The Effect of Data Breach Disclosure Laws on Analysts' Forecasts

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Abstract

This study investigates the impact of Data Breach Disclosure Laws (DBDLs) on analyst forecast characteristics. Exploiting the staggered adoption of state-level DBDLs in the United States, we employ a difference-in-differences (DiD) design to identify the effects. We measure analyst forecast characteristics using forecast error and forecast dispersion, which capture the forecast accuracy and disagreement, respectively. Our results show that the implementation of DBDLs is associated with a significant reduction in both forecast error and forecast dispersion, suggesting that enhanced disclosure requirements improve the information environment and reduce uncertainty faced by analysts. The findings are robust to a range of alternative model specifications, different definitions of the treatment variable, and additional sensitivity analyses. Overall, this study provides evidence that regulatory disclosure aimed at improving information transparency can enhance the quality of disclosed information, thereby improving analysts' forecasting characteristics.

Résumé

Cette étude examine l'impact des lois sur la divulgation des violations de données (DBDL) sur les caractéristiques des prévisions des analystes. En exploitant l'adoption progressive de ces lois aux États-Unis, nous utilisons une méthode des différences dans les différences (DiD) pour en identifier les effets. Nous mesurons les caractéristiques des prévisions des analystes à l'aide de l'erreur de prévision et de la dispersion des prévisions, qui reflètent respectivement la précision et le degré de divergence des prévisions. Nos résultats montrent que la mise en œuvre des DBDL est associée à une réduction significative tant de l'erreur de prévision que de la dispersion des prévisions, ce qui suggère que le renforcement des obligations de divulgation améliore l'environnement informationnel et réduit l'incertitude à laquelle sont confrontés les analystes. Ces conclusions sont robustes face à toute une série de spécifications de modèles alternatives, à différentes définitions de la variable de traitement et à des analyses de sensibilité supplémentaires. Dans l'ensemble, cette étude montre que les obligations réglementaires de divulgation visant à améliorer la transparence de l'information peuvent renforcer la qualité des informations divulguées, améliorant ainsi les caractéristiques des prévisions des analystes.

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Introduction

Data breaches have become an increasingly salient risk in this digital economy, raising concerns about firms' data security practices and disclosure transparency. In response, many jurisdictions have introduced Data Breach Disclosure Laws (DBDLs) that require firms to publicly disclose incidents. While a growing amount of research examines the market consequences of data breaches and related disclosure requirements, relatively less is known about how such regulations affect the information environment from the perspective of analysts.

This paper studies whether DBDLs improve the quality of analysts' earnings forecasts. In capital markets, analysts play a central role in processing information from firms and then providing forecasts to investors. Mandatory disclosure can enhance the accessibility and credibility of information at the firm level, reduce information asymmetry and uncertainty, thereby improving the accuracy of predictions and reducing differences among analysts. At the same time, it may also pose a risk of encouraging firms to engage in more short-term behaviors and internal transactions. Therefore, whether these regulatory changes lead to more accurate predictions remains an empirical question.

To address this issue, this study exploits the staggered adoption of state-level DBDLs in the United States and implements a difference-in-differences (DiD) research design. We evaluate analysts' predictions using two indicators—forecast error and forecast dispersion, which reflect the accuracy and variability of the analysts' expectations, respectively. The results show that the adoption of DBDLs is associated with a significant reduction in both forecast error and forecast dispersion, suggesting an improvement in the information environment faced by analysts.

Overall, this study contributes to the literature in three ways. Firstly, it extends the growing research on data breach disclosure by focusing on its implications for information intermediaries. Secondly, it adds to the literature on analyst behavior by highlighting the role of regulatory disclosure in shaping forecast quality. Finally, the findings have policy implications by suggesting that disclosure requirements can improve not only transparency for investors but also the efficiency of information processing in capital markets.

Literature Review

Data Breach Disclosure Laws

Background and Evolution

The requirement for companies to disclose data breaches mainly originated in the 21st century. The US does not have a single comprehensive federal data breach notification law; however, several federal regulations and industry-specific rules address cybersecurity risks and data breach disclosure requirements. These sectoral laws govern particular areas such as healthcare, finance, and education, and incorporate requirements for breach notification and data protection within their respective domains (Daly, 2018). One of the prominent legislations is the Health Insurance Portability and Accountability Act (HIPAA), which applies to the healthcare sector and requires HIPAA-covered entities to provide a notification following a breach of unsecured protected health information. The threshold is that more than 500 individuals are involved in the breach, and the notifications must be provided within 60 days of discovery (United States Department of Health & Human Services, 2013).

In 2011, the U.S. Securities and Exchange Commission (SEC) issued guidance that requires firms to disclose key managerial decisions related to cybersecurity risks. This includes the firm's exposure to cyber threats, insurance policies that provide coverage for cyberattacks, etc. (SEC, 2011). Starting from 2023, the SEC requires public companies to report material cybersecurity incidents on Form 8-K within 4 business days of determining materiality. However, these regulations are limited in pertinence or delayed reporting (Liu & Ni, 2024; Hamin, 2023).

Relative to the federal government, the United States states adopt formal laws at an earlier stage. California was the first state to pass such legislation in 2002, which requires companies, nonprofit organizations, and government agencies to notify California consumers if their personal information is compromised by unauthorized access (Joerling, 2010). The enactment of the Database Breach Notification Security Act ("SB1386") followed a data breach at a state-operated data storage facility in California, which exposed more than 250,000 state employees to the risk of personal information leakage. The data center operators admitted a lack of security procedures in protecting the system, revealing the insufficiency of data security protection measures at that time. After that, the SB1386 took effect on July 1, 2003 (Skinner, 2003).

Over the following decades, other states subsequently and gradually enacted similar state-level data breach disclosure laws. By late March 2018, all 50 U.S. states had adopted such laws, and these states mandate that both corporations and non-commercial organizations transparently report incidents involving data breaches or the improper handling of personal information (Ashraf & Sunder, 2023). **Table 1** demonstrates the detailed process of data breach disclosure laws across all U.S. states, with special markings for federal districts and inhabited territories. The data are primarily hand-collected from Perkin Coie (2024), and missing or unclear objects are verified on the state legislature's official website. The original sources for each state and when states sign into law are summarized in Appendix A.

Regulatory Variations Among U.S. States

While these laws generally follow a similar overarching framework, they differ in the formulation and implementation of certain detailed provisions. Taking California as an example, all U.S. states have adopted similar data breach notification laws based on it. Some states' laws depart from the California model by introducing a harm threshold requirement. Under these provisions, notification to affected individuals is legally required only if the data breach is likely to result in a specified level of damage—such as a reasonable likelihood of harm or material adverse consequences—being experienced by those impacted (Daly, 2018).

In addition, individual states may impose different timelines for breach notification. Some jurisdictions, such as the District of Columbia, mandate that affected entities disclose the incident as promptly as possible, whereas others, like Colorado, mandate notification within 30 days, while Florida requires it within 45 days (Chen, Hilary & Tian, 2024). Additionally, enforcement mechanisms vary: while certain states, such as Georgia, do not outline explicit penalties for noncompliance, others stipulate specific legal consequences for violations. Some punishments are imposed through administrative fines; for example, Massachusetts imposes fines up to $50,000 per violation, while some other states allow private right of action—California and Illinois allow individuals to sue for damages resulting from a data breach (Foley & Lardner LLP, 2025).

In fact, the various DBDL requirements, including notification timelines and reporting thresholds, are posing challenges for firms operating across multiple states. As noted by Greenwood and Vaaler (2023), "For firms doing business with customers in three different states, a given data breach could easily prompt review of three different notification triggers for three different potential recipients mandating three different types of notification information", firms need to tailor their data breach response strategies to meet the specific requirements of each state. This regulatory complexity not only increases operational costs but also causes risks of non-compliance due to potential oversight.

Analyst Forecast Behavior

Analyst forecasts play a crucial role in financial markets by guiding investor expectations and influencing asset prices. Accurate forecasts could help to reduce information asymmetry and enhance market efficiency, while a high degree of forecast dispersion is often interpreted as a sign of uncertainty, which may lead to market volatility. The academic literature identifies several key factors that shape analysts' forecast behaviors, typically grouped into three broad categories:

analyst-specific factors, firm-specific characteristics, and external environmental conditions.

In this study, we examine a new factor: data breach disclosure law. Beyond analyst-specific, firm-specific, and external environmental factors, the quality of the information environment is also an important determinant of analyst forecast quality. Prior literature suggests that analysts rely heavily on publicly available information to form expectations about future firm performance (Lang & Lundholm, 1996; Hope, 2003). When firms provide more timely, transparent, and reliable disclosures, information asymmetry between firms and market participants may be reduced, enabling analysts to make more accurate and consistent forecasts. Conversely, limited or incomplete disclosure may increase uncertainty and hinder analysts' ability to interpret firm fundamentals. Therefore, disclosure regulations can affect analysts not only by influencing corporate behavior, but also by shaping the information environment in which analysts operate. This perspective is particularly relevant in the context of data breach disclosure laws, which are designed to enhance the availability and transparency of cybersecurity-related information.

Intersection of Cybersecurity and Financial Information

Following the examination of factors that affect the accuracy and dispersion of analysts' forecasts, it is essential to explore the impact of cybersecurity incidents, which is a notable external threat. Cyberattacks have rapidly transitioned from purely technological concerns into significant financial events, influencing market perceptions, corporate values and analyst forecasting behaviors. A study highlights that cyberattacks can lead to increased market volatility and expansion of financial risks (Jimmy, 2024). The disclosure of a cyberattack can also adversely affect firms operating in the same industry as the targeted firm, altering investors' perceptions of risk within that sector (Cobos & Cakir, 2024).

In addition, Kamiya et al. (2021) find that cyberattacks cause significant shareholder wealth loss when the loss of personal information is involved, and about 1.1% loss in market value follows, pointing out that information leakage is the key point in network security. As mentioned by Akey et al. (2023), data breaches represent one of the most prominent forms of cyber risk, particularly among publicly traded firms in the United States. The key characteristics that make data breaches special are their fatality, unavoidability and unpredictability. The US Council of Economic Advisers also describes cyber threats as "occurring across firms in patterns that are difficult to anticipate" (Liu & Ni, 2024). No matter how solid the internal system is, it is quite difficult for firms fully protect themselves from data breach incidents (Kamiya et al., 2021). From 2005 to 2010, data breaches compromised an estimated 350 million records (Shaw, 2009). With the advent of the Internet era, data leakage incidents have become more frequent.

The number of data breach incidents has increased substantially in recent years, rising from 1,108 in 2020 to 3,158 in 2024 (Statista, 2025). Correspondingly, data breaches have become increasingly frequent, and their financial consequences can be substantial.

From analysts' perspective, data breaches introduce uncertainty into firms' operations and financial health, and the lack of timely and detailed information about breaches can hinder analysts' ability to adjust their earnings forecasts accurately. In response, many jurisdictions have introduced data breach disclosure regulations, including the European Union (GDPR), Canada (PIPEDA), and Australia (Notifiable Data Breaches).

Despite the growing importance of data breach disclosure regulations, their implications for analysts' forecasting behavior remain underexplored. In particular, it is unclear whether such regulations improve or impair analysts' ability to generate accurate forecasts.

On the one hand, DBDLs may improve analyst forecast quality through several channels related to firms' information environments and risk management practices. First, prior studies find that DBDLs reduce a firm's cyber risk exposure by incentivizing stronger cyber-related investments and more actions taken by managers (Ashraf & Sunder, 2023), which may improve forecast accuracy by stabilizing operating environments. Second, firms often increase corporate social responsibility (CSR) engagement following the adoption of DBDLs (Zhang, 2024), which may help signal long-term strategic orientation and ease analyst uncertainty. Third, another potential mechanism operates through improvement in internal control and information quality. Prior studies suggest that mandatory disclosure regulations encourage firms to strengthen internal governance and monitoring systems in order to comply with reporting requirements (Ashraf & Sunder, 2023). Better internal controls may improve the reliability of information, thereby reducing the information asymmetry between firms and market participants. As analysts rely heavily on publicly available information when forming earnings expectations, improvements in internal controls and disclosure quality may help analysts generate more accurate forecasts.

On the other hand, several studies suggest that the implementation of DBDLs may unintentionally increase uncertainty and complexity. For instance, Liu and Ni (2024) find that firms respond to mandatory disclosure laws by engaging in real earnings manipulation and reducing patenting activities, reflecting a shift toward short-termism that could distort analysts' ability to interpret financial signals. Evidence further indicates that DBDLs are associated with increased stock price crash risks (Obaydin, Xu & Zurbruegg, 2024), a higher level of insider trading (Chen, Hilary & Tian, 2024), exacerbating the information asymmetry and complicating analysts' task of forecasting future characteristics.

Hypotheses Development

Building on the existing literature, the objective of this study is to examine whether state-level Data Breach Disclosure Laws influence analyst forecast quality. Specifically, this study investigates whether the enactment and stringency of DBDLs affect analyst forecast error and forecast dispersion. By connecting cybersecurity disclosure regulation with the analyst information environment, this study extends prior research on both DBDLs and analyst forecasting behavior.

Existing research suggests that the consequences of DBDLs may not be uniformly positive (Liu & Ni, 2024). On the one hand, DBDLs may improve analyst forecast quality by enhancing disclosure transparency and encouraging firms to invest more heavily in cybersecurity risk management (Zhang, 2024). Better disclosure practices may reduce information asymmetry and provide analysts with more timely and reliable information regarding cyber-related risks. As a result, analysts may be able to form more accurate and more consistent earnings expectations.

On the other hand, DBDLs may also increase uncertainty and complexity (Liu & Ni, 2024; Chen, Hilary & Tian, 2024; Rosati et al., 2017). Mandatory disclosure requirements may reveal additional risks, increase market concerns regarding cybersecurity vulnerabilities, or encourage strategic managerial responses. These effects may complicate analysts' interpretation of firm fundamentals and potentially reduce forecast quality. Therefore, both positive and negative effects are theoretically plausible, and the overall impact of DBDLs on analyst forecast quality remains uncertain.

Therefore, whether DBDLs improve or impair analyst forecast quality remains an open empirical question. To address this question, this study empirically examines how the enactment and stringency of DBDLs across U.S. states affect analyst forecast quality. Given these competing theoretical predictions, we formulate the following hypothesis: DBDLs do not significantly alter analysts' forecasting quality if neither the positive nor the negative effects are obvious or have been neutralized. Therefore, the basic hypothesis is set as a null:

H_0: Data breach disclosure laws have no significant effect on analyst forecast error and forecast dispersion.

Research Design

Model

Due to the staggered adoption of data breach disclosure laws across U.S. states, we employ a Difference-in-Differences (DiD) research design to examine the effect of laws on analyst forecasting characteristics. Specifically, we estimate the following ordinary least squares (OLS) regression model:

$$FORECAST_{i,t} = \beta_i + \beta_t + \beta_1 LAW_{i,t} + \beta_n \sum CONTROLS_{i,t} + e_{i,t}$$

Where i indexes the firm, and t indexes the year. $FORECAST$ represents analyst forecast outcomes, and it is measured using either analyst forecast error or forecast dispersion. The test variable LAW is an indicator variable that equals 1 if a firm's headquarters state has enacted a data breach disclosure law by year t, and 0 otherwise. $CONTROLS$ represents a set of firm-level characteristics that may influence analysts' forecasting behavior.

β_i and β_t respectively represent firm and year fixed effects. The coefficient of interest is β_1, which captures the effect of data breach disclosure laws on analyst forecast outcomes. Standard errors are clustered at the state level because the treatment variable LAW varies at the state level (Guo & Fluharty, 2024).

Key Variables

Treatment Variable

DBDL Indicator: An indicator variable equal to 1 if a firm's headquarters state has enacted a data breach disclosure law in year t, 0 otherwise.

Outcome Variables

Forecast Error: The absolute difference between the analyst earnings forecast and the realized earnings per share (EPS), scaled by the absolute value of the mean analyst forecast for the corresponding firm-year.

Forecast Dispersion: The standard deviation of analyst earnings forecasts for a given firm-year, scaled by the absolute value of the mean analyst forecast. We require a minimum of three forecasts for firms per year to calculate analysts' forecast dispersion (Bochkay et al., 2022; Cheong & Thomas, 2011).

Control Variables

The academic literature has identified several key factors that shape analysts' forecast behavior, typically grouped into three broad categories: analyst-specific factors, firm-specific characteristics, and external environmental conditions.

Analyst-specific Factors

Analysts differ significantly due to many reasons, including their experience, specialization, and forecasting behaviors, all of which are attributes specific to the individual analyst's quality. Prior studies document that analyst-specific characteristics-such as forecast age, frequency, specialization, ability, portfolio complexity, and resources availability-are important determinants of forecast accuracy (Barniv et al., 2005; Myring & Wrege, 2009; Athavale et al., 2013). Among these drivers, experience plays a particular vital role in the accuracy of analyst forecasts (Rahman, Zhang & Dong, 2019). According to Mikhail, Walther & Willis (1997), an analyst's firm-specific experience helps to increase the forecast accuracy. When the analyst knows more about a specific firm and its operating mode, the forecast is more likely to be based on facts, which finally leads to minor forecasting errors. Maines et al. (1997) state that experienced analysts' forecasts are much more accurate than those of less experienced.

Some objective conditions that analysts possess, rather than their innate abilities, can also affect analysts' forecast accuracy and precision. For instance, Clement (1999) observes a negative relationship between the number of companies an analyst covers and the precision of that analyst's forecasts. In other words, as the analyst's coverage universe broadens, forecast accuracy tends to diminish. An analyst's forecast accuracy tends to improve when their coverage is concentrated within a specific industry, allowing for greater specialization and deeper domain knowledge (Jacob, Lys & Neale, 1999). In addition, analyst portfolio complexity and the number of resources the analyst has access to are also possible triggers.

Firm-specific Characteristics

Analyst forecasting accuracy and dispersion are also heavily influenced by firm-specific characteristics. One key factor is firm size, which has been shown to have a positive association with forecasting accuracy. Large firms are typically subject to broader analyst coverage and tend to provide more comprehensive and reliable financial disclosures, thereby enabling analysts to make more precise predictions (Hutira, 2016). In contrast, firms characterized by higher levels of complexity—such as those with diverse lines of business or extensive international operations—often introduce additional layers of uncertainty, which can contribute to greater dispersion in analyst forecasts.

Moreover, the quality of financial reporting is an important source for analysts to get information. Lang and Lundholm (1996) demonstrate a positive correlation between the accuracy of analyst forecasts and the extent of corporate disclosure. Holland (1998) finds that analyst forecast accuracy improves when firms provide comprehensive information, including descriptive narratives and explanatory notes that help interpret financial data. Hope (2003) shows that when firms disclose their accounting policies, analysts are better equipped to produce accurate predictions.

Beyond traditional financial disclosures, studies indicate that the transparency of nonfinancial information also plays a significant role in shaping the quality of analyst forecasts. Dhaliwal et al. (2012) use data on corporate social responsibility (CSR) reports from firms across 31 countries and find that the publication of such reports is associated with a reduction in analysts' financial forecast errors. This effect is more pronounced in countries where CSR disclosures are considered an important component of corporate transparency. Similarly, Yu (2010) finds that analysts can predict firm earnings with greater precision when companies include more thorough and detailed governance information in their annual reports.

External Environmental Factors

In addition to firm-level attributes and analyst-specific factors, external environmental conditions also play a crucial role in shaping the accuracy of analyst forecasts, such as macroeconomic trends and the broader regulatory environment.

Previous studies have demonstrated that changes in accounting standards have a direct impact on the accuracy of analysts' earnings forecast. Several studies focus on the adoption of International Financial Reporting Standards (IFRS) within the EU, and the general consensus is its positive role. Supporting this view, Horton, Serafeim and Serafeim (2013) find that both mandatory and voluntary adoption of IFRS improve the precision of analysts' financial forecasts and lead to a significant reduction in forecast errors.

When taking U.S. Generally Accepted Accounting Principles (U.S. GAAP) into consideration, one study finds that forecast accuracy is notably higher when analysts based their estimates on financial data prepared under IFRS or U.S. GAAP, as compared to estimates derived from German GAAP (Ernstberger, Krotter & Stadler, 2008). Hodgdon et al. (2008) examine the association between analysts' earnings forecast errors and firms' adherence to IFRS disclosure requirements, using both an unweighted and a weighted index to measure compliance. The study reveals a negative relationship between forecast errors and the level of IFRS compliance, which means that firms that more fully conformed to IFRS disclosure standards enabled analysts to produce more accurate earnings forecasts.

When the perspective is broadened to the overall economic policy of a country or even to the global business cycle, it becomes clear that changes in the larger environment cannot be ignored. A study finds that a higher level of economic policy uncertainty may lead to greater analysts' forecast errors and forecast dispersion (Chourou, Purda & Saadi, 2021). As noted by Espahbodi, Espahbodi and Espahbodi (2015), both the magnitude and the dispersion of forecast errors have been steadily increasing during 1993-2013.

In summary, analyst forecast accuracy and dispersion are multifaceted phenomena influenced by a combination of analyst-specific skills, firm-level transparency and external economic and regulatory conditions. These factors involve variables that are set as control variables in this model, including GENERAL_EXPERIENCE, SPECIFIC_EXPERIENCE, SPECIALIZATION, FORECAST_AGE, BREADTH, SIZE, LEVERAGE, MTB, ROA, LOSS, CASH. The specific definition and measurement of all variables are shown in Appendix B.

Sample Selection

The sample selection process starts with 149,658 firm-year observations from COMPUSTAT. After merging with the Loughran and McDonald dataset, we remove observations with missing or invalid headquarters state information, resulting in 88,535 observations. We further exclude firms in the financial and utilities industries and retain only observations with complete key firm-level variables, yielding 60,105 firm-years. After dropping observations with missing control variables, the sample is reduced to 56,328 observations. We then merge this dataset with DBDL adoption years based on firms' headquarters states.

Analyst forecast data are obtained from the Institutional Brokers' Estimate System (I/B/E/S), initially consisting of 725,259 observations. To ensure reliable measurement of forecast dispersion, we require at least three analyst forecasts per firm-year. We then aggregate analyst-level forecasts to the firm-year level by taking the mean of each variable.

Next, we merge the processed I/B/E/S data with the firm-level dataset and DBDL indicators. After excluding observations with missing values required to construct the main variables, the final sample consists of 27,118 firm-year observations. These selection procedures are summarized in Appendix C.

In the regression analysis, singleton observations are dropped due to the inclusion of fixed effects, resulting in a slightly reduced sample of 26,378 observations.

Industry classification follows the Standard Industrial Classification (SIC) system. Following prior literature, we winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of extreme values.

Empirical Results

Descriptive Statistics and Correlation Analysis

Table 2 represents the descriptive statistics of the main variables used in the analysis. The final sample consists of 27,118 firm-year observations. The mean value of the treatment variable LAW is 0.782, indicating that approximately 78.2% of the observations occur after the adoption of data breach disclosure laws in the firm's headquarters state.

The mean of FORECAST_ERROR is 0.404, while the mean of FORECAST_DISPERSION is 0.288, suggesting substantial variation in analysts' forecast accuracy and disagreement across firms. Regarding firm characteristics, the average firm size (SIZE) is 6.914 and the mean return on assets (ROA) is 0.052, which are comparable to those reported in prior studies (Beardsley, Robinson & Wong, 2021). In addition, approximately 33.8% of the firm-year observations report negative earnings (LOSS).

Table 3 reports the pairwise Pearson correlation matrix for the main variables. Overall, consistent with prior literature, firm size (SIZE) and profitability (ROA) are negatively correlated with forecast error and forecast dispersion, indicating that analysts tend to produce more accurate forecasts for larger and more profitable firms (AYRES & DOLVIN, 2022). In contrast, loss firms (LOSS) exhibit higher forecast errors, reflecting greater uncertainty in forecasting their earnings. The correlations between the treatment variable LAW and the forecast outcome variables are relatively small, highlighting the importance of using regression analysis to identify the causal effect of the policy change.

Baseline Regression Results

Table 4 reports the baseline regression results examining the effect of data breach disclosure laws on analyst forecast outcomes. The coefficient on LAW, the variable of interest, is negative and statistically significant across both model specifications.

In column (1), where the dependent variable is FORECAST_ERROR, the coefficient on LAW is -0.050 and statistically significant at the 10% level. This result suggests that the adoption of data breach disclosure laws is associated with a reduction in analyst forecast errors. Considering that the mean value of forecast error in the sample is 0.404, the estimated coefficient implies an approximately 12% decrease in forecast errors following the implementation of the law.

In column (2), using FORECAST_DISPERSION as the dependent variable, the coefficient of LAW is -0.037 and significant at 5% level. This finding indicates that the enactment of data breach disclosure laws also reduces the level of disagreement among analysts. Given that the average forecast dispersion is 0.288, the magnitude suggests a decline of about 13% in analyst forecast dispersion.

The control variables generally exhibit signs consistent with prior literature (Chourou, Purda & Saadi, 2021; Jung et al., 2019). For example, firms reporting losses (LOSS) are associated with significantly higher forecast errors and dispersion, reflecting greater uncertainty in forecasting their earnings. In contrast, firms with higher cash holdings (CASH) tend to exhibit lower forecast errors and dispersion. In addition, FORECAST_AGE is negatively associated with both forecast error and dispersion, suggesting that forecasts issued closer to the earnings announcement are more accurate and less dispersed.

Overall, these results support the hypothesis that enhanced information disclosure through data breach disclosure laws improves the information environment and leads to more accurate and less dispersed analyst forecasts.

Parallel Trend Assumption

To assess the validity of the parallel trend assumption in the difference-in-differences design, we estimate an event-study specification that includes indicators relative to the adoption of data breach disclosure laws. Following Bourveau, Lou and Wang (2018), we replace LAW by dummy variables for two years prior to the adoption (LAW_{t-2}), one year prior (LAW_{t-1}), the adoption year (LAW_{t}), one year after (LAW_{t+1}), and two or more years after the adoption (LAW_{t+2}). For example, LAW_{t-2} is 1 for the calendar year two years before the disclosure law is signed and 0 otherwise.

Table 5 reports the results. Consistent with the parallel trend assumption, the coefficients on the pre-treatment indicators, LAW_{t-2} and LAW_{t-1} are negative but statistically insignificant for both FORECAST_ERROR and FORECAST_DISPERS. This suggests that there are no systematic differences in trends between treated and control firms prior to the enactment of data breach disclosure laws.

In contrast, the coefficients on LAW_{t} are negative and significant for both dependent variables, indicating that analyst forecast error and dispersion decline in the year of policy adoption. These findings provide evidence supporting the validity of the identification strategy.

Stacked Regression

To address the potential bias arising from staggered treatment timing in the standard two-way fixed effects specification (firm-fixed effect and year-fixed effect), we implement the stacked difference-in-difference approach following recent literature (Ashraf & Sunder, 2023). Specifically, this method constructs separate samples for each cohort of states adopting data breach disclosure laws and then stacks these cohorts into a single dataset for estimation.

For each cohort, the dataset is restricted to two years around each treatment year—one year prior to the adoption (t-1) and the adoption year (t). Treated firms are those headquartered in states that adopt the DBDL in the given cohort year, while control firms are those headquartered in states that have not yet adopted by that year. States that have already adopted the DBDL prior to the cohort year are excluded from the corresponding sample. For example, California is the first state to adopt the DBDL in 2002, so treated observations in the first event-cohort dataset are all firms that are headquartered in California for 2001 and 2002. Similarly, for the 2005 dataset, treated firm-years comprise firms in the states that passed the DBDLs in 2005 and control firms are those in the states that have not passed the law by 2005. At the same time, firms' headquarters located in California are excluded from the 2005 dataset and subsequent years. Following this pattern, the number of observations in each subset decreases, and finally, all the cohorts are combined to form a unified dataset.

As a result of this procedure, the sample size is reduced to 5,591 observations, and the results are reported in **Table 6**. The coefficient on LAW remains negative and statistically significant for both forecast error and forecast dispersion, indicating that the main findings are robust to alternative identification strategies. These results reinforced the conclusion that DBDL improve the information environment and enhance the accuracy of analyst forecasts.

Robustness Tests

To examine the robustness of the baseline findings, we conduct several additional tests. To be specific, we assess whether the results are sensitive when using alternative methods of clustering specification, an alternative definition of the law, and a different method to construct all the firm-year variables. Shown in Panels A, B, and C of **Table 7**. the estimated effects of DBDL remain negative and significant, providing further support for the main conclusion that these laws improve analysts' forecast outcomes.

Alternative Fixed Effects and Clustering Specifications

Table 7 Panel A reports the results using alternative model specifications. In columns (1) and (3), we cluster the standard errors at both state and calendar year levels. The coefficient on LAW remains negative and statistically significant for both forecast error and forecast dispersion, consistent with the baseline findings.

In columns (2) and (4), we further include industry × year fixed effects to control for time-varying and industry-specific shocks, while continuing to control for firm fixed effects and cluster standard errors at the state level. This group is designed to eliminate the possibility of external factors having different effects across industries, and the results remain consistent. All these results suggest that the main findings are reliable for different fixed effects selections and clustering structures, and are unlikely to be driven by industry shocks.

Alternative Definition of Law Timing

We next examine whether the findings are sensitive to the definition of the treatment variable. Instead of using the baseline indicator, we construct an alternative measure based on the year the border state signed, LAW_BORDER. This variable equals to1 if the firm's headquarters state or any geographically adjacent state has enacted a DBDL by year t, and 0 otherwise. Firms headquartered in non-contiguous U.S. territories (e.g., Puerto Rico) have no geographically adjacent states and therefore are coded as having no spillover exposure from neighboring states. As shown in Panel B, the coefficient on LAW_BORDER remains negative and statistically significant in both specifications. This result indicates that regardless of how we measure the point in time at which data breach disclosure regulations have an impact on firms, they will affect the behavior of analysts' predictions.

Alternative Aggregation Method

Finally, we test whether the results depend on the method used to aggregate analyst-level forecasts to the firm-year level. In the baseline analysis, variables are collapsed using the mean value. As a robustness check, we reconstruct variables using the median value and re-estimate the main regressions. Reported in Panel C, the coefficient on LAW remains negative and statistically significant for both forecast error and forecast dispersion. This evidence indicates that the baseline findings are not driven by the choice of aggregation method.

Sensitivity Tests

To further assess the sensitivity of baseline findings, we perform additional analyses. After modifying the sample selection criteria, the study reports the results in **Table 8**.

In Panel A, we restrict the sample to observations prior to 2011. This selection is based on the Securities and Exchange Commission (SEC, 2011), which provides guidance on the disclosure obligations relating to cybersecurity risks and cyber incidents. The process aims to mitigate concerns that regulatory developments may influence the results. Despite the reduction of sample size, the coefficient on LAW remains negative and statistically significant for both forecast error and forecast dispersion. This suggests that the documented effect is not driven by later-period dynamics or regulatory changes.

In Panel B, we exclude 2005 and 2006, during which the adoption of DBDLs is highly concentrated in these two years. This test addresses the concern that the baseline results may be influenced by the clustering of policy changes in specific years. The estimated coefficients on LAW remain negative and statistically significant, indicating that the main findings are not sensitive to the inclusion of these policy-intensive years.

Taken together, these findings suggest that the estimated effects are stable across alternative sample constructions and unlikely to be driven by specific sample periods or policy timing.

Conclusion

This thesis examines the effect of data breach disclosure laws on analysts' forecasting outcomes. Using the staggered adoption of state-level regulations and a difference-in-differences framework, the analysis provides evidence that such laws are associated with improved forecast accuracy and reduced dispersion among analysts. These results suggest that mandatory disclosure enhances the overall information environment, thereby facilitating more precise and consistent expectations.

The findings remain robust across a range of specifications and sample restrictions, indicating that the documented effects are not driven by specific model choices or time periods. Overall, the evidence supports the view that regulatory disclosure requirements can play a meaningful role in reducing information asymmetry and improving the quality of financial information processing.

This study has several implications. By showing that disclosure regulations affect not only market reactions but also the behavior of information intermediaries, it highlights an additional channel through which regulation can influence capital markets. At the same time, the results underscore the importance of transparency in environments characterized by information uncertainty and rapid technological change.

This study is subject to several limitations. First, the sample is restricted to U.S. publicly listed firms, which may limit the generalizability of the findings to other institutional settings or private firms. Future research could extend the analysis to different countries or examine whether similar effects hold in alternative regulatory environments. Second, although this study provides evidence that data breach disclosure laws improve the information environment faced by analysts, it does not directly examine the underlying mechanisms. Future research may further explore these channels.

Appendix A

State	Bill Code	Signed Year	Source
CA	SB1386	2002	Perkins Coie *Security Breach Notification Chart*
AR	SB1167	2005	Perkins Coie *Security Breach Notification Chart*
CT	SB650	2005	Perkins Coie *Security Breach Notification Chart*
DE	HB116	2005	Perkins Coie *Security Breach Notification Chart*
GA	SB230	2005	Perkins Coie *Security Breach Notification Chart*
IL	HB1633	2005	Perkins Coie *Security Breach Notification Chart*
LA	SB205	2005	Perkins Coie *Security Breach Notification Chart*
ME	LD1671	2005	Perkins Coie *Security Breach Notification Chart*
MN	HF2121	2005	Perkins Coie *Security Breach Notification Chart*
MT	HB732	2005	Perkins Coie *Security Breach Notification Chart*
NC	SB1048	2005	Perkins Coie *Security Breach Notification Chart*
ND	SB2251	2005	Perkins Coie *Security Breach Notification Chart*
NJ	A4001	2005	Perkins Coie *Security Breach Notification Chart*
NV	SB347	2005	Perkins Coie *Security Breach Notification Chart*
NY	AB4254	2005	Perkins Coie *Security Breach Notification Chart*
OH	HB104	2005	Perkins Coie *Security Breach Notification Chart*
PA	SB712	2005	Perkins Coie *Security Breach Notification Chart*

RI		2005	IT Governance USA
TN	HB2170	2005	Perkins Coie *Security Breach Notification Chart*
WA	SB6043	2005	Perkins Coie *Security Breach Notification Chart*
PR	HB1184	2005	Perkins Coie *Security Breach Notification Chart*
AZ	SB1338	2006	Perkins Coie *Security Breach Notification Chart*
CO	HB1119	2006	Perkins Coie *Security Breach Notification Chart*
HI	SB2290	2006	Perkins Coie *Security Breach Notification Chart*
ID	SB1374	2006	Perkins Coie *Security Breach Notification Chart*
KS	SB196	2006	Perkins Coie *Security Breach Notification Chart*
MI	SB309	2006	Perkins Coie *Security Breach Notification Chart*
NE	LB879	2006	Perkins Coie *Security Breach Notification Chart*
NH	HB1660	2006	Perkins Coie *Security Breach Notification Chart*
UT	SB69	2006	Perkins Coie *Security Breach Notification Chart*
VT	S284	2006	Perkins Coie *Security Breach Notification Chart*
WI	SB164	2006	Perkins Coie *Security Breach Notification Chart*
MA	HB4144	2007	Perkins Coie *Security Breach Notification Chart*
MD	HB208	2007	Perkins Coie *Security Breach Notification Chart*
OR	SB583	2007	Perkins Coie *Security Breach Notification Chart*
WY		2007	Perkins Coie *Security Breach Notification Chart*

TX		2007	Perkins Coie *Security Breach Notification Chart*
DC		2007	Perkins Coie *Security Breach Notification Chart*
AK	HB65	2008	Perkins Coie *Security Breach Notification Chart*
IA	SF2308	2008	Perkins Coie *Security Breach Notification Chart*
OK	HB2245	2008	Perkins Coie *Security Breach Notification Chart*
SC	SB453	2008	Perkins Coie *Security Breach Notification Chart*
VA	18.2-186.6	2008	Perkins Coie *Security Breach Notification Chart*
WV	SB340	2008	Perkins Coie *Security Breach Notification Chart*
VI		2008	Perkins Coie *Security Breach Notification Chart*
MO	HB62	2009	Perkins Coie *Security Breach Notification Chart*
MS	HB582	2010	Perkins Coie *Security Breach Notification Chart*
KY	HB232	2014	Perkins Coie *Security Breach Notification Chart*
FL	SB1524	2014	Perkins Coie *Security Breach Notification Chart*
NM	HB15	2017	Perkins Coie *Security Breach Notification Chart*
AL	SB318	2018	Perkins Coie *Security Breach Notification Chart*
SD	SB62	2018	Perkins Coie *Security Breach Notification Chart*

Appendix B

Variable	Definition	Data Source
LAW	= 1 if the fiscal-year end of firm i's year t is equal to or after the firm i's home state j (i.e., business headquarters state) has signed into a breach disclosure law and 0 otherwise.	Manual Collection
STATE	The state where a firm is located as shown in the business address.	Loughran and McDonald 10-X Header Data
FORECAST_ERROR	The absolute difference between the analysts' forecasts and the firm's actual earnings per share scaled by mean consensus estimate. *abs(VALUE - ACTUAL) / abs(mean_value)*	I/B/E/S and authors' calculations
FORECAST_DISPERSION	Standard deviation in analysts' earnings forecasts at the end of the fiscal year, scaled by the mean consensus estimate. *sd_value / abs(mean_value)*	I/B/E/S and authors' calculations
LAW_BORDER	= 1 if a data breach disclosure law is signed in either the firm's home state or any neighboring state by year t, and 0 otherwise.	Manual Collection
GENERAL_EXPERIENCE	Number of years the analyst has covered since the analyst's first forecast in IBES. *year_forecast - first_forecast*	I/B/E/S and authors' calculations
SPECIFIC_EXPERIENCE	Number of years the analyst has covered the firm. *year_forecast - first_specific*	I/B/E/S and authors' calculations
BREADTH	Total number of firms followed by the analyst.	I/B/E/S and authors' calculations

SPECIALIZATION	Share of reports issued in one industry out of total coverage.	I/B/E/S and authors' calculations
FORECAST_AGE	The number of days from the analyst forecast issuance date to the forecast period end date. *ANNDATS - FPEDATS*	I/B/E/S and authors' calculations
SIZE	The natural logarithm of total assets. *ln(at)*	Compustat
LEVERAGE	The ratio of the sum of short-term debt and long-term debt to total assets. *(dltt + dlc) / at*	Compustat
MTB	The ratio of the market value of equity to the book value of equity. *(csho * prcc_f) / ceq*	Compustat
DEBT	The ratio of total liabilities to total assets. *lt / at*	Compustat
ROA	The ratio of EBITDA to total assets. *ebitda / at*	Compustat
LOSS	= 1 if the net income is negative for the firm in year t, 0 otherwise.	Compustat
CASH	The ratio of cash and short-term investment to total assets. *che / at*	Compustat

Appendix C

Sample	Observations	
US firms covered by Compustat for the period 2000-2024		149,658
Merged with Loughran and McDonald 10-X Header Data (firm location)		
Less: Not matched observations	(39,723)	
Less: Firms with changing headquarters state	(18,915)	
Less: Observations without valid U.S. state identifiers	(2,485)	
		88,535
Less: Firms from the financial industry or utilities industry	(28,430)	
		60,105
Less: Observations with missing financial data	(3,777)	
		56,328
Merged with DBDL's signed year		
		56,328
Merged with I/B/E/S (analyst forecast) data		
Less: Observations without matched IBES data	(29,210)	
Final Sample		27,118
Total number of firms		4,045

Table 1 The Distribution of Years When States Sign into a Data Breach Disclosure Law

Year	State	Total
2002	CA	1
2005	AR, CT, DE, GA, IL, IN, LA, ME, MN, MT, NC, ND, NJ, NV, NY, OH, PA, RI, TN, WA, (PR)	21
2006	AZ, CO, HI, ID, KS, MI, NE, NH, UT, VT, WI	32
2007	MA, MD, OR, WY, TX, (DC)	37
2008	AK, IA, OK, SC, VA, WV, (VI)	43
2009	MO	44
2010	MS	45
2014	KY, FL	47
2017	NM	48
2018	AL, SD	50

Table 2 Summary Statistics

	N	Mean	p5	Median	p95	SD
LAW	27118	0.782	0.000	1	1	0.413
SIZE	27118	6.914	4.224	6.833	9.883	1.715
LEVERAGE	27118	0.21	0.000	0.182	0.57	0.191
MTB	27118	4.655	0.802	2.723	14.331	6.777
DEBT	27118	0.468	0.112	0.471	0.85	0.225
ROA	27118	0.052	-0.432	0.108	0.273	0.217
CASH	27118	0.256	0.008	0.158	0.828	0.259
LOSS	27118	0.338	0.000	0	1	0.473
BREADTH	27118	11.086	6.000	10.375	18	4.344
FORECAST_AGE	27118	-96.765	-167.75	-91.525	-47.333	37.758
FORECAST_ERROR	27118	0.404	0.009	0.079	1.5	1.315
FORECAST_DISPERSION	27118	0.288	0.007	0.07	1.2	0.767
GENERAL_EXPERIENCE	27118	6.757	0.429	6.545	14	4.176
SPECIFIC_EXPERIENCE	27118	2.37	0.000	1.778	6.8	2.189

Table 3 Pairwise Correlations

Panel A

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) FORECAST_ERROR	1.000												
(2) LAW	0.022	1.000											
(3) SIZE	-0.101	0.122	1.000										
(4) LEVERAGE	0.004	0.075	0.386	1.000									
(5) MTB	-0.035	0.075	0.031	0.206	1.000								
(6) DEBT	0.000	0.071	0.420	0.792	0.331	1.000							
(7) ROA	-0.112	-0.093	0.451	0.099	-0.040	0.141	1.000						
(8) CASH	0.042	0.085	-0.478	-0.392	0.140	-0.440	-0.607	1.000					
(9) LOSS	0.233	0.050	-0.386	-0.045	0.040	-0.083	-0.652	0.430	1.000				
(10) BREADTH	-0.005	0.252	0.224	0.109	0.166	0.088	-0.092	0.108	0.063	1.000			
(11) FORECAST_AGE	-0.068	0.173	0.045	0.038	0.046	0.024	-0.001	0.021	-0.016	0.130	1.000		
(12) GENERAL_EXPER	0.003	0.614	0.218	0.191	0.121	0.164	-0.044	-0.025	0.017	0.425	0.226	1.000	
(13) SPECIFIC_EXPE	-0.078	0.357	0.445	0.167	0.023	0.197	0.221	-0.234	-0.221	0.248	0.089	0.570	1.000

Panel B

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) FORECAST_DISPE	1.000												
(2) LAW	0.007	1.000											
(3) SIZE	-0.066	0.122	1.000										
(4) LEVERAGE	0.019	0.075	0.386	1.000									
(5) MTB	-0.030	0.075	0.031	0.206	1.000								
(6) DEBT	0.015	0.071	0.420	0.792	0.331	1.000							
(7) ROA	-0.061	-0.093	0.451	0.099	-0.040	0.141	1.000						
(8) CASH	0.013	0.085	-0.478	-0.392	0.140	-0.440	-0.607	1.000					
(9) LOSS	0.263	0.050	-0.386	-0.045	0.040	-0.083	-0.652	0.430	1.000				
(10) BREADTH	0.001	0.252	0.224	0.109	0.166	0.088	-0.092	0.108	0.063	1.000			
(11) FORECAST_AGE	-0.093	0.173	0.045	0.038	0.046	0.024	-0.001	0.021	-0.016	0.130	1.000		
(12) GENERAL_EXPER	-0.012	0.614	0.218	0.191	0.121	0.164	-0.044	-0.025	0.017	0.425	0.226	1.000	
(13) SPECIFIC_EXPE	-0.070	0.357	0.445	0.167	0.023	0.197	0.221	-0.234	-0.221	0.248	0.089	0.570	1.000

Table 4 Baseline Regression

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
LAW	-0.050*	-0.037**
	(-1.83)	(-2.12)
SIZE	-0.024	-0.011
	(-0.88)	(-0.74)
LEVERAGE	-0.282***	-0.079
	(-2.90)	(-1.03)
MTB	-0.007***	-0.004***
	(-3.93)	(-3.18)
DEBT	0.386***	0.137**
	(3.89)	(2.22)
ROA	0.475**	0.343*
	(2.60)	(1.98)
CASH	-0.179**	-0.129***
	(-2.56)	(-2.71)
LOSS	0.645***	0.505***
	(22.11)	(22.02)
BREADTH	0.003*	0.003**
	(1.76)	(2.47)
FORECAST_AGE	-0.002***	-0.002***
	(-8.24)	(-9.93)
GENERAL_EXPERIENCE	-0.008	-0.010***
	(-1.40)	(-3.03)
SPECIFIC_EXPERIENCE	-0.001	-0.000
	(-0.08)	(-0.01)
_cons	0.121	0.075
	(0.56)	(0.59)
N	26378	26378
R^2	0.475	0.317

Table 5 Parallel Trend Assumption

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
LAW_{t-2}	-0.026	-0.011
	(-0.73)	(-0.46)
LAW_{t-1}	-0.034	0.005
	(-1.12)	(0.23)
LAW_{t}	-0.080**	-0.047*
	(-2.28)	(-1.78)
LAW_{t+1}	-0.071	-0.035
	(-1.60)	(-1.36)
LAW_{t+2} and beyond	-0.068	-0.028
	(-1.56)	(-0.86)
SIZE	-0.023	-0.011
	(-0.86)	(-0.73)
LEVERAGE	-0.283***	-0.080
	(-2.89)	(-1.04)
MTB	-0.007***	-0.004***
	(-3.93)	(-3.19)
DEBT	0.385***	0.137**
	(3.87)	(2.22)
ROA	0.473**	0.342*
	(2.59)	(1.98)
CASH	-0.178**	-0.129***
	(-2.53)	(-2.70)
LOSS	0.646***	0.505***
	(22.09)	(22.02)
BREADTH	0.003*	0.003**
	(1.75)	(2.47)
FORECAST_AGE	-0.002***	-0.002***
	(-8.26)	(-9.93)
GENERAL_EXPERIENCE	-0.008	-0.010***
	(-1.41)	(-3.03)
SPECIFIC_EXPERIENCE	-0.000	-0.000
	(-0.07)	(-0.01)
N	26378	26378
R^2	0.475	0.317

Table 6 Stacked Regression

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
Treated Indicator	-0.087***	-0.051**
	(-3.18)	(-2.34)
SIZE	-0.157***	-0.076**
	(-3.31)	(-2.17)
LEVERAGE	0.257	0.177
	(0.67)	(0.97)
MTB	-0.020***	-0.015***
	(-2.70)	(-2.79)
DEBT	0.136	-0.055
	(0.55)	(-0.30)
ROA	-0.158	-0.086
	(-0.41)	(-0.30)
CASH	-0.289	-0.226
	(-1.49)	(-1.29)
LOSS	0.401***	0.392***
	(4.16)	(5.74)
BREADTH	0.026***	0.017***
	(3.16)	(3.65)
FORECAST_AGE	-0.003***	-0.002***
	(-5.33)	(-6.42)
GENERAL_EXPERIENCE	-0.033	-0.016
	(-1.29)	(-0.77)
SPECIFIC_EXPERIENCE	-0.021	-0.040
	(-0.57)	(-1.41)
_cons	0.930***	0.534**
	(3.07)	(2.34)
N	5591	5591
R^2	0.477	0.466

Table 7 Robustness Tests

Panel A: Alternative Fixed Effects and Clustering Specifications

	(1)	(2)	(3)	(4)
	FORECAST_ERROR		FORECAST_DISPERSION	
LAW	-0.050*	-0.103***	-0.037*	-0.066***
	(-1.81)	(-4.36)	(-1.95)	(-3.84)
SIZE	-0.024	-0.023	-0.011	-0.018
	(-0.92)	(-1.10)	(-0.73)	(-1.37)
LEVERAGE	-0.282**	-0.366***	-0.079	-0.161*
	(-2.49)	(-3.57)	(-0.81)	(-1.92)
MTB	-0.007***	-0.009***	-0.004***	-0.006***
	(-3.58)	(-4.42)	(-3.09)	(-3.32)
DEBT	0.386***	0.375***	0.137	0.175*
	(2.96)	(3.29)	(1.54)	(1.97)
ROA	0.475**	0.658***	0.343*	0.477***
	(2.48)	(5.41)	(2.00)	(3.56)
CASH	-0.179***	-0.119	-0.129***	-0.119**
	(-2.85)	(-1.56)	(-3.24)	(-2.28)
LOSS	0.645***	0.593***	0.505***	0.463***
	(17.83)	(15.39)	(18.68)	(20.07)
BREADTH	0.003	0.003	0.003*	0.003*
	(1.22)	(1.09)	(1.83)	(1.86)
FORECAST_AGE	-0.002***	-0.002***	-0.002***	-0.002***
	(-8.44)	(-8.92)	(-9.53)	(-8.55)
GENERAL_EXPE	-0.008*	-0.002	-0.010***	-0.004
RIENCE	(-1.77)	(-0.18)	(-3.31)	(-1.03)
SPECIFIC_EXPER	-0.001	-0.009	-0.000	-0.001
IENCE	(-0.09)	(-0.96)	(-0.01)	(-0.20)
_cons	0.121	0.181	0.075	0.129
	(0.58)	(0.96)	(0.57)	(1.04)
N	26378	24232	26378	24232
R^2	0.475	0.572	0.317	0.431
Year FE	Yes		Yes	
Firm FE	Yes	Yes	Yes	Yes
Industry× Year FE		Yes		Yes
Clustering	State and Year	State	State and Year	State

Notes: Differences in sample size across specifications arise from alternative clustering methods, as singleton observations are dropped in state-level clustering**.**

Panel B: LAW Defined Using Neighboring State's Signed Years

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
POST_LAW_BORDER	-0.076***	-0.050**
	(-3.21)	(-2.59)
SIZE	-0.024	-0.011
	(-0.88)	(-0.75)
LEVERAGE	-0.279***	-0.078
	(-2.85)	(-1.01)
MTB	-0.007***	-0.004***
	(-3.93)	(-3.18)
DEBT	0.384***	0.136**
	(3.86)	(2.19)
ROA	0.475**	0.343*
	(2.60)	(1.98)
CASH	-0.178**	-0.128***
	(-2.54)	(-2.73)
LOSS	0.646***	0.505***
	(22.08)	(22.03)
BREADTH	0.003*	0.003**
	(1.79)	(2.49)
FORECAST_AGE	-0.002***	-0.002***
	(-8.25)	(-9.97)
GENERAL_EXPERIENCE	-0.008	-0.010***
	(-1.41)	(-3.04)
SPECIFIC_EXPERIENCE	-0.001	-0.000
	(-0.09)	(-0.02)
_cons	0.147	0.088
	(0.66)	(0.65)
N	26378	26378
R^2	0.475	0.317

Panel C: Alternative Aggregation Using Median Values

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
LAW	-0.044*	-0.036**
	(-1.90)	(-2.10)
SIZE	-0.028	-0.011
	(-1.43)	(-0.80)
LEVERAGE	-0.248**	-0.079
	(-2.44)	(-1.02)
MTB	-0.006***	-0.005***
	(-3.90)	(-3.34)
DEBT	0.369***	0.146**
	(3.53)	(2.30)
ROA	0.385***	0.334*
	(3.04)	(1.93)
CASH	-0.140**	-0.135***
	(-2.22)	(-2.83)
LOSS	0.464***	0.505***
	(17.40)	(22.31)
BREADTH	0.002	0.001
	(0.83)	(0.29)
FORECAST_AGE	-0.002***	-0.001***
	(-8.41)	(-7.09)
GENERAL_EXPERIENCE	-0.004	-0.009***
	(-1.31)	(-4.06)
SPECIFIC_EXPERIENCE	-0.001	0.002
	(-0.40)	(0.53)
_cons	0.196	0.214*
	(1.28)	(1.80)
N	26378	26378
R^2	0.493	0.313

Table 8 Sensitivity Analyses

Panel A: Sample Restricted to Pre-2011 Period

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
LAW	-0.071***	-0.056***
	(-3.23)	(-3.48)
SIZE	-0.096	-0.046
	(-1.48)	(-1.41)
LEVERAGE	-0.306**	-0.088
	(-2.10)	(-0.66)
MTB	-0.011***	-0.006**
	(-3.90)	(-2.42)
DEBT	0.480***	0.119
	(4.12)	(1.22)
ROA	0.330**	0.200
	(2.44)	(1.20)
CASH	-0.208	-0.126*
	(-1.67)	(-1.70)
LOSS	0.652***	0.518***
	(11.91)	(13.96)
BREADTH	0.005	0.003
	(0.92)	(1.01)
FORECAST_AGE	-0.002***	-0.002***
	(-7.23)	(-10.26)
GENERAL_EXPERIENCE	0.012	0.011
	(0.67)	(0.91)
SPECIFIC_EXPERIENCE	-0.025	-0.029**
	(-1.53)	(-2.67)
_cons	0.475	0.251
	(1.21)	(1.10)
N	11673	11673
R^2	0.367	0.334

Panel B: Sample Excluding 2005 and 2006

	(1) FORECAST_ERROR	(2) FORECAST_DISPERSION
LAW	-0.079**	-0.043**
	(-2.61)	(-2.06)
SIZE	-0.026	-0.013
	(-0.94)	(-0.89)
LEVERAGE	-0.274**	-0.088
	(-2.63)	(-1.08)
MTB	-0.007***	-0.005***
	(-4.10)	(-3.21)
DEBT	0.416***	0.151**
	(3.58)	(2.16)
ROA	0.519***	0.359**
	(3.03)	(2.15)
CASH	-0.169**	-0.126**
	(-2.13)	(-2.21)
LOSS	0.636***	0.498***
	(21.28)	(19.64)
BREADTH	0.003	0.003**
	(1.61)	(2.24)
FORECAST_AGE	-0.002***	-0.002***
	(-8.25)	(-9.94)
GENERAL_EXPERIENCE	-0.008	-0.010***
	(-1.44)	(-3.04)
SPECIFIC_EXPERIENCE	0.002	0.002
	(0.32)	(0.47)
_cons	0.158	0.098
	(0.69)	(0.73)
N	24114	24114
R^2	0.491	0.324

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