-2.203***	-1.369***
	(0.42)	(-1.75)	(-7.80)	(-5.74)	(0.11)	(-1.72)	(-6.04)	(-5.02)
$NetWorth_t$	0.063	0.005	-0.225***	-0.126***	-0.024*	-0.007	-0.107***	-0.072***
	(1.06)	(0.29)	(-5.45)	(-4.03)	(-1.83)	(-0.92)	(-4.64)	(-4.46)
$CurrentRatio_t$	-0.005	0.023***	0.021***	0.012**	-0.005	0.016***	0.004***	-0.001
	(-0.51)	(4.47)	(3.51)	(2.37)	(-1.48)	(9.61)	(2.67)	(-0.90)
MtB_t	0.030*	0.028***	0.016***	0.017***	-0.006*	0.008***	0.006***	0.005
	(1.85)	(3.95)	(3.30)	(3.32)	(-1.66)	(4.86)	(2.66)	(1.32)
$Size_t$	-0.033*	0.005***	-0.011***	-0.008***	0.008	0.002***	-0.004***	-0.003***
	(-1.80)	(3.64)	(-4.04)	(-3.15)	(1.14)	(4.27)	(-4.40)	(-2.77)
PPE_t	-0.210*	0.013*	0.069***	0.021	-0.046	-0.002	-0.009	-0.008
	(-1.89)	(1.67)	(3.40)	(1.20)	(-1.15)	(-0.83)	(-1.40)	(-1.41)
R-squared	0.544	0.103	0.111	0.170	0.421	0.071	0.051	0.070
N	2843	3865	3467	2024	18614	18883	17128	12000
Measure				Banking_amt				
FE	Firm/Yr	Year	Year	Year	Firm/Yr	Year	Year	Year

Panel B. Disasters, Violations, Bank Loans, and Banking Relationships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$		$\Delta DebtCF_{t+1}$		$\Delta Margin_{t+1}$	
	High banking relationship				No relationship			
$Disaster_t$	-0.001		0.018***		0.011**		0.006*	
	(-0.15)		(3.01)		(2.57)		(1.94)	
$Disaster_t$ x $Violation_t$	0.008		-0.047**		-0.019		0.004	
	(0.25)		(-2.32)		(-1.46)		(0.43)	
DS_amt_t		-0.000		0.003***		0.002**		0.001*
		(-0.07)		(2.63)		(2.00)		(1.73)
DS_amt_t x $Violation_t$		0.001		-0.010***		-0.002		0.001
		(0.15)		(-2.91)		(-0.73)		(0.34)
$Violation_t$	-0.018	-0.015	0.025	0.025*	0.002	-0.004	-0.001	-0.000
	(-0.76)	(-0.79)	(1.58)	(1.81)	(0.26)	(-0.45)	(-0.12)	(-0.01)
R-squared	0.023	0.023	0.068	0.068	0.031	0.031	0.072	0.072
N	2425	2425	3610	3610	11969	11969	16714	16714
Measure	Banking_amt							
Control	Yes							
FE	Year							

Panel C. Alternative Banking Relationship Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Margin_{t+1}$							
	High banking relationship				No relationship			
$Disaster_t$	0.018***		0.032***		0.006*		0.006**	
	(3.01)		(3.73)		(1.94)		(2.07)	
$Disaster_t$ x $Violation_t$	-0.047**		-0.049*		0.004		-0.001	
	(-2.32)		(-1.76)		(0.43)		(-0.16)	
DS_amt_t		0.003***		0.005***		0.001*		0.001**
		(2.63)		(2.73)		(1.73)		(1.98)
DS_amt_t x $Violation_t$		-0.010***		-0.012**		0.001		-0.000
		(-2.91)		(-2.34)		(0.34)		(-0.18)
$Violation_t$	0.025	0.025*	0.031	0.035*	-0.001	-0.000	0.002	0.002
	(1.58)	(1.81)	(1.47)	(1.79)	(-0.12)	(-0.01)	(0.24)	(0.27)
R-squared	0.068	0.068	0.083	0.083	0.072	0.072	0.069	0.069
N	3610	3610	1796	1796	16714	16714	18528	18528
Measure	Banking_num		Banking_dum		Banking_num		Banking_dum	
Control	Yes							
FE	Year							

Table 8. Disasters, Violations, and Business Activities

This table presents the impact of natural disasters and covenant violations on firms' business activities. We follow Nini, Smith, and Sufi (2012) to define dependent variables used. The dependent variables are log differences in total assets (Δ*Size*), property, plant, and equipment (Δ*PPE*), sales (Δ*Sale*), changes in capital expenditures (Δ*CAPEX*), and acquisitions (ΔA*cquisi*), operating incomes (Δ*profit*), operating costs (Δ*Opcost*), and return on equity (Δ*ROE*). In Panel B, we divide the sample into high and low groups, based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Disasters, Violations, and Business Activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Size_t$	ΔPPE_t	$\Delta CAPEX_t$	$\Delta Acquisi_t$	$\Delta Profit_t$	$\Delta Sale_t$	$\Delta Opcost_t$	ΔROE_t
$Disaster_t$	-0.019***	-0.018***	-0.003***	-0.001	-0.004**	-0.019***	-0.001	-0.003
	(-4.40)	(-4.21)	(-3.54)	(-0.59)	(-2.35)	(-4.79)	(-0.09)	(-0.33)
$Disaster_t$ x $Violation_t$	-0.018	-0.032***	-0.002	-0.014**	0.004	-0.001	-0.004	0.041
	(-1.54)	(-2.62)	(-0.95)	(-1.99)	(1.14)	(-0.10)	(-0.31)	(1.57)
$Violation_t$	0.011	0.017*	0.001	0.012**	-0.003	-0.001	0.004	-0.047**
	(1.14)	(1.74)	(0.55)	(2.24)	(-1.11)	(-0.15)	(0.35)	(-2.12)
$Profit_t$	0.300***	0.303***	0.039***	-0.034***	0.320***	0.357***	0.094**	0.684***
	(8.96)	(8.12)	(6.79)	(-3.62)	(20.50)	(9.93)	(2.05)	(7.39)
$Leverage_t$	0.247***	0.199***	-0.001	0.113***	-0.023	0.121***	0.129***	0.046
	(7.04)	(5.76)	(-0.36)	(9.11)	(-1.18)	(4.38)	(3.47)	(0.71)
$IntExp_t$	-2.685***	-2.052***	-0.158***	-1.081***	0.414***	-0.472**	-1.441***	-0.518
	(-8.37)	(-7.10)	(-5.17)	(-7.33)	(3.99)	(-2.28)	(-5.34)	(-0.77)
$NetWorth_t$	0.051**	0.063***	0.003	-0.028***	0.008	0.113***	0.073**	0.025
	(2.31)	(2.85)	(1.07)	(-3.50)	(0.56)	(6.19)	(2.51)	(0.57)
$CurrentRatio_t$	0.004	-0.003	-0.000	-0.002***	-0.001	-0.010***	-0.015***	-0.003
	(1.58)	(-1.28)	(-0.62)	(-3.00)	(-0.87)	(-5.02)	(-6.95)	(-0.80)
MtB_t	0.025***	0.021***	0.002***	0.006***	0.002	0.019***	0.023***	0.010
	(3.65)	(3.35)	(3.44)	(3.47)	(1.58)	(2.95)	(3.47)	(0.94)
$Size_t$	0.011***	0.008***	-0.001***	-0.001	-0.002***	0.006***	-0.001	0.003
	(7.38)	(5.11)	(-2.69)	(-1.19)	(-3.48)	(4.34)	(-0.29)	(0.92)
PPE_t	0.019*	0.093***	0.038***	-0.020***	0.008*	0.032***	-0.064***	-0.004
	(1.82)	(8.60)	(12.25)	(-5.49)	(1.96)	(3.05)	(-5.60)	(-0.20)
R-squared	0.132	0.119	0.076	0.028	0.157	0.160	0.080	0.027
N	22751	22748	22665	21392	22745	22751	22745	22729
FE	Year							

Panel B. Investment Activities by Capabilities to Access Funds

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔPPE_t					
	High group			Low group		
$Disaster_t$	-0.016***	-0.022***	-0.028***	-0.017***	-0.018***	-0.017***
	(-2.99)	(-2.60)	(-2.72)	(-2.78)	(-2.79)	(-3.72)
$Disaster_t$ x $Violation_t$	-0.022	-0.038	-0.015	-0.042**	-0.008	-0.035***
	(-1.33)	(-1.38)	(-0.43)	(-2.25)	(-0.46)	(-2.77)
$Violation_t$	0.014	0.020	0.009	0.028*	0.009	0.018*
	(1.09)	(0.83)	(0.34)	(1.86)	(0.70)	(1.70)
R-squared	0.110	0.155	0.146	0.178	0.096	0.123
N	11356	4139	3864	11345	8072	18884
Measure	KZ	MSCI	Banking_amt	KZ	MSCI	Banking_amt
Control	Yes					
FE	Year					

Table 9. Robustness Test – Natural Disaster Types

This table presents the regressions of changes in debt-to-cash flow ratios (Δ*DebtCF*) and log differences in loan margins (Δ*Margin*) on individual types of disasters. *Hurricane* is an indicator variable that equals to one if firm is affected by hurricanes given firm-year. *SevereStorm*, *WinterStrom*, and *Wildfire* are similarly defined to represent severe storms, winter storms, and wildfires, respectively. The sample is divided into high and low groups based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Individual Disaster Impacts and Financial Constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$				$\Delta Margin_{t+1}$			
	Non-constrained							
Type	Hurricane	SevereStorm	WinterStorm	Wildfire	Hurricane	SevereStorm	WinterStorm	Wildfire
$Type_t$	0.020***	0.012**	0.012*	0.013**	0.014**	0.014***	0.017***	0.010**
	(2.61)	(2.27)	(1.87)	(2.23)	(2.24)	(3.14)	(2.63)	(1.98)
$Type_t$ x $Violation_t$	-0.039	-0.021	-0.006	0.016	-0.027	-0.031**	-0.017	-0.029**
	(-1.37)	(-1.07)	(-0.30)	(0.85)	(-1.56)	(-2.26)	(-0.93)	(-1.97)
$Violation_t$	-0.002	-0.002	-0.002	-0.002	0.018*	0.017*	0.017*	0.017*
	(-0.22)	(-0.22)	(-0.16)	(-0.19)	(1.74)	(1.66)	(1.69)	(1.72)
R-squared	0.029	0.026	0.026	0.027	0.071	0.079	0.073	0.068
N	4559	6063	4711	5244	6398	8707	6674	7462
Control	Yes							
FE	Year							

Panel B. Individual Disaster Impacts and ESG Engagements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$				$\Delta Margin_{t+1}$			
	High ESG-rated							
Type	Hurricane	SevereStorm	WinterStorm	Wildfire	Hurricane	SevereStorm	WinterStorm	Wildfire
$Type_t$	0.000	0.016**	0.017*	0.013*	0.016**	0.015**	0.011	0.008
	(0.03)	(2.41)	(1.78)	(1.84)	(1.99)	(2.40)	(1.19)	(1.18)
$Type_t$ x $Violation_t$	0.005	0.002	-0.015	0.012	-0.062***	-0.046***	-0.024	-0.031**
	(0.21)	(0.08)	(-0.44)	(0.52)	(-4.04)	(-2.95)	(-1.15)	(-2.04)
$Violation_t$	-0.005	-0.006	-0.007	-0.007	0.032***	0.030**	0.031***	0.032***
	(-0.31)	(-0.34)	(-0.43)	(-0.45)	(2.82)	(2.57)	(2.64)	(2.82)
R-squared	0.050	0.031	0.036	0.034	0.100	0.124	0.111	0.090
N	1599	2165	1503	1845	2322	3259	2208	2742
Control	Yes							
FE	Year							

Panel C. Individual Disaster Impacts and Banking Relationships

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta DebtCF_{t+1}$				$\Delta Margin_{t+1}$			
	High banking relationship							
Type	Hurricane	SevereStorm	WinterStorm	Wildfire	Hurricane	SevereStorm	WinterStorm	Wildfire
$Type_t$	0.001	-0.006	-0.002	0.002	0.021**	0.020***	0.019**	0.021***
	(0.04)	(-0.58)	(-0.13)	(0.17)	(2.17)	(2.99)	(2.23)	(2.74)
$Type_t$ x $Violation_t$	-0.028	-0.002	0.035	0.016	-0.046*	-0.051**	-0.040	-0.052**
	(-0.52)	(-0.06)	(0.92)	(0.43)	(-1.69)	(-2.43)	(-1.43)	(-2.27)
$Violation_t$	-0.020	-0.017	-0.019	-0.020	0.023	0.024	0.024	0.024
	(-0.85)	(-0.73)	(-0.82)	(-0.84)	(1.45)	(1.50)	(1.52)	(1.51)
R-squared	0.035	0.032	0.035	0.028	0.069	0.073	0.072	0.070
N	1515	2055	1586	1746	2255	3060	2369	2596
Control	Yes							
FE	Year							

Table A1. Logistic Regression of Covenant Violations

This table presents panel logistic regressions of covenant violations on natural disaster impacts. The dependent variable is *Violation*, an indicator variable that is equal to one if a firm reports covenant violations in its 10-K filings. The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires) and *DS_amt*, the log of disaster assistance amounts approved by the FEMA. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Violation			
$Disaster_t$	0.191**	0.199**	0.216**			
	(2.15)	(2.45)	(2.36)			
DS_amt_t				0.042***	0.038**	0.049***
				(2.75)	(2.49)	(2.91)
$Profit_t$	-1.241***	-0.989***	-0.997**	-1.271***	-1.000***	-1.022**
	(-2.84)	(-3.06)	(-2.28)	(-2.91)	(-3.10)	(-2.35)
$Leverage_t$	2.269***	1.142***	1.944***	2.285***	1.154***	1.964***
	(5.64)	(3.50)	(4.67)	(5.67)	(3.53)	(4.71)
$IntExp_t$	5.069	-1.496	5.318	4.952	-1.567	5.205
	(1.58)	(-0.61)	(1.64)	(1.55)	(-0.64)	(1.61)
$NetWorth_t$	-0.456	0.032	-0.342	-0.453	0.035	-0.333
	(-1.47)	(0.14)	(-1.07)	(-1.46)	(0.15)	(-1.04)
$CurrentRatio_t$	-0.032	0.010	-0.040	-0.033	0.010	-0.042
	(-0.88)	(0.30)	(-1.10)	(-0.90)	(0.30)	(-1.14)
MtB_t	-0.057	-0.057	-0.102**	-0.056	-0.057	-0.101**
	(-1.27)	(-1.40)	(-2.18)	(-1.26)	(-1.38)	(-2.16)
$Size_t$	0.062	-0.001	0.028	0.066	-0.004	0.025
	(1.01)	(-0.03)	(0.36)	(1.07)	(-0.09)	(0.32)
PPE_t	-0.217	-1.125***	-0.736	-0.208	-1.126***	-0.736
	(-0.43)	(-4.24)	(-1.40)	(-0.41)	(-4.24)	(-1.40)
N	7525	22789	7525	7525	22789	7525
Firm FE	Yes	No	Yes	Yes	No	Yes
Year FE	No	Yes	Yes	No	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Additional Financing Activities

This table exhibits the impact of natural disasters on additional financing activities. The dependent variables are changes in leverage (Δ*Leverage*), public debt issuance (Δ*PubDebt*), private debt issuance (Δ*PvtDebt*), net equity issuance (Δ*NewEq*), total payout (Δ*Payout*), dividend payout (Δ*Dividend*), and share repurchase (Δ*Repo*) that are proxies of additional firms' financing activities. The variables of interest are *Disaster*, an indicator variable if a firm is affected by natural disasters (hurricanes, severe storms, winter storms, and wildfires). Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta Leverage_t$	$\Delta PubDebt_t$	$\Delta PvtDebt_t$	$\Delta NewEq_t$	$\Delta Payout_t$	$\Delta Dividend_t$	$\Delta Repo_t$
$Disaster_t$	-0.016***	-0.007***	-0.009***	0.001	-0.003	0.000	-0.000
	(-5.12)	(-3.71)	(-3.49)	(0.37)	(-0.53)	(1.31)	(-0.90)
$Profit_t$	-0.040	-0.010	-0.027	-0.082***	0.087***	0.002	0.021***
	(-1.47)	(-0.81)	(-1.28)	(-4.25)	(2.81)	(0.85)	(6.09)
$Leverage_t$	0.426***	0.127***	0.284***	-0.022*	-0.058**	0.000	-0.004
	(11.20)	(11.53)	(9.19)	(-1.68)	(-2.33)	(0.08)	(-1.56)
$IntExp_t$	-3.449***	-0.825***	-2.498***	0.470**	0.216	0.017	0.021
	(-7.02)	(-6.59)	(-6.50)	(2.47)	(0.69)	(0.82)	(0.94)
$NetWorth_t$	-0.136***	-0.041***	-0.091***	0.034***	0.029	0.005	0.002
	(-4.24)	(-3.86)	(-3.51)	(3.02)	(1.31)	(1.53)	(1.18)
$CurrentRatio_t$	0.007***	0.006***	-0.000	0.002	-0.001	0.000	-0.000
	(2.84)	(5.03)	(-0.26)	(1.20)	(-0.15)	(0.01)	(-0.54)
MtB_t	0.015**	0.006***	0.008*	0.008***	0.007**	0.001***	0.002***
	(2.54)	(4.44)	(1.82)	(3.33)	(2.39)	(2.81)	(2.79)
$Size_t$	0.002	0.008***	-0.006***	0.000	0.008***	0.000**	0.000***
	(1.47)	(13.11)	(-5.11)	(0.01)	(4.21)	(2.43)	(3.64)
PPE_t	0.007	0.013***	-0.009	0.019***	0.021*	0.002**	0.000
	(0.68)	(2.84)	(-1.27)	(2.93)	(1.77)	(2.44)	(0.33)
r2	0.118	0.047	0.080	0.011	0.016	0.008	0.036
N	22222	22222	22222	20413	22216	22222	20615
FE				Year			

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Survivorship Bias

This table investigates the potential for survivorship bias in our sample selection. We retain firm-year samples that persist across all our sample periods and analyze lenders' responses to covenant violations caused by disasters, based on firms' abilities to access funds. The dependent variable is the log differences in loan margins (Δ*Margin*), and we divide the sample into high and low groups, based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\Delta Margin_{t+1}$			
$Disaster_t$	0.008**	0.011**	0.004	0.014*	0.012	0.028***	0.005
	(1.99)	(1.96)	(0.60)	(1.94)	(1.57)	(3.06)	(0.94)
$Disaster_t$ x $Violation_t$	-0.021	-0.045**	0.010	-0.052***	-0.001	-0.081**	-0.007
	(-1.59)	(-2.21)	(0.67)	(-2.86)	(-0.05)	(-2.39)	(-0.51)
$Violation_t$	0.014	0.032*	-0.011	0.040***	-0.008	0.065**	0.003
	(1.27)	(1.95)	(-1.11)	(2.93)	(-0.34)	(2.40)	(0.30)
R-squared	0.097	0.107	0.092	0.164	0.107	0.099	0.102
N	9598	5481	4110	2542	3714	1558	8040
Group	All	Non FC	High FC	High ESG	No ESG	High Bank	No Bank
Control				Yes			
FE				Year			

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4. Confounding and Latent Variables

This table investigates the potential for confounding and latent variables affecting natural disaster occurrences. We incorporate fixed effects of year, state, and industry to address geographical and industrial differences in natural disaster impacts. The dependent variable is the log differences in loan margins (Δ*Margin*), and we divide the sample into high and low groups, based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\Delta Margin_{t+1}$			
$Disaster_t$	0.009***	0.014***	0.004	0.014**	0.012**	0.018***	0.007**
	(3.11)	(3.19)	(1.17)	(2.19)	(2.15)	(2.91)	(2.02)
$Disaster_t$ x $Violation_t$	-0.005	-0.028**	0.019*	-0.044***	0.002	-0.051**	0.005
	(-0.53)	(-2.10)	(1.70)	(-2.96)	(0.12)	(-2.44)	(0.54)
$Violation_t$	0.003	0.016	-0.012	0.032***	-0.008	0.028*	-0.002
	(0.45)	(1.61)	(-1.41)	(2.69)	(-0.61)	(1.71)	(-0.28)
R-squared	0.076	0.091	0.076	0.146	0.098	0.093	0.079
N	20316	10214	10024	3854	7483	3606	16705
Group	All	Non FC	High FC	High ESG	No ESG	High Bank	No Bank
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5. Placebo Test

This table investigates the efficacy of disaster treatment effects. We randomly assign disaster impacted placebo groups (*Placebo*) among non-disaster impacted firms and examine the potential placebo effect of disasters. The dependent variable is the log differences in loan margins (Δ*Margin*), and we divide the sample into high and low groups, based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\Delta Margin_{t+1}$			
$Placebo_t$	-0.003	-0.001	-0.004	-0.002	-0.008	-0.001	-0.002
	(-0.60)	(-0.09)	(-0.65)	(-0.17)	(-1.07)	(-0.10)	(-0.53)
$Placebo_t$ x $Violation_t$	0.006	0.014	-0.003	-0.016	0.011	-0.015	0.009
	(0.49)	(0.74)	(-0.17)	(-0.55)	(0.45)	(-0.54)	(0.64)
$Violation_t$	-0.001	0.010	-0.016	0.043*	-0.019	0.028	-0.005
	(-0.06)	(0.67)	(-1.39)	(1.96)	(-1.02)	(1.25)	(-0.49)
R-squared	0.063	0.073	0.075	0.106	0.095	0.115	0.056
N	8198	4120	4048	1271	2744	1427	6770
Group	All	Non FC	High FC	High ESG	No ESG	High Bank	No Bank
Control				Yes			
FE				Year			

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6. Endogenous Treatment Effects of Disasters

This table investigates the potential for endogenous treatment effect of disaster occurrences. We use the Heckman correction and endogenous treatment regressions to correct bias from non-randomly selected disaster affected samples. We first estimate the probability of disaster occurrence with state and year, and then, replace *Disaster* with *DS_hat*. The dependent variable is the log differences in loan margins (Δ*Margin*), and we divide the sample into high and low groups, based on *KZ*, *MSCI*, and *Banking_amt*. Control variables include profit, leverage, interest expense, net worth, current ratio, market-to-book, total assets, and tangibility. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distributions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\Delta Margin_{t+1}$			
DS_hat_t	0.043***	0.033	0.038*	0.052**	0.030	0.076**	0.041***
	(3.00)	(1.12)	(1.82)	(2.13)	(1.15)	(2.47)	(2.63)
DS_hat_t x $Violation_t$	-0.005	-0.028**	0.019*	-0.042***	0.002	-0.048**	0.004
	(-0.58)	(-2.11)	(1.75)	(-2.81)	(0.11)	(-2.36)	(0.44)
$Violation_t$	0.004	0.017*	-0.011	0.031***	-0.008	0.026	-0.001
	(0.55)	(1.66)	(-1.34)	(2.70)	(-0.60)	(1.64)	(-0.12)
N	20316	10217	10024	3859	7485	3610	16706
Group	All	Non FC	High FC	High ESG	No ESG	High Bank	No Bank
Control				Yes			
FE				Year			

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2.

Overvaluation, Diminishing Profitability, and Acquisitions

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Abstract:
We find that a firm is more likely to engage in acquisitions when its private information, measured by changes in purchase obligations, predicts that future profitability will fall and thus that its shares are overvalued in the current stock market. Overvalued acquirers are as likely to pay with stock as non-overvalued acquirers, suggesting that these firms do not necessarily take advantage of overvalued stock. Such acquisitions are followed by increases in profitability and generate positive announcement returns that are similar in magnitude to those generated by non-overvalued acquirers. In addition, bidding period returns on overvalued acquirers are higher than those on similarly overvalued non-acquirers. Being an overvalued acquirer is not associated with executive compensation structure or ownership, suggesting that these acquisitions are less likely to be driven by managers' private incentives. The results suggest overall that managers engage in acquisitions to boost profitability when their private information predicts diminishing profitability rather than to take advantage of overvaluation and that such acquisitions benefit shareholders.

JEL classification: G30, G32
Keywords: overvaluation, information asymmetry, M&A, profitability

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1. Introduction

Several studies on mergers and acquisitions (M&A) find that high market-to-book firms acquire low market-to-book targets using stock as a payment method (Rhodes-Kropf, Robinson, and Viswanathan, 2005; Dong, Hirshleifer, Richardson, and Teoh, 2006; Ang and Cheng, 2006). This finding is consistent with theories based on information asymmetry-driven mispricing, in which overvalued acquirers buy less overvalued targets to take advantage of the financial market's misvaluation of their firms by paying with overvalued stock (Rhodes-Kropf and Viswanathan, 2004). However, mispricing could be attributable to market irrationality (Shleifer and Vishny, 2003), and high market-to-book firms' acquisition of low market-to-book targets is also consistent with q theory, in which high q acquirers seek low q targets (Jovanovic and Rousseau, 2002). As such, because most empirical studies rely on the market price of equity when defining either q, information asymmetry-driven mispricing, or behavioral anomaly-driven mispricing, the mechanism behind such acquisitions is still unclear. The goal of this paper is to investigate whether and how information asymmetry-driven mispricing shapes corporate acquisitions by exploiting managers' private information about future performance.

As a proxy for private information about future performance, we take advantage of purchase obligations (POs) that are yet to be disclosed. Lee (2021) proposes that managers increase (decrease) POs based on their predictions regarding demand for their firms' products– that is, whether demand increases (decreases) in the near future. In addition, information regarding POs is disclosed in 10-Ks after the year-end and thus changes in POs remain private information during a given year. Therefore, changes in POs can proxy for

mispricing with respect to managers' private information. We define ΔPO^{t+1}[20] as PO^{t+1} minus lagged PO^{t+1}, in which PO^{t+1} presents POs that are due in the following year scaled by total assets.[1] [21] Negative ΔPO^{t+1} indicates decreases in forecast profitability and thus contemporaneous overvaluation. We additionally define OV^{t+1}, an indicator variable that is assigned the value of one if ΔPO^{t+1} is negative and zero otherwise. We focus on acquisitions that are completed after the fiscal year-end of acquisition announcements to ensure that we can separate acquirers' POs from targets' POs in the years of acquisition announcements. In addition, we include only acquisition announcements issued at least 6 months into the fiscal year to address the concern that acquisition decisions might be made before sufficient private information is collected.

We find that a firm is more likely to engage in acquisitions when its shares are overvalued in the current stock market. In particular, a one-standard-deviation decrease in ΔPO^{t+1} is associated with an increase in acquisition propensity of 0.3 percentage points, which accounts for approximately 7.0% of acquisition probability. Similarly, being overvalued is associated with an increase in acquisition propensity of 0.7 percentage points, which accounts for 16.3% of acquisition probability. These results are consistent with prior studies' findings that use the market value of equity to measure overvaluation. Unlike prior studies' findings, however, we do not find evidence that overvalued acquirers use stock as a method of payment. Overvalued acquirers are as likely as non-overvalued acquirers to

[20] We also define ΔPO^{rest}, which is calculated using POs that are due after t+1. Many firms do not report POs that are due after t+1, however, and the reporting varies significantly even within a firm. Therefore, in this paper we use POs that are due within one year to measure mispricing.

[21] The correlation coefficient between our measure of overvaluation and that of Rhodes-Kropf, Robinson, and Viswanathan (2005) is -0.007 and statistically insignificant.

use stock swaps for payments.[22] The result implies that firms whose private information suggests overvaluation in the current stock market do not necessarily take advantage of overvalued stock. This is consistent with Fu, Lin, and Officer's (2013) finding that the extent to which acquirers are more overvalued than their targets in stock deals is similar in magnitude to the relative overvaluation of acquirers in cash deals.

Our results suggest that a firm with declining POs engages in an acquisition to counteract diminishing profitability. In particular, ΔPO^{t+1} is positively associated with $\Delta Profit^{t+1}$, which is defined as $Profit_{t+1}$ minus $Profit_t$, in which *Profit* is operating income before depreciation scaled by total assets. However, being an acquirer more than offsets this relationship. For example, a one-standard-deviation decrease in ΔPO^{t+1} is associated with a decrease in $\Delta Profit^{t+1}$ of 0.003, but when a firm engages in acquisitions there is an additional effect–a one-standard-deviation decrease in ΔPO^{t+1} is associated with an increase in $\Delta Profit^{t+1}$ of 0.008. Similarly, being overvalued is associated with a decrease in $\Delta Profit^{t+1}$ of 0.006, but when an overvalued firm engages in acquisitions there is an additional effect of an increase in $\Delta Profit^{t+1}$ of 0.014, accounting for 13.5% of the standard deviation of $\Delta Profit^{t+1}$. As such, managers who forecast that future profitability will fall appear to engage in acquisitions to counteract declining profits.

To test whether such acquisitions benefit shareholders, we analyze stock returns around the announcement date. We find that overvalued acquirers on average earn positive and statistically significant announcement returns. In particular, three-day cumulative

[22] It is possible that our sample deals are special cases in which PO information will be disclosed before merger completion. Knowing that targets will learn about POs before completion, acquirers may choose not to rely on stock as a method of payment. However, targets may obtain acquirers' PO information even before 10-K filings, as non-disclosure and non-compete agreements reduce information asymmetry between the parties.

abnormal stock returns, CAR(-1,+1), on overvalued acquirers are, on average, 1.23%. This magnitude is similar to those on non-overvalued acquirers, which earn 1.05% and the difference is statistically insignificant. In contrast, the CAR(-1,+1) on similarly-overvalued non-acquirers are insignificant during the same three-day period. The positive announcement returns on overvalued acquirers are consistent with investors' viewing acquisitions as the products of value-enhancing corporate decisions similar to those made by non-overvalued acquirers.

We find similar results when we investigate stock returns during the bidding period, a period running from one day before a merger announcement to one day after the date of deal completion. As overvalued acquirers, by definition, will experience a loss in value, we compare their returns with those on similarly overvalued non-acquirers (Ang and Cheng, 2006). We find that overvalued acquirers earn bidding period returns of 3.22%, while similarly overvalued non-acquirers earn 0.97% during the same period. On the other hand, the bidding period returns on non-overvalued acquirers are slightly higher than those on overvalued acquirers, but the difference is statistically insignificant. The results of analyses of stock price reactions suggest that acquisitions made by overvalued acquirers are beneficial to acquirers' shareholders.

On the other hand, we find no evidence that acquisitions made when ΔPO^{t+1} is negative are associated with managers' private incentives. As such, the results suggest overall that managers engage in acquisitions to boost profitability rather than to take advantage of overvalued stock when private information predicts diminishing profitability and that such acquisitions benefit shareholders.

We contribute to the literature by showing that information asymmetry that is related to future performance plays an important role in explaining acquisitions, although acquirers do not necessarily take advantage of information asymmetry-driven overvaluation. Our results suggest that overvalued acquirers buy growth when they forecast that future performance will deteriorate, a finding that is related to Rhodes-Kropf, Robinson, and Viswanathan's (2005) finding. The authors show that although high market-to-book firms buy low market-to-book targets, this behavior is driven by firm-specific deviations from short-run average value. In particular, they find that low long-run value-to-book firms acquire high long-run value-to-book targets, suggesting that firms with few growth opportunities acquire targets that offer better long-run growth opportunities. To the extent that long-run value-to-book is closely related to managers' future performance forecasts,[23] our finding–that a firm that predicts its future profitability will fall engages in acquisitions to increase profitability–is compatible with Rhodes-Kropf, Robinson, and Viswanathan (2005). In addition, the authors state on page 584 of their paper that, "however, the fact that two countervailing effects are at work (high M/B buys low M/B, but low long-run value to book buys high long-run value to book) means that rational explanations cannot explain our findings unless it contains some element of asymmetric information as a key ingredient." We show that mispricing that is caused by information asymmetry indeed plays an important role in explaining acquisitions.

Our results are also consistent with motivations for acquisitions suggested in Jensen (1986), who argues that firms with low growth prospects use acquisitions as a way of buying growth when the market's growth expectations are overblown. Unlike Jensen's

[23] The correlation coefficient between our measure of overvaluation and long-run value-to-book of Rhodes-Kropf, Robinson, and Viswanathan (2005) is positive (0.03) and statistically significant.

(1986) suggestion, however, our results–namely that neither executive compensation nor ownership is associated with the probability of being an overvalued acquirer, that overvalued acquirers earn returns as large as those earned by non-overvalued acquirers, and that overvalued acquirers increase shareholder wealth–together suggest that these acquisitions are less likely to be driven by agency motives.

Our finding that overvalued acquirers do not necessarily use stock as a method of payment is inconsistent with results reported in several papers (Rhodes-Kropf, Robinson, and Viswanathan, 2005; Dong, Hirshleifer, Richardson, and Teoh, 2006; Ang and Cheng, 2006). Our finding is, however, consistent with recent studies that suggest that stock payments are not necessarily used by overvalued acquirers. For example, Eckbo, Makaew, and Thorburn (2018) reject the proposition that opportunistic acquirers use stock to make payments by showing that the better the target knows the acquirer the higher is the probability that equity is used as a medium of payment. de Bodt, Cousin, and Officer (2022) suggest that academics misinterpret the correlation between acquirer valuation and the use of stock as the method of payment as evidence supporting misvaluation-based theories of the method of payment. According to the authors, this is because incentives to use pooling were high for highly valued acquirers and acquirers had to pay targets fully with stock to apply for pooling. Similarly, de Bodt, Cousin, and Roll (2018) emphasize the important role the abolishment of pooling-of-interests accounting played in affecting how the method of payment for acquisitions is chosen.

Fu, Lin, and Officer (2013), on the other hand, show that high market-to-book acquirers pay higher takeover premiums than what is implied by an extrapolation of pre-bargaining market-to-book values. According to Eckbo, Makaew, and Thorburn (2018), it

is as if targets reverse-engineer initial market mispricing of acquirers, consistent with the reduction in information asymmetry between the two parties that is associated with non-disclosure and non-compete agreements. Fu, Lin, and Officer (2013) suggest that, as an alternative strategy, a firm can conduct a seasoned equity offering to take advantage of overvaluation.

The remainder of this paper proceeds as follows. In Section 2 we describe the data and present the variables we use. We present empirical results in Section 3. We conclude in Section 4.

2. Data and summary statistics

2.1. Data and variables

We obtain accounting information from Compustat. We hand collect PO information from contractual obligations sections of 10-K filings. We expand Lee's (2021) sample to all industries in the Compustat universe except for financial or utilities. We obtain mergers and acquisitions data from Refinitiv Securities Data Company Platinum Financial Securities Data (SDC) and stock-return data from the Center for Research in Security Prices (CRSP). CEO compensation data comes from the Execucomp dataset.

Our sample period is 2004-2018. We exclude any M&A deal the value of which is less than 10 million dollars. To be included in the sample, an acquirer must purchase more than a 50 percent share in a target and own a 100 percent share upon completion of an acquisition. We also restrict our sample to firms that make acquisition announcements at least 6 months into a fiscal year. This restriction addresses the concern that an M&A decision was made early in the year before a manager had collected enough private

information that is reflected in changes in POs. Lastly, an acquisition must have been completed after the fiscal year-end of the announcement year to ensure that we can measure only changes in an acquirer's POs that are not combined with those of a target. We exclude firms with missing POs.[24] We also eliminate firms with non-positive total assets and sales of less than 10 million dollars.

The variables used in the analyses are defined as follows. *M&A* is an indicator variable that is assigned the value of one for a year in which a firm makes an announcement of an acquisition and zero otherwise. ΔPO^{t+1} is calculated as PO^{t+1} minus lagged PO^{t+1}, in which PO^{t+1} is the dollar amount of POs due in the following year (t+1) scaled by assets. OV^{t+1} is an indicator variable that is assigned the value of one if ΔPO^{t+1} is negative and zero otherwise. Similarly, ΔPO^{rest} is calculated as PO^{rest} minus lagged PO^{rest}, in which PO^{rest} is the dollar amount of POs due after t+1 scaled by assets. OV^{rest} is an indicator variable that is assigned the value of one if ΔPO^{rest} is negative and zero otherwise.

$Stockpay^{100\%}$ ($Stockpay^{50\%}$) is an indicator variable that is assigned the value of one when an acquirer pays a target entirely (more than half) in stock and zero otherwise. $Stockpay^{\%}$ is the ratio of a payment in stock shares to the total payment in an acquisition deal. As explained above, we define $\Delta Profit^{t+1}$ as $Profit_{t+1}$ minus $Profit_t$, in which $Profit_t$ is return on assets computed as operating income before depreciation scaled by total assets.

We include commonly used control variables in our analysis. Firm size (*Size*) is the natural logarithm of total assets and leverage (*Leverage*) is market leverage defined as debt over the sum of debt and the market value of equity, in which the market value of equity is

[24] Alternatively, we repeat the analyses after replacing missing POs with zeros for firms that are mandated to report POs but do not. In doing so, we eliminate firms that never report POs during the entire sample period. All results remain qualitatively the same.

the number of shares outstanding times price of a share of stock. Tobin's Q (*Q*) is the sum of debt and the market value of equity scaled by total assets. Sales growth (*SalesGrowth*) is defined as sales minus lagged sales scaled by lagged sales. *Capex* is capital expenditures scaled by total assets. *R&D* is research and development expenses scaled by total assets. Cash holdings (*Cash*) is cash and cash equivalents scaled by total assets. We define *Sales* as sales over total assets and *Tangibility* as property, plants, and equipment scaled by total assets. Annual stock returns (*Return*) are a market-adjusted cumulative abnormal daily stock returns for the fiscal year. CAR(-1,+1) are three-day cumulative abnormal stock returns starting one day before acquisition announcements. $CAR^{bidding}$ is calculated as market-adjusted cumulative abnormal daily stock returns during a bidding period, a period running from one day before a merger announcement to one day after the date of deal completion. *DealSize* is the value of an acquisition transaction scaled by an acquirer's total assets. $Bonus^{Profit}$ is an indicator variable that is assigned the value of one if a CEO has earnings performance incentives and zero otherwise. $Ownership^{CEO}$ is the percentage of total shares owned by a firm's CEO.

RRV is a misvaluation measure of Rhodes-Kropf, Robinson, and Viswanathan (2005). We follow Appendix A of Fu, Lin, and Officer (2013) to calculate *RRV*.

$$RRV = Ln(M_{it}) - \left[\bar{\alpha}_{0j} + \bar{\alpha}_{1j}Ln(B_{it}) + \bar{\alpha}_{2j}Ln(|NI_{it}|) + \bar{\alpha}_{3j}\mathrm{I}^{-}Ln(|NI_{it}|) + \bar{\alpha}_{4j}\left(\frac{D}{V}\right)_{it}\right],$$

where *M* and *B* are the market value and the book value of equity. *NI* is net income and I^{-} is an indicator variable that is assigned the value of one if net income is negative and zero otherwise. D/V is the market leverage ratio. The subscript j indicates industry. $\bar{\alpha}_j$ is the time-series average of $\hat{\alpha}_{jt}$, the estimated α_{jt} of the within-industry cross-sectional regressions of

$$Ln(M_{it}) = \alpha_{0jt} + \alpha_{1jt}Ln(B_{it}) + \alpha_{2jt}Ln(|NI_{it}|) + \alpha_{3jt}\mathrm{I}^{-}Ln(|NI_{it}|) + \alpha_{4jt}\left(\frac{D}{V}\right)_{it} + \varepsilon_{it}.$$

All variables are defined in the Appendix and winsorized at the 1% level.

2.2. Summary statistics

Table 1 reports the summary statistics for our sample. Panel A presents firm characteristics and deal characteristics separately for the full sample and the acquisition sample. The acquisition sample consists of firm-year observations in which a firm makes an acquisition announcement. For our sample firms, approximately 8.4% of their POs relative to their total assets are due in the following year. Although PO^{rest} accounts for 6.6% of total assets, the variation is substantial. The median value of PO^{rest} is 0.004 and the 75th percentile is 0.028. The standard deviation of PO^{rest} is 0.045 and 45% of sample firms report zero PO^{rest}. As most firms report only POs that are due in the following year, we focus mostly on PO^{t+1}. The acquisition sample exhibits an average PO^{t+1} that is smaller than the average in the full sample and a larger mean of PO^{rest} than is observed in the full sample. ΔPO^{t+1} and ΔPO^{rest} are on average 0.000 and -0.002, respectively, for the full sample. As such, sample firms are almost equally distributed between overvalued and undervalued as measured by ΔPO^{t+1}. On the other hand, the average value of ΔPO^{t+1} for the firms in the acquisition sample is -0.001 and the median value is also slightly negative. As such, the acquisition sample exhibits decreasing POs compared to the full sample. Acquirers have, on average, larger total assets (*Size*), higher return on assets (*Profit*), and higher stock returns (*Return*). Other variables are similar between the two groups. *DealSize*

is on average 0.392 and acquirers are more likely to pay with cash than with stock. Only 6.1% of acquisitions are paid entirely with stock.[25]

Panel B presents the correlation matrix between ΔPO^{t+1}, changes in performance, and other mispricing proxies. ΔPO^{t+1} is significantly positively correlated with changes in profits and sales growth in the following year, supporting the proposition that ΔPO^{t+1} predicts future profitability and performance. ΔPO^{t+1} is significantly positively correlated with the market-to-book ratio. Meanwhile, ΔPO^{t+1} is not significantly correlated with the misvaluation measure of Rhodes-Kropf, Robinson, and Viswanathan (2005).

We present PO^{t+1} and ΔPO^{t+1} by industry in Panel C. We use 1-digit SIC codes to classify industries. We find that agriculture, forestry, and fishing (SIC 0100-0999), wholesale and retail (SIC 5000-5999), as well as manufacturing industries (SIC 2000-3999) exhibit above-mean value of PO^{t+1}. Service industries (SIC 7000-8999), on the other hand, have smaller PO^{t+1} than other industries.

Table 1. About Here

3. Empirical results

3.1. Overvaluation and acquisitions

Unlike most prior studies that use public information to determine whether a firm is overvalued, we take advantage of POs to identify overvaluation. In particular, we follow Lee (2021) and use changes in POs as a proxy for information asymmetry–driven mispricing: Positive (negative) changes in POs indicate that managers forecast that

[25] In our sample, 48% of deals are paid entirely with cash.

performance will improve (be worse) in the following year but investors do not have this information. Therefore, the firm's stock is undervalued (overvalued) in the current market.

We examine whether a firm is more likely to engage in acquisitions when changes in POs are negative and thus its shares are overvalued in the current stock market. To do so, we run a regression of *M&A* on the variables that we use to measure overvaluation, which comprise ΔPO^{t+1}, ΔPO^{rest}, OV^{t+1}, and OV^{rest}. We control for *Size*, *Leverage*, *Q*, *SalesGrowth*, *Profit*, *Capex*, *Cash*, *Sales*, *Tangibility* and *R&D*. We also control for contemporaneous stock returns (*Return*) to control for information reflected in stock prices. Therefore, the coefficient estimates on our overvaluation variables capture the effect of information over and above what the market already knows. We control for firm fixed effects and industry-year fixed effects in all regressions. Standard errors are clustered at the firm level.

Table 2 reports the result of the analyses. The dependent variable is *M&A* in all columns. The variables of interest in column (1) are ΔPO^{t+1} and ΔPO^{rest}. The coefficient on ΔPO^{t+1} is negative and statistically significant, indicating that a firm is more likely to engage in acquisitions when it predicts that future profitability will diminish and thus its stock is overvalued in the current market. In contrast, the coefficient on ΔPO^{rest} is statistically insignificant. This likely reflects the fact that PO^{rest} is a noisy variable. The variable of interest in column (2) is ΔPO^{t+1}. The estimated coefficient on ΔPO^{t+1} is negative and statistically significant, suggesting that overvaluation is positively associated with the probability that acquisitions occur. In particular, the coefficient, -0.065, suggests that a one-standard-deviation decrease in ΔPO^{t+1} is associated with an increase in acquisition propensity of 0.3 percentage points, which accounts for 7.0% of acquisition probability.

The variables of interest for column (3) are OV^{t+1} and OV^{rest}. The coefficient on OV^{t+1} is positive and statistically significant, while the coefficient on OV^{rest} is statistically insignificant. The variable of interest for column (4) is OV^{t+1}. As is the case with column (3), here the coefficient on OV^{t+1} is positive and statistically significant, suggesting that being overvalued based on information reflected in POs that come due in the following year is associated with increases in acquisition propensity of 0.7 percentage points, which accounts for 16.3% of acquisition probability. As such, the results presented in this table suggest that information asymmetry-driven overvaluation is positively associated with acquisition propensity, which is consistent with prior studies' findings that use the market value of equity to measure overvaluation.[26]

The coefficient on *Return* is positive and statistically significant at the 1% level in all columns, suggesting that firms are likely to engage in acquisitions when their stock increases in value. The coefficient on *Leverage* is negative and statistically significant in all columns, suggesting that firms are less likely to acquire targets when they are highly levered. The coefficient on *Profit* is positive and statistically significant in all columns, suggesting that firms are likely to acquire targets when they perform well.

Table 2. About Here

3.2. Payment methods

As mentioned in the introduction, prior studies find that the level of equity overvaluation increases the probability that stock shares are used as the method of payment.

[26] Fu, Lin, and Officer (2013) find that two-thirds of acquirers are overvalued.

We examine whether acquirers with decreasing POs are more likely to use stock as the payment method in our sample. In particular, we run regressions of $Stockpay^{100\%}$, $Stockpay^{50\%}$, and $Stockpay^{\%}$ on our measures of mispricing. We control for industry-year fixed effects in all regressions.

We present the results in Table 3. The variable of interest is ΔPO^{t+1} for odd-numbered columns and OV^{t+1} for even-numbered columns. The dependent variable is $Stockpay^{100\%}$ for columns (1) and (2). The coefficient on ΔPO^{t+1} in column (1) is negative but statistically insignificant. Similarly, the coefficient on OV^{t+1} shown in column (2) is negative but statistically insignificant. These results suggest that whether an acquisition is conducted using stock for an entire payment is not associated with mispricing measured by POs. The dependent variable for columns (3) and (4) is $Stockpay^{50\%}$. The coefficients on ΔPO^{t+1} in column (3) and OV^{t+1} in column (4) are both negative and statistically insignificant. It appears that whether an acquisition is conducted using mostly stock as the form of payment is not associated with changes in POs. The dependent variable for columns (5) and (6) is $Stockpay^{\%}$. Again, the coefficients on ΔPO^{t+1} in column (5) and OV^{t+1} in column (6) are statistically insignificant. The coefficient on *DealSize* is positive and statistically significant in all columns, suggesting that acquirers are more likely to pay with stock when the size of the transaction relative to their assets is larger. The coefficient on *Profit* is negative and statistically significant in all columns, suggesting that firms are likely to pay with stock shares when cash flows are low. As such, the results shown in this table suggest that whether a firm is overvalued based on information reflected in POs is not related to the method of payment used in acquisitions. In other words, overvalued acquirers in our sample are as likely to use stock as the method of payment as non-overvalued acquirers.

This finding is consistent with de Bodt, Cousin, and Officer (2022), who suggest that the spurious relationship between overvaluation and the use of stock as a method of payment arises because the choice of pooling accounting is an endogenous omitted variable. In particular, incentives to use pooling were strong for highly valued acquirers and acquirers had to pay targets entirely with stock to apply for pooling. Fu, Lin, and Officer (2013) show that high market-to-book acquirers are likely to pay with stock, but they pay higher takeover premiums than what is implied by an extrapolation of the pre-bargaining market-to-book values. According to Eckbo, Makaew, and Thorburn (2018), it is as if targets reverse-engineer initial market mispricing of the bidder shares. As such, contrary to some prior studies' findings, overvalued acquirers in our sample do not appear to take advantage of targets' shareholders by using overvalued stock as the method of payment in transactions.

Table 3. About Here

3.3. Overvaluation-driven acquisitions and profitability

We investigate the possibility that an overvalued firm that predicts lower profitability in the near future engages in an acquisition as a way to counteract deteriorating profitability. To do so, we investigate the association between overvaluation and changes in profitability in the following year. In particular, we run a regression of $\Delta Profit^{t+1}$ on ΔPO^{t+1} (ΔPO^{rest}) and its interaction with *M&A*. We also run similar regressions in which we replace ΔPO^{t+1} (ΔPO^{rest}) with OV^{t+1} (OV^{rest}). We control for firm fixed effects and industry-year fixed effects in all regressions and standard errors are clustered at the firm level.

We present the results in Table 4. The dependent variable for all columns is $\Delta Profit^{t+1}$. The variables of interest for column (1) are ΔPO^{t+1} x *M&A* and ΔPO^{rest} x *M&A*. Consistent with the proposition that ΔPO^{t+1} predicts profitability in the next period, the coefficient on ΔPO^{t+1} is positive and statistically significant at the 1% level. On the other hand, the coefficient on interaction between ΔPO^{t+1} and *M&A* is negative and statistically significant. In contrast, the coefficients on ΔPO^{rest} and ΔPO^{rest} x *M&A* are statistically and economically insignificant. The coefficients on ΔPO^{t+1} and ΔPO^{t+1} x *M&A* remain similar in column (2) when we drop ΔPO^{rest} and ΔPO^{rest} x *M&A* from the regression. The coefficient estimates suggest that a one-standard-deviation decrease in ΔPO^{t+1} is associated with a decrease in $\Delta Profit^{t+1}$ of 0.003, but when a firm engages in acquisitions, there is an additional effect whereby a one standard-deviation decrease in ΔPO^{t+1} is associated with an increase in $\Delta Profit^{t+1}$ of 0.008, which accounts for 7.7% of the standard deviation of $\Delta Profit^{t+1}$.

The variables of interest for column (3) are OV^{t+1} x *M&A* and OV^{rest} x *M&A*. The coefficient on OV^{t+1} is negative and statistically significant at the 1% level, suggesting that OV^{t+1} predicts diminishing profitability. However, the coefficient on interaction between OV^{t+1} and *M&A* is positive and statistically significant at the 5% level, suggesting that when an overvalued firm engages in acquisitions, there is an increase in $\Delta Profit^{t+1}$. The coefficients on OV^{rest} and OV^{rest} x *M&A*, on the other hand, are both statistically insignificant. The coefficients on OV^{t+1} and OV^{t+1} x *M&A* remain similar in column (4) when we drop OV^{rest} and OV^{rest} x *M&A* from the regression. To put these results into perspective, the estimated coefficients indicate that being overvalued is associated with a decrease in $\Delta Profit^{t+1}$ of 0.006, but when an overvalued firm engages in acquisitions, there

is an additional effect of an increase in $\Delta Profit^{t+1}$ of 0.014, which accounts for 13.5% of the standard deviation of $\Delta Profit^{t+1}$. As such, the results presented in this table suggest overall that a decrease in POs is associated with a decrease in profitability but acquisitions by firms with decreasing POs generally more than offset the diminishing profitability.

Table 4. About Here

3.4. Stock Returns

Although we suggest that overvalued firms with diminishing profitability forecasts engage in acquisitions as a way to manage profits, whether such acquisitions benefit acquirers' shareholders are unclear. This is because shareholder wealth depends on the premium paid to a target and the synergies generated by the acquisition. For an acquirer's shareholders to benefit from an acquisition, the acquirer should be able to negotiate favorable exchange terms or create large enough synergies to compensate for an unfavorable exchange ratio. Fu, Lin, and Officer (2013) show that high premiums and negative synergies make acquisitions driven by overvaluation unattractive to long-term acquirer shareholders. Ang and Cheng (2003) show, on the other hand, that acquirers' overvaluation generally exceeds targets' premium-adjusted overvaluation and acquirers' shareholders' gains in wealth. In this section, we analyze stock returns following acquisition announcements to determine whether overvalued acquirers in our sample succeed at increasing shareholder wealth. We consider both short-term announcement returns and bidding period stock returns.

We first compute cumulative abnormal returns over a three-day window, CAR(-1,+1). We then compare CAR(-1,+1) of overvalued acquirers with those of non-overvalued acquirers. We use ΔPO^{t+1} to determine whether a firm is overvalued, based on the results shown in Table 2 and Table 3. We also compare CAR(-1,+1) of overvalued acquirers with those of similarly overvalued non-acquirers that are selected via a matching procedure. We match overvalued acquirers with overvalued non-acquirers based on year, industry, ΔPO^{t+1}, *Size*, and *Q*.

The results are presented in Panel A of Table 5. The average CAR(-1,+1) for overvalued acquirers is approximately 1.23% and is statistically significant. Overvalued non-acquirers, on the other hand, earn 0.29% during the same period. The difference in CAR(-1,+1) between overvalued acquirers and overvalued non-acquirers, 0.94%, is statistically significant at the 1% level. On the other hand, the average CAR(-1,+1) for non-overvalued acquirers is approximately 1.05% and is statistically significant at the 1% level. The difference in CAR(-1,+1) between overvalued acquirers and non-overvalued acquirers, 0.19%, is neither economically nor statistically significant. The positive and statistically significant announcement returns on overvalued acquirers indicate short-term wealth gains for their shareholders. In addition, the gains are similar in magnitude to those associated with non-overvalued acquirers.

We next examine the implications of acquisitions for longer-term shareholder wealth. To do so, we analyze bidding period returns, $CAR^{bidding}$.[27] Because overvalued acquirers, by definition, will experience diminishing profitability and thus lower returns once POs are disclosed, our test focuses on comparing overvalued acquirers and similarly overvalued

[27] The average bidding period is 122 days.

non-acquirers. We also compare the bidding period returns on overvalued acquirers against those on non-overvalued acquirers.

Panel B reports the results of the analyses of the bidding period returns. Overvalued acquirers earn positive abnormal returns during the bidding period. In particular, the average $CAR^{bidding}$ on overvalued acquirers is 3.22%, which is statistically significant at the 1% level. On the other hand, similarly overvalued (matched) non-acquirers earn, on average, 0.97%, which is statistically insignificant, over the same period. The difference in $CAR^{bidding}$ between overvalued acquirers and similarly overvalued non-acquirers is statistically significant. These results suggest that shareholders of overvalued acquirers benefit from the deals we observe in our sample. Non-overvalued acquirers' $CAR^{bidding}$ is 3.92%, which is higher than $CAR^{bidding}$ on overvalued acquirers. However, the difference is neither statistically nor economically significant. As such, the results shown in this table suggest that overvalued acquirers increase shareholder wealth.

The results shown in Table 3 – Table 5 suggest that acquisitions by firms with decreasing POs exhibit increases in shareholder wealth and that this value creation is attributable to increases in profitability, possibly due to positive synergies. Contrary to some prior studies' findings, overvalued acquirers in our sample do not appear to take advantage of targets' shareholders by using overvalued stock as the method of payment in transactions.

Table 5. About Here

3.5. Executive compensation and ownership

We examine whether a CEO with stronger incentives to increase profitability (firm value) engages in acquisitions to a greater extent when POs predict diminishing profitability (firm value). We first consider bonuses that are tied to earnings. A CEO whose bonus is tied to earnings is expected to care about profitability to a greater extent and thus may engage in profitability-increasing acquisitions when he or she is given a forecast of diminishing profitability. Therefore, we test whether having a CEO's bonuses tied to profitability is associated with a propensity to engage in acquisitions when POs suggest that profitability will be diminishing. In particular, we investigate the association between *M&A* and interaction between $Bonus^{Profit}$ and ΔPO^{t+1} (OV^{t+1}).

We also consider a CEO's ownership stake in a firm. A CEO with a large ownership stake has a stronger incentive to increase firm value. Therefore, when a CEO's private information suggests that firm value will fall, he or she may engage in value-enhancing acquisitions. For these analyses, we investigate the association between $Ownership^{CEO}$ and ΔPO^{t+1} (OV^{t+1}).

The results are presented in Table 6. The dependent variable for all columns is *M&A*. We control for firm fixed effects and industry-year fixed effects and standard errors are clustered at the firm level. The variable of interest for column (1) is interaction between $Bonus^{Profit}$ and ΔPO^{t+1}. The coefficient of interest is negative and statistically insignificant. The variable of interest for column (2) is interaction between $Bonus^{Profit}$ and OV^{t+1}. Again, the coefficient of interest is negative and statistically insignificant. These results are inconsistent with the proposition that a tendency to engage in acquisitions when POs predict diminishing profitability is more pronounced for CEOs with bonuses tied to profitability than for CEOs whose compensation is not subject to such a condition.

The variable of interest for column (3) is interaction between $Ownership^{CEO}$ and ΔPO^{t+1}. The coefficient of interest is statistically insignificant. The variable of interest for column (4) is interaction between $Ownership^{CEO}$ and OV^{t+1}. Again, the coefficient of interest is statistically insignificant. These results do not support the hypothesis that a CEO's ownership stake is positively associated with a propensity to engage in acquisitions when POs predict diminishing firm value. As such, the results shown in this table suggest that CEOs' private incentives do not play a significant role in the acquisition decisions that we document in this paper.[28]

Table 6. About Here

4. Conclusion

A number of studies have examined the association between overvalued stock and acquisitions. Although several papers find that high market-to-book firms acquire low market-to-book targets, it is not clear whether such acquisitions are driven by investment opportunities, information asymmetry–driven mispricing, or behavioral anomaly–driven mispricing. In this study, we focus on information asymmetry–driven mispricing and investigate whether and how overvaluation plays an important role in explaining corporate acquisitions. In doing so, we exploit pre-disclosed changes in purchase obligations to measure a manager's private information.

We find that a firm is more likely to engage in acquisitions when its private

[28] We find that the level of corporate governance, measured by the entrenchment index (Bebchuk, Cohen, and Ferrell, 2008), is unrelated to the propensity to engage in acquisitions when POs suggest overvaluation.

information predicts that future profitability will fall and thus understands that its shares are overvalued in the current stock market. Such acquisitions are followed by increases in profitability and generate positive announcement returns that are similar in magnitude to returns on non-overvalued acquirers. Furthermore, bidding period returns on overvalued acquirers are higher than those on similarly overvalued non-acquirers. We find that overvalued acquirers are as likely to use stock as the payment method as are non-overvalued acquirers, contrary to results reported in some earlier studies. Our finding is, however, consistent with de Bodt, Cousin, and Officer's (2022) suggestion that academics misinterpret the correlation between acquirer valuation and the use of stock shares as the method of payment as evidence supporting misvaluation-based theories of the method of payment. It is also consistent with Eckbo, Makaew, and Thorburn's (2018) rejection of the notion that opportunistic acquirers use stock shares as a method of payment. The results presented in this paper suggest that firms that are overvalued based on managers' private information engage in acquisitions to increase firm value by counteracting diminishing profitability rather than by taking advantage of overvalued stock.

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Appendix. Variable Definitions

Variable	Description
PO^{t+1}	The dollar amount of purchase obligations due in the following year scaled by total assets
PO^{rest}	The dollar amount of purchase obligations due after t+1 scaled by total assets
ΔPO^{t+1}	PO^{t+1} minus lagged PO^{t+1}
ΔPO^{rest}	PO^{rest} minus lagged PO^{rest}
OV^{t+1}	An indicator variable that is assigned the value of one if ΔPO^{t+1} is negative and zero otherwise
OV^{rest}	An indicator variable that is assigned the value of one if ΔPO^{rest} is negative and zero otherwise
M&A	An indicator variable that is assigned the value of one if a firm announces acquisition transactions in a given firm-year and zero otherwise
$Stockpay^{100\%}$	An indicator variable that is assigned the value of one when an acquirer pays a target entirely in stock for transactions and zero otherwise
$Stockpay^{50\%}$	An indicator variable that is assigned the value of one when an acquirer pays a target more than half in stock for transactions and zero otherwise
$Stockpay^{\%}$	The proportion of stock shares in a payment to the total payment in an acquisition deal
DealSize	The value of an acquisition transaction scaled by an acquirer's total assets
CAR(-1,+1)	Three-day cumulative abnormal stock returns starting one day before acquisition announcements
$CAR^{bidding}$	Market-adjusted cumulative abnormal daily stock returns during a bidding period, a period running from one day before a merger announcement to one day after the date of deal completion
$Bonus^{Profit}$	An indicator variable that is assigned the value of one if a CEO has earnings performance incentives and zero otherwise
$Ownership^{CEO}$	Percentage of total shares owned by a CEO

Profit	Return on assets. oibdp/at
$\Delta Profit^{t+1}$	$Profit_{t+1}$ minus $Profit_t$
Size	Firm size. Natural log of total assets(at)
Leverage	Market leverage. (dlc + dltt)/(prcc_f ∗ cshpri + dlc + dltt)
Q	Tobin's Q. (prcc_f ∗ cshpri + dlc + dltt)/at
SalesGrowth	Sales growth. $(sale_t - sale_{t-1})/sale_{t-1}$
Capex	Capital expenditures. capx/at
R&D	R&D expenses. xrd/at after replacing missing xrd with 0 if xsga is non-missing.
Cash	Cash holdings. che/at
Sales	Sales. sale/at
Tangibility	Asset tangibility. ppent/at
Return	Annual stock return. Daily CAR measured from -250 to -10 days from fiscal year-ends
RRV	Misvaluation measure of Rhodes-Kropf, Robinson, and Viswanathan (2005)

Table 1. Descriptive Statistics

This table reports summary statistics for our sample firms. The full sample consists of all Compustat firms (except for financial firms and public utilities) that disclosed non-zero purchase obligations on their 10-K filings between 2004 and 2018. We eliminate firms with non-positive total assets and sales of less than 10 million dollars. For our acquisition sample, we exclude any deal the value of which is less than 10 million dollars. To be included in the sample, an acquirer must purchase more than 50 percent of the target's shares and own 100 percent of those shares upon completion. We also restrict our sample to firms that make acquisition announcements at least 6 months into a fiscal year. Lastly, an acquisition must have been completed after the fiscal year-end of the announcement year. Panel A shows summary statistics for variables used in our analyses. Panel B presents correlations matrix between ΔPO^{t+1}, future profitability, and a mispricing measure (RRV). Panel C reports summary statistics for PO^{t+1} and ΔPO^{t+1} by industry (SIC 1-digit). All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution.

Panel A. Summary Statistics

	Full sample						Acquisition sample					
	N	Mean	Med	SD	25%	75%	N	Mean	Med	SD	25%	75%
PO^{t+1}	14226	0.084	0.042	0.129	0.013	0.102	606	0.069	0.037	0.106	0.013	0.085
PO^{rest}	14226	0.066	0.004	0.467	0.000	0.028	606	0.077	0.006	0.515	0.000	0.036
ΔPO^{t+1}	14226	0.000	0.000	0.045	-0.009	0.011	606	-0.001	-0.000	0.038	-0.008	0.008
ΔPO^{rest}	14226	-0.002	0.000	0.054	-0.003	0.001	606	0.000	0.000	0.057	-0.004	0.002
OV^{t+1}	14226	0.489	0.000	0.500	0.000	1.000	606	0.513	1.000	0.500	0.000	1.000
OV^{rest}	14226	0.401	0.000	0.490	0.000	1.000	606	0.469	0.000	0.499	0.000	1.000
Size	14226	7.106	7.081	1.761	5.825	8.307	606	8.080	8.054	1.684	6.900	9.171
Leverage	14226	0.212	0.147	0.224	0.018	0.327	606	0.221	0.161	0.212	0.056	0.329
Q	14226	1.698	1.272	1.355	0.872	2.008	606	1.702	1.401	1.119	0.968	2.115
SalesGrowth	14226	0.127	0.066	0.398	-0.019	0.177	606	0.142	0.075	0.416	-0.007	0.175
Profit	14226	0.059	0.077	0.149	0.026	0.127	606	0.091	0.090	0.086	0.056	0.134
Capex	14226	0.054	0.035	0.058	0.019	0.065	606	0.045	0.030	0.050	0.016	0.055
Cash	14226	0.189	0.120	0.193	0.043	0.270	606	0.167	0.112	0.162	0.041	0.236
Sales	14226	1.082	0.901	0.729	0.581	1.396	606	0.934	0.747	0.713	0.518	1.078
Tangibility	14226	0.269	0.196	0.229	0.090	0.387	606	0.235	0.170	0.202	0.082	0.335
RND	14226	0.045	0.005	0.090	0.000	0.055	606	0.037	0.012	0.057	0.000	0.055
Return	14226	0.044	0.036	0.418	-0.170	0.249	606	0.103	0.081	0.315	-0.070	0.257
$\Delta Profit^{t+1}$	12508	-0.004	-0.000	0.104	-0.024	0.020	530	-0.008	-0.005	0.055	-0.024	0.011
M&A	14226	0.043	0.000	0.202	0.000	0.000	606	1.000	1.000	0.000	1.000	1.000
DealSize							606	0.392	0.131	1.381	0.046	0.389
$Stockpay^{\%}$							606	0.129	0.000	0.281	0.000	0.000
$Stockpay^{100\%}$							606	0.061	0.000	0.240	0.000	0.000
$Stockpay^{50\%}$							606	0.114	0.000	0.318	0.000	0.000

Panel B. Correlation Matrix

	ΔPO^{t+1}	$\Delta Profit^{t+1}$	$SalesGrowth^{t+1}$	Q	RRV
ΔPO^{t+1}	1.000				
$\Delta Profit^{t+1}$	0.039^{***}	1.000			
$SalesGrowth^{t+1}$	0.072^{***}	0.356^{***}	1.000		
Q	0.031^{***}	0.012	0.216^{***}	1.000	
RRV	-0.007	0.061^{***}	0.096^{***}	0.212^{***}	1.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel C. Purchase Obligations by Industry (SIC 1 digit)

	PO^{t+1}						ΔPO^{t+1}					
	N	Mean	Med	SD	25%	75%	N	Mean	Med	SD	25%	75%
0 (Agricul.)	44	0.101	0.041	0.138	0.010	0.155	44	0.012	0.003	0.042	-0.003	0.022
1 (Mining)	1043	0.044	0.023	0.068	0.009	0.052	1043	-0.003	-0.000	0.036	-0.009	0.007
2 (Manufac.)	2960	0.087	0.048	0.125	0.016	0.108	2960	-0.002	0.000	0.048	-0.010	0.010
3 (Manufac.)	4991	0.090	0.057	0.105	0.021	0.115	4991	0.001	0.000	0.047	-0.012	0.015
4 (Transp.)	989	0.073	0.048	0.085	0.017	0.100	989	0.000	0.000	0.046	-0.010	0.011
5 (Trade)	1988	0.143	0.073	0.223	0.016	0.207	1988	0.001	0.000	0.054	-0.011	0.014
7 (Services)	1714	0.037	0.017	0.066	0.008	0.039	1714	0.001	0.000	0.029	-0.004	0.005
8 (Services)	497	0.030	0.015	0.038	0.005	0.044	497	0.001	0.000	0.029	-0.004	0.005
Total	14226	0.084	0.042	0.129	0.013	0.102	14226	0.000	0.000	0.045	-0.009	0.011

Table 2. Overvaluation and Acquisitions

This table presents the results of analyses of the association between acquisition propensity and PO-based overvaluation measures. For all columns, the dependent variable is *M&A*, an indicator variable that is assigned the value of one if a firm is an acquirer in a given firm-year and zero otherwise. The variables of interest are $\Delta POt+1$ and $\Delta PO rest$ (OV^{t+1} and OV^{rest}). ΔPO^{t+1} (ΔPO^{rest}) is defined as PO^{t+1} (PO^{rest}) minus lagged PO^{t+1} (PO^{rest}), where PO^{t+1} (PO^{rest}) is PO due in t+1 (t+2 and thereafter) scaled by total asset. OV^{t+1} (OV^{rest}) is an indicator variable that is assigned the value of one if ΔPO^{t+1} (ΔPO^{rest}) is negative and zero otherwise. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution. We control for firm fixed effects and industry-year fixed effects in all regressions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
			M&A	
ΔPO^{t+1}	-0.070*	-0.065*		
	(-1.86)	(-1.67)		
ΔPO^{rest}	0.018			
	(0.48)			
OV^{t+1}			0.007*	0.007**
			(1.92)	(2.05)
OV^{rest}			0.003	
			(0.65)	
$Size_{t-1}$	-0.019**	-0.019**	-0.019**	-0.019**
	(-2.42)	(-2.41)	(-2.41)	(-2.41)
$Leverage_{t-1}$	-0.065***	-0.064***	-0.063***	-0.064***
	(-3.43)	(-3.43)	(-3.37)	(-3.39)
Q_{t-1}	0.000	0.000	0.000	0.000
	(0.16)	(0.16)	(0.16)	(0.15)
$SalesGrowth_{t-1}$	-0.002	-0.002	-0.002	-0.002
	(-0.34)	(-0.32)	(-0.30)	(-0.31)
$Profit_{t-1}$	0.057***	0.057***	0.056***	0.056***
	(2.80)	(2.84)	(2.79)	(2.78)
$Capex_{t-1}$	-0.005	-0.006	-0.003	-0.003
	(-0.09)	(-0.11)	(-0.06)	(-0.06)
$Cash_{t-1}$	0.037	0.037	0.037	0.037
	(1.52)	(1.53)	(1.54)	(1.53)
$Sales_{t-1}$	-0.009	-0.010	-0.010	-0.010
	(-1.15)	(-1.16)	(-1.17)	(-1.15)
$Tangibility_{t-1}$	0.045	0.046	0.043	0.044
	(1.23)	(1.24)	(1.18)	(1.18)
RND_{t-1}	-0.048	-0.048	-0.048	-0.048
	(-1.10)	(-1.08)	(-1.08)	(-1.08)
$Return_t$	0.014***	0.014***	0.014***	0.014***
	(3.29)	(3.29)	(3.23)	(3.25)
R^2	0.061	0.061	0.061	0.061
Observations	14226	14226	14226	14226
Firm FE	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Overvaluation and Method of Payment

This table presents the results of the analyses of payment methods used in acquisitions. The dependent variables are $Stockpay^{100\%}$, $Stockpay^{50\%}$, and $Stockpay^{\%}$ for columns (1)-(2), (3)-(4), and (5)-(6), respectively. $Stockpay^{100\%}$ ($Stockpay^{50\%}$) is an indicator variable that is assigned the value of one when an acquirer pays a target entirely (more than half) in stocks for the transactions and zero otherwise. $Stockpay^{\%}$ is the ratio of stock payments to total payments in acquisition deals. The variable of interest is ΔPO^{t+1} for odd-numbered columns and OV^{t+1} for even-numbered columns. ΔPO^{t+1} is defined as PO^{t+1} minus lagged PO^{t+1}, where PO^{t+1} is PO due in t+1 scaled by total assets. OV^{t+1} is an indicator variable that is assigned the value of one if ΔPO^{t+1} is negative and zero otherwise. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution. We control for industry-year fixed effects in all regressions. Standard errors are clustered at the industry level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Stockpay^{100\%}$		$Stockpay^{50\%}$		$Stockpay^{\%}$	
ΔPO^{t+1}	-0.307		-0.366		-0.096	
	(-0.70)		(-0.71)		(-0.19)	
OV^{t+1}		-0.001		-0.021		-0.022
		(-0.08)		(-0.84)		(-1.01)
$Size_{t-1}$	-0.004	-0.005	-0.003	-0.005	-0.012	-0.013*
	(-0.72)	(-1.07)	(-0.28)	(-0.53)	(-1.55)	(-1.80)
$Leverage_{t-1}$	0.130**	0.131**	0.034	0.042	0.107	0.114
	(2.13)	(2.10)	(0.44)	(0.50)	(1.57)	(1.59)
Q_{t-1}	0.001	0.001	0.005	0.006	0.005	0.006
	(0.05)	(0.07)	(0.27)	(0.33)	(0.32)	(0.38)
$SalesGrowth_{t-1}$	0.006	0.008	0.072	0.076	0.042	0.045
	(0.15)	(0.17)	(1.04)	(1.14)	(0.92)	(0.99)
$Profit_{t-1}$	-0.524**	-0.511**	-0.557**	-0.550**	-0.623***	-0.629***
	(-2.22)	(-2.10)	(-2.32)	(-2.38)	(-2.86)	(-2.95)
$Capex_{t-1}$	0.043	0.063	-0.742	-0.692	-0.633	-0.599
	(0.15)	(0.23)	(-1.09)	(-1.06)	(-1.53)	(-1.53)
$Cash_{t-1}$	0.108	0.113	0.170	0.180	0.251**	0.258**
	(1.11)	(1.13)	(1.46)	(1.50)	(2.10)	(2.10)
$Sales_{t-1}$	-0.012	-0.010	0.026	0.031	0.014	0.017
	(-0.59)	(-0.52)	(0.96)	(1.07)	(0.54)	(0.64)
$Tangibility_{t-1}$	0.063	0.050	0.329**	0.306**	0.309***	0.296***
	(0.76)	(0.62)	(2.32)	(2.30)	(3.09)	(3.14)
RND_{t-1}	0.257	0.269	0.244	0.260	0.068	0.074
	(0.88)	(0.89)	(0.94)	(0.98)	(0.23)	(0.25)
$Return_t$	0.049	0.045	0.063	0.056	-0.002	-0.006
	(0.96)	(0.81)	(1.16)	(0.93)	(-0.05)	(-0.12)
DealSize	0.041***	0.041***	0.053**	0.052**	0.052**	0.051**
	(3.21)	(3.19)	(2.34)	(2.28)	(2.44)	(2.39)
R^2	0.147	0.146	0.141	0.141	0.179	0.180
Observations	634	634	634	634	634	634
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Acquisitions and Changes in Profitability

This table presents the results of analyses of changes in profitability. The dependent variable is $\Delta Profit^{t+1}$, which is defined as $Profit_{t+1}$ minus $Profit_t$. The variables of interest are interaction between *M&A* and our overvaluation measures, which are ΔPO^{t+1}, ΔPO^{rest}, OV^{t+1}, and OV^{rest}. ΔPO^{t+1} (ΔPO^{rest}) is defined as PO^{t+1} (PO^{rest}) minus lagged PO^{t+1} (PO^{rest}), where PO^{t+1} (PO^{rest}) is PO due in t+1 (t+2 and thereafter) scaled by total assets. OV^{t+1} (OV^{rest}) is an indicator variable that is assigned the value of one if ΔPO^{t+1} (ΔPO^{rest}) is negative and zero otherwise. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution. We control for firm fixed effects and industry-year fixed effects in all regressions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
		$\Delta Profit^{t+1}$		
ΔPO^{t+1} x M&A	-0.175*	-0.185**		
	(-1.85)	(-2.06)		
ΔPO^{rest} x M&A	-0.027			
	(-0.41)			
ΔPO^{t+1}	0.068***	0.071***		
	(2.62)	(2.81)		
ΔPO^{rest}	0.014			
	(0.40)			
OV^{t+1} x M&A			0.012**	0.014**
			(2.27)	(2.35)
OV^{rest} x M&A			0.007	
			(1.12)	
OV^{t+1}			-0.006***	-0.006***
			(-3.02)	(-2.95)
OV^{rest}			0.000	
			(0.17)	
M&A	-0.004	-0.004	-0.013**	-0.011***
	(-1.30)	(-1.29)	(-2.56)	(-2.66)
$Size_{t-1}$	-0.011***	-0.011***	-0.011***	-0.011***
	(-2.60)	(-2.59)	(-2.61)	(-2.62)
$Leverage_{t-1}$	0.026**	0.026**	0.025**	0.025**
	(2.20)	(2.20)	(2.15)	(2.15)
Q_{t-1}	-0.006***	-0.006***	-0.006***	-0.006***
	(-2.91)	(-2.90)	(-2.92)	(-2.92)
$SalesGrowth_{t-1}$	-0.004	-0.004	-0.004	-0.004
	(-0.92)	(-0.91)	(-0.95)	(-0.95)
$Profit_{t-1}$	-0.239***	-0.238***	-0.237***	-0.237***
	(-6.38)	(-6.29)	(-6.25)	(-6.25)
$Capex_{t-1}$	-0.046	-0.047	-0.051	-0.052
	(-0.68)	(-0.69)	(-0.75)	(-0.76)
$Cash_{t-1}$	0.009	0.009	0.010	0.010
	(0.62)	(0.64)	(0.66)	(0.65)
$Sales_{t-1}$	-0.003	-0.003	-0.003	-0.003
	(-0.54)	(-0.55)	(-0.57)	(-0.58)
$Tangibility_{t-1}$	0.023	0.023	0.025	0.025
	(0.87)	(0.87)	(0.95)	(0.95)
RND_{t-1}	-0.007	-0.006	-0.005	-0.006
	(-0.11)	(-0.10)	(-0.09)	(-0.09)
$Return_t$	-0.013***	-0.013***	-0.013***	-0.013***
	(-3.29)	(-3.30)	(-3.25)	(-3.25)
R^2	0.197	0.197	0.197	0.197
Observations	12508	12508	12508	12508
Firm FE	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Stock Returns

This table presents the results of analyses of stock returns. CAR(-1,+1) is the three-day cumulative abnormal stock returns starting one day before acquisition announcements. $CAR^{bidding}$ is calculated as market-adjusted cumulative abnormal daily stock returns during a bidding period, a period running from one day before the merger announcement to one day after the date of deal completion. Overvalued acquirers (OV aq) are the acquirer firms with OV^{t+1} equals one. Overvalued non-acquirers (OV naq) are non-acquirers with OV^{t+1} equals one that are matched to overvalued acquirers based on the year, industry, ΔPO^{t+1}, *Size*, and *Q*. We conduct k-nearest neighbors matching with 3 neighbors. Non-overvalued acquirers (NOV aq) are defined as the acquirers with OV^{t+1} equals zero. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Announcement returns (%)

	OV aq	OV naq	Diff	OV aq	NOV aq	Diff
CAR(-1,+1)	1.234***	0.290*	0.944***	1.234***	1.048***	0.186
t-statistics	3.283	1.933	2.613	3.283	2.924	0.356

Panel B. Bidding period returns (%)

	OV aq	OV naq	Diff	OV aq	NOV aq	Diff
$CAR^{bidding}$	3.217***	0.970	2.248*	3.217***	3.915***	-0.698
t-statistics	3.050	1.250	1.756	3.050	4.078	-0.485

Table 6. CEO Incentives and Acquisition

This table reports the results of the analyses conducted to determine whether a CEO with stronger incentives to increase profitability engages in acquisitions to a greater extent when POs indicate diminishing profitability. In column (1) ((2)), we investigate the association between *M&A* and interaction between $Bonus^{Profit}$ and ΔPO^{t+1} (OV^{t+1}), where $Bonus^{Profit}$ is an indicator variable if a CEO has earnings performance incentives. In column (3)-(4), we repeat the same regression with $Ownership^{CEO}$, where $Ownership^{CEO}$ is the percentage of total shares owned by a CEO. ΔPO^{t+1} is defined as PO^{t+1} minus lagged PO^{t+1}, where PO^{t+1} is PO due in t+1 scaled by total assets. OV^{t+1} is an indicator variable that is assigned the value of one if ΔPO^{t+1} is negative and zero otherwise. All variables are defined in the Appendix and are winsorized at 1% in both tails of the distribution. We control for firm fixed effects and industry-year fixed effects in all regressions. Standard errors are clustered at the firm level and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)
		M&A		
ΔPO^{t+1} x $Bonus^{Profit}$	-0.098			
	(-0.59)			
OV^{t+1} x $Bonus^{Profit}$		-0.011		
		(-0.72)		
ΔPO^{t+1} x $Ownership^{CEO}$			-0.001	
			(-0.18)	
OV^{t+1} x $Ownership^{CEO}$				-0.000
				(-0.46)
ΔPO^{t+1}	0.071		-0.040	
	(0.53)		(-0.61)	
OV^{t+1}		0.013		0.010*
		(1.01)		(1.71)
$Bonus^{Profit}$	-0.015	-0.010		
	(-1.20)	(-0.71)		
$Ownership^{CEO}$			-0.001	-0.001
			(-1.25)	(-1.02)
$Size_{t-1}$	-0.047***	-0.047***	-0.026**	-0.026**
	(-3.16)	(-3.15)	(-2.27)	(-2.29)
$Leverage_{t-1}$	-0.030	-0.032	-0.064**	-0.064**
	(-0.77)	(-0.80)	(-2.21)	(-2.20)
Q_{t-1}	0.002	0.002	0.005	0.005
	(0.28)	(0.29)	(1.17)	(1.16)
$SalesGrowth_{t-1}$	0.000	0.001	-0.025***	-0.025***
	(0.02)	(0.05)	(-3.42)	(-3.41)
$Profit_{t-1}$	0.126***	0.123***	0.094**	0.092**
	(2.72)	(2.65)	(2.57)	(2.52)
$Capex_{t-1}$	-0.037	-0.049	-0.005	-0.009
	(-0.23)	(-0.31)	(-0.05)	(-0.09)
$Cash_{t-1}$	0.053	0.054	0.037	0.037
	(0.94)	(0.96)	(0.98)	(0.97)
$Sales_{t-1}$	-0.013	-0.014	-0.010	-0.012
	(-0.75)	(-0.80)	(-0.75)	(-0.83)
$Tangibility_{t-1}$	0.067	0.069	0.090	0.088
	(0.98)	(1.01)	(1.53)	(1.50)
RND_{t-1}	-0.230	-0.231	-0.166**	-0.168**
	(-1.62)	(-1.62)	(-2.06)	(-2.08)
$Return_t$	0.018**	0.018**	0.016**	0.015**
	(1.97)	(1.99)	(2.32)	(2.30)
R^2	0.124	0.124	0.079	0.080
Observations	5839	5839	8146	8146
Firm FE	Yes	Yes	Yes	Yes
Ind-Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$