How Data Breach Notification Laws reshape corporate debt structure

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Abstract

Data are increasingly recognized as critical assets for firms' competitive advantages, yet they are largely absent from financial reports, limiting research on their impact on corporate behavior. Due to the unique vulnerability of data assets to cyber risks, particularly through data breaches, all U.S. states have gradually enacted Data Breach Notification (DBN) laws over recent decades, requiring firms to promptly disclose any data breaches. In this paper, we examine the ex-ante cyber risk associated with data assets on firms' debt maturity structures, utilizing the staggered difference-in-differences (DID) approach provided by the implementation of DBN laws. Our findings show that following the adoption of DBN laws, firms in affected states exhibit a tendency towards using more short-term debt financing. In exploring the underlying mechanisms, we find that this shift is primarily observed among firms characterized by higher liquidity risk, greater information asymmetry, and less financial flexibility. In cross-sectional tests, we find heterogeneous effects of DBN laws on firms' debt maturity structure across firms with different sizes, technology intensity, asset intangibility, exposure to cybersecurity risk, and litigation risk. Our further analyses reveal that the reduction in debt maturity following the adoption of DBN laws enhances firms' financial reporting quality, improves investment efficiency, and increases firms' cash holding. Additionally, DBN laws adoption has significant impact on firms' choice of different types of debt instruments.

Keywords: Data Breach Notification Laws, Data assets, Debt maturity

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1 Introduction

Data is increasingly recognized as valuable asset for firms (e.g., Veldkamp, 2023). This is evident from the tendency of investors to be more tolerant of losses incurred by technology firms, given the significant commercial value attributed to the data gathered by these firms. However, like other internally generated intangible assets (Lim et al., 2020), data assets are difficult to quantify and are largely omitted from financial reports, which limits research on their impact on corporate behavior. A unique feature of data assets is their vulnerability to cyber risks, particular through data breaches. These breaches can jeopardize firms' reputations, cause financial loss, harm overall firm value, and influence financing decisions (Akey et al., 2020; Gogolin et al., 2021; Kamiya et al., 2021; Florackis et al., 2023; Lattanzio and Ma, 2023; Liu et al., 2025). For example, in 2017, Moody's downgraded Equifax's credit outlook from stable to negative, marking the first time cybersecurity issues were explicitly cited as the reason for a credit rating downgrade.[2] Evidence such as this underscores the importance of thoroughly examining how cybersecurity risks associated with data assets and their related regulations impact firms' capital structure decisions.

To investigate the impacts of cyber risks associated with data assets, our study utilizes the Data Breach Notification (DBN) laws gradually adopted by all U.S. states between 2002 and 2018. Before these laws, firms were not required to disclose data breaches. Subsequent to the adoption of DBN laws, firms are mandated to promptly disclose occurrences of data breaches without unreasonable delay to notify their customers and other affected parties. Though the likelihood of experiencing a data breach may remain unchanged, the obligation to disclose such breaches publicly significantly increases a firm's ex-ante risk of incurring future costs related to disclosed breaches. For instance, Boasiako and Keefe (2021) argue that mandatory DBN laws increase a firm's ex-ante risk of costs from disclosed breaches, leading firms to hold more cash as a precaution. Cao et al. (2023) find that DBN laws, which mandate firms to disclose both current and past data breaches, lead to increased stock price crash risk.

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[2] For details, see "*Equifax just became the first company to have its outlook downgraded for a cyber attack*": https://www.cnbc.com/2019/05/22/moodys-downgrades-equifax-outlook-to-negative-cites-cybersecurity.html.

Our paper aims to explore how DBN laws influence firms' debt maturity structure, an important integral part of corporate capital structure. Firms often hold a combination of both short- and long-term debt and rebalance the maturity profile gradually (Hu et al., 2024). Choosing the optimal debt maturity structure is vital for corporate financial strategy, as it involves a trade-off between ensuring sufficient liquidity and managing associated costs and risks (Diamond, 1991; Berger et al., 2005). Prior research on trends in corporate debt maturity structures shows that these choices are dynamic and have evolved significantly across different periods. For example, Custodio et al. (2013) report a decline in the mean proportion of long-term debt from 49% in 1976 to 21% in 2000, while Byun et al. (2021) document a significant increase in the median proportion of long-term debt from 29.6% in 2000 to 58.6% in 2017. In addition, equity markets do not price all debt-related risks equally. A firm's levered equity risk profile, as captured by standard risk factors, appears to depend on its debt maturity structure (Friewald et al., 2022). Specifically, equity returns have been found to rise with increasing proportion of short-term debt, but this positive relationship does not extend to long-term debt holdings (Friewald et al. 2022).

The impact of ex-ante cyber risk associated with data assets on firms' debt maturity structures has not been clearly established by prior research. We propose two competing hypotheses and conduct a comprehensive analysis to explore how firms adjust their debt maturity structures following the adoption of DBN laws. On the one hand, affected firms may tend to use more long-term debt. This perspective is supported by two key arguments. First, by mandating prompt disclosure of any detected data breaches, DBN laws can expose firms to higher liquidity risk due to greater uncertainty in future earnings and cash flows, stemming from factors such as increased litigation risk, direct costs to address security issues, and reputational damage (Romanosky et al., 2014; Huang and Wang, 2020; Boasiako and Keefe, 2021; Kamiya et al., 2021; Wei and Zhu, 2024). This heightened risk makes it difficult for firms with short-term debt to roll over credit as obligations mature, which could result in inefficient liquidation (Diamond, 1991; Guedes and Opler, 1996). To mitigate this renewal risk, firms may be more inclined to utilize long-term debt.

Second, the adoption of DBN laws aim to help reduce information asymmetry, which may lead firms to favor long-term debt over short-term debt. By mandating prompt disclosure of any detected breaches, these laws aim to enhance transparency regarding firms' data security practices and impacts of breaches (Obaydin et al., 2024). This gives equity investors clearer visibility into risks and therefore translating to a lower equity risk premium and reduced cost of equity (Ashraf and Sunder, 2021). As a result, firms may be able to borrow long-term due to the improved perception of risk and the associated reduction in the cost of equity capital.

On the other hand, a competing view suggests that firms may be more inclined to utilize short-term debt following the adoption of DBN laws. This perspective is supported by three key arguments. First, while long-term debt offers a potential buffer against the risk of denied loan renewals, its effectiveness is limited. Firms that disclose data breaches face higher credit risk due to higher cash flow volatility, potential declines in credit rating, and greater bankruptcy risks (Kamiya et al., 2021). Lenders are aware of the heightened credit risk associated with longer-term debt and consequently demand higher returns (Guedes and Opler, 1996), making it less attractive for firms. This dynamic is further confirmed by Agarwal et al. (2024), who observed an increase in the cost of debt for firms in U.S. states that enacted DBN laws. As a result, firms experiencing increased liquidity risk due to DBN legislation may find themselves constrained to shorter-term debt markets.

Second, DBN laws may worsen information asymmetry between firms and stakeholders (Obaydin et al., 2024). While mandated disclosure of breaches increases visibility for equity investors and lowers equity risk premium (Ashraf and Sunder, 2021), it also incentivizes managerial discretion in reporting. Post DBN laws adoption, managers have been found to selectively withhold negative information, leading to higher stock price crash risk (Cao et al., 2024; Obaydin et al., 2024) and undermining the laws' transparency goals. This heightened information asymmetry prompts firms to prefer short-term debt, which allows lenders to better monitor managerial behavior and demand timely financial disclosures during renegotiations (Myers, 1977; Diamond, 1991; Rajan and Winton, 1995; Stulz, 2001; Giannetti, 2003; Datta et al., 2005; Dang et al., 2018). High-quality firms may also prefer short-term debt as it is less likely to be mispriced than long-term debt, thereby signalling managerial confidence (Flannery, 1986; Barclay and Smith, 1995; Goyal and Wang, 2013). Consequently, DBN laws may inadvertently encourage firms to pursue short-term debt to manage information asymmetry and investor expectations.

Third, DBN laws could encourage firms to prioritize financial flexibility by favoring short-term debt to adapt to new disclosure standards and address unforeseen costs from data breaches. Research shows that firms in DBN-affected states hold more cash to buffer against these costs, reduce dividends, and increase share buybacks (Boasiako and Keefe, 2018; Wei and Zhu, 2024). To further enhance flexibility, firms might reduce long-term investments in innovative projects (Wang et al., 2024). This strategy preserves liquidity and decreases their reliance on long-term debt. This strategy, along with decreased long-term assets, makes firms less likely to issue long-term debt (Guedes and Opler, 1996).

To test the above two competing hypotheses, we collect data on U.S. listed firms over the period from 1997 to 2015 and investigate the impact of DBN laws, which were gradually adopted in different states in the U.S., on firms' debt maturity. Our main findings reveal a significant decline in the debt maturity of affected firms following the adoption of DBN laws. To further explore the potential mechanisms, including heightened liquidity risk, the potentially worsened information environment, and firms' willingness to maintain financial flexibility, we conduct a series of subsample tests. The mechanism analyses show that the negative effect of DBN laws on debt maturity is mainly observed among firms with higher ex-ante liquidity risk, higher information asymmetry, and less ex-ante financial flexibility. These results lend supporting evidence to the three possible mechanisms we have proposed. Furthermore, we observe that the negative impact of DBN laws is significant among larger firms and those operating in industries characterized by lower technology intensity, higher asset intangibility, higher litigation risk, and elevated cyber risk. Moreover, following the enactment of DBN laws, we find consequent effects on financial reporting quality, investment efficiency, and cash holdings. In additional tests, we find that firms' choice of different debt instruments is also influenced by DBN laws adoption. Specifically, firms reduce the issuance of public debt following DBN laws adoption.

The contributions of our study are two-fold. First, we offer a novel perspective on examining the impacts of data assets, specifically the ex-ante cybersecurity risk induced by data asset-related regulations, on firms' debt maturity structures. Since internally generated intangible assets are largely omitted from financial statements and are difficult to quantify, research on their impact on corporate behavior remains limited (Lim et al., 2020). Recent studies have begun to explore the relationship between intangible assets and corporate capital structure. For instance, Lim et al. (2020) find that identifiable intangible assets can support debt financing as effectively as tangible assets, enhancing the financing capacity of firms lacking tangible assets. While data is increasingly recognized as one of the most valuable assets for firms, its impact on corporate behavior is still underexplored. Utilizing the staggered adoption of DBN laws in the U.S., our study investigates how the risks associated with data assets influence firms' debt maturity structures. In this regard, our paper also contributes to the growing literature on the consequences of cybersecurity threats arising from the digitalization of the U.S. economy (Boasiako and Keefe, 2021; Gogolin et al., 2021; Kamiya et al., 2021; Cao et al., 2023; Florackis et al., 2023). Second, our paper extends the existing research on the determinants of firms' debt maturity structures. Previous studies have shown that a firm's debt maturity structure is influenced by accounting policies, financial flexibility, liquidity risk, information asymmetry, agency costs, and external environments (e.g., Stohs and Mauer, 1996; Kang et al., 2017; Wang, 2020; Ee et al., 2023). In this context, our study contributes to the literature on debt structure by introducing a novel factor, the ex-ante cybersecurity risk, that has the potential to reshape the composition of corporate debt.

The remainder of the paper is organized as follows. Section 2 provides background on DBN laws, reviews related literature, and develops hypotheses. Section 3 describes the data, sample, and variable construction. Section 4 presents baseline results and robustness tests. Section 5 explores potential mechanisms. Section 6 examines heterogenous effects. Section 7 offers additional analyses. Section 8 concludes.

2 Related literature and hypotheses development

2.1 DBN laws in the United States

The importance of data assets has been underscored by the rise of the digital economy. Many countries are now integrating data assets into their accounting frameworks to better reflect the true intrinsic value of corporations and to enhance the protection of these assets.[3] These assets include various forms of data, such as customer information, intellectual property, and operational data. The value of data assets lies in their potential to generate economic benefits, support decision-making, and enhance competitive advantage. However, dependence on data also exposes organizations to cybersecurity risks, which can result in substantial financial losses and reputational damage.[4] Existing literature emphasizes that the increasing frequency and sophistication of cyberattacks pose significant threats to organizations (Gordon et al., 2020).

In response to the emerging challenges from cyber risks associated with data assets, all U.S. states adopted DBN laws between 2002 and 2018. For instance, California was the first state to enact a DBN laws in 2002, requiring breached firms to notify authorities and affected customers when data breaches occur. Before these laws were enacted, U.S. firms had no legal obligation to disclose data breaches. Since the adoption of DBN laws, firms are now mandated to promptly disclose occurrences of data breaches without unreasonable delay to customers and other affected parties. Although the likelihood of experiencing a data breach may remain unchanged, the obligation to disclose such breaches publicly significantly increases a firm's ex-ante risk of incurring future costs related to these disclosures (e.g., Boasiako and Keefe, 2021; Cao et al., 2023). This regulatory setting allows for the examination of the impact of ex-ante cyber risks associated with data assets on firm behavior.

2.2 Related literature and hypotheses development

Debt maturity structure refers to the timeline over which a firm's debt obligations are scheduled for repayment. It encompasses both short-term debt (due within a year) and long-term debt (due in more than a year). Choosing an optimal debt maturity structure is a critical aspect of corporate financial strategy. Firms typically trade off various factors to ensure sufficient liquidity, while managing the costs and risks associated with debt

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[3] See *China Treats Data As An Asset—Here's Why Your Business Should, Too*: https://www.forbes.com/sites/forbestechcouncil/2024/04/18/china-treats-data-as-an-asset-heres-why-your-business-should-too/?sh=2c719772905b

[4] Anecdotal evidence is substantial; for example, in April 2021, Facebook experienced a severe data breach that exposed the private information of over 530 million users. This incident led to fines imposed by the Data Protection Commission and significant economic losses for Facebook's users. See "*Personal Data Of 533 Million Facebook Users Leaks Online*": https://www.forbes.com/sites/ajdellinger/2021/04/03/personal-date-of-533-million-facebook-users-leaks-online/.

(Diamond, 1991; Berger et al., 2005). In response to cybersecurity risk, firms may adjust their financial strategies accordingly. Cybersecurity risk impacts the cost of debt, as firms with greater vulnerabilities often face higher premiums due to perceived risks by lenders. Research indicates that lenders demand higher interest rates or more stringent covenants from firms with greater cybersecurity vulnerabilities, reflecting the increased default risk associated with potential cyber incidents (Kamiya et al., 2021).

Our paper aims to explore the effects of ex-ante cyber risk associated with data assets on firms' debt maturity structure, a relationship not clearly established by prior research. We propose two competing hypotheses to clarify the impact of DBN laws adoption on debt maturity. The first hypothesis predicts that firms are more likely to utilize long-term debt following adoption of the DBN laws. Two related arguments support this hypothesis. First, DBN laws adoption may expose firms to higher liquidity risk. This is because DBN mandates prompt disclosure of any detected data breaches, thereby subjecting firms to greater uncertainty in future earnings and cash flows due to increased litigation risk, direct costs to remedy security issue, and potential indirect costs from reputational damage, lost customers, higher cybersecurity, and insurance expenses (Romanosky et al., 2014; Huang and Wang, 2020; Kamiya et al., 2021; Wei and Zhu, 2024). This added risk exposure stemming from DBN compliance exacerbates liquidity risk for firms holding primarily short-term debt because they may be struggled to roll over credit when those short-term obligations mature, hence may face inefficient liquidation (Diamond, 1991; Guedes and Opler, 1996). Using long-term debt, however, shields firms from this denied renewal risk over the longer lifecycle of the debt obligations. Given that DBN laws are expected to increase firms' liquidity risk following data breaches, firms may seek to replace short-term debt with more long-term debt.

Second, DBN laws are designed to enhance transparency around data security practices and breach impacts. By mandating prompt disclosure of any detected breaches, the laws transform previously private information into public knowledge (Schwartz and Janger, 2007). This increased transparency not only encourages firms to invest in digital infrastructure to improve data security (Romasnosky et al. 2011; Gordon et al. 2018), but also provides equity investors with clearer visibility into potential risks associated with investing in these firms. As a result, with reduced uncertainty around their operations, firms may experience a lower equity risk premium and reduced cost of equity (Ashraf and Sunder, 2021; Elmawazini et al., 2023). Consequently, this improved perception among investors can result in enhanced creditworthiness, which makes long-term debt more attractive. Firms may prefer long-term debt as it typically offers more favorable repayment terms that allow them to lock in financing at a lower cost for an extended period of time.

The competing hypothesis posits that firms gravitate towards short-term debt following the adoption of DBN laws. This hypothesis is supported by the following three arguments. First, while the heightened liquidity risk provides some incentive for firms to extend debt maturities post-DBN adoption, they may not be able to do so as lenders demand higher returns to bear greater credit risk over the longer term (Guedes and Opler, 1996). In fact, prior research finds that firms located in the U.S. states that adopted the DBN laws experienced an increase in their cost of debt following the laws' enactment (Agarwal et al., 2024). Firms disclosing data breaches are exposed to higher credit risk due to higher cash flow volatility, decline in credit rating, and increased bankruptcy risks (Kamiya et al. 2021). Consequently, they encountered higher loan spreads and more unfavorable loan terms, such as collateral requirements and more covenants (Huang and Wang, 2020). Therefore, firms facing elevated liquidity risk may have little choice but to borrow in the short-term debt markets where funding remains relatively accessible.

Second, DBN laws have the potential to deteriorate firms' information environment. While the aim of DBN laws is to increase transparency around data security practices and breach impacts (Obaydin et al., 2024), the reality is disclosures mandated by these laws may contribute to greater information asymmetries between firms and their stakeholders. Although improved infrastructure may lower breach risks, effectively preventing breaches is difficult due to data systems' complexity (Murciano-Goroff, 2019). Recognizing this, managers can choose to build reputation through transparent reporting or selectively withholding adverse news to project a positive outlook in the short-term (Obaydin et al., 2024). Hence, whether DBN adoption truly reduce information asymmetry depends on managerial disclosure strategies (Obaydin et al., 2024). Prior research suggests that information asymmetry may instead worsen after DBN laws adoption. The adoption of DBN laws has been linked to higher stock price crash risk as managers temporarily stockpile negative financial news (Cao et al., 2024; Obaydin et al., 2024). Firms were also more likely to engage in real earnings manipulation through production and operation management post DBN adoption (Liu and Ni, 2024). In addition, firms provided less detailed breach information post DBN adoption, though breaches were disclosed faster (Ashraf et al., 2022). This incomplete disclosure may undermine the law's objective of increasing transparency over time if the managerial incentive to potentially withhold bad news overpowers the benefits of proactively investing in cybersecurity prevention.

As a result, firms facing heightened information asymmetries resulting from potential data breaches become more likely to issue short-term debt, which entails lower information costs than long-term debt (Barclay and Smith, 1995). Specifically, since short-term debt requires more frequent refinancing (Myers, 1977; Diamond, 1991), it allows the lenders to credibly threaten non-renewal as an incentive for managers to act in lenders' interest (Giannetti, 2003). Lenders can also demand timely and reliable disclosures on finances and investments during renegotiations to safeguard their interests (Dang et al., 2018). Hence, short-term debt can serve as an effective monitoring tool for lenders and help enhance transparency (Rajan and Winton, 1995; Stulz, 2001; Datta et al., 2005). The opportunity to assess managerial behavior afforded by short-term debt is specifically beneficial following data breaches where managers may be incentivised to withhold bad news (Obaydin et al., 2024; Cao et al., 2024).

Furthermore, with the presence of managerial disclosure strategies post DBN adoption, it can be challenging for investors to price long-term debt accurately to reflect credit risk. This may prompt high-quality borrowers to gravitate towards short-term debt financing since short-term debt tends to be less mispriced than long-term debt and can act as a credible signal of managerial confidence in the firm's prospects (Flannery, 1986; Barclay and Smith, 1995; Goyal and Wang, 2013). By voluntarily taking on increased refinancing risk through the issuance of short-term debt, high-quality managers can convey to the market their private information that the firm is sufficiently sound to continually rollover its debts.

Third, maintaining financial flexibility could motivate firms to rely on short-term debt following the DBN adoption. The DBN adoption may prompt adjustments to the funding needs and firms' financing strategies as they adapt to new disclosure standards.

Specifically, responding to data breach incidents may require unforeseen financial expenditures. Rather than locking in long-term debts that restrict alternatives for several years, short-term debt allows firms to address temporary cash needs while preserving financial flexibility. This enables firms to respond rapidly to changing regulations or market sentiments around data breaches and protection. The need to maintain financial flexibility is evidenced by firms located in states affected by DBN laws holding more cash as a buffer against disclosure-related costs, as well as paying less dividend and increasing share-buybacks following the DBN adoption (Boasiako and Keefe, 2018; Wei and Zhu, 2024). In addition, prior research shows that firms experiencing a cybersecurity attack significantly increased their cash holdings in the years following the incident and this trend persisted for up to three years after the breach (Garg, 2020). This purposefully cash hoarding likely acts as a precautionary move to ensure readily available funds for potential breach costs and contingencies farther into the future. Moreover, to maintain financial flexibility, firms are found to reduce long-term investment in innovative projects post DBN adoption (Wang et al., 2024). By holding back on initiatives with distant payoffs, firms preserve liquidity. With reduced long-term investments, firms therefore have less long-term assets in place to be backed by more long-term debt, thereby are more inclined to issue short-term debt (Guedes and Opler, 1996). This strategy reduces their ability and incentive to tap the long-term debt markets.

Taken together, whether firms respond to DBN laws adoption by issuing more long-term or short-term debt remain an empirical question. Based on above arguments, we develop our hypotheses as follows:

Hypothesis 1a: After the adoption of DBN laws, debt maturity of affected firms would increase.

Hypothesis 1b: After the adoption of DBN laws, debt maturity of affected firms would decrease.

3 Data, sample, and variables

3.1 Data and Sample

Our sample includes all non-financial (excluding SIC codes 6000–6999) and non-utility (excluding SIC codes 4900–4999) public firms in the U.S. Our sample spans from 1997 to 2015, starting five years before California's DBN laws adoption in 2002 and extending five years after Mississippi's DBN laws adoption in 2010, thus covering most of the years when states adopted these laws. Our sample ends in 2015, following Boasiako and Keefe (2021) and Ashraf and Sunder (2023), to avoid including years after 2018 when all states had adopted DBN laws. Extending beyond 2018 would eliminate control states, thereby undermining the difference-in-differences design by removing valid comparisons and risking biased estimates. The specific years of DBN laws adoption across states are identified from publicly available records.[5] We obtain data on firms' debt structure from S&P Capital IQ database, and data on debt ratings and other firm-level financial information from the Compustat and the Center for Research in Security Prices (CRSP) databases. We exclude observations with missing information on key variables in our analysis. Our final sample consists of 45,606 firm-year observations.

3.2 Variables

3.2.1 Debt maturity structure measures

Following prior studies (Datta et al., 2005; Saretto and Tookes, 2013; Ee et al., 2023), we construct two sets of measures to capture firms' debt maturity structure. The first measure, *WMAT*, is calculated as the principal-weighted maturity of all outstanding debt at the firm-year level. This measure directly captures the debt maturity in terms of remaining years. The second set of measures, *LTD1*, *LTD2*, *LTD3,* and *LTD4*, are calculated as the ratio of adjusted long-term debt scaled by total debt. For instance, *LTD3*, is defined as the ratio of long-term debt deduct debt maturing in 2 and 3 years scaled by total debt.

[5] See: https://www.itgovernanceusa.com/data-breach-notification-laws

3.2.2 Identification of DBN laws adoption

DBN laws require organizations that experience any data breach to notify affected customers and relevant parties in a timely manner and implement remedial actions as prescribed by state legislation. Following previous research (Boasiako and Keefe, 2021; Ashraf et al., 2022; Ashraf and Sunder, 2023; Cao et al., 2024), we construct the dummy variable *DBN*, which equals 1 if the firm's incorporation state has adopted DBN laws in a given year, and 0 otherwise. Given the nature of state-level DBN laws, the adoption is unlikely to be influenced by local firms' financing activities, which can help mitigate potential endogeneity concerns.

3.2.3 Control variables

In line with previous studies (Custodio et al., 2013; Ee et al., 2023), we include a comprehensive set of variables that may influence firms' debt structure as controls in our empirical analyses. Specifically, we control for firm size (*SIZE*), firm age (*AGE*), profitability (*ROA*), change in earnings per share (*ABE*), stock price volatility (*ASETVOL*), asset maturity (*ASETMAT*), leverage (*LEV*), fixed assets (*PPE*), capital expenditure (*CAPX*), market-to-book ratio (*MTB*), cash holdings (*CASH*), sales growth (*GROWTH*), R&D expenditure (*RD*), and S&P long-term debt rating (*RATE*).

Table 1 presents descriptive statistics for all variables used in our analysis. All continuous variables are winsorized at the 1% level on both tails. Detailed variable definitions are provided in Appendix A. The descriptive statistics for the main variables are in line with prior literature on debt maturity (Datta et al., 2005; Saretto and Tookes, 2013; Gul and Goodwin, 2010; Custodio et al., 2013; Ee et al., 2023). The average value of principal-weighted debt maturity of our sample is 3.318, with median value being 3.382. The treatment group represents 41.5% of the observations in the sample.

[Insert Table 1 here]

4 Baseline results

4.1 Baseline regression: DBN laws and debt maturity structure

To examine the impact of DBN laws on the debt maturity structure of affected firms, we employ a DID regression model, specified as follows:

$$Debt\ maturity_{it} = \alpha + \beta DBN_{i,t-1} + \sum Controls_{i,t-1} + FirmFE + Ind * YearFE + \varepsilon_{it} \quad (1)$$

where *Debt maturity* represents the debt maturity structure of firms (*WMAT*, *LTD1*, *LTD2*, *LTD3*, and *LTD4*). *DBN* is a dummy variable that equals 1 if the firm's incorporation state has adopted DBN laws in a given year, and 0 otherwise. $\sum Controls$ consists of a range of control variables including *SIZE*, *AGE*, *ROA*, *ABE*, *ASETVOL*, *ASETMAT*, *LEV*, *PPE*, *CAPX*, *MTB*, *CASH*, *GROWTH*, *RD*, and *RATE*. We also control for the firm- and industry-year-fixed effects. Robust standard errors are clustered at the state level. Detailed variable definitions are provided in Appendix A.

The coefficient of key interest is thus β, which captures the impact of DBN laws on affected firms' debt maturity structure after controlling for other determinants. Table 2 reports the baseline results with principal-weighted debt maturity (*WMAT*) and total long-term debt deduct debt maturing in 2 and 3 years scaled by total debt (*LTD3*) as dependent variables. We include firm- and industry-year fixed effects across all columns to ensure robust estimation. The coefficients on DBN_{t-1} remain significantly negative across all specifications, regardless of whether control variables are included. These results provide strong evidence supporting our hypothesis that firms reduce their reliance on long-term debt in response to the adoption of DBN laws. Regarding the economic significance, for example, in Column (3), the coefficient on DBN_{t-1} is -0.0407, suggesting that, on average, firms' principal-weighted average debt maturity decreases by 4.07% following the adoption of DBN laws by their incorporation states. This change corresponds to 1.23% (1.20%) of the mean (median) value of *WMAT* in our sample. Similarly, in Column (4), the usage of long-term debt maturing in more than three years (*LTD3*) declines by 4%, which is equivalent to 8.89% (8.57%) of the mean (median) value of the sample.

[Insert Table 2 here]

4.2 Robustness tests

We conduct several robustness tests to strengthen our baseline results. First, to validate the parallel trends assumption in our DID setting, we adopt the dynamic DID model to estimate the dynamic effects of DBN laws adoption on debt maturity, in line with prior literature (e.g., Bertrand and Mullainathan, 2003; Bourveau et al., 2018; Ashraf, 2022; Ashraf and Sunder, 2023). To conduct the dynamic DID analysis, we include key variables as follows: *DBN(t-2)*, which equals 1 if firm *i*'s year *t* is two years before the year in which its headquarter state passed the DBN laws, and 0 otherwise; *DBN(t-1)*, which equals 1 if firm *i*'s year *t* is one year before the year in which its headquarter state passed the DBN laws, and 0 otherwise; *DBN*, which equals 1 for years starting from the adoption of state-level DBN laws; *DBN(t)*, which equals 1 if firm *i*'s year *t* is the year in which its headquarter state passed the DBN laws; *DBN(t+1)*, which equals 1 if firm *i*'s year *t* is one year after the year in which its headquarter state passed the DBN laws; and *DBN(t+2…n)*, which equals 1 if firm *i*'s year *t* is the second year and later after its headquarter state passed the DBN laws. The results are reported in Table 3. The coefficients on both *DBN(t-2)* and *DBN(t-1)* are insignificant, indicating that the parallel trends assumption holds.

[Insert Table 3 here]

Second, to ensure that our baseline results are specifically attributable to the adoption of DBN laws in the states where firms are headquartered, we perform placebo tests. We conduct 1,000 simulations, randomly generating adoption years and treated states within the actual reform period. Thus, we generate 1,000 placebo samples and create a distribution of placebo estimates. Following this, we re-estimate the impacts of these pseudo-events (DBN laws) on pseudo-treated states using the complete set of control variables included in our baseline DID regression. If our results were driven by unobserved shocks coinciding with DBN adoption, we would expect the coefficient on DBN_{t-1} to remain significant, even when both the assignment of treated states and adoption years are randomized.

Figure 1 displays the empirical cumulative distribution function and the density of the estimated DBN coefficients. As expected, the placebo law-enforcement variable's estimated coefficients exhibit a central tendency around zero. Our benchmark estimates from Table 2, represented by vertical lines at 0.0407 in Column (3) and 0.400 in Column (4), respectively, fall outside the range of the estimated coefficients generated by the placebo simulations. This suggests that our main findings are unlikely to be influenced by random occurrences.

[Insert Figure 1 here]

Third, we address endogeneity concerns arising from self-selection bias and omitted variables by applying propensity score matching and the Oster (2019) methodology. The parallel trends assumption, required for identification, posits no systematic differences in debt maturity structure between treatment and control firms in the absence of DBN laws adoption. To implement the matching procedure, firms headquartered in states that have enacted DBN laws (treatment group) are systematically paired with comparable firms from states that have not implemented such laws (control group). We estimate the probit regression with the dependent variable coded as one for treatment firms and zero for control firms, including firm-level control variables from Eq. (1). Panel A of Table 4 presents the probit model results in Column (1), while Columns (2) and (3) show the nearest-neighbour propensity score matching results for outcome variables *WMAT* and *LTD3*, respectively. The consistency between Column (1) and Columns (2) and (3) suggests no violation of the parallel trends assumption. We then re-estimate the baseline model by employing data from three years before and passed DBN adoption. The coefficients on DBN_{t-1} in Columns (1) and (2) of Panel B in Table 4 remain statistically significant with fixed effects, confirming that firms in DBN-adopting states favor short-term debt post-adoption, consistent with our main findings.

We also apply the method proposed by Oster (2019) to assess potential omitted variable bias, following Donohoe et al. (2022). This approach evaluates the stability of coefficient estimates and changes in *R*-squared between regressions with and without control variables. If the coefficient remains consistent as *R*-squared rises upon including controls, concerns about omitted variable bias can be minimized. According to Oster (2019), a delta value greater than 1 or less than -1 indicates that omitted variable bias is likely negligible. Panel C in Table 4 presents results from two approaches of the Oster test. Column (1) indicates that the true β is likely bounded between [-0.0538, -0.0407] for

WMAT and [-0.0553, −0.0401] for *LTD3* as dependent variables. According to Oster (2019), sensitivity of β estimates can be assessed by verifying (1) whether the bound falls within the 99.5% confidence interval for the coefficient, and (2) whether the bounds exclude zero. In this analysis, the bounds for β are within the 99.5% confidence intervals of *DBN*, which range from [-0.0828, -0.0107] for *WMAT* and [-0.0715, -0.0084] for *LTD3*, and exclude zero, indicating that unobserved factors comparable to the controlled variables are unlikely to drive β. Column (2) shows δ values of -3.65 and -2.33, both below -1, further supporting that selection and omitted variable biases are unlikely to significantly impact our findings.

Fourth, to mitigate the concerns of the potential bias in staggered DID design, we further refine our analysis by implementing a "stacked regression" approach (Cengiz et al., 2019; Barrios, 2022; Baker et al., 2022). We follow the approach detailed in Ashraf and Sunder (2023). Specifically, we construct event-cohort datasets, each confined to a two-year window centered around the treatment year, encompassing one year prior to and one year following the adoption of the treatment. For instance, the 2002 event-cohort dataset includes observations from 2001 and 2002; the 2005 event-cohort dataset includes observations from 2004 and 2005, etc. Within each cohort, firms headquartered in states that enacted the treatment law during that period are considered treated, while firms in states yet to adopt the law serve as controls. For example, in the 2005 cohort, firms located in states that enacted the law in 2005 are treated, while those in states that had not yet enacted it by 2005 serve as controls (with firms from states that adopt the laws before 2005 excluded from that cohort).

We then consolidate all event-cohort datasets into a single dataset and re-estimate our main model, fully saturating it with cohort-specific indicators as outlined by Baker et al. (2022) and Barrios (2022). Results in Columns (1) and (2) of Panel C in Table 4 show the DBN coefficient remains statistically significant and negative, with an effect size similar to our primary findings. Overall, Table 4 supports the robustness of our results, with minimal influence from selection, omitted variable biases, or limitations of the DID design.

[Insert Table 4 here]

Lastly, Table 5 presents robustness tests using alternative debt maturity structure measures (*LTD1, LTD2,* and *LTD4*) and alternative fixed effects. *LTD1* is the proportion of long-term debt relative to total debt, and *LTD2* and *LTD4* represent the proportions of long-term debt maturing in over two, four, and five years, respectively, relative to total debt. Panel A shows the results with firm- and industry-year fixed effects. Panel B includes firm- and year- fixed effects. Panel C includes year- and industry- fixed effects. Panel D includes firm-, year-, and state- fixed effects. The coefficients on DBN_{t-1} remain negative and statistically significant, showing the robustness of our baseline results to these alternative specifications.

In Panel E of Table 5, we examine the possibility that our results might be driven predominantly by firms in high-tech industries, which are more vulnerable to data breaches, or by firms located in regions with a greater awareness of cyber risks. Thus, in Columns (1) and (2) of Panel E, we exclude firms which headquarter states are in Silicon Valley and observe that our results remain consistent. In Columns (3) and (4), we exclude observations from the global financial crisis period (2008 and 2009). In Columns (1) and (2) of Panel F, we remove observations that firms headquarter states adopting the law in 2005—24 out of 50 states—to confirm that our findings are not solely influenced by this cohort. In addition, to address concerns that firms' most recently documented headquarters in the Compustat database might not accurately reflect their actual locations at the time of each law's enactment, we adjust for geographically dispersed industries. In Columns (3) and (4) of Panel F, we exclude firms in retail, transportation, and wholesale sectors (Agrawal & Matsa, 2013), as these firms are less impacted by staggered state-level adoption of the DBN laws. Even with these exclusions, we continue to observe evidence supporting the shortening of debt maturity post-law adoption.

[Insert Table 5 here]

5 Mechanism analyses

Our baseline results suggest that firms turn to rely more on short-term debt following the adoption of DBN laws. In this section, we explore three potential mechanisms of this observed effects.

5.1 Liquidity risk

Following the adoption of DBN laws, firms are exposed to increased liquidity risk. The disclosure of data breaches leads to heightened credit risk due to greater cash flow volatility, deteriorating credit ratings, and elevated bankruptcy risks (Kamiya et al., 2021). Consequently, firms facing significant liquidity risks may be compelled to rely more heavily on short-term debt markets, where funding remains relatively more accessible. Thus, we expect that firms with high liquidity risk increase the proportion of short-term debt after DBN adoption.

To examine this mechanism, we construct four proxies for liquidity risk: cash flow volatility (Keefe and Yaghoubi, 2016), credit rating (Ericsson and Renault, 2006), Altman's Z-score (Altman, 1968), and Ohlson's O-score (Ohlson, 1980). Cash flow volatility is measured as the standard deviation of yearly cash flows from operations divided by total assets over the past five fiscal years. *RATE* is the numerical value assigned to a firm's S&P credit rating; it takes the value of 1 for an S&P rating of AAA, 2 for an S&P rating of AA+, and so on. Altman's Z-score is calculated following Altman's (1968) model, where a value above 3 signals a lower risk of financial distress. We employ the O-score as outlined by Ohlson (1980), which takes higher values with a greater likelihood of bankruptcy. We then divided our sample into high and low liquidity risk subgroups based on whether the liquidity risk proxy was above or below the median value of the full sample, except for the Altman's Z-score, which was split at a threshold of 3. Table 6 indicates that firms with higher liquidity risk, evidenced by greater cash flow volatility, lower credit ratings, lower Altman's Z-scores (below 3), and higher Ohlson's O-scores, tend to increase their reliance on short-term debt more after the adoption of DBN laws. The differences in the coefficients between high and low liquidity risk groups are statistically significant. These findings support our conjecture that heightened liquidity risk leads affected firms to rely more on short-term debt.

[Insert Table 6 here]

5.2 Information asymmetry

Prior research indicates that information environment may worsen following the adoption of DBN laws, as firms may withhold unfavorable information and engage in earnings manipulation, thereby elevating the risk of stock price crashes (Obaydin et al., 2024; Cao et al., 2024; Liu and Ni, 2024). While firms are required to disclose breaches more promptly, the disclosures often lack detail (Ashraf et al., 2022), potentially undermining the objective of enhanced transparency. Consequently, affected firms with higher information asymmetry may be more likely to issue short-term debt with lower information costs (Barclay and Smith, 1995). This type of debt offers a more frequent refinancing opportunity, which enables lenders to monitor managers more effectively (Myers, 1977; Diamond, 1991; Giannetti, 2003; Dang et al. 2018).

To test this mechanism, we divide the sample into high and low information asymmetry subgroups based on analyst forecast dispersion (Mansi et al., 2011), analyst forecast error (Mansi et al., 2011), and total accruals (Dechow and Dichev, 2002; Bhattacharya et al., 2013) and conduct subsample tests. Analyst forecast dispersion is quantified as the standard deviation of earnings forecasts, normalized by the stock price at the conclusion of the prior fiscal year. Analyst forecast error is defined as the absolute value of the median forecast error, also scaled by the stock price at the end of the preceding fiscal year. The total accruals are estimated using the modified Dechow and Dichev (2002) model. We classify a firm into high (low) subgroup if the proxy for information asymmetry is above (below) the sample median. The results are presented in Table 7. Consistent with our conjecture, the significantly negative coefficients on DBN_{t-1} are only observed among high information asymmetry subgroups, indicating that firms with greater information asymmetry are more inclined to issue short-term debt following the adoption of DBN laws. In addition, the differences in the coefficients between high and low information asymmetry groups are statistically significant.

[Insert Table 7 here]

5.3 Financial flexibility

The DBN laws adoption may prompt firms to revise their funding needs and financing strategies to comply with new disclosure requirements. Responding to data breaches often incurs unforeseen costs, making short-term debt more appealing than long-term commitments that limit flexibility. Short-term debt provides firms with the liquidity to address immediate cash needs while allowing them to quickly adapt to changing regulations and market perceptions surrounding data breaches and data security. In addition, firms have been found to reduce long-term investment after the adoption of DBN laws (Wang et al., 2024), which can incentivize them to align this reduced long-term investment with lower levels of long-term debt. Thus, we anticipate that firms facing higher debt financing constraints experience more severe shock from DBN laws and adjust their debt maturity accordingly.

We utilize three measures of financial constraints (i.e., capital expenditure, debt financing constraints, and equity financing constraints) to divide the sample into subgroups based on whether the firm's financial constraints proxy is above (High) or below (Low) the median value. Capital expenditure is measured as firms' capital expenditure scaled by total book assets at the beginning of the year. Debt-focused delay investment score (debt constraints) and equity-focused delay investment score (equity constraints) are developed by Hoberg and Maksimovic (2015), which are based on the textual analysis of firm liquidity disclosures in the Management's Discussion and Analysis (MD&A) section of 10-K fillings. Higher delay investment scores indicate a greater likelihood firms will curtail investments due to liquidity challenges (Hoberg and Maksimovic, 2015), which suggests greater financial constraint. The results in Panels A and B of Table 8 indicate that only firms with high ex-ante capital expenditures (Boasiako and Keefe, 2021) and higher constraints in obtaining debt financing (Hoberg and Maksimovic, 2015) significantly reduce their use of long-term debt following DBN adoption. The differences in the coefficients between high and low financing constraints groups are statistically significant. Panel C of Table 8 shows that firms, regardless of their level of equity financing constraints (Hoberg and Maksimovic, 2014), exhibit a significant reduction in the use of long-term debt.

[Insert Table 8 here]

Taken together, in exploring the mechanisms, our results show that the adoption of DBN laws leads to a reduced use of long-term debt by affected firms, driven by the heightened liquidity risk, a worsened information environment, and firms' intention to maintain financial flexibility.

6 Cross-sectional tests

In this section, we investigate cross-sectional heterogeneity in the treatment effect to provide further insights into how DBN laws impact debt maturity across firms with varying characteristics. Specifically, we analyze how the effect of DBN on debt maturity varies across different: (i) firm size, (ii) technology intensity, (iii) asset intangibility, (iv) litigation risk, and (v) cybersecurity risk.

6.1 Firm size

We first consider the influence of firm size. Larger firms are often more visible in the market as compared to smaller firms. When they experience a data breach, the negative news can have a more pronounced impact on their reputation, as the incident affects more employees, customers, and business partners (Gordon et al., 2018; Al-Sartawi, 2020). However, larger firms often have more resources to mitigate reputational losses and repair risks, thus reducing the persistence of these effects. For instance, Wang et al. (2024) provide evidence that the innovation capacity of smaller firms is more vulnerable to cybersecurity threats, primarily due to their limited resources for risk mitigation. To examine the moderating effect of firm size on the impact of DBN laws on debt maturity structure, we split our sample into large and small firm groups based on the sample median total sales and estimate the impact of DBN laws using the two subsamples. Results in Panel A of Table 9 indicate that, for both debt maturity measures—*WMAT* and *LTD3*—the coefficients on *DBN* are negative and significant in the subsample of larger firms only. These findings are consistent with the notion that larger firms, due to their higher profile and broader stakeholder base, experience more severe effects and consequently tend to utilize more short-term debt following the DBN laws adoption compared to smaller firms.

6.2 Technology intensity

Lee (2019) suggests that high-technology industries are disproportionately affected by data breaches, given their extensive involvement in technological processes and sensitive data handling. However, Kamiya et al. (2021) argue that firms operating in technology-driven sectors may invest more in cybersecurity, as the benefits of enhanced security often justify the costs. To explore how these differing dynamics influence firms' debt financing behavior, we examine the moderating effect of technological intensity by segmenting firms into high and low product differentiation groups using product differentiation scores developed by Hoberg and Phillips (2016). Firms' product differentiation score is a proxy for technology intensity and is associated with greater R&D investment and proprietary technology development (Hoberg and Phillips, 2016). Panel B of Table 9 shows that, following DBN adoption, firms in less technology-intensive industries exhibit a more substantial shift toward short-term debt compared to those in high-tech industries, consistent with the conjecture that technology intensive firms have stronger shelter to cybersecurity issues.

6.3 Asset intangibility

Asset intangibility, closely linked to a firm's exposure to cyberattacks, is another key factor in understanding debt maturity responses to DBN laws. High asset intangibility often correlates with extensive computerized data and other digital assets, which increase susceptibility to breaches. Based on Kamiya et al. (2021) and Wang et al. (2024), we hypothesize that firms with high asset intangibility face greater cyberattack risks, and thus, DBN laws adoption leads to a more pronounced decrease in debt maturity for these firms. Panel C of Table 9 presents the results from subgroup regressions based on firms' asset intangibility, which is calculated as one minus the ratio of property, plant, and equipment to total assets (Kamiya et al., 2021). In line with our expectation, debt maturity declines more after DBN adoption among firms with high asset intangibility than among those with lower intangibility.

6.4 Cybersecurity risk

We further examine how cybersecurity risk moderates the relationship between DBN and debt maturity. Prior studies indicate that certain industries, due to inherent characteristics, are more vulnerable to cyberattacks and face elevated cybersecurity risks (Ashraf et al., 2022; Ettredge et al., 2018; Ettredge & Richardson, 2003). We posit that firms in high cybersecurity risk industries are subject to more frequent cyberattacks and thus experience a more pronounced impact from DBN laws. The results are shown in Panel D of Table 9. Following Wang et al. (2024), we classify industries such as manufacturing, retail trade, information, finance and insurance, healthcare, and social assistance as high exposure to cybersecurity risk sectors (IBM, 2017). Consistent with our conjecture, the inverse relationship between DBN and debt maturity is particularly pronounced for firms operating in higher cybersecurity risk industries.

6.5 Litigation risk

Finally, we consider the influence of litigation risk, given that firms with higher litigation exposure are particularly susceptible to data breaches. Such firms may face higher costs from lawsuits and disputes initiated by their shareholders, making the external monitoring role of short-term debt even more essential (Francis et al., 1994; Arena, 2018). Consequently, we expect the impact of DBN on debt maturity to be more pronounced among firms in high litigation risk industries. Panel E in Table 9 reports the results, where we classify industries with high litigation risk following Francis et al. (1994). High litigation risk industries refer to biotech sectors (SICs 2833–2836, 8731–8734), computers sectors (SICs 3570–3577, 7370–7374), electronics sectors (SICs 3600–3674), and retail sectors (SICs 5200–5961). The inverse relationship between DBN and debt maturity is stronger among firms operating in higher litigation risk industries than among those in lower litigation risk industries, which indicates the sensitivity of these firms to DBN impacts.

[Insert Table 9 here]

7 Further analyses

7.1 Subsequent effects of DBN and debt maturity

The preceding sections show that debt maturity tends to decrease following the adoption of DBN laws. In this section, we further explore potential outcomes stemming from this reduction in debt maturity. The finance and accounting literature identifies two main advantages of short-term debt: enhanced monitoring and improved corporate governance mechanisms. First, prior studies suggest that short-term debt reduces the risk of financial misreporting by increasing lender monitoring frequency of managerial activities (Rajan and Winton, 1995; Datta et al., 2005; Gul and Goodwin, 2010; Fung and Goodwin, 2013). Accordingly, we expect that shortened debt maturities post-DBN adoption may enhance financial reporting quality by mitigating misreporting risk.

Second, prior studies suggest that lower debt maturity incentivizes more rigorous monitoring on managerial actions, which reduces agency problems and improves investment efficiency by addressing both overinvestment and underinvestment issues (Myers, 1977; Datta et al., 2005; Biddle and Hilary, 2006; McNichols and Stubben, 2008; Biddle et al., 2009; Chen et al., 2011; Gomariz and Ballesta, 2014). Thus, we anticipate that DBN-induced reductions in debt maturity may translate into higher investment efficiency.

Last, while shorter debt maturities offer monitoring benefits, they also introduce refinancing risk, as firms face the possibility of adverse shifts in market conditions or higher refinancing costs (Diamond, 1991; Froot et al., 1993). Cash reserves, however, can mitigate this risk by providing a buffer against asset sales or inefficient liquidation to meet debt obligations. As a result, firms may bolster their cash holdings to offset refinancing risk associated with shorter-term debt (Harford et al., 2014). Therefore, we conjecture that DBN-induced reductions in debt maturity also correlate with increased cash holdings.

In Table 10, we present the results examining the effects of reduced debt maturity following the adoption of DBN laws on financial reporting quality, investment efficiency, and cash holdings. In Panel A, the dependent variable is financial reporting quality, calculated as the average of three standardized proxies following McNichols and Stubben (2008), Kasznik (1999) based on Jones (1991), and Dechow and Dichev (2002). We derive the residuals from each model, take their absolute values, and multiply by -1; a higher value thus signifies higher financial reporting quality. The results show a negative, significant coefficient for both *WMAT* and *LTD3*, implying that firms with shorter debt maturities exhibit improved reporting quality, consistent with findings by Fung and Goodwin (2014). Moreover, the positive and statistically significant interaction term between these debt measures (*WMAT* and *LTD3*) and *DBN* suggests that the DBN-driven maturity reduction further enhances financial reporting quality.

In Panel B of Table 10, we assess the impact of reduced debt maturity following DBN adoption on firms' investment efficiency, using a measure based on Biddle et al. (2009). Specifically, we calculate investment efficiency by first obtaining the residuals from the Biddle et al. (2009) model, then taking their absolute values and multiplying by -

1, where higher values indicate greater investment efficiency. Results indicate a negative relationship between long-term debt and investment efficiency, aligning with Gomariz and Ballesta (2014). The positive and significant interaction terms between long-term debt measures and DBN further indicate that DBN-induced reductions in debt maturity improve investment efficiency.

Finally, we examine the impact of reduced debt maturity following DBN adoption on firms' cash holdings. Panel C of Table 10 reveals a negative relationship between both measures of long-term debt and cash holdings, calculated as the natural logarithm of cash scaled by book assets, consistent with findings by Harford et al. (2014). The positive and significant interaction terms indicate that the DBN-induced reduction in debt maturity is associated with increased cash holdings, confirming our expectations.

[Insert Table 10 here]

7.2 The effects of DBN on debt choice: public debt vs bank loan

In the context of U.S. public firms, two primary avenues for debt financing are the issuance of debt securities to external investors (public debt) and direct borrowing from financial intermediaries (bank loans) (Chen et al., 2021). On the one hand, when it comes to public debt, external lenders are notably sensitive to information. Therefore, firms that have experienced data breaches leading to reputation damage and reduced customer trust may encounter challenges when seeking public debt financing. On the other hand, financial institutions possess an inherent advantage in gathering private data and closely monitoring firms facing cybersecurity risks. These institutions view breached firms as carrying elevated default and information risks, often translating into less favorable loan terms (Huang and Wang, 2021). Consequently, the impact of DBN laws adoption on the debt structures of firms remains an open question that requires exploration.

To address how firms' debt choice changes after DBN adoption, we follow Chen et al. (2023) and Bae et al. (2024) and construct the following model:

$$Debt\ choice_{it} = \alpha + \beta DBN_{i,t-1} + \sum Controls + FirmFE + Ind * YearFE + \varepsilon_{it} \quad (2)$$

where i and t denote the individual firm and the corresponding year, respectively. Debt choice structure ($Debt\ choice_{it}$) is captured through either the percentage of public debt or bank loans to total assets. *DBN* is a binary variable equal to 1 if the focal state has passed DBN laws in the year *t,* and 0 otherwise. $\sum Controls$ consists of a range of firm's financial characteristics including firm size, leverage, tangibility, profitability, market to book ratio, rating, and investment grade. We also control for the firm- and industry-year fixed effects.

Table 11 presents the results examining the impact of DBN laws adoption on firms' debt financing choices. Columns (1) and (2) display the results with public debt as the dependent variable, and Columns (3) and (4) show the results with bank debt as the dependent variable. The findings reveal a negative and significant relationship between DBN laws adoption and public debt measure, suggesting that firms reduce their usage of public debt following the adoption of DBN laws. In contrast, the results concerning bank loans are not statistically significant. Overall, our analysis suggests that firms decrease their reliance on public debt after the DBN laws adoption, with no significant effect observed on bank loan usage.

[Insert Table 11 here]

To further examine the impact of DBN laws adoption on different debt instruments, following the methodology of Chen et al. (2023), we divide public debt into three categories: senior bonds and notes, subordinated bonds and notes, and commercial paper. Similarly, we categorize bank debt into term loans and revolving credit facilities. Descriptive statistics for these debt components are reported in Panel A of Table 12, showing comparability with Chen et al. (2023).

Table 12 Panel B displays the regression results. The ratios of various debt instruments serve as the dependent variables, shedding light on changes in debt instrument usage following DBN laws adoption. In the public debt regressions, the coefficients on DBN in Columns (1) to (3) are consistently negative. Notably, the coefficients on DBN are both negative and statistically significant in the regression for senior bonds and notes, as well as for commercial paper. This finding is consistent with our earlier finding that firms tend to gravitate to short-term debt post DBN laws adoption. However, surprisingly, we find that the usage of commercial papers, a short-term debt, reduces following the DBN laws adoption. This suggests that firms did not universally increase short-term debt usage post DBN laws adoption, but rather selectively increased the issuance of certain types of short-term debt. In bank loan regressions, Columns (4) and (5) show a significant increase in the proportion of term loans, accompanied by a significant decrease in revolving credit. Again, this suggests that firms subject to new DBN laws did not uniformly increase short-term debt usage. Instead, they selectively increased the issuance of term loans while reduced the usage of revolving credit facilities. Given the uncertainty nature of revolving credit, by shifting from revolving credit facilities to term loans, firms can reduce their overall risk profile in the face of heightened legal risks from DBN laws adoption, while still preserving sufficient financing flexibility through term loans usage.

[Insert Table 12 here]

8 Conclusion

Data assets have become essential to firm competitiveness in the contemporary business environment. Despite ongoing challenges in their measurement and valuation, the risks inherent to data assets have become increasingly prominent, leading to stricter regulatory oversight in the digital era. This study demonstrates that the adoption of Data Breach Notification laws has resulted in a shift in corporate debt financing behavior. Specifically, firms subject to DBN laws exhibit a greater reliance on short-term debt financing. Our findings remain robust across an extensive series of robustness checks, addressing the endogeneity issues, including self-selection bias, omitted variable bias, and inherent limitations associated with the DID design.

Our mechanism tests reveal three mechanisms contributing to this shift: heightened liquidity risk, exacerbated information asymmetry, and firms' tendency to maintain financial flexibility. These findings highlight the significant influence of ex-ante risks associated with data assets on corporate debt financing decisions. Further cross-sectional analyses reveal that the impact of DBN laws on debt maturity structure is particularly pronounced among larger firms, firms operating in less technology intensive industries, firms with high levels of intangible assets, firms having higher litigation risk, and firms with higher cybersecurity exposure. In addition, our findings indicate that the reduction in debt maturity following DBN laws adoption is associated with improved financial reporting quality, enhanced investment efficiency, and increased cash holdings. Upon further examination of firms' post DBN debt choice decisions, we observe a shift towards reduced reliance on public debt, with notable decline in the issuance of senior bonds, notes, and commercial papers.

Our study broadly adds to the growing literature on the interplay between cybersecurity regulation and corporate finance. Moreover, our study underscores that incorporating the financial implications of data breaches into strategic decision-making will be essential for long-term financial stability and sustained competitive advantage.

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Table 1. Descriptive statistics

This table presents the summary statistics of the variables used in our analysis from 1997 to 2015. Variable definitions are provided in Appendix A. All the continuous variables are winsorized at the 1% and 99% levels.

Variable	Mean	p25	p50	p75	SD	N
WMAT	3.318	1.854	3.382	4.738	1.594	40949
LTD1	0.714	0.536	0.872	0.982	0.336	45606
LTD2	0.567	0.157	0.685	0.923	0.379	38944
LTD3	0.450	0.004	0.467	0.822	0.383	41898
LTD4	0.351	0.000	0.251	0.681	0.364	38730
LTD5	0.255	0.000	0.055	0.503	0.324	37994
DBN	0.415	0.000	0.000	1.000	0.493	45606
SIZE	5.410	3.737	5.421	7.021	2.272	45606
AGE	2.639	1.946	2.708	3.332	0.824	45606
ROA	0.031	0.018	0.102	0.161	0.332	45606
ABE	-0.008	-0.039	0.005	0.034	0.550	45606
ASETVOL	0.115	-0.506	0.273	0.879	0.911	45606
ASETMAT	9.345	2.528	5.423	11.513	12.407	45606
LEV	0.211	0.016	0.175	0.344	0.200	45606
PPE	0.255	0.075	0.177	0.367	0.231	45606
CAPX	0.055	0.016	0.034	0.066	0.066	45606
MTB	2.208	1.084	1.476	2.259	3.309	45606
CASH	0.193	0.027	0.101	0.285	0.223	45606
GROWTH	0.212	-0.036	0.074	0.222	0.848	45606
RATING	10.941	9.000	12.000	14.000	3.454	45606
RD	0.057	0.000	0.000	0.061	0.128	45606

Table 2. Baseline regressions: DBN laws and debt maturity structure

This table reports the results from estimating Equation (1) using *WMAT* and *LTD3* as dependent variables. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

	(1)	(2)	(3)	(4)
	WMAT	*LTD3*	*WMAT*	*LTD3*
DBN_{t-1}	-0.0471***	-0.0440**	-0.0407**	-0.0400**
	(-2.98)	(-2.54)	(-2.59)	(-2.55)
$SIZE_{t-1}$			0.295***	0.307***
			(10.39)	(10.05)
AGE_{t-1}			-0.319**	-0.170
			(-2.50)	(-1.27)
ROA_{t-1}			0.0014	-0.0092
			(0.12)	(-0.88)
ABE_{t-1}			0.0114***	0.0091**
			(3.93)	(2.47)
$ASETVOL_{t-1}$			0.0848***	0.0890***
			(5.95)	(6.78)
$ASETMAT_{t-1}$			-0.0113	-0.0054
			(-1.17)	(-0.65)
LEV_{t-1}			0.167***	0.168***
			(12.76)	(12.39)
PPE_{t-1}			0.0283	0.0248
			(1.39)	(1.26)
$CAPX_{t-1}$			0.0296***	0.0291***
			(3.72)	(3.30)
MTB_{t-1}			0.0105	0.0102
			(0.96)	(0.88)
$CASH_{t-1}$			0.0172	0.0132
			(1.16)	(0.93)
$GROWTH_{t-1}$			0.0061	0.0089**
			(1.59)	(2.24)
RD_{t-1}			-0.0104	-0.0118
			(-0.77)	(-1.00)
$RATE_{t-1}$			0.0906***	0.0864***
			(5.40)	(4.65)
CONSTANT	-0.0197***	-0.0074	-0.0709***	-0.0769***
	(-3.14)	(-1.08)	(-4.47)	(-4.70)
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	40949	41898	37994	38867
adj. R^2	0.613	0.525	0.621	0.530

Table 3. Dynamic Difference-in-Differences Analysis

This table reports the results of estimating the dynamic effects of DBN laws adoption on debt maturity. *DBN(t-2)* is a dummy variable that equals 1 if firm *i*'s year *t* is two years before the year in which its headquarter state passed the DBN laws, and 0 otherwise; *DBN(t-1)* equals 1 if firm *i*'s year *t* is one year before the year in which its headquarter state passed the DBN laws, and 0 otherwise. *DBN* equals 1 for years starting from the adoption of DBN laws. *DBN(t)* equals 1 if firm *i*'s year *t* is the year in which its headquarter state passed the DBN laws; *DBN(t+1)* equals 1 if firm *i*'s year *t* is one year after the year in which its headquarter state passed the DBN laws, and *DBN(t+2…n)* equals 1 if firm *i*'s year *t* is the second year or later after its headquarter state passed the DBN laws. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent Variable	*WMAT*		*LTD3*	
	(1)	(2)	(3)	(4)
DBN(*t-2*)	0.0028	-0.0061	-0.0001	-0.0003
	(0.20)	(-0.46)	(-0.01)	(-0.02)
DBN(*t-1*)	-0.0056	-0.0059	0.0104	0.0117
	(-0.35)	(-0.35)	(0.50)	(0.51)
DBN	-0.0418**		-0.0369**	
	(-2.51)		(-2.04)	
DBN(*t*)		-0.0324*		-0.0214
		(-1.72)		(-0.88)
DBN(*t+1*)		-0.0323**		-0.0390**
		(-2.36)		(-2.30)
DBN(*t+2…n*)		-0.0523**		-0.0521**
		(-2.36)		(-2.23)
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	37994	37994	38867	38867
adj. R^2	0.621	0.613	0.530	0.518

Table 4. Addressing self-selection bias, omitted variable issues, and biases in DID design

This table presents regression results addressing endogeneity concerns due to self-selection bias and omitted variable issues, using the propensity score matching method and the Oster test. Panel A reports coefficient estimates from the probit model used to generate propensity scores for treatment and control groups, where the dependent variable is an indicator set to 1 if a firm is headquartered in a state that adopted DBN laws in year *t*, and 0 otherwise. Panel B provides coefficient estimates for changes in debt maturity around DBN adoption for both treatment and control firms, with control variables omitted for conciseness. Panel C applies Oster's (2019) method to assess omitted variable bias. In Column (1), we assume that R^2 becomes 1.3 times of the initial R^2 with omitted variables, estimating the adjusted "true" β bound with controls and finding it remains within the original 99.5% confidence interval. In Column (2), we calculate the δ value at β = 0, confirming that omitted variables do not substantially challenge our findings. Panel D reports the results of employing the stacked regression research design to mitigate concerns raised by Goodman-Bacon (2021) regarding generalized DID research designs. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Diagnostic regression

	(1) Pre-match	(2) Post-match for *WMAT*	(3) Post-match for *LTD3*
$SIZE_{t-1}$	0.688***	0.0158	0.0121
	(49.52)	(0.58)	(0.13)
AGE_{t-1}	0.240***	-0.0248	-0.00272
	(25.16)	(-1.55)	(-0.05)
ROA_{t-1}	-0.151***	-0.0203	-0.109
	(-13.15)	(-0.69)	(-1.11)
ABE_{t-1}	0.00224	-0.0153	-0.0138
	(0.28)	(-0.88)	(-0.24)
$ASETVOL_{t-1}$	0.127***	-0.0185	0.0467
	(9.33)	(-0.71)	(0.55)
$ASETMAT_{t-1}$	0.214***	0.0377	-0.0738
	(19.10)	(1.58)	(-0.92)
LEV_{t-1}	0.00726	0.00782	0.0658
	(0.55)	(0.33)	(0.90)
PPE_{t-1}	-0.254***	-0.0346	0.0704
	(-16.42)	(-1.23)	(0.79)
$CAPX_{t-1}$	-0.0356***	0.0214	-0.0356
	(-2.83)	(0.97)	(-0.51)
MTB_{t-1}	-0.100***	-0.0420	-0.188
	(-7.96)	(-1.13)	(-1.53)
$CASH_{t-1}$	0.159***	0.00909	0.0975
	(14.16)	(0.38)	(1.33)
$GROWTH_{t-1}$	-0.0420***	-0.00824	-0.0745
	(-4.70)	(-0.42)	(-0.96)
RD_{t-1}	0.0282***	-0.00526	-0.0915
	(2.64)	(-0.22)	(-1.23)
$RATE_{t-1}$	-0.350***	-0.0137	-0.0372
	(-25.18)	(-0.58)	(-0.50)
CONSTANT	-0.235***	0.00321	-0.0121
	(-25.55)	(0.19)	(-0.23)
Year × Ind FE	Y	Y	Y
Firm FE	Y	Y	Y
N	57051	6781	5788
Pseudo R^2	0.0734	0.0005	0.0037

P value of Chi-squared	0.000	0.588	0.823

Panel B: Regression results

	(1)	(2)
	WMAT	*LTD3*
DBN_{t-1}	-0.024**	-0.053**
	(-2.14)	(-2.18)
Controls	Y	Y
Year × Ind FE	Y	Y
Firm FE	Y	Y
N	7872	7994
adj. R^2	0.494	0.621

Panel C: The Oster (2019) approach

Dependent variable	**Parameter Assumptions**	
	(1) Identified set	**(2) δ for $\beta = 0$**
WMAT	[-0.0538, -0.0407]	−3.65
LTD3	[-0.0553, −0.0401]	−2.33

Panel D: Stacked Regression results

	(1)	(2)
	WMAT	*LTD3*
DBN_{t-1}	-0.0645**	-0.0787**
	(-2.22)	(-2.34)
Controls	Y	Y
Year × Ind FE	Y	Y
Firm FE	Y	Y
N	21593	22072
adj. R^2	0.64	0.54

Table 5. Other robustness tests

This table reports the results of estimating Equation (1) using alternative measures of debt maturity. We include the results for *WMAT* and *LTD3* for comparison purposes. Panel A presents the results with firm and year-industry fixed effects. Panel B shows the results with firm and year fixed effects, while Panel C reports the results with year and industry fixed effects. Panel D reports the results with firm, year, and state fixed effects. Panels E and F report the results based on various subsamples. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Panel A	(1)	(2)	(3)	(4)	(5)
	WMAT	*LTD1*	*LTD2*	*LTD3*	*LTD4*
DBN_{t-1}	-0.0407**	-0.0326**	-0.0380**	-0.0400**	-0.0546***
	(-2.59)	(-2.04)	(-2.49)	(-2.55)	(-2.86)
Controls	Y	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
N	37994	45606	38944	38867	38730
adj. R^2	0.621	0.510	0.539	0.530	0.494
Panel B	(1)	(2)	(3)	(4)	(5)
	WMAT	*LTD1*	*LTD2*	*LTD3*	*LTD4*
DBN_{t-1}	-0.0421***	-0.0298*	-0.0370**	-0.0468***	-0.0559***
	(-2.92)	(-1.73)	(-2.59)	(-3.24)	(-3.57)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
N	37994	45606	38944	38867	38730
adj. R^2	0.620	0.511	0.539	0.528	0.491
Panel C	(1)	(2)	(3)	(4)	(5)
	WMAT	*LTD1*	*LTD2*	*LTD3*	*LTD4*
DBN_{t-1}	-0.0760***	-0.0566**	-0.0745***	-0.0772***	-0.0767***
	(-4.14)	(-2.21)	(-3.55)	(-3.77)	(-4.53)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
N	37994	45606	38944	38867	38730
adj. R^2	0.397	0.241	0.338	0.346	0.317
Panel D	(1)	(2)	(3)	(4)	(5)
	WMAT	*LTD1*	*LTD2*	*LTD3*	*LTD4*
DBN_{t-1}	-0.0515***	-0.0356**	-0.0469***	-0.0528***	-0.0602***
	(-3.97)	(-2.09)	(-3.62)	(-3.69)	(-4.15)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y
N	37994	45606	38944	38867	38730
adj. R^2	0.595	0.486	0.521	0.521	0.496

Panel E

	Exclude firms headquartered in Silicon Valley		Exclude financial crisis period (2008-2009)	
	(1)	(2)	(3)	(4)
	WMAT	LTD3	WMAT	LTD3
DBN_{t-1}	-0.0357**	-0.0360**	-0.0506***	-0.0543***
	(-2.04)	(-2.18)	(-2.78)	(-3.44)
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	37007	37863	34378	35179
adj. R^2	0.623	0.532	0.624	0.537

Panel F

	Exclude states adopt law in 2005		Exclude firms in geographically dispersed industries	
	(1)	(2)	(3)	(4)
	WMAT	LTD3	WMAT	LTD3
DBN_{t-1}	-0.0387**	-0.0360**	-0.0402**	-0.0433**
	(-2.56)	(-2.28)	(-2.13)	(-2.67)
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	23331	23859	30304	31038
adj. R^2	0.615	0.523	0.613	0.525

Table 6. Liquidity risk mechanism

This table presents the regressions results of debt maturity augmented with different proxies for liquidity risk. In Panels A, B, and D, the full sample is split into high and low liquidity risk groups based on whether each observation is above or below the median value of three measures: cash flow volatility (Keefe and Yaghoubi, 2016), RATE (Ericsson and Renault, 2006), and Ohlson's O-score (Ohlson, 1980). RATE is the numerical value assigned to S&P credit rating, where the value 1 corresponds to an S&P rating of AAA; 2 corresponds to AA+, and so on. In Panel C, a firm is classified as high liquidity risk firm if its Altman's (Altman, 1968) Z-score is lower than 3. The subsample regression results are reported in Panels A to D. We examine the significance of the difference between the coefficients for high and low groups using Fisher's Permutation test. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent Variable:	*WMAT*		*LTD3*	
Panel A: The role of cash flow volatility				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.102^{***}	0.0418	-0.113^{***}	0.0600^{**}
	(-4.24)	(1.55)	(-3.64)	(2.08)
Fisher's Permutation test	P = 0.00		P = 0.00	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	17208	17209	17608	17608
adj. R^2	0.531	0.601	0.420	0.508
Panel B: The role of credit rating				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.115^{***}	-0.0459	-0.126^{***}	-0.0224
	(-3.46)	(-0.69)	(-3.12)	(-0.30)
Fisher's Permutation test	P = 0.02		P = 0.06	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	8128	4431	8305	4545
adj. R^2	0.436	0.444	0.334	0.308
Panel C: The role of Altman's Z score				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0430^{**}	-0.0511	-0.0316	-0.0747
	(-2.13)	(-1.06)	(-1.30)	(-1.59)
Fisher's Permutation test	P = 0.03		P = 0.20	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	24538	12936	25077	13263
adj. R^2	0.661	0.593	0.575	0.482
Panel D: The role of Ohlson's O score				

	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0583**	-0.0357	-0.0512**	-0.0352
	(-2.21)	(-1.34)	(-2.04)	(-1.43)
Fisher's Permutation test	P = 0.04		P = 0.02	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	18970	18971	19120	19121
adj. R^2	0.680	0.533	0.584	0.428

Table 7. Information asymmetry mechanism

This table presents the regression results for debt maturity, augmented with various proxies for information asymmetry. The full sample is split into high and low information asymmetry groups based on whether each observation is above or below the median value of three measures: analyst forecast dispersion (Mansi et al., 2010), analyst forecast error (Mansi et al., 2010), and total accruals (Dechow and Dichev, 2002; Bhattacharya et al., 2012). The subsample regression results are reported in Panels A to C. We examine the significance of the difference between the coefficients for high and low groups using Fisher's Permutation test. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent Variable:	WMAT		LTD3	
Panel A: The role of analyst forecast dispersion				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0429**	-0.0116	-0.0405**	-0.0181
	(-2.15)	(-0.34)	(-2.13)	(-0.45)
Fisher's Permutation test	P = 0.07		P = 0.05	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	7553	7553	7712	7712
adj. R^2	0.643	0.506	0.553	0.411
Panel B: The role of analyst forecast error				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0485**	-0.0177	-0.0392**	-0.0113
	(-2.55)	(-0.61)	(-2.17)	(-0.30)
Fisher's Permutation test	P = 0.05		P = 0.08	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	7817	7816	8183	8184
adj. R^2	0.636	0.524	0.548	0.426
Panel C: The role of total accruals				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0816***	-0.0211	-0.0799***	-0.0306
	(-3.77)	(-0.81)	(-2.87)	(-1.25)
Fisher's Permutation test	P = 0.02		P = 0.03	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	17549	17549	17951	17951
adj. R^2	0.582	0.635	0.476	0.551

Table 8. Financial flexibility mechanism

This table presents the regression results for debt maturity, augmented with various proxies for financial constraints. The full sample is split into high and low financial constraints groups based on whether each observation is above or below the median value of three proxies: capital expenditures (Boasiako and Keefe, 2021), constraints on obtaining debt financing (Hoberg and Maksimovic, 2014), and the level of equity financing constraints (Hoberg and Maksimovic, 2014). The subsample regression results are reported in Panels A to C. We examine the significance of the difference between the coefficients for high and low groups using Fisher's Permutation test. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent Variable:	*WMAT*		*LTD3*	
Panel A: The role of capital expenditure				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0827***	-0.0398	-0.0930***	-0.0268
	(-3.68)	(-1.37)	(-2.91)	(-0.94)
Fisher's Permutation test	P = 0.02		P = 0.03	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	20380	17525	20868	17909
adj. R^2	0.635	0.626	0.536	0.535
Panel B：The role of debt constraints				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0608**	-0.0219	-0.0711**	-0.0165
	(-2.29)	(-0.80)	(-2.49)	(-0.60)
Fisher's Permutation test	P = 0.06		P = 0.04	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	17079	13377	17484	13683
adj. R^2	0.629	0.624	0.526	0.536
Panel C：The role of equity constraints				
	(1) High	(2) Low	(3) High	(4) Low
DBN_{t-1}	-0.0634*	-0.0571**	-0.0641*	-0.0511*
	(-1.71)	(-2.13)	(-1.77)	(-1.96)
Fisher's Permutation test	P = 0.11		P = 0.20	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	14162	16294	14455	16712
adj. R^2	0.650	0.619	0.553	0.519

Table 9. Cross-sectional tests

This table presents the results of cross-sectional tests. As shown in Panel A, the sample is divided based on firm size, which is measured as the natural logarithm of sales. In Panel B, firms are categorized as high technology investment firms according to product differentiation scores developed by Hoberg and Phillips (2016). The high technology investment group consists of firms with a product differentiation score greater than the median value. Panel C presents results from partitioning firms by asset intangibility, measured as one minus the ratio of property, plant, and equipment to total assets. In Panel D, the sample is divided into high and low cyber risk industries based on the criteria outlined by IBM (2017), with high cyber risk industries including financial services, information and communications, manufacturing, retail, and healthcare. In Panel E, we classify high litigation risk industries based on Francis et al. (1994), including biotech (SICs 2833–2836, 8731–8734), computers (SICs 3570–3577, 7370–7374), electronics (SICs 3600–3674), and retail (SICs 5200–5961). We examine the significance of the difference between the coefficients for high and low groups using Fisher's Permutation test. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent Variable:	*WMAT*		*LTD3*	
Panel A: Firm Size				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0763***	0.0232	-0.0815**	0.0407
	(-3.14)	(0.72)	(-2.66)	(1.39)
Fisher's Permutation test	P = 0.068		P = 0.076	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	22296	15698	22817	16050
adj. R^2	0.527	0.560	0.418	0.478
Panel B: Technology Intensity				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0011	-0.0999***	-0.0117	-0.0929***
	(-0.04)	(-3.46)	(-0.35)	(-3.24)
Fisher's Permutation test	P = 0.006		P = 0.008	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	17580	20414	17967	20900
adj. R^2	0.654	0.600	0.571	0.498
Panel C: Assets Intangibility				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0804**	-0.0326	-0.0916**	-0.0312
	(-2.65)	(-1.27)	(-2.54)	(-1.05)
Fisher's Permutation test	P = 0.054		P = 0.065	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

N	24589	13405	25172	13695
adj. R^2	0.608	0.675	0.512	0.579
Panel D: Cybersecurity Risk				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.109**	-0.0310	-0.132**	-0.0306
	(-2.25)	(-1.37)	(-2.23)	(-2.23)
Fisher's Permutation test	P = 0.006		P = 0.008	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	12158	25836	12058	26809
adj. R^2	0.620	0.615	0.543	0.521
Panel E: Litigation Risk				
	(1)	(2)	(3)	(4)
	High	Low	High	Low
DBN_{t-1}	-0.0752*	-0.0222	-0.0841**	-0.0239
	(-1.97)	(-0.60)	(-2.07)	(-0.79)
Fisher's Permutation test	P = 0.064		P = 0.076	
Controls	Y	Y	Y	Y
Year × Ind FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
N	12158	25836	12058	26809
adj. R^2	0.620	0.615	0.543	0.521

Table 10 Subsequent effects of DBN laws adoption and debt maturity

This table reports OLS regression results examining the subsequent impacts of shortened debt maturity post-DBN laws adoption. Panel A investigates the effect of DBN on the relation between debt maturity and financial reporting quality. Panel B explores the effect of DBN on the relation between debt maturity and investment efficiency. Panel C reports the results of the effect of DBN on the relationship between debt maturity and corporate cash holdings. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Panel A: Relationship between debt maturity and financial reporting quality				
Dependent Variable	*Financial Reporting Quality*			
	(1)	(2)	(3)	(4)
DBN_{t-1}	-0.0323**	-0.0161	-0.0327**	-0.0163
	(-2.00)	(-1.11)	(-2.05)	(-1.15)
$WMAT_{t-1}$	-0.0804***	-0.0238***		
	(12.37)	(3.96)		
$DBN_{t-1} \times WMAT_{t-1}$	0.0462**	0.0400**		
	(2.64)	(2.04)		
$LTD3_{t-1}$			-0.0612***	-0.0192***
			(10.24)	(3.50)
$DBN_{t-1} \times LTD3_{t-1}$			0.0315**	0.0276***
			(2.13)	(2.61)
Controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Industry × year FE	Y	Y	Y	Y
Observations	37634	35138	38506	35948
Adjusted R^2	0.484	0.523	0.484	0.523
Panel B: Relationship between debt maturity and investment efficiency				
Dependent Variable	*Investment Efficiency*			
	(1)	(2)	(3)	(4)
DBN_{t-1}	-0.0346**	-0.0582***	-0.0339**	-0.0612***
	(-2.23)	(-3.96)	(-2.22)	(-4.24)
$WMAT_{t-1}$	-0.0759***	-0.0712***		
	(-7.39)	(-6.88)		
$DBN_{t-1} \times WMAT_{t-1}$	0.0317**	0.0448***		
	(2.15)	(3.35)		
$LTD3_{t-1}$			-0.0718***	-0.0610***
			(-7.11)	(-6.09)
$DBN_{t-1} \times LTD3_{t-1}$			0.0363**	0.0423***
			(2.55)	(3.27)
Controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Industry × year FE	Y	Y	Y	Y
Observations	17755	17533	18143	17919
Adjusted R^2	0.40	0.73	0.42	0.75
Panel C: Relationship between debt maturity and cash holdings				
Dependent Variable	*Cash Holdings*			
	(1)	(2)	(3)	(4)
DBN_{t-1}	0.162***	0.0209***	0.165***	0.0210***
	(19.63)	(4.60)	(20.27)	(4.69)
$WMAT_{t-1}$	-0.177***	-0.000610		

	(-33.37)	(-0.19)		
$DBN_{t-1} \times WMAT_{t-1}$	0.0431***	0.0134***		
	(5.43)	(3.17)		
$LTD3_{t-1}$			-0.163***	-0.00348
			(-31.08)	(-1.12)
$DBN_{t-1} \times LTD3_{t-1}$			0.0367***	0.0140***
			(4.78)	(3.44)
Controls	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Industry × year FE	Y	Y	Y	Y
Observations	44957	40305	45991	41235
Adjusted R^2	0.58	0.74	0.51	0.74

Table 11. DBN laws adoption and debt choice

This table presents the regression analysis exploring the connection between DBN adoption and a firm's debt structure. *Public debt* is defined as the proportion of the sum of senior bonds, subordinated bonds, and commercial paper to total assets. *Bank debt* is represented by the proportion of the sum of revolving credit and term loans to total assets. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Dependent variable:	Public debt		Bank debt	
	(1)	(2)	(3)	(4)
DBN_{t-1}	-0.0702**	-0.0675**	-0.00382	-0.00999
	(-2.10)	(-2.30)	(-0.11)	(-0.27)
$SIZE_{t-1}$		0.0550*		-0.0180
		(1.82)		(-0.62)
LEV_{t-1}		0.444***		0.329***
		(17.44)		(16.87)
PPE_{t-1}		-0.0837***		0.0732***
		(-3.55)		(3.67)
$PROFIT_{t-1}$		-0.00979		0.0159**
		(-1.57)		(2.48)
MTB_{t-1}		0.000805		0.00887
		(0.09)		(1.07)
$RATE_{t-1}$		0.134***		-0.0702
		(2.87)		(-1.56)
$INVESTGR_{t-1}$		-0.101		0.0672
		(-1.40)		(0.76)
Constant	0.170***	0.225***	0.120***	0.164***
	(11.01)	(8.97)	(7.19)	(8.83)
Firm FE	Y	Y	Y	Y
Industry × year FE	Y	Y	Y	Y
N	30056	29674	30056	29674
adj. R^2	0.593	0.647	0.556	0.581

Table 12. DBN laws adoption and various types of debt instruments

This table presents the distribution of various types of debt instruments and the regression results examining the impact of DBN laws adoption on the choice of these instruments. Panel A summarizes the statistics for the different types of debt instruments. Panel B displays the regression results that explore the relationship between DBN adoption and the choice of specific debt instruments. T-statistics are presented in parentheses below the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are described in Appendix A.

Panel A Summary Statistics of debt instrument by types

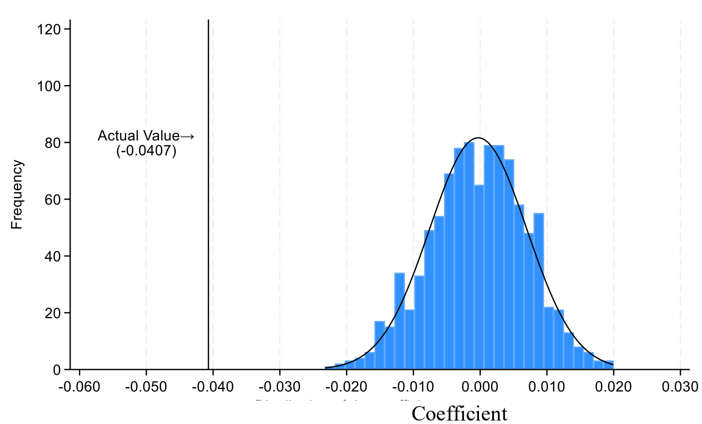
Variable	Mean	Median	SD	25%	75%
Senior bonds and notes	0.192	0.000	0.340	0.000	0.201
Subordinated bonds and notes	0.017	0.000	0.093	0.000	0.000
Commercial paper	0.002	0.000	0.017	0.000	0.000
Term loan	0.110	0.000	0.027	0.000	0.000
Revolving credit	0.079	0.000	0.220	0.000	0.000

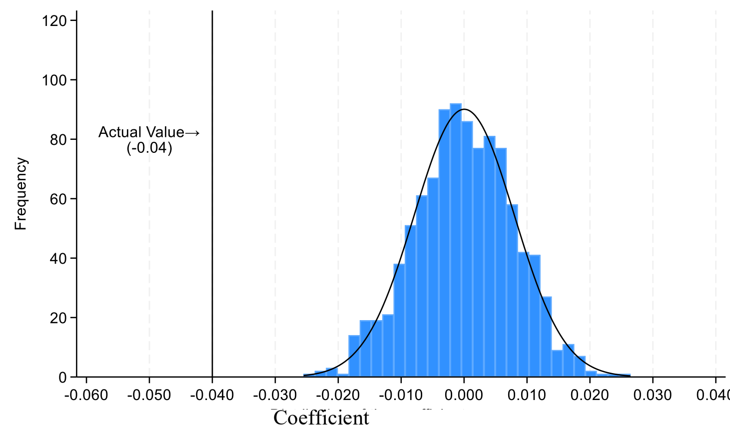
Panel B. The impact of DBN laws adoption on different types of debt instruments

	Public debt			Bank debt	
Dependent variable	Senior bonds and notes (1)	Subordinated bonds and notes (2)	Commercial paper (3)	Term loan (4)	Revolving credit (5)
DBN_{t-1}	-0.0148**	-0.0136	-0.00119**	0.0227**	-0.0340***
	(-2.12)	(-0.76)	(-2.35)	(2.63)	(-3.46)
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Industry × year FE	Y	Y	Y	Y	Y
N	29674	29674	29674	29674	29674
adj. R^2	0.569	0.577	0.415	0.420	0.397

Figure 1: Distribution of Placebo Coefficient Estimates.

This figure presents the results of placebo tests, which randomize both the assignment of treated states (without replacement) and the selection of enactment years (randomly chosen from the sample period of 1997–2015). Specifically, we estimate the effect of pseudo-events on pseudo-treated states using the full set of control variables from the baseline regression, recording the coefficients and standard errors from each of the 1,000 placebo tests. The vertical line represents the actual coefficient from our baseline regression. The histogram on the left corresponds to results where the dependent variable is $WMAT_t$, while the histogram on the right corresponds to results where the dependent variable is $LTD3_t$.





Appendix A. Variable definitions

Variable	Definition
WMAT	Debt maturity in years, which is defined as the principal-weighted maturity of all debt.
LTD1	Proportion of long-term debt relative to total debt.
LTD2	Proportion of long-term debt, excluding debt due within 2 years, relative to total debt.
LTD3	Proportion of long-term debt, excluding debt due within 2 and 3 years, relative to total debt.
LTD4	Proportion of long-term debt, excluding debt due within 2, 3, and 4 years, relative to total debt.
DBN	Dummy variable coded as 1 for years starting from the adoption of the state-level DBN laws, and 0 otherwise.
DBN (t)	Dummy variable coded as 1 if firm *i*'s year *t* is the year in which firm *i*'s headquarter state has passed the DBN law, and 0 otherwise.
SIZE	Natural logarithm of total sales.
AGE	Natural logarithm of the number of years a firm has been listed in the merged CRSP/Compustat database.
ROA	Ratio of operating income to total assets.
ABE	Change in earnings per share from year $t-1$ to year t, divided by the share price at the end of year t.
ASETVOL	Standard deviation of stock returns for the fiscal year, multiplied by the market value of equity, and then divided by the market value of assets.
ASETMAT	Weighted maturity of the firm's assets, defined as: (gross PPE divided by depreciation expense, times gross PPE divided by total assets) plus (current assets divided by cost of goods sold, times current assets divided by total assets).
LEV	Ratio of total debt (long-term debt plus debt in current liabilities) to book value of assets.
PPE	Net PPE divided by the book value of total assets.
CAPEX	Ratio of capital expenditure to total book assets at the beginning of the year.
MTB	Firm's market-to-book ratio, which is defined as the market value of assets (equity market capitalization plus the book value of other liabilities), divided by the book value of assets.
CASH	Ratio of cash and marketable securities to total book assets at the beginning of the year.
GROWTH	Compound growth rate in sales.
RATE	Numerical value assigned to firm's S&P credit rating, where the value 1 corresponds to an S&P rating of AAA; 2 corresponds to AA+, and so on.
RD	Ratio of R&D expenses to total assets.
Cash flow volatility	Standard deviation of yearly cash flows from operations divided by total assets over the past five fiscal years.
Z-score	Altman's Z score (1968). Dummy variable coded as 1 if Z-score is higher than 3, and 0 otherwise.
O-score	Ohlson's O-score (1980). Dummy variable coded as 1 if the score is higher than sample median, and 0 otherwise.
Analyst forecast dispersion	Absolute value of the median forecast errors, scaled by the stock price at the end of the previous fiscal year.

Analyst forecast error	Absolute value of the median forecast errors, scaled by the stock price at the end of the previous fiscal year.
Total accruals	Calculated using the modified Dechow and Dichev (2002) model.
Debt constraints	Debt-focused delay score developed by Hoberg and Maksimovic (2015), which measures a firm's constraints in obtaining debt financing.
Equity constraints	Equity-focused delay score developed by Hoberg and Maksimovic (2015), which measures a firm's constraints in obtaining equity financing.
Technology intensity	Product differentiation scores developed by Hoberg and Phillips (2016), high technology investment firms are firms with product differentiation score above the sample median value.
Asset intangibility	One minus total property, plant, and equipment scaled by total book assets
Litigation risk	Firms in biotech (SICs 2833–2836, 8731–8734), computers (SICs 3570–3577, 7370–7374), electronics (SICs 3600–3674), and retail (SICs 5200–5961) (Francis et al., 1994).
Cyber security risk	Industries such as manufacturing, retail trade, information, finance and insurance, healthcare, and social assistance are defined as high cybersecurity risk sectors (IBM, 2017).
Public debt	Proportion of the sum of senior bonds, subordinated bonds, and commercial paper to total assets.
Bank debt	Proportion of the sum of revolving credit and term loans to total assets.
INVESTGR	A binary variable set to 1 if the firm holds an investment-grade long-term debt rating (BBB- or higher) from S&P, and 0 otherwise.
PROFIT	Ratio of income before extraordinary items to total assets.

Appendix B. DBN Laws adopted in the U.S. states from 2002 to 2018

State	Year	State	Year
California	2002	Nebraska	2006
Arkansas	2005	New Hampshire	2006
Connecticut	2005	Pennsylvania	2006
Delaware	2005	Rhode Island	2006
Georgia	2005	Utah	2006
Illinois	2005	Vermont	2006
Indiana	2005	Wisconsin	2006
Louisiana	2005	Maryland	2007
Maine	2005	Oregon	2007
Minnesota	2005	Texas	2007
Nevada	2005	Wyoming	2007
New Jersey	2005	Massachusetts	2007
New York	2005	Alaska	2008
North Carolina	2005	Iowa	2008
North Dakota	2005	Oklahoma	2008
Ohio	2005	South Carolina	2008
Tennessee	2005	Virginia	2008
Washington	2005	West Virginia	2008
Arizona	2006	Missouri	2009
Colorado	2006	Mississippi	2010
Hawaii	2006	Florida	2014
Idaho	2006	Kentucky	2014
Kansas	2006	New Mexico	2017
Michigan	2006	Alabama	2018
Montana	2006	South Dakota	2018