**Contagion or competitive effects?: Lenders' response to peer firm cyberattacks**

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**Abstract**

This study examines whether and when cybersecurity events of peer firms in an industry influence the cost of private debt for other firms in the industry. If lenders adjust expectations about industry-wide cyber risk based on peer cyberattacks, a contagion effect likely exists whereby non-breached borrowers face higher loan spreads. If, however, lenders view cyberattacks as idiosyncratic risks, a competitive effect may dominate whereby non-breached borrowers benefit through reductions in loan spreads. Unlike other firm-specific events (i.e., bankruptcies, restatements) shown to have contagion effects in determining a firm's cost of debt, the results provide evidence of competitive effects for cybersecurity events. These effects are more pronounced for non-term and shorter duration loans, and for industries with high growth and low leverage. Collectively, the evidence suggests cyberattacks provide firm-specific information to lenders and competitors benefit from this intra-industry information transfer.

**Keywords:** contagion; cybersecurity; data breaches; business risk; technology; loan spreads
**JEL Classifications:** G21; G32; L14; O33
**Data Availability:** Data are available from sources identified in the text.

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## 1. Introduction

Cybersecurity risk is a relatively new phenomenon receiving significant attention.[1] With the increasing use of technology, firms are exposed to cyber risk during the normal course of business. "In a digitally connected world, cybersecurity presents ongoing risks and threats to our capital markets and to companies operating in all industries" (Securities and Exchange Commission (SEC) 2018, p.2). One line of research examines the consequences of cyberattacks on firms in the form of reputation losses (e.g., Akey et al. 2021), shareholder wealth losses (e.g., Haislip et al. 2019; Kamiya et al. 2021), and higher financing costs (e.g., Sheneman 2017; Huang and Wang 2021). A second line of research examines the effects of cyberattacks on the stock prices of industry peer firms. Haislip et al. (2019) finds evidence that peer firms' market values are negatively affected by competitors' cyberattacks. Expanding the investigation, recent work by Kamiya et al. (2021) confirms that intra-industry peer stock prices are negative on average (contagion effects) but positive for firms with better performance and better governance (competitive effects).

Despite cybersecurity attacks being significant and costly firm events, there is no evidence on whether, or to what extent, the pricing of debt capital for other firms in the same industry is affected by cyberattacks of competitors. This paper attempts to fill this gap by examining the intra-industry effects of cybersecurity attacks on bank loan contracting. Unlike the equity market, the private debt market is characterized as having private information exchanges between borrowers and lenders. Such private communication can include, among other things, information about borrowers' control environments, governance structures, and cybersecurity investments.[2] The

[1] Cybersecurity risk is broadly defined as the potential for business losses (e.g., operational, financial, reputational) in the digital domain.
[2] Anecdotal evidence from private communication with U.S. commercial lenders suggests cybersecurity risk is considered in loan pricing models as a qualitative factor.

private communication channel of debt contracting suggests that results related to peer firms' market values may not extend to the debt market. Because the private debt market provides the majority of external financing for publicly traded firms, it is important to understand how lenders respond to competitor risks when negotiating contracts. In addition, because cybersecurity risk is a relatively *new* risk, it is plausible that prior findings on intra-industry contagion in debt contracting may not extend to cybersecurity.[3]

Although prior literature finds breached firms experience increases in the cost of capital after a cyberattack, the expected relation with peer cyberattacks is not as clear. On the one hand, peer cyberattacks may signal greater industry-specific cyber risk. Existing evidence suggests cyberattacks are correlated within industries (e.g., Ettredge and Richardson 2003). Lenders learn about the likelihood of a breach and the loss distribution of cybersecurity risk for a given industry. In this case, non-breached borrowers are likely to be adversely affected by higher costs of debt (i.e., contagion effects). On the other hand, peer cyberattacks may be viewed as idiosyncratic events related to firm-specific factors, rather than industry-wide trends. For example, data breaches may indicate that management has not invested appropriately in sufficient information technology systems or lacks resources for monitoring cybersecurity risk. Survey evidence suggests successful cyberattacks cause customers to lose trust in breached firms and this lack of confidence manifests itself in reduced spending (Conradt 2015; Petru 2014). In this case, peer cyberattacks are good news for non-breached borrowers as customers shift business away from breached firms and toward non-breached competitors. The expectation of increased sales likely benefits non-breached borrowers through reductions in loan spreads (i.e., competitive effects). Thus, it is an open empirical question as to whether a contagion or a competitive effect dominates.

[3] Industry contagion effects in the form of higher loan spreads have been documented for bankruptcy filings and restatements [e.g., Hertzel and Officer (2012); Files and Gurun (2018)].

Consistent with prior studies examining contagion effects, I examine how cyberattacks announced by industry peers, defined as firms in the same 4-digit SIC code, influence the loan spread of borrowers. Successful cyberattacks occur when firms fail to protect proprietary information about stakeholders (e.g., customers, employees). I measure peer cyberattacks in the year prior to a borrower's loan origination date. If a contagion (competitive) effect dominates, I expect a positive (negative) association between peer cyberattacks and borrower loan spreads.

Using a sample of 11,575 loan initiations and 1,122 cyberattacks from 2005 to 2019, I find significant decreases in loan spreads following peer cyberattacks, suggesting a competitive effect exists in the private debt contracting setting. Based on a univariate comparison, I find the average spread on loans to industry peers following a single cyberattack is 15 basis points lower than the average spread on loans originated when there are no peer cyberattacks. After controlling for borrower attributes, loan attributes, credit market conditions, and various fixed effects, the multivariate analyses are consistent with the univariate evidence, although the effect is reduced.

I conduct a series of additional tests to provide further support for the association between peer cyberattacks and borrower loan spreads. I provide evidence that the competitive effect I document is concentrated in loans where lenders have the ability to use a time limit to reprice risk into a loan. Specifically, the competitive effect is concentrated in loans used for short-term financing (i.e., revolvers) and shorter duration loans. I also find the competitive effect occurs in industries with strong financial performance as measured by high industry asset growth, high industry investment growth, and low industry leverage. These results are consistent with the intuition that competitors benefit from peer cyberattacks only when the overall industry has strong financial performance.

I find limited evidence of contagion effects in non-price loan terms of new loan originations around industry peer cyberattacks. I consider the effect on three non-spread contractual terms: loan structure, collateral, and loan size. While I find no difference in syndicate structure or in the use of collateral, I do find evidence that loan size declines. This result is consistent with lenders reducing their exposure (relative to their overall loan portfolio) to firms in industries with high cybersecurity risk.

The final set of analyses investigates the extent to which industry privacy regulation influences the relation between loan spreads and peer cyberattacks. I focus on two industries with significant privacy legislation—telecommunications and healthcare. The results suggest borrowers in these industries do not benefit from peer cyberattacks. Instead, these industries show evidence of contagion effects. For example, comparing firms in the telecommunications industry to all other industries, I find a positive correlation between cyberattacks and loan spreads, suggesting lenders are adjusting (upward) their assessment of cybersecurity risk in that industry.

This study enhances our understanding of the consequences of cyberattacks and contributes to the extant literature. This paper extends the work of Kamiya et al. (2021), who study the risk management and stock market effects of cyberattacks. Kamiya et al. (2021) report on average contagion effects in stock prices, although competitive effects emerge for peer firms in highly competitive industries and in close proximity to breached firms. I show that the negative consequences of peer cyberattacks in the equity market do not extend to the debt market. In fact, the opposite is true in that cyberattacks benefit non-breached peers through reductions in loan spreads. This study also contributes to the literature examining contagion in the private debt market. Interestingly, while prior work finds contagion effects related to peer bankruptcies and restatements (e.g., Hertzel and Officer 2012; Files and Gurun 2018), competitive effects for cybersecurity events dominate.

This study also has implications for discussions surrounding cybersecurity investment and disclosure requirements. The SEC has issued guidance for firms that material cyberattacks should be disclosed (SEC 2011; SEC 2018). For several years, various regulatory agencies (e.g., Federal Trade Commission, SEC) have called for greater investment in cybersecurity (Bush 2014; Aguilar 2014). Despite these calls to prevent cyberattacks, it is unclear whether such calls for action have been heeded. This study provides further evidence that effective cybersecurity investments, including methods for preventing firms from becoming cyberattack targets, provide indirect benefits in the form of reduced financing costs (i.e., lower costs of debt).

## 2. Background

The objective of this study is to examine whether cyberattacks positively or negatively affect the cost of debt for industry peers. Cyberattacks result from firms failing to protect proprietary information and provide a signal to firm stakeholders regarding the potential loss distribution surrounding cybersecurity risk (Kamiya et al. 2021). Cybersecurity risk is perceived by investors as a growing threat to firms' future performance and managers view cybersecurity risk as a high priority (PwC 2018; Marsh 2019). Because of the frequency, magnitude, and cost of cyberattacks, the SEC has issued cyber risk disclosure guidance to firms (SEC 2011; SEC 2018) and has created a separate reporting unit focusing on cyber risk (SEC 2017).[4]

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[4] On June 15, 2021, the SEC announced the first settlement over violations related to deficient cybersecurity disclosure controls. According to the SEC's press release, without admitting or denying the charges, First American Financial Corporation agreed to a cease-and-desist order and a monetary fine (SEC 2021a). Additional settlements have been announced related to companies misleading investors about cyberattacks and companies having deficient cybersecurity controls that resulted in successful cyberattacks (SEC 2021b; SEC 2021c).

Much of the extant literature on cybersecurity focuses on the cost of capital effects for breached firms. Prior work on cyberattacks finds average cumulative abnormal returns between -0.84 percent and -1.88 percent (Kamiya et al. 2021; Campbell et al. 2003). Besides shareholder wealth losses, firms experiencing cyberattacks face an increase in the cost of debt, a decrease in the number of lenders providing private debt financing, a decrease in loan size, and an increase in the use of performance pricing (Sheneman 2017).

Although prior literature suggests cyberattacks are important firm events affecting credit risk, few papers examine peer effects. Haislip et al. (2019) find that non-breached industry peers experience increases in audit fees. In addition, Ashraf (2022) finds that peer data breaches are associated with changes in risk factor disclosures. This paper adds to the literature on peer effects by examining whether the increase in credit risk associated with cyberattacks affects the cost of debt for non-breached industry peers.

Prior literature has shown that lenders use industry information in setting loan contract terms. Amiram et al. (2017) provide evidence that industry risk (i.e., growth risk, structural risk, sensitivity risk, and overall risk) is positively associated with loan spreads. Hertzel and Officer (2012) find evidence of industry contagion effects in bank lending after a competitor files for bankruptcy. Similarly, Files and Gurun (2018) provide evidence that lenders respond to restatements by increasing the cost of debt after competitor and major customer restatements. If a cyberattack provides a signal to lenders that industry-related cyber risk is higher than lenders anticipated (i.e., the cyberattack provides adverse information), lenders are likely to increase the cost of debt for that industry. In this case, a cyberattack creates contagion effects, as evidenced by increases in loan spreads of industry competitors.

However, a successful cyberattack conveys information about the ability of firms in an industry to protect proprietary information relative to their peers. A cyberattack reveals that a breached firm has less effective internal control systems relative to its peers.[5] The reputation loss of the breached firm may benefit its competitors if lenders view the cyberattack as a firm-specific risk. In this case, a cyberattack benefits industry competitors (i.e., non-breached firms) as evidenced by decreases in loan spreads. It is ultimately an empirical question as to whether a contagion or competitive effect dominates.

## 3. Data

### 3.1. Corporate loan data

I begin with loan contract data of 30,512 unique loans from Dealscan between 2006 and 2019. Dealscan is a Loan Pricing Corporation (LPC) database containing detailed loan information on commercial loans, including the origination and maturity dates, the purpose and size of the loan, and the loan pricing terms. Because the cyberattack data starts in 2005 (see Section 3.2) and I study the effects of cyberattacks by firms in the same industry as the borrower in the 12 months prior to each loan origination, the loan sample begins in 2006. I remove 4,903 observations lacking information on loan spread, maturity, and loan size, and another 2,861 observations associated with firms experiencing cyberattacks (i.e., breached firms). An additional 11,173 observations are deleted because of missing Compustat and/or CRSP data. The final sample consists of 11,575 loans. Table 1, Panel A, presents the time series of loans in the final sample. The number of loans originated in a given year ranges from a low of 488 in 2009 to a high of 1,155 in 2006. Besides a

[5] A limitation of this study is that I am unable to distinguish between firms not being cyberattack targets and firms that are targeted but successfully defend against cyberattacks.

slight decrease in loan originations after the 2008 financial crisis, there are no noteworthy patterns in the loan origination data.

Table 1, Panel B, shows the distribution of loans by industry of the borrower using the Fama and French 12 industry categorization. The sample of loans is distributed across several industries with the highest concentrations in manufacturing (12.9 percent), business equipment (11.8 percent), wholesale and retail (10.5 percent), energy (8.9 percent), and other (17.1 percent).

### 3.2. Cyberattack data

I obtain data on cyberattacks from the Privacy Rights Clearinghouse (PRC), which compiles information about data breaches from governmental agencies and from media sources. The sample of data breaches begins in 2005, when the PRC began collecting this information, and extends through 2018. The PRC data includes information on the breached firm's name, the date the breach became public, and a brief description of the breach. I manually match each firm in the PRC database to Compustat and Dealscan, resulting in a sample of 1,122 breaches. Table 1, Panel A, displays the time series of the sample of cyberattacks. Coverage of breaches is reduced in the latter part of the sample, which is likely to occur because of the delay between reporting and occurrence of cyberattacks.

Panel B of Table 1 provides the distribution of cyberattacks by industry. The breaches are well distributed across industries with the highest concentrations in finance (26.6 percent), wholesale and retail (19.6 percent), business equipment (13.1 percent), and other (12.8 percent).

To construct a measure of peer cyberattacks, the primary variable of interest, I identify the number of cyberattacks experienced in the borrower's industry in the 12 months prior to the loan origination date. I define a borrower's peers as firms in the same four-digit SIC code. Firms experiencing a breach are excluded from the sample to ensure the results from peer breaches are not influenced by breached firms.

## 4. Research Design

The primary dependent variable in the analyses is loan spread (*Spread*), measured as the natural logarithm of all-in spread drawn. To identify the effect of peer cyberattacks on loan spreads, I estimate the following regression where the unit of observation is a single loan:

$$Spread_t = \beta_0 + \beta_1 Count\ peer\ breach_{t-1} + \beta_i \Sigma CONTROLS + \varepsilon. \quad (1)$$

The primary variable of interest is *Count peer breach*, which captures the number of cyberattacks experienced in the borrower's industry in the 12 months prior to loan origination. A positive coefficient on $\beta_1$ implies a contagion effect exists for cyberattacks. A negative coefficient on $\beta_1$ implies a competitive effect dominates.

*CONTROLS* is a vector of firm-specific, loan-specific, and macroeconomic factors shown by prior literature to affect a firm's loan contract terms. I control for borrower size because larger firms are expected to be less risky than smaller firms (Berk 1995). I include control variables for leverage and cash flow volatility, which are expected to be positively associated with borrowing costs. I include a control variable for profitability and expect a negative association with spreads because profitable firms are generally thought to be able to borrow at lower costs. In addition to leverage and profitability, which can influence default risk, I include Altman's (1968) Z-score to further control for default risk. Because a higher Z-score indicates better financial health and lower default risk, I expect a negative coefficient on default risk. I control for tangibility because firms with a significant proportion of tangible assets should have a lower cost of debt. I also include market-to-book as a proxy for firm growth. It is possible that a negative coefficient will result if lenders favorably view the firm's growth opportunities. It is also possible that a positive coefficient will result if lenders view the firm as high risk.

I also include controls for loan-specific variables, including loan maturity, loan size, and performance pricing. Because lenders generally charge lower interest rates for shorter duration loans and larger loans, I expect a positive coefficient on loan maturity and a negative coefficient on loan size (Graham et al. 2008). I include a control variable for performance pricing, which adjusts loan spreads based on changes in borrowers' credit quality (Asquith et al. 2005; Vasvari 2008). Loans with performance pricing are expected to have lower spreads.

I control for macroeconomic factors that influence loan spread (i.e., credit spread, term spread). Year fixed effects are included in the model to ensure unobservable time-series changes do not influence the results. I also include industry, loan type, and loan purpose fixed effects. Standard errors are clustered by borrower and year to account for cross-sectional and serial dependence (Petersen 2009). Variable definitions are included in Appendix A.

## 5. Results

### 5.1. Descriptive statistics

Table 2 presents summary statistics for the sample of loans from Dealscan. Of the 11,575 sample observations, 2,167 (18.7 percent) initiate a loan after one or more of their peers experience a cyberattack with a mean of 2.33 cyberattacks (untabulated) and a maximum of 20, which occurs in the financial services industry. The mean (median) spread, in basis points, is 228.89 (200.00), which is similar to that of prior literature examining peer effects on loan spreads (e.g., Files and Gurun 2018; Hertzel and Officer 2012). On average, sample firms borrow $611 million per loan with a maturity of 54 months. The majority of the sample loans (89.1 percent) are syndicated with each loan having an average of eight lenders. Regarding borrower characteristics, the sample firms have an average of $10.7 billion in total assets. The sample has average market-to-book and profitability ratios of 2.77 and 0.12, respectively. Overall, the sample firms are large and appear economically strong.

Table 3 provides the pairwise Pearson correlations for the regression variables. Consistent with prior literature, *Spread* has strong negative correlations of -0.33 with *Size*, of -0.22 with *Profitability*, and of -0.29 with *Default Risk*. *Spread* has a modest negative correlation of -0.10 with *Market-to-Book*, suggesting firms with fewer growth opportunities face higher costs of debt. *Loan Size* is also negatively correlated with *Spread* (-0.30), suggesting the existence of economies of scale. As expected, *Spread* is positively correlated with *Leverage* (0.20) and *Loan Maturity* (0.12). Finally, the primary variable of interest, *Count peer breach*, is negatively correlated with *Spread* (-0.03).

### 5.2. Multivariate analyses

Table 4 presents the results examining the effect of industry cyberattacks on loan spreads. Column (1) presents the results after including all control variables, loan type and loan purpose fixed effects, and industry fixed effects. The variable of interest, *Count peer breach*, has a negative and significant coefficient (*t*-statistic of -2.67). Column (2) substitutes industry fixed effects with year fixed effects. *Count peer breach* continues to have a negative and statistically significant coefficient (*t*-statistic of -2.29). Column (3) incorporates the full fixed effect structure and similar results obtain. In Column (4), to ensure the peer cyberattack results are not driven by industry performance, I add a control variable for industry profitability. I continue to find a negative and statistically significant coefficient on *Count peer breach* (*t*-statistic of -2.17). These results imply peer firms benefit when their competitors experience cyberattacks through a reduction in loan spreads.[6]

Economically speaking, the coefficient on *Count peer breach* indicates that an additional peer cyberattack decreases a borrower's spread by 0.9 to 1.8 percent (2.05 to 4.08 basis points), on average.[7] To put this effect in a broader context, it is larger than the effect identified by peer restatements (0.43 basis points) but smaller than the effect of cyberattacks on the breached firm (30 basis points) (Files and Gurun 2018; Sheneman 2017).

## 6. Additional Analyses

### 6.1. Validation tests

The primary results in the study provide evidence that peer cyberattacks are negatively associated with borrower loan spreads. In this section, I provide further support for the main results by conducting a series of validity tests using cross-sectional analyses related to loan characteristics and industry performance.

#### 6.1.1. Cross-sectional analyses on loan characteristics

The first set of validation tests provides better identification by showing that peer borrowers receive the greatest benefits in cases where lenders are likely to have the greatest flexibility in renegotiating loan contracts. I perform cross-sectional tests based on two sample partitions: (1) revolver/non-revolver loan type; and (2) shorter/longer loan maturity.

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[6] To ensure the robustness of the results, I re-perform the main analysis using an alternate measure of industry cyberattacks. Specifically, *Peer Breach* is an indicator variable equal to one if a peer cyberattack occurred, and zero otherwise. The relation between *Peer Breach* and *Spread* is negative and statistically significant with *t*-statistics ranging from -1.86 to -3.68, depending on model specification.

[7] Because the dependent variable is in logarithmic form, the coefficient estimate represents the $(e^{\beta}-1) \times 100$ percentage change in loan spread based on a one-unit change in the independent variable. Economic magnitude is discussed relative to the sample's mean loan spread of 228.89 basis points (Table 2).

First, I examine whether the magnitude of the association between peer cyberattacks and borrower loan spreads is greatest for loans used for short-term financing. I partition the sample based on whether loans are classified in Dealscan as revolver or non-revolver loans.[8] Revolvers are typically used for short-term cash flow demands while non-revolvers (e.g., term loans) are used for long-term investment. From the lenders' perspective, longer-term contracts are associated with greater liquidity risk and higher loan spreads.[9] Columns (1) and (2) of Table 5 report the results of this cross-sectional test. Consistent with expectation, the magnitude of the negative association between *Count peer breach* and *Spread* is larger for revolvers. Specifically, the estimated coefficient on *Count peer breach* is negative and marginally significant in the revolver loan subsample ($z$-statistic of -1.68). Interestingly, the coefficient on *Count peer breach* is positive in the non-revolver subsample ($z$-statistic of 1.86). A test for coefficient differences across the revolver and non-revolver subsamples indicates the coefficient on *Count peer breach* is statistically different between the subsamples (chi-sq. of 6.25). These results suggest lenders reduce loan spreads for non-breached firms when competitors experience cyberattacks and the borrower originates short-term financing.[10]

Next, I examine whether the association between peer cyberattacks and borrower loan spreads is greater for shorter duration loans. I predict that a borrower is more likely to benefit from competitors' cyberattacks when the borrower is originating a loan with a shorter contractual maturity because short-term debt is considered less risky. I partition the sample based on median

[8] I rely on DealScan's loan type variable and include 364-day facilities, revolvers, and lines of credit as revolvers.
[9] This general relation is present in the sample as evidenced by the positive correlation (0.124) between *Spread* and *Loan Maturity* (see Table 3).
[10] Strahan (1999) posits that borrower size is correlated with loan type, suggesting large firms rely on bonds for long-term investment while small firms rely on bank loans. To examine whether the term/non-term loan distinction is merely a proxy for borrower size, I partition the sample based on borrower size (i.e., total assets). Comparing the largest borrowers (i.e., top quintile) with the remaining 80 percent of the sample, the estimated coefficient on *Count peer breach* is not statistically significant in either subsample. A test for coefficient differences across the borrower size subsamples indicates the coefficient on *Count peer breach* is not statistically different (chi-sq. of 0.14).

loan maturity and compare shorter duration loans (i.e., maturity less than sample median) with longer duration loans (i.e., maturity greater than or equal to sample median).[11] Columns (3) and (4) of Table 5 report the results of this cross-sectional test. Consistent with expectation, the magnitude of the association between *Count peer breach* and *Spread* is larger for shorter duration loans. Specifically, the estimated coefficient on *Count peer breach* is negative and statistically significant in the shorter duration subsample (*z*-statistic of -2.93) and not statistically significant in the longer duration subsample (*z*-statistic of -0.12). A test for coefficient differences across the shorter and longer duration subsamples indicates the coefficient on *Count peer breach* is statistically different between the subsamples (chi-sq. of 5.34). These results support the prediction that non-breached firms benefit more when short-term debt is issued, which allows lenders the ability to use a time limit to reprice risk, relative to long-term debt.

### 6.1.2. Cross-sectional analyses on industry performance

In the next set of validation tests, I provide evidence that competitors benefit the most from peer cyberattacks when the industry has strong financial performance. I perform cross-sectional tests based on three sample partitions: (1) high/low industry asset growth; (2) high/low industry investment growth; and (3) high/low industry leverage.

I begin by examining whether the magnitude of the association between peer cyberattacks and borrower loan spreads is greatest for high growth industries. I proxy for growth using asset growth and investment growth. Asset growth is measured as current year total assets less prior year total assets, scaled by prior year total assets. Investment growth is measured as current year

[11] There is significant clustering of loan maturity in the sample with 5,451 of the 11,575 observations (47.1 percent) having a loan maturity of 5 years. Because of this clustering, a median split of the sample cannot produce two equal subsamples. In untabulated analysis, I perform the cross-sectional analysis on loan maturity using terciles. Comparing the shorter maturity to the longer maturity tercile, the estimated coefficient on *Count peer breach* is negative and statistically significant in the shorter maturity subsample (*z*-statistic of -2.67) but not statistically significant in the longer maturity subsample (*z*-statistic of 0.53). A test for coefficient differences across the maturity subsamples indicates the coefficient on *Count peer breach* is statistically different (chi-sq. of 5.29).

investments, calculated as the sum of capital expenditures and research and development expenses less acquisitions, less prior year investments, scaled by prior year investments. I predict that borrowers are more likely to benefit from peer cyberattacks when their industry has, on average, higher growth. Columns (1) and (2) of Table 6 report the results of this cross-sectional test using asset growth as the proxy. I partition the sample into above and below median based on average industry-year growth. Consistent with expectation, the magnitude of the association between *Count peer breach* and *Spread* is larger for high asset growth industries. Specifically, the estimated coefficient on *Count peer breach* is negative and statistically significant in the high industry asset growth subsample (*z*-statistic of -2.96) and not statistically significant in the low industry asset growth subsample (*z*-statistic of -0.26). A test for coefficient differences across the high and low asset growth subsamples indicates the coefficient on *Count peer breach* is significantly different (chi-sq. of 4.19).

Columns (3) and (4) of Table 6 report the results using investment growth as the proxy. Similar to the asset growth results, the magnitude of the association between *Count peer breach* and *Spread* is larger for high investment growth industries. Specifically, the estimated coefficient on *Count peer breach* is negative and statistically significant in the high industry investment growth subsample (*z*-statistic of -2.68) and not statistically significant in the low industry investment growth subsample (*z*-statistic of -0.79). A test for coefficient differences across the high and low investment growth subsamples indicates the coefficient on *Count peer breach* is marginally different (chi-sq. of 2.93). Taken together, these results suggest peer cyberattacks impact loan spreads to a greater extent for borrowers operating in higher growth industries.

Next, I examine whether the magnitude of the association between peer cyberattacks and borrower loan spreads varies based on the indebtedness of the industry. I expect borrowers to benefit more when their industry has lower levels of debt. Columns (5) and (6) present the results. I partition the sample into quintiles based on mean industry-year leverage and compare the highest quintile to the lower four quintiles. Consistent with expectation, the negative association between *Count peer breach* and *Spread* is not present in industries with high leverage. Specifically, the estimated coefficient on *Count peer breach* is not statistically significant in the high leverage subsample ($z$-statistic of 1.02) and negative and statistically significant in the low leverage subsample ($z$-statistic of -2.35). A test for coefficient differences across the subsamples indicates the coefficient on *Count peer breach* is marginally different (chi-sq. of 3.73). These results support the prediction that borrowers benefit from peer cyberattacks to a greater extent when overall industry debt levels are low.

### 6.2. Non-spread contractual terms and loan structures

The analyses thus far have focused on loan spread and the competitive effects associated with cyberattacks in the same industry as the borrower. In this section, I examine non-spread contractual terms that have the potential to be affected by cybersecurity risk. For example, Sheneman (2017) finds that fewer lenders lend to borrowers after a cybersecurity breach and that lenders reduce the size of loans for borrowers after a breach. I examine whether the effects on non-spread contractual terms for breached firms are also present for peer firms after controlling for other determinants of the contractual features of loan contracts.

Table 7 presents the results of three regressions analyzing whether competitive effects affect syndicate size, the probability that the borrower has to provide collateral, and the size of the loan.[12] I do not observe significant effects of peer firm cyberattacks on syndicate size or the use of

[12] There is a loss of 2,552 observations for the collateral test because this information is missing in Dealscan. In untabulated analysis, I follow Beatty et al. (2019) and code missing collateral data as loans with collateral. Results are unchanged.

collateral. However, I do find evidence of a reduction in loan size, on average, following peer cyberattacks. This suggests lenders are reducing their overall exposure to high cybersecurity risk industries by reducing the size of loans to borrowers in these industries.

### 6.3. Industry privacy regulation

In this section, I explore the extent to which industry privacy regulation affects the relation between loan spreads and peer cyberattacks by focusing on two significant pieces of privacy legislation. First, the Telecommunications Act of 1996, in Section 702, required firms to protect the confidentiality of customer information. On the one hand, the Telecommunications Act of 1996 may provide strong incentives for these firms to bolster data controls. On the other hand, prior to the Telecommunications Act of 1996, the telecommunications industry was already heavily regulated through various legislation and monitoring by regulators (e.g., Federal Communications Commission, various state regulators). I bifurcate the sample by whether the borrower is or is not regulated by the Telecommunications Act of 1996 (i.e., the borrower is or is not in the telecom industry based on the Fama and French 12-industry categorization). Table 9, Columns (1) and (2), presents the results. Interestingly, the coefficient on *Count peer breach* is positive and significant for the telecom partition, suggesting a contagion effect among the telecom industry. The coefficient on *Count peer breach* is negative and significant for the non-telecom partition, which is consistent with the main analysis documenting the existence of a competitive effect for cyberattacks. A test for coefficient differences across the telecom and non-telecom subsamples indicates the coefficient on *Count peer breach* is statistically different (chi-sq. of 11.52).

Second, in 1996, Congress passed the Health Insurance Portability and Accountability Act (HIPAA). One of the primary tenets of HIPAA is to protect private health information by requiring healthcare organizations to implement and monitor data security measures. On the one hand, implementing such legislation suggests healthcare organizations, relative to other industries, should be better insulated from cyberattacks because of the additional internal control systems required under HIPAA. On the other hand, the requirement of healthcare organizations to protect patient information may not extend to other internal control systems. I bifurcate the sample by whether the borrower is or is not regulated by HIPAA (i.e., the borrower is or is not in the healthcare industry based on the Fama and French 12-industry categorization). Table 9, Columns (3) and (4), presents the results. The coefficient on *Count peer breach* is positive but insignificant for the healthcare partition while the coefficient on *Count peer breach* continues to be negative and significant for the non-healthcare borrowers. Additionally, a test for coefficient differences across the healthcare and non-healthcare subsamples indicates the coefficient on *Count peer breach* is statistically different (chi-sq. of 3.98).

The results from this section suggest lenders' responses to peer cyberattacks vary by industry. Interestingly, the results imply that lenders may be adjusting expectations upward for cyber risk in the telecommunications industry while adjusting expectations downward for other industries without specific privacy laws.

## 7. Conclusion

This study examines the intra-industry information transfer effect of cybersecurity events. Building upon prior work examining contagion effects of cyber risk in the equity market, I provide evidence that peer cyberattacks are associated with significant competitive effects in the private debt market, as indicated by decreases in loan spreads. Cross-sectional analyses reveal these findings are concentrated in loans used for short-term cash flow demands and loans with shorter durations. In addition, the competitive effects are present in industries with high growth and low leverage.

This study is subject to several important caveats. The results are subject to potential endogeneity concerns. Unlike prior literature that examines contagion effects of cyberattacks using stock market reactions (e.g., Kamiya et al. 2021), this study relies upon a long-window research design. Because I measure peer cyberattacks in the year prior to loan origination, I cannot make causal inferences about peer cyberattacks and loan spreads. As with any long-window study, there is the possibility that omitted factors may influence the results.

Despite the limitations described above, the results of this study are likely to be of interest to academics and policy makers. The paper contributes to the debt contracting and contagion literatures by demonstrating the consequences of cyberattacks. Because cyber risk is an emerging risk that is not well understood, the results are likely to be useful to policy makers as they continue to debate regulation establishing minimum standards related to cybersecurity investment.

## Appendix A. Variable Definitions

| Variable | Definition |
|---|---|
| Dependent variables | |
| *Spread* | The natural logarithm of all-in spread drawn, calculated as the amount the borrower pays in basis points over LIBOR for each dollar drawn down. |
| *Number of lenders* | The natural logarithm of the total number of lenders involved in a single loan. |
| *Collateral* | Indicator variable equal to one if the loan requires collateral, zero otherwise. |
| *Loan size* | The natural logarithm of the loan facility amount. |
| Test variables | |
| *Count peer breach* | The number of cybersecurity breaches in the 12-month period prior to loan origination by firms with the same four-digit SIC code as the borrowing firm. |
| Control variables | |
| *Size* | The natural logarithm of total assets. |
| *Market-to-book* | Market value of equity, scaled by book value. |
| *Leverage* | Long-term debt plus debt in current liabilities, scaled by total assets. |
| *Profitability* | Operating income before depreciation, scaled by total assets. |
| *Tangibility* | Net property, plant, and equipment, scaled by total assets. |
| *Cash flow volatility* | The natural logarithm of the standard deviation of the change in quarterly cash flows from operations over the four fiscal years prior to the loan. |
| *Default risk* | Altman's (1968) Z-score is calculated as follows: 1.2*(WCAP/AT) + 1.4*(RE/AT) + 3.3*(EBIT/AT) + 0.6*(PRCC_F*CSHO/LT) + 0.999*(SALE/AT). |
| *Loan maturity* | The natural logarithm of the loan maturity measured in months. |
| *Performance pricing* | An indicator variable equal to one if the loan facility utilizes performance pricing (e.g., firm's credit rating, firm's financial ratios), and zero otherwise. |
| *Credit spread* | Credit spread is the difference in the yield between the AAA and BAA corporate bonds, obtained from the Federal Reserve Bank of St. Louis. |
| *Term spread* | Term spread is the difference in the yield between the 10-year and 2-year Treasury bonds, obtained from the Federal Reserve Board of Governors. |
| *Industry profitability* | The mean profitability for each firm in the borrower's industry. |

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**Table 1**
Distribution of loans and cyberattacks by year and industry

*Panel A: Loans and cyberattacks by year*

| Year | Number of loans | Number of breaches |
|---|---|---|
| 2005 | n/a | 35 |
| 2006 | 1,155 | 111 |
| 2007 | 1,099 | 97 |
| 2008 | 749 | 53 |
| 2009 | 488 | 38 |
| 2010 | 800 | 116 |
| 2011 | 980 | 109 |
| 2012 | 862 | 100 |
| 2013 | 955 | 128 |
| 2014 | 879 | 112 |
| 2015 | 882 | 39 |
| 2016 | 747 | 57 |
| 2017 | 773 | 68 |
| 2018 | 676 | 53 |
| 2019 | 530 | 6 |
| Total | 11,575 | 1,122 |

*Panel B: Loans and cyberattacks by industry*

| Industry | Number of loans | Number of breaches |
|---|---|---|
| Consumer nondurables | 708 | 40 |
| Consumer durables | 383 | 22 |
| Manufacturing | 1,490 | 38 |
| Energy | 1,035 | 12 |
| Chemicals | 497 | 6 |
| Business equipment | 1,365 | 147 |
| Telecom | 408 | 66 |
| Utilities | 801 | 13 |
| Wholesale, retail | 1,212 | 220 |
| Healthcare | 786 | 116 |
| Finance | 911 | 298 |
| Other | 1,979 | 144 |
| Total | 11,575 | 1,122 |

This table presents the distribution of the sample of loans and the sample of cyberattacks by year (Panel A) and industry (Panel B). Industry is defined using four-digit SIC codes. For ease of presentation, the sample is presented using the Fama and French 12-industry categorization.

**Table 2**
Summary statistics

| *Variables* | Mean | Median | Std. dev. |
|---|---|---|---|
| *Count peer breach* | 0.44 | 0.00 | 1.46 |
| *Spread (basis points)* | 228.89 | 200.00 | 156.10 |
| *Number of lenders (count)* | 8.35 | 7.00 | 6.52 |
| *Collateral* | 0.73 | 1.00 | 0.44 |
| *Loan size ($ millions)* | 610.89 | 300.00 | 1,060.86 |
| *Size* | 7.74 | 7.69 | 1.66 |
| *Market-to-book* | 2.77 | 2.02 | 4.69 |
| *Leverage* | 0.31 | 0.29 | 0.21 |
| *Profitability* | 0.12 | 0.11 | 0.08 |
| *Tangibility* | 0.31 | 0.22 | 0.27 |
| *Cash flow volatility* | 4.61 | 4.58 | 1.57 |
| *Default risk* | 1.37 | 1.26 | 1.34 |
| *Loan maturity (months)* | 53.96 | 60.00 | 19.46 |
| *Performance pricing* | 0.39 | 0.00 | 0.49 |
| *Credit spread* | 1.03 | 0.92 | 0.38 |
| *Term spread* | 1.30 | 1.41 | 0.90 |
| *Industry profitability* | 0.12 | 0.12 | 0.04 |

This table presents the descriptive statistics for the variables used in the regression models. Variables are defined in Appendix A.

**Table 3**
Pearson correlation coefficients

| | *Variables* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | *Spread* | -- | | | | | | | | | | | | | |
| (2) | *Count peer breach* | **-0.031** | -- | | | | | | | | | | | | |
| (3) | *Size* | **-0.334** | **0.044** | -- | | | | | | | | | | | |
| (4) | *Market-to-book* | **-0.097** | 0.008 | -0.005 | -- | | | | | | | | | | |
| (5) | *Leverage* | **0.204** | **-0.031** | **0.153** | **-0.025** | -- | | | | | | | | | |
| (6) | *Profitability* | **-0.220** | 0.001 | -0.024 | **0.196** | **-0.036** | -- | | | | | | | | |
| (7) | *Tangibility* | -0.020 | **-0.056** | **0.148** | **-0.062** | **0.212** | 0.023 | -- | | | | | | | |
| (8) | *Cash flow volatility* | **-0.361** | **0.030** | **0.926** | 0.024 | **0.083** | **0.099** | **0.127** | -- | | | | | | |
| (9) | *Default risk* | **-0.288** | **-0.060** | **-0.053** | **0.142** | **-0.373** | **0.484** | **-0.212** | **0.055** | -- | | | | | |
| (10) | *Loan maturity* | **0.124** | -0.015 | **-0.035** | 0.022 | **0.066** | **0.102** | -0.021 | **-0.050** | **0.042** | -- | | | | |
| (11) | *Loan size* | **-0.303** | -0.011 | **0.667** | **0.063** | **0.141** | **0.124** | **0.117** | **0.647** | **0.057** | **0.136** | -- | | | |
| (12) | *Performance pricing* | **-0.178** | 0.016 | **-0.084** | **0.026** | **-0.148** | **0.108** | 0.023 | **-0.061** | **0.126** | -0.008 | 0.007 | -- | | |
| (13) | *Credit spread* | **0.132** | -0.012 | **-0.098** | **-0.057** | **-0.068** | -0.023 | **0.045** | **-0.078** | -0.024 | **-0.253** | **-0.154** | **0.094** | -- | |
| (14) | *Term spread* | **0.308** | 0.018 | -0.009 | **-0.046** | -0.017 | **-0.037** | **0.033** | 0.003 | **-0.033** | **-0.060** | **-0.030** | -0.002 | **0.198** | -- |

The table reports Pearson correlations for the variables used in the regression models. Bolded values indicate significance at the 1% level. Variables are defined in Appendix A.

**Table 4**
Peer firm cyberattacks and loan spread

| *Variables* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Count peer breach* | -0.018** | -0.009** | -0.009** | -0.009** |
| | (-2.67) | (-2.29) | (-2.16) | (-2.17) |
| *Size* | -0.097*** | -0.105*** | -0.087*** | -0.087*** |
| | (-5.96) | (-6.05) | (-5.34) | (-5.30) |
| *Market-to-book* | -0.004 | -0.005* | -0.004* | -0.004* |
| | (-1.74) | (-2.09) | (-1.81) | (-1.81) |
| *Leverage* | 0.519*** | 0.470*** | 0.447*** | 0.447*** |
| | (8.01) | (7.91) | (7.98) | (7.98) |
| *Profitability* | -1.130*** | -1.121*** | -1.044*** | -1.044*** |
| | (-8.07) | (-8.72) | (-7.86) | (-7.53) |
| *Tangibility* | 0.004 | 0.045 | 0.034 | 0.034 |
| | (0.09) | (1.58) | (0.73) | (0.72) |
| *Cash flow volatility* | -0.002 | -0.012 | -0.023** | -0.023** |
| | (-0.15) | (-1.13) | (-2.18) | (-2.19) |
| *Default risk* | -0.059*** | -0.048*** | -0.056*** | -0.056*** |
| | (-8.19) | (-7.29) | (-7.76) | (-7.77) |
| *Loan maturity* | 0.071*** | 0.049** | 0.057*** | 0.057*** |
| | (3.79) | (2.34) | (3.18) | (3.16) |
| *Loan size* | -0.070*** | -0.081*** | -0.088*** | -0.088*** |
| | (-6.39) | (-6.39) | (-7.05) | (-7.05) |
| *Performance pricing* | -0.108*** | -0.052*** | -0.047*** | -0.047*** |
| | (-5.14) | (-3.64) | (-3.15) | (-3.15) |
| *Credit spread* | 0.174*** | 0.133*** | 0.141*** | 0.141*** |
| | (3.43) | (3.10) | (3.36) | (3.35) |
| *Term spread* | 0.222*** | 0.109** | 0.108** | 0.108** |
| | (5.85) | (2.69) | (2.75) | (2.75) |
| *Industry profitability* | | | | -0.002 |
| | | | | (-0.01) |
| Year fixed effects | No | Yes | Yes | Yes |
| Industry fixed effects | Yes | No | Yes | Yes |
| Loan type fixed effects | Yes | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes |
| Observations | 11,575 | 11,575 | 11,575 | 11,575 |
| Adj. R-squared | 0.553 | 0.571 | 0.592 | 0.592 |

The table reports the regression results where the dependent variable is *Spread*, which is calculated as the natural logarithm of all-in spread drawn. *Count peer breach* is the number of cybersecurity breaches experienced by firms in the borrower's four-digit SIC industry in the 12 months prior to loan origination. Remaining variables are defined in Appendix A. The constant is unreported. Standard errors are clustered by firm and year. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 5**
Loan characteristics, peer firm cyberattacks, and loan spread

| | Loan type partition | | Loan maturity partition | |
|---|---|---|---|---|
| | Revolvers | Non-revolvers | Shorter | Longer |
| *Variable* | (1) | (2) | (3) | (4) |
| *Count peer breach* | -0.008* | 0.011* | -0.021*** | -0.001 |
| | (-1.68) | (1.86) | (-2.93) | (-0.12) |
| Controls | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Loan type fixed effects | No | No | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes |
| Observations | 8,523 | 3,052 | 4,103 | 7,472 |
| Adj. R-squared | 0.548 | 0.499 | 0.530 | 0.650 |
| **Wald tests for coefficient differences:** | | | | |
| [Revolvers]*Count peer breach* – [Non-revolvers]*Count peer breach* = 0 | Chi-Sq.: | 6.25** | | |
| [Shorter]*Count peer breach* – [Longer]*Count peer breach* = 0 | | | Chi-Sq.: | 5.34** |

The table reports the regression results where the dependent variable is *Spread*, which is calculated as the natural logarithm of all-in spread drawn. *Count peer breach* is the number of cybersecurity breaches experienced by firms in the borrower's four-digit SIC industry in the 12 months prior to loan origination. Columns (1) and (2) report subsamples based on loan type. Columns (3) and (4) report subsamples based on loan maturity. Tests for coefficient differences between the subsamples are conducted by using seemingly unrelated estimation and the Wald test. Remaining variables are defined in Appendix A. The constant is unreported. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 6**
Industry performance, peer firm cyberattacks, and loan spread

| | Asset growth partition | | Investment growth partition | | Extreme leverage partition | |
|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low |
| *Variable* | (1) | (2) | (3) | (4) | (5) | (6) |
| *Count peer breach* | -0.017*** | -0.001 | -0.017*** | -0.004 | 0.009 | -0.010** |
| | (-2.96) | (-0.26) | (-2.68) | (-0.79) | (1.02) | (-2.35) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan type fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,740 | 5,835 | 5,631 | 5,977 | 2,278 | 9,297 |
| Adj. R-squared | 0.572 | 0.581 | 0.575 | 0.568 | 0.568 | 0.571 |
| **Wald tests for coefficient differences:** | | | | | | |
| [High]*Count peer breach* – [Low]*Count peer breach* = 0 | Chi-Sq.: | 4.19** | Chi-Sq.: | 2.93* | Chi-Sq.: | 3.73* |

The table reports the regression results where the dependent variable is *Spread*, which is calculated as the natural logarithm of all-in spread drawn. *Count peer breach* is the number of cybersecurity breaches experienced by firms in the borrower's four-digit SIC industry in the 12 months prior to loan origination. Columns (1) and (2) report subsamples based on industry asset growth. Columns (3) and (4) report subsamples based on industry investment growth. Columns (5) and (6) report subsamples based on industry leverage. Tests for coefficient differences between the subsamples are conducted by using seemingly unrelated estimation and the Wald test. Remaining variables are defined in Appendix A. The constant is unreported. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 7**
Peer firm cyberattacks and non-spread loan contract terms

| DV = | *No. of lenders* | *Collateral* | *Loan size* |
|---|---|---|---|
| *Variables* | (1) | (2) | (3) |
| *Count peer breach* | 0.001 | -0.002 | -0.043** |
| | (0.07) | (-0.57) | (-2.41) |
| *Size* | 0.161*** | -0.046*** | 0.464*** |
| | (12.18) | (-4.17) | (16.03) |
| *Market-to-book* | 0.001 | -0.002 | 0.007*** |
| | (0.81) | (-1.26) | (3.25) |
| *Leverage* | 0.119** | 0.381*** | 0.223** |
| | (2.19) | (11.32) | (2.73) |
| *Profitability* | 0.384** | -0.559*** | 1.077*** |
| | (2.50) | (-7.90) | (4.03) |
| *Tangibility* | 0.029 | -0.053 | 0.039 |
| | (0.56) | (-1.37) | (0.37) |
| *Cash flow volatility* | 0.001 | -0.041*** | 0.085** |
| | (0.12) | (-4.06) | (2.58) |
| *Default risk* | 0.013 | -0.011 | 0.050*** |
| | (1.24) | (-1.68) | (3.28) |
| *Loan maturity* | 0.242*** | 0.110*** | 0.356*** |
| | (8.45) | (10.01) | (7.57) |
| *Loan size* | 0.244*** | -0.038*** | |
| | (15.11) | (-3.95) | |
| *Performance pricing* | 0.249*** | -0.106*** | 0.263*** |
| | (9.28) | (-8.18) | (8.45) |
| *Credit spread* | -0.005 | -0.004 | -0.010 |
| | (-0.20) | (-0.36) | (-0.28) |
| *Term spread* | -0.039* | 0.016 | 0.063 |
| | (-1.79) | (0.86) | (1.23) |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Loan type fixed effects | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes |
| Observations | 11,575 | 8,993 | 11,575 |
| Adj. R-squared | 0.481 | 0.376 | 0.551 |

The table reports the regression results for non-spread loan contract terms. *Count peer breach* is the number of cybersecurity breaches experienced by firms in the borrower's four-digit SIC industry in the 12 months prior to loan origination. In Column (1), the dependent variable is *Number of lenders*, measured as the natural logarithm of the number of lenders. In Column (2), the dependent variable is *Collateral*, which is an indicator variable equal to one if the loan requires collateral, zero otherwise. In Column (3), the dependent variable is *Loan size*, which is measured as the natural logarithm of the loan facility amount. Remaining variables are defined in Appendix A. The constant is unreported. Standard errors are clustered by firm and year. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 8**
Industry privacy laws, peer firm cyberattacks, and loan spread

| | Telecom partition | | Healthcare partition | |
|---|---|---|---|---|
| | Yes | No | Yes | No |
| *Variable* | (1) | (2) | (3) | (4) |
| *Count peer breach* | 0.057*** | -0.010** | 0.018 | -0.011*** |
| | (2.95) | (-2.56) | (1.28) | (-2.87) |
| Controls | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Loan type fixed effects | Yes | Yes | Yes | Yes |
| Loan purpose fixed effects | Yes | Yes | Yes | Yes |
| Observations | 408 | 11,167 | 786 | 10,789 |
| Adj. R-squared | 0.589 | 0.571 | 0.657 | 0.565 |
| **Wald tests for coefficient differences:** | | | | |
| [Yes]*Count peer breach* – [No]*Count peer breach* = 0 | Chi-Sq.: | 11.52*** | Chi-Sq.: | 3.98** |

The table reports the regression results where the dependent variable is *Spread*, which is calculated as the natural logarithm of all-in spread drawn. *Count peer breach* is the number of cybersecurity breaches experienced by firms in the borrower's four-digit SIC industry in the 12 months prior to loan origination. Columns (1) and (2) report subsamples based on industries with and without the Telecommunications Act of 1996 privacy regulations, respectively. Columns (3) and (4) report subsamples based on industries with and without HIPAA privacy regulations, respectively. Tests for coefficient differences between the subsamples are conducted by using seemingly unrelated estimation and the Wald test. Remaining variables are defined in Appendix A. The constant is unreported. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.