Defining Current and Expected Financial Constraints using AI: Reinterpreting the Cash Flow Sensitivity of Cash*

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Abstract

We propose a new approach to identify firm-level financial constraints by applying artificial intelligence to text of 10-K filings by U.S. public firms from 1993 to 2021. Leveraging transformer-based natural language processing, our model captures contextual and semantic nuances often missed by traditional text classification techniques, enabling more accurate detection of financial constraints. A key contribution is to differentiate between constraints that affect firms presently and those anticipated in the future. These two types of constraints are associated with distinctly different financial profiles: while firms expecting future constraints tend to accumulate cash preemptively, currently constrained firms exhibit reduced liquidity and higher leverage. We show that only firms anticipating financial constraints exhibit significant cash flow sensitivity of cash, whereas currently constrained and unconstrained firms do not. This calls for a narrower interpretation of this widely used cash-based constraints measure, as it may conflate distinct firm types – unconstrained and currently constrained – and fail to capture all financially constrained firms. Our findings underscore the critical role of constraint timing in shaping corporate financial behavior.

Keywords: Financial Constraints, Artificial Intelligence, Expectations, Cash, Cash Flow, Corporate Finance Behavior.

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1 Introduction

Financial constraints shape firms' corporate decisions – such as investment and liquidity management – but also inform broader debates in asset pricing, monetary policy, firm dynamics, and entrepreneurship, among other areas.[1] Various theories pinpoint the frictions from which these constraints arise (information asymmetries, debt overhang, transaction costs, moral hazard or cost of contract enforcement). Despite their foundational role in determining firm behavior, financial constraints remain challenging to directly observe. With growing access to rich textual disclosures and advances in textual processing via artificial intelligence (AI), a new avenue has opened for directly capturing how firms perceive and describe their financial limitations.

We develop a novel firm-level measure of financial constraints based on the text of annual 10-K filings submitted by publicly listed U.S. firms.[2] Our methodology leverages recent advances in natural language processing – specifically fine-tuned Bidirectional Encoder Representations from Transformers (BERT) models – to detect constraint-related disclosures within the Management Discussion and Analysis (MD&A) sections of 10-K documents.[3] Unlike previous text-based approaches, that for example rely on word frequency counts, our method leverages the deep semantic understanding enabled by modern language models to incorporate syntax, word order and contextual nuance. BERT reads text bi-directionally, making it a particularly well suited tool to extract context-aware information from full-length financial disclosures.

Our approach sets a new standard for the identification and interpretation of financial

[1] In the corporate finance literature, see e.g. Fazzari et al. (1988), Gomes (2001), Almeida et al. (2004), Hennessy and Whited (2007), Denis and Sibilkov (2009), Lian and Ma (2021). On financial constraints and monetary policy, see e.g. Gertler and Gilchrist (1994), Ottonello and Winberry (2020), for firm dynamics, see e.g. Cooley and Quadrini (2001), Caggese et al. (2019), for asset prices, see e.g. Gomes et al. (2006), Whited and Wu (2006), Belo et al. (2019), and for entrepreneurship, see e.g. Kerr and Nanda (2010), Howell (2017).

[2] 10-K filings are detailed annual reports that U.S. public companies submit to the Securities and Exchange Commission, providing standardized disclosures on financial performance, risks, liabilities, and operations. Their detailed disclosure and regulatory consistency make them an ideal source for identifying financial constraints.

[3] The class of BERT models was introduced by Devlin et al. (2019) and quickly became state-of-the-art across numerous natural language processing tasks. Variants and descendants of BERT continue to be used in production systems, such as in components of the Google search engine.

constraints. We train BERT models using a rigorous and resource-intensive process that relies on human labeling. We construct annual, firm-level financial constraint measures, spanning 1993-2021, for the vast majority of the financial statement data in the Compustat universe. Consistent with extant findings in the literature, our measure shows that financially constrained firms are smaller and younger than their unconstrained counterparts, exhibit lower cash flow and dividend payments, have higher indebtedness, R&D intensity and Tobin's Q. Moreover, in addition to these firm characteristics it also satisfies a number of other validation exercises, e.g. its relation with existing constraint proxies and external validation. This also includes the two diagnostic checks proposed by Farre-Mensa and Ljungqvist (2016) to identify firms that are plausibly constrained and which have proven challenging for many existing measures.

A key innovation is our ability to distinguish between current and expected financial constraints. This timing dimension uncovers economically significant heterogeneity that previous measures overlook due to their inability to capture and interpret complex context-dependent narratives. Among constrained firms, only 13% face currently binding constraints, while 65% anticipate constraints in future, and 22% report constraints at present and in future. Firms in these categories differ systematically not only in their observable financial positions, but also in their strategic responses. Those anticipating future constraints tend to accumulate cash, beyond the level of unconstrained firms, and this tendency strengthens with the constraints' expected severity. This is consistent with a precautionary savings motive, whereby firms proactively build liquidity buffers in anticipation of potential financing frictions. In contrast, currently constrained firms have substantially lower cash-to-asset ratios than unconstrained peers, irrespective of constraint severity, suggesting that liquidity has already been drawn down to sustain operations during financial stress. These patterns extend to other balance sheet components. Firms currently experiencing financial constraints show markedly higher levels of debt-to-asset ratios and leverage (measured as total liabilities over total assets) than those expecting constraints in the future, pointing to a more challenging financial situation. Working capital declines monotonically in constraint severity, and is con-

sistently lower among currently constrained firms relative to those anticipating constraints in future.

Our work has fundamental implications for understanding the relation between firms' cash dynamics and financial constraints. In particular, for the interpretation of the cash flow sensitivity of cash introduced by Almeida et al. (2004) as a means of capturing financially constrained firms. Their work has become foundational in empirical corporate finance, influencing a wide range of debates, including studies on firm liquidity management, investment behavior, and the identification of financing constraints.[4] Their theoretical framework demonstrates that firms facing potential future financial constraints save a portion of internal cash flows as a precaution against the risk of being unable to access external finance in the future. This contrasts with the behavior of unconstrained firms, which have greater access to external funding and therefore exhibit no sensitivity of cash holdings to internal cash flows.

While the implications of the theoretical Almeida et al. (2004) model have been widely used to inform empirical work, conversely we provide the first correctly specified empirical test of their model. This is feasible because our financial constraints measure allows us to explicitly distinguish between firms currently facing constraints, those anticipating future constraints, and those that are fully unconstrained. Existing empirical methods cannot distinguish between these states, interpreting a firm's cash flow sensitivity of cash as an indicator of financial constraints in general. In contrast, we show that only firms anticipating financial constraints exhibit cash flow sensitivity of cash, whereas neither currently constrained nor unconstrained firms do. These patterns are robust across a wide range of specifications. While our findings validate the theoretical model's core predictions, they also underscore that empirical applications – which abstract from the time dimension of financial

[4]The cash flow sensitivity of cash has been widely adopted to study topics such as corporate liquidity policies (e.g. Denis and Sibilkov (2009)), the effects of credit shocks (e.g. Acharya et al. (2013), Nikolov et al. (2019)), cross-country differences in financial development (e.g. Khurana et al. (2006)), and firm responses to monetary policy (e.g. Gürkaynak et al. (2022), Bräuning et al. (2023)). It has also spurred methodological debates about the identification of financial constraints and remains a benchmark in the evaluation of constraint proxies.

constraints emphasized in the theoretical framework – risk misinterpreting the cash flow sensitivity of cash as a universal signal of financial constraints. This calls for a narrower interpretation of the widely used Almeida et al. (2004) constraints measure, as it may conflate distinct firm types – unconstrained and currently constrained – and fail to capture all financially constrained firms.

Our ability to measure financial constraints hinges on the way we train our language models.[5] To capture the nuanced expressions of constraint-specific language within MD&A sections, we implement a rigorous, multi-stage fine-tuning procedure that adapts a BERT model to our classification task. Fine tuning requires training data. Constructing a representative training sample by manually reading and classifying MD&A sections is prohibitively time consuming — each document contains thousands of words, and the subtle ways in which financial constraints are discussed require careful, contextual reading. As a result, it is not feasible to hand-label a sufficiently large and diverse sample to train modern language models using traditional annotation alone. To overcome this challenge, we build our training data set by developing a more efficient iterative approach. We begin with a small, manually labeled seed set of paragraph sized text segments and progressively expand it by having the AI model identify and suggest additional, informative or ambiguous examples from the corpus. These suggestions are then reviewed and reclassified by human annotators and subsequently added to the training sample. This active learning strategy with human-in-the-loop is repeated over several iterations. While extremely resource intensive as readers must annotate each paragraph, a key advantage is that the process concentrates annotation efforts on the parts of the corpus most likely to improve the model's classification performance, particularly in areas where the model is uncertain or prone to error.

Focusing labeling resources on the most diagnostically useful segments allows us to train models that learn from a much broader range of language than would be possible through random sampling alone. This results in a model that is not merely attuned to standard

[5]While BERT-based models provide a powerful foundation for natural language understanding, their off-the-shelf versions are not tailored to the subtle and often implicit ways in which financial constraints are discussed in corporate filings.

constraint terminology, but capable of recognizing financial constraints even when described in subtle, firm-specific, or implicit terms. Human annotators not only determine whether a text segment reflects the presence of financial constraints, but also label the severity of the constraint (mild, moderate, or severe) and its timing (current, future, or both time horizons). The three trained BERT models that classify constraint status, severity and timing achieve convincing out-of-sample performance on financial constraints, including accuracy scores of 94%, 92% and 98%, respectively.[6]

Our methodological approach has four key advantages over existing strategies to capture constraints. First, it mitigates the sampling bias that arises when training data is selected purely through keyword filtering, a limitation that affects much of the prior literature. Second, it enhances generalizability across industries, firm size, time, and reporting style by teaching the model to recognize constraint-related discourse patterns rather than relying on fixed vocabularies. This ensures that the measure retains its interpretability when applied to out-of-sample observations. Third, it allows us to move beyond simplistic frequency-based heuristics to determine the severity of constraints: even a single paragraph or sentence may be sufficient to flag the presence of substantial financial constraints. Prior approaches often equate severity with the number of times particular terms appear, but this risks both false positives and false negatives. We show that the relation between severity and the number of constrained paragraphs is modest. By accounting for the context in which words are used, AI enables a more refined assessment — allowing the model to detect severe constraints even when they are mentioned only once, and to ignore repeated but inconsequential uses of generic financial language. Finally, our approach allows us to go beyond the pure classification of whether a firm is constrained. AI enables us to extract further information from the text discussing financial constraints, for example, their time horizon. In doing so, our framework opens new avenues for empirical research on the origins, effects, and evolution of financial constraints.

The remainder of the paper proceeds as follows. In Section 2, we discuss our work

[6]Accuracy shows the proportion of correct classifications out of all classifications.

in relation to the existing literature. Section 3 provides an overview about the data and in Section 4, we train AI models to identify financial constraints, their severity and time horizon. Section 5 provides evidence on the validity of our financial constraints measure. In Section 6 we revisit the cash flow sensitivity of cash and Section 7 concludes.

2 Literature

Our study contributes to two related literatures. A growing body of research draws insights into firms' behavior using textual analysis. Early approaches rely on pre-defined word lists drawn from psychological or financial dictionaries (e.g. Tetlock (2007); Loughran and McDonald (2011)), while a second wave of articles use shallow supervised machine learning methods for textual understanding (e.g. Kogan et al. (2009), Li et al. (2010), Jegadeesh and Wu (2013)).[7] The limitations of these approaches are that they struggle to capture the complex, context-dependent nature of corporate narrative and fall short of full contextual understanding. Recent developments deploy more targeted textual measures using machine learning or structured dictionaries tailored to specific financial or macroeconomic dimensions, such as risk (e.g. Hassan et al. (2019)), innovation (e.g. Kelly et al. (2021)), or monetary policy (e.g. Hansen et al. (2017)).[8] Within the domain of financial constraints, Hoberg and Maksimovic (2015), Bodnaruk et al. (2015), and Buehlmaier and Whited (2018) apply text-based techniques to identify constrained firms based on 10-K filings. However, these approaches still rely on, what appears from today's perspective as, simplified models of language, such as bag-of-words techniques or static term frequencies, which cannot fully reflect the richness of managerial communication. Our work builds on this foundational research but adopts a more sophisticated natural language processing framework and, by leveraging

[7]Shallow machine learning techniques, such as support vector machines or logistic regression applied to bag-of-words or Term Frequency-Inverse Document Frequency (TF-IDF) representations, marked an advance over dictionary-based approaches by allowing models to learn predictive relationships between textual features and financial outcomes. Unlike static word lists, these methods adapt to training data and can capture more nuanced patterns, though they still lack true contextual understanding.

[8]For detailed surveys on the literature on textual analysis, see Loughran and McDonald (2016) and Ash and Hansen (2023).

transformer-based models trained on financial text and fine-tuned through active learning, we move beyond the limitations of dictionary methods and static embeddings.[9]

In parallel, our paper advances the longstanding empirical challenge of classifying financial constraints. Traditional approaches rely on structural models or reduced-form proxies derived from accounting data (e.g. Kaplan and Zingales (1997); Whited and Wu (2006); Hadlock and Pierce (2010)). These measures remain widely used, but may lack external validation and firm-specific nuance.[10] Alternative methods, such as survey-based indicators (e.g. Campello et al. (2010)) or credit spread models (e.g. Chava and Roberts (2008)), offer additional insight but are typically limited in scope, representativeness or availability.

A strand of this literature focuses on firms' observable financial decisions as indirect proxies for constraints. A prominent example is the cash flow sensitivity of cash proposed by Almeida et al. (2004), which builds on their theoretical insight that firms anticipating future financing constraints tend to accumulate cash from internal cash flows. Almeida et al. (2004) significantly advanced the empirical toolkit for studying financial constraints and the cash flow sensitivity of cash became a benchmark measure in corporate finance and macro-financial research.[11] We test their theoretical framework and confirm that firms expecting future constraints exhibit a significant cash flow sensitivity of cash. However, our results also reveal a key limitation of this approach in existing empirical applications: it fails to differentiate between currently constrained and unconstrained firms. Consequently, using the cash flow sensitivity of cash as a general indicator of financial constraints, regardless of timing, can be misleading. Our findings suggest that while their measure reflects precautionary saving behavior in anticipation of future constraints, it is not well suited to identifying contemporaneously constrained firms.

[9]Related work applying advanced natural language processing includes e.g. Kölbel et al. (2024) on climate risk disclosures, Pfeifer and Marohl (2023) of central bank communication and Gentzkow et al. (2019) on political polarization in economic narratives.

[10]See Farre-Mensa and Ljungqvist (2016) for a critique of standard constraint proxies.

[11]The cash flow sensitivity of cash remains a key diagnostic tool for identifying which firms are financially constrained. We cannot do justice to the vast related literature here. Important contributions in addition to those discussed in Section 1 are e.g. Acharya et al. (2007), Han and Qiu (2007), Harford et al. (2008), Bates et al. (2009), Duchin (2010), Almeida et al. (2012), Bao et al. (2012), Erel et al. (2015), Duong et al. (2020), Bartram et al. (2022), Granja et al. (2022), Almeida et al. (2024).

These findings shed new light on a longstanding debate in the literature. While widely used, the interpretation of the cash flow sensitivity of cash has been subject to scrutiny. Some studies raise concerns about confounding motives such as risk management or agency frictions (e.g. Bates et al. (2009)), while others question its validity as a constraint proxy (e.g. Riddick and Whited (2009), Farre-Mensa and Ljungqvist (2016)). We reconcile these divergent perspectives by showing that the measure is a useful proxy, but only to capture firms anticipating financial constraints.

Recent efforts in identifying financial constraints have turned toward textual data as a scalable and complementary source of firm-level constraint information. Bodnaruk et al. (2015) construct a dictionary of constraint-related terms and analyze their frequency within firms' 10-K filings. Hoberg and Maksimovic (2015) use a dictionary-based bag-of-words approach – counting the frequency of constraint-related terms in the MD&A sections of 10-K filings from 1997-2009 – to provide separate debt- or equity-based constraints measures. Buehlmaier and Whited (2018) construct a training sample to estimate a firm's probability of financial constrainedness as a function of the words in its MD&A section. They subsequently apply this fitted probability model to predict firm's financial constraints status across the whole sample and analyze the relation of financial constraints and stock returns.

These approaches' advantage lies in their ability to harness the firm-specific narrative richness embedded in textual disclosures. However, due to technological constraints they either ignore linguistic structure or rely on manually curated keyword lists, limiting their capacity to capture contextual nuance and deeper semantic meaning. Building on this foundation, we advance the natural language processing of dictionary-based methods by introducing a context-aware, data-driven approach. Our contribution is a multi-dimensional classification framework that leverages the language used by firms themselves, incorporating the surrounding context in which financial constraints are discussed. Our approach not only improves the precision of constraint measurement, and enables us to distinguish between current and anticipated constraints, uncovering previously unobserved heterogeneity in constraint dynamics.

3 Data

We retrieve information on financial constraints from firms' annual regulatory 10-K filings with the Securities and Exchange Commission (SEC) between 1993 and 2021.[12] Firms' 10-K filings must comply with the SEC's Regulation S-K disclosure requirements. To identify the presence and nature of financial constraints in these detailed textual accounts, we focus on the Management's Discussion and Analysis (MD&A) sections of each 10-K report. This is consistent with the practice in existing studies on financial constraints, see e.g. Hoberg and Maksimovic (2015), Bodnaruk et al. (2015), and Buehlmaier and Whited (2018). The SEC mandates firms discuss their sources of financing and their current and expected future liquidity needs in the MD&A.

We pre-process and clean the MD&A data in three steps. First, we pre-process the MD&A text using the open-source python library, *unstructured*, to remove non-narrative content such as tables, figures, and headings. This allows the BERT model to focus on the section's substantive textual content. Second, we segment the text into paragraphs so the model analyzes a complete, self-contained discussion. If a paragraph exceeds BERT's 512-token context window limit, we apply a rolling window technique with a 400-token window that includes an up-to-100-token overlap to divide the text appropriately.[13] Third, some MD&A sections are very brief and therefore lack sufficient information for our analysis. We thus exclude MD&A sections in the bottom percentile of the word count distribution, these contain 164 words or fewer. Appendix A.1 provides further detail on the 10-K data extraction process.

The second data source we use is Compustat North America, from which we extract the Annual Financial Statements between 1993 and 2021. We apply standard data cleaning procedures used in the literature (see e.g. Hoberg and Maksimovic (2015), Buehlmaier and Whited (2018) and Görtz et al. (2023)). Specifically, we exclude firms that do not

[12] We extract 10-K filings from the SEC Edgar Database using the Notre Dame Software Repository for Accounting and Finance (SRAF).

[13] A text segment of 512 tokens consists of around 250-350 words. 12.4% of all paragraphs exceeded the 512 token limit.

use the US Dollar as their reporting currency, those in highly-regulated (SIC codes 4900-4999) or the financial (SIC codes 6000-6999) sectors, those with zero or missing total assets, or those for which sales or the sum of common and preferred stock is zero or negative. Following Hoberg and Maksimovic (2015) and Buehlmaier and Whited (2018), we exclude firm-year observations as soon as a firm is in financial distress, measured as those that have filed for bankruptcy protection and are undergoing liquidation, as our focus is on regularly operating firms. Further detail on variable definitions and the cleaning of individual Compustat variables is provided in Appendix A.2.

We are able to match 73.3% of the observations in the Compustat data set to MD&As in the 10-K filings. This matching rate is in line with rates achieved in the literature, see e.g. the matching rate of 63.8% in Chu et al. (2021). Indeed, when we exclude the first three sample years, when many filings are digitally unavailable as they were submitted in paper format, the matching rate is 82.1%. Further details and statistics related to the matching process are provided in Appendix A.3. The final merged Compustat-MD&A data set contains 11,582 firms, 96,093 firm-year observations and 7,501,167 text segments.

4 Identifying Financial Constraints Using AI

We use BERT, a deep learning model developed for natural language understanding tasks, to identify financially constrained firms. Its transformer architecture processes text bidirectionally, meaning it learns context from both the left and right of each word, thereby capturing nuanced meanings and context. Pre-trained on large text corpora, BERT can be fine-tuned for various natural language processing tasks.[14]

[14]BERT models are in essence generative models that predict a text-token based on surrounding text-tokens. However, they can easily be adapted to classification tasks by replacing the output layer with a suitable classification layer.

4.1 Training BERT to Detect Financial Constraints

The voluminous MD&A data make it impossible to read and classify all text segments by hand. Even constructing a representative hand-classified training sample within a reasonable time horizon is infeasible since it must encompass a sufficiently diverse range of text passages. By fine-tuning a BERT model, we use AI to identify text segments in pre-processed MD&A sections discussing financial constraints. Fine-tuning the BERT model relies on a training data set, developed in Section 4.1.1.[15] The efficacy of these models hinges on the diversity of their training data which must capture the various phrases firms use to describe and discuss financial constraints and ensure the language used is representative of the broader corpus. Training a model on a biased sample would lead to skewed extrapolations, resulting in confounded and unreliable predictions. We mitigate these issues by implementing an Active Learning methodology with human-in-the-loop and evaluate model performance in Section 4.1.2.

4.1.1 Generating the Training Data: Seed and Active Learning Samples

We create the training data set in four steps. First, a trained reader classifies text segments on whether they indicate financial constraints or not.[16] Once two independent readers agree on a constrained/unconstrained classification, a text segment becomes part of our seed training sample which comprises 251 text segments (228 firm-year pairs) that indicate financial constraints and 2,000 text segments (224 firm-year pairs) without financial constraints.

In the second step, we begin the Active Learning process using the seed sample as training data to fine tune a FinBERT model which allows us to capture the patterns and signals indicative of financial constraints within the text segments.[17] Active Learning is a supervised

[15]Fine-tuning is the process, by which a pre-trained model is adapted to a new task – in our case classification. BERT models in particular benefit from pre-training, meaning that they require much less data than an entirely untrained model to adapt to a new task. See for example Raffel et al. (2020).

[16]We provide detailed guidelines to each reader on what constitutes financial constraints.

[17]FinBERT is a BERT variant specifically pre-trained on extensive financial corpora. It provides an advanced starting point for understanding financial language.

machine learning technique where the algorithm selectively queries a human annotator to label the most informative data points from an unlabeled data set. This iterative process begins with a small, hand-labeled training data set and progressively enhances the model's performance by focusing on data points that are expected to provide the most significant improvement upon labeling. By concentrating on these informative instances, Active Learning aims to achieve high accuracy with fewer hand-labeled examples, thereby optimizing the annotation effort and efficiently improving the model's accuracy.

Third, we use the trained BERT model to classify a randomly selected set of text segments from the set of MD&A documents (independent of our seed training data) determining whether they indicate financial constraints. We then select a subset of these text segments including, a) all those text segments classified by the model as indicative of financial constraints, b) text segments for which the model indicates a particularly high classification uncertainty, and c) further randomly selected text segments. Each BERT-labeled text segment is then assessed by two human readers who cross check the classification made by the trained model. By concentrating on uncertain and minority class samples, the Active Learning approach helps us to efficiently expand our training data set with examples that are most likely to improve the model's performance, especially in recognizing rare but critical instances.

In the fourth step, we add those text segments assessed in step three, for which both human readers agree on a classification, to our initial training data. Importantly, the human readers may override the BERT model's labels, allowing the process to correct for any AI misclassifications. The consistency between labels assigned by BERT and the human readers are used to monitor the model's performance on data unseen by the model. Subsequently, we fine tune the FinBERT model using this extended training data set.

We iterate steps three and four ten times at which point performance is deemed sufficiently high.[18] In each iteration, the human readers manually evaluate the model's predic-

[18]Following iteration ten the agreement rate between humans and the AI is 95% and precision – the share of all AI-identified constrained (unconstrained) cases out of all constrained (unconstrained) cases – is 91% and 97% for financially constrained and unconstrained text segments, respectively.

tions and we add approximately 2,000 newly BERT-classified and reader-checked constrained and unconstrained text segments to the training data set used in step two. An off-the-shelf FinBERT model is then fine tuned using the expanded training data. The iterative process allows us to expand the sample, validate the model's performance in every iteration, and improve its ability to classify unseen data. Further details on steps one to four, as well as statistics on the model's performance improvements over the ten iterations are provided in Appendix B.1.

Our Active Learning approach with human-in-the-loop verification is more effective than random sampling, because it enriches the training data with informative examples that help the model learn faster and more accurately. Focusing on the minority class and edge cases exposes the model to text segments it struggles to classify, thereby enhancing its ability to generalize and detect financial constraints in an imbalanced data set.[19] In our case, Active Learning strikes a balance between two approaches and is key to generating a sufficiently large and representative data set. One approach randomly selects and labels many text segments to ensure that the training sample is representative of the population. However, this is very time consuming and infeasible in our context. The other approach selects a small sample, typically based on external criteria, which is much quicker and often applied in the literature. This, however, is unlikely to yield a training sample that is representative of the population.

In the context of an imbalanced data set and infrequent passages referring to financial constraints, the Active Learning strategy has two key advantages. First, it allows us to begin with a moderate number of examples from MD&A documents to train the BERT model, and then use the model to select additional examples which humans can label. This results in high out-of-sample model performance yet manageable input from human readers. Second, the process allows us to evaluate model performance on completely unseen data, and correct AI

[19]Where an outcome such as financial constraints is infrequently observed, it is important to train the model on this minority class. Otherwise, the model could perform very well simply by classifying all text segments as unconstrained. Our adapted strategy has proven to be successful in the computer science literature. For recent surveys of active learning with imbalanced classes, see Aggarwal et al. (2021) or Chen et al. (2024).

labels inconsistent with humans annotations that may occur in previous training iterations. After ten iterations, the final training data set consists of 23,839 labeled text segments. Of these 5,251 (18,588) have been labeled as financially constrained (unconstrained) by the human readers.

4.1.2 Training the Constraint Classifier Model to Identify Financial Constraints

The previous section describes how we generate an informative training data set. We use 70% of the training data set's text segments for training and retain 15% each for validation and testing samples.[20] We first train a binary classifier that identifies whether or not a text segment contains indications of financial constraints.

The starting point for training is the off-the-shelf FinBERT model. We refer to the trained version as the Constraint Classifier Model. Technical details on the training of this model are provided in Appendix B.2. Training a binary classifier reflects the nature of our training data where human readers performed this binary task. The validation data set is used to evaluate performance while training, and avoid overfitting. The test data set is completely unseen by the Constraint Classifier Model and used after training to evaluate out-of-sample performance. This step allows us to check whether the Constraint Classifier Model generalizes effectively to unseen test data, while avoiding overfitting on the training data set.[21] Preventing overfitting is important as we subsequently apply the Constraint Classifier Model to the vast corpus of MD&A text segments to identify text segments indicative of financial constraints.

Evaluating the Constraint Classifier Model's performance on the test data set uses a set of standard metrics. Accuracy is the proportion of correct predictions out of all predictions made, offering a general measure of model performance. The model's accuracy reaches 94%, showcasing its ability to correctly classify a large majority of text segments. Recall evaluates the proportion of actual cases of financial constraints that were correctly identified in our

[20] Sample splits are performed using proportional stratified sampling to ensure an even balance between constrained and unconstrained text segments across training, validation and testing data sets.

[21] Overfitting occurs when a model learns the training data too well, including its noise and idiosyncrasies, resulting in poor generalization to unseen data.

test data set. Recall is notably high at 87%, showing the model captures the vast majority of financial constraints cases in the data. Precision indicates that of all AI-identified segments with financial constraints, a high share of 86% are correctly identified as having financial constraints.

There is a trade-off between precision and recall. A model could achieve perfect recall by labeling every text segment indicating financial constraints, thereby correctly identifying 100% of all financially constrained segments, at the cost of many false positives. The F1 score balances these competing objectives, combining precision and recall into a single metric by taking their harmonic mean.[22] An F1 score of 86% suggests that the model strikes a strong balance between precision and recall, effectively minimizing both false positives and false negatives. The Receiver Operating Characteristic Area Under the Curve (ROC AUC) metric measures the performance of a binary classification model by analyzing its ability to distinguish between two classes, in our case financially constrained and unconstrained.[23] It evaluates the model's performance across all possible classification thresholds rather than focusing on a single cut-off point. The model's ROC AUC score of 98% indicates a high level of discriminative ability: if one were to randomly select an example from each class, the model would assign a higher probability of indicating financial constraints to the constrained example in 98 out of 100 cases. This reflects the model's robust and reliable ability to discriminate between the two outcomes, regardless of where the decision boundary is set.[24]

Table 1 summarizes the performance metrics. It underscores the efficacy of our classifier and illustrates its practical applicability to accurately detect financial constraints in text segments and serve as a reliable tool in our analysis. Our statistics are strong in the context of the literature. For example, Calabrese et al. (2024) use neural networks to predict

[22]The F1 score equals $2 \cdot (Precision \cdot Recall)/(Precision + Recall)$.

[23]Generally, classes refer to categories of possible labels that could be applied to a data point, while labels refer to the actual classes that are assigned to the data point in question.

[24]The decision boundary refers to the probability cut-off at which an example is assigned to a specific class rather than another. As detailed in Appendix B.1, throughout the paper we adhere to the standard in the literature and use 0.5 as our cut-off, see e.g. Rosa (2010). Appendix B.2 shows that this cut-off is not binding in our application as the distribution is concentrated near zero for the unconstrained and close to one for the constrained text segments.

financial constraints in the Italian manufacturing industry and report values of accuracy, precision and recall of between 70% and 75%. The baseline model in Buehlmaier and Whited (2018) correctly classifies 77% of observations in a Factiva-based training sample, while their accuracy statistics for their equity and debt samples are 91% and 82%, respectively.

Table 1: Constraint Classifier Model Performance on the Test Data Set

	Accuracy	Recall	Precision	ROC AUC	F1 Score
Constraint Classifier Model	94.14%	86.81%	86.13%	98.13%	86.47%

We evaluate performance using the 15% test sample.

4.2 Classifying Statements on Financial Constraints Using BERT

Beyond the binary classification of text segments' constrained status, the richness of our textual data also provides insights into their severity and temporal scope. We therefore extend the analysis by training two additional FinBERT models. These classify the financially constrained text segments based on the constraint's severity (mild, moderate, severe) and time horizon (current, future). Each dimension allows for an 'unclear' option where the data cannot be mapped to a specific label. The severity labels are exclusive, i.e. for a constrained text segment, constraints can either be mild, moderate or severe. The time horizon labels however are non-exclusive, i.e for a text which indicates that constraints bind in the current financial year and in future, we classify the time horizon as Current & Future. For further information on the two classifiers and their labels, see Appendix C.1.

To train the two additional BERT models, we extract a subset of text segments from the training sample (see Section 4.1.1) classified as financially constrained. Our readers classify them along the time horizon and severity dimensions, with the final classification for each segment dependent on agreement between at least two readers. We label approximately 1,000 text segments for each classification dimension, allocate 70% of each data set for training off-the-shelf FinBERT models, 15% for validation, and reserve 15% as a holdout test set that is unseen by the models to evaluate out-of-sample performance.[25]

[25]Further information on the training of classification-specific BERT models is provided in Appendix B.3.

Table 2 summarizes each classification model's performance. The metrics for the Time Horizon and Severity classifiers indicate strong model performance across all dimensions.[26] The Time Horizon Classifier Model's accuracy is 98%. The F1 score of 98% reflects this robust performance, with precision (97%) and recall (99%) showing a strong balance and demonstrating the model's ability to identify nearly all relevant labels while minimizing false positives. Similarly, the Severity Classifier Model performs well with an accuracy of 92%. Its F1 (92%), precision (92%) and recall (92%) scores indicate a good balance between identifying financial constraints' varying severity while minimizing incorrect classifications.[27]

Table 2: Performance Metrics of the Two Classifier Models on the Test Data Sets

Model	Accuracy	F1 Score	Precision	Recall
Severity Classifier Model	91.92 %	91.95 %	92.04 %	91.92 %
Time Horizon Classifier Model	98.40 %	97.82 %	96.65 %	99.02 %

Performance has been evaluated on the 15% test sample. Metrics for Time Horizon have been calculated using micro-averaging suitable for non-exclusive multi-label classification. See Appendix C.2 for details.

4.3 Aggregating Text Segment Classifications to the Firm Level

In this section, we aggregate the individual text segment scores to the firm-year level. We discuss this aggregation separately for the binary financial constraints indicator as well as the severity and time financial constraints dimensions.

4.3.1 The Binary Financial Constraints Indicator

Table 3 overviews the text segments in MD&A sections classified as constrained or unconstrained by the binary Constraint Classifier Model. On average, an MD&A section contains 78.58 text segments. Documents are lengthy, with the mean (90^{th} percentile) segment within an MD&A section containing 102 (147) words. Many companies do not mention financial

[26] Owing to the multi-label nature of the Time Horizon classifiers, we calculate the accuracy, precision, recall, and F1 Score using micro-averaging methods suitable for non-exclusive multi-label classification. Details are provided in Appendix C.2.

[27] Examples of text segments and their classifications by the BERT models are provided in Appendix C.3.

constraints at all: at the median, one text segment per MD&A section is classified as constrained. However, some firms refer more frequently to the discussion of financial constraints: at the 90^{th} (95^{th}) percentile they discuss the matter in 3 (4) text segments, encompassing roughly 6% (8%) of the MD&A section.

Table 3: Summary Statistics on Text Segments in MD&A Documents

	Mean	p10	p25	p50	p75	p90	p95	p99
Total Number of Words within MD&A	7687.86	2003	3652	6771	10639	14556	17314	23526
Total Number of Text Segments within MD&A	78.58	23	38	65	104	152	187	272
Words per Text Segment within MD&A	101.70	69.26	80.50	95.21	117.73	147.11	161.02	178.79
Number of Constrained Text Segments within MD&A	1.13	0	0	1	2	3	4	8
% of Constrained Text Segments within MD&A	1.96	0.00	0.00	0.56	2.56	5.56	8.33	16.33

4.3.2 The Severity of Firms' Financial Constraints

We first provide provide an overview of the distribution of text segments' financial constraint severity. Panel A of Table 4 shows in data column one that among all constrained text segments, 24.2% are classified as mild, 62.2% as moderate and 13.8% as severe.[28] Column three shows that approximately 9.5% of firm-year observations contain at least one text segment discussing severe constraints, whereas columns four and five report that 5.1% and 2.5% of MD&A sections contain one or two text segments of this classification, respectively. Hence, the vast majority of MD&A sections contains a very limited number of text segments that are classified to be severe. The same holds for those text segments classified as moderate and mild.

Classifying the severity of a corporation's financial constraints based on an MD&A section requires an aggregation strategy that synthesizes the information across individual text segments. A commonly used approach in the literature – particularly in the context of static word embedding methods – relies on count-based measures, such as the frequency of relevant terms or the proportion of text devoted to the topic. While such metrics may correlate with

[28] 1.7% of constrained text segments classified as 'unclear' in their severity. As discussed in Appendix C, not all text segments can be clearly mapped to a severity level. These cases are identified by our human reviewers and labeled accordingly. The model is trained to recognize these cases and we disregard them in the following analysis.

the overall severity of financial constraints, they offer, at best, a coarse approximation. For instance, some firms may express acute financial distress in a single text segment, flagging severe constraints that pose an immediate risk to survival, e.g. their ability to continue as a going concern. A count-based metric would underestimate severity in such cases. Conversely, many firms with several mentions of financial constraints may refer to mild limitations, such as those related to financing a specific investment project, which do not threaten core operations. In these cases, count-based metrics would overstate the severity of constraints. BERT's capacity for a nuanced understanding of text and contextual meaning allows us to move beyond these limitations. We apply the Severity Classification BERT model introduced in Section 4.2 to assess the intensity of financial constraints at the text segment level. This enables us to better distinguish between firms facing truly severe constraints and those referencing more marginal financial limitations.

We now turn to aggregating the segment-level information to define the financial constraint status of a whole MD&A section, i.e. to the firm-year level. We define firms as severely financially constrained in years where their MD&A document contains at least one text segment discussing severe financial constraints. Beyond the one or more text segments discussing severe financial constraints, the MD&A document may contain text segments discussing mild or moderate constraints. As these are of secondary importance to the firm, we deem it severely constrained. It is always those text segments indicating the strongest constraints, that determine the overall classification of the MD&A document. We coin these text segments the *decisive segments*. In the case above, these decisive segments would be the one or more text segments in an MD&A section mentioning severe financial constraints.

We define firms to be moderately (mildly) constrained in years in which they file a MD&A document that contains at least one segment discussing moderate (mild) financial constraints, and no text segments that discuss severe (severe or moderate) financial constraints. Analogously to the classification above, it is those text segments with the strongest financial constraints that determine the overall classification of the MD&A document. The decisive segments are those classified as moderate (mild). Our classification goes beyond

the count-based metrics applied in the previous literature, because our AI model is able to detect context-dependent nuances within text segments. This enables us to link the severity of firm-level financial constraints to the discussion of the most substantive financing frictions in an MD&A document.

Panel B of Table 4 (second data column) shows that 51% of firm-year observations mention that they are in some way financially constrained, even if briefly. Some of the constraints may be very mild while others are rather severe. 9.5% of firm-year observations contain at least one text segment classified as implying severe financial constraints. A further 29.0% are classified as moderately constrained, 12.6% as mildly constrained. This is broadly in line with previous studies' findings. For example, Hadlock and Pierce (2010) report 37% of firms are to some extent financially constrained.[29] Using survey data, Campello et al. (2010) find 40% of firms are somewhat affected and about 20% (22% of small firms and 16% of large firms) are very affected by credit constraints in the aftermath of the 2008 crisis. In articles using continuous constraints indices, an often applied classification is to single out the top 20% or 30% as the group of most severely constrained firms (Hoberg and Maksimovic (2015), Linn and Weagley (2024), Buehlmaier and Whited (2018)).

Panel B also tabulates the probability of constraint severity based on the number of constrained segments within an MD&A. For example, where a document contains one constrained text segment, the probability that the text describes mild and moderate constraints is 41.4% and 51.5%, respectively. Only 7.1% of this group's MD&As are classified as severely constrained. As the number of constrained text segments increases, the severity distribution skews towards more substantial constraints, which is consistent with more constrained firms dedicating greater attention to these issues. However, the data also show that it would be wrong to draw the simple conclusion that a larger volume of constrained text segments always correlates with tougher constraints. Among the firm-year observations containing six

[29]They read a random sample of 10-K reports and manually classify these on a five-point severity scale. They then use an ordered logit model to classify a larger sample of publicly registered firms between 1995 and 2004 and find around 6.5% of firms are clearly financially constrained which is slightly less than our share of severely constrained firms (9.5%). The share of firms that are potentially or likely financially constrained is around 33% which is roughly equal to the share of firms we classify as moderately constrained.

to ten constrained segments, only 42% are classified as severely constrained. Some companies thus dedicate a relatively large part of their MD&A to discussing constraints without these constraints necessarily being a critical threat to their operations. A key insight from this analysis is to evaluate the efficacy of count-based approaches to measuring financial constraints used in the literature. Simply equating the number of constrained segments with constraint severity results in an indicator containing measurement error. As an illustration, a document with at least ten constrained text segments would be classified as severe on a purely count-based measure. However, Panel B shows that there is only a 53% probability that a firm-year observation is severely constrained based on observing at least ten constrained text segments.

Table 4: Summary Statistics of Severity of Constraints

Panel A: Text Segments	Share (%) among all constrained text segments	Share (%) of all MD&A documents with number of text segments labeled as constrained						
		0	≥ 1	1	2	3-5	6-10	>10
Segments classified as Mild	24.02	78.62	21.38	15.12	4.67	1.35	0.20	0.04
Segments classified as Moderate	62.15	64.60	35.40	16.79	9.20	7.01	1.95	0.45
Segments classified as Severe	13.83	90.48	9.52	5.07	2.47	1.70	0.24	0.04
Segments classified as Unclear	1.66	98.03	1.97	1.55	0.30	0.11	0.01	0.00

Panel B: MD&A Documents	Whole Sample		Probability of FC severity (in %) conditional on number of constrained segments in MD&As					
	Count	Share (%)	1	2	3-5	6-10	>10	≥ 1
Unconstrained MD&As	48513	48.84	-	-	-	-	-	-
Mildly Constrained MD&As	12541	12.63	41.37	20.37	6.39	3.06	0.90	24.68
Moderately Constrained MD&As	28821	29.02	51.51	63.23	60.56	54.85	46.13	56.72
Severely Constrained MD&As	9451	9.52	7.13	16.40	33.05	42.09	52.97	18.60

In Panel B, 'Mildly Constrained' refers to MD&As with at least one mention of mild constraints, but no mention of moderate or severe constraints. 'Moderately Constrained' refers to MD&As with at least one mention of moderate constraints, but no mention of severe. 'Severely Constrained' refers to MD&As with at least one mention of severe constraints.

4.3.3 The Time Horizon of Firms' Financial Constraints

We use the decisive text segments' time horizon to determine financial constraints' time horizon for an entire MD&A document. However, an MD&A document may contain multiple decisive text segments, potentially resulting in ambiguity about the associated time horizon. For example, consider a document with four decisive text segments indicating severe financial constraints. If all four segments discuss financial constraints in future, the associated time horizon is clear. However, if one decisive text segment is associated with constraints in future and three in the present, the classification of the time horizon of the MD&A document is less clear. For this reason, we proceed in two steps to determine the time horizon of an MD&A

document's financial constraints. In the first step, we handle the unambiguous cases and in the second step, we apply judgment to classify the cases that are less clear.

In the first step, a MD&A document is assigned a time horizon of 'Current', 'Future', or 'Current & Future' if all decisive text segments have a time horizon classifier associated with exactly one of these respective labels. Panel A of Table 5 displays the distribution of MD&A documents by the number of decisive text segments. The vast majority of constrained firms have between one and three decisive text segments, although a few firms have more than ten. This relatively low number of decisive text segments per MD&A document helps in identifying the time horizon of financial constraints. Panel B of Table 5 reports on the left side the distribution of firm-year observations that are classified using the unambiguous classification procedure of step one. It is apparent that the time horizon of the vast majority of MD&A documents can be classified unambiguously. Given the low number of decisive text segments, they often point towards the same time horizon and only a minority (18% of the observations) is deemed indeterminate.

In the second step, we classify the indeterminate cases as follows. We calculate the share of current and future labels among the decisive text segments within an MD&A document. If the share of one of the categories exceeds 75%, the MD&A document is classified to belong to this particular category; otherwise, it is classified as Current & Future as the decisive text segments will contain discussions that relate to financial constraints in the present and future and none of the time horizons substantially dominate the other. The right side of Panel B shows the distribution of observations after applying the second classification step. There are very small changes (shown in parenthesis) in the number of observations classified as either Current or Future. There is however an increase in the number of observations classified as Current & Future, since most of the decisive text segments within an MD&A document in the indeterminate category contain a mix of Current, Future, or Current & Future labels.[30]

[30]The subsequent econometric results rely on the larger sample after step two, however they remain robust using the observations classified unambiguously in the first step.

A key contribution of our work is to differentiate financial constraints by time horizon and we highlight that most constraints pertain to the future. Panel B provides a frequency distribution of constraint time horizons using the sample after the second classification step. The vast majority of mildly constrained firms (91%) discuss financial constraints solely in relation to the future, with only a small share linking them to the current (3%) or both current and future (6%) time horizons. Among moderately constrained firms, future constraints dominate (69%), with a significant portion (25%) reporting a mix of current and future constraints. As the severity of financial constraints increases, the distribution continues to shift, with present constraints substantially gaining prominence: 46% of severely constrained firms report current constraints, 37% experience a mix of current and future constraints, and only 17% anticipate severe constraints in the future alone. These statistics underscore the need to differentiate financial constraints not only in terms of their severity but also with respect to their time horizon.

Table 5: Distributions of Decisive Text Segments and Time Horizon Classifications

Panel A	**Firm-Year Obs. by Number of Decisive Text Segments Per MD&A**						
Number of Decisive Segments	1	2	3	4–5	6–7	8–9	≥10
Mildly Constrained MD&As	9013	2682	388	342	56	48	12
Moderately Constrained MD&As	14333	7519	2633	2677	849	391	419
Severely Constrained MD&As	5035	2451	975	710	151	71	58
All Constrained MD&As	28381	12652	3996	3729	1056	510	489

Panel B		**Number of Firm-Year Observations Classified by Time Horizon of Financial Constraints**						
		After First Classification Step				After First and Second Classification Step		
		Current	Future	Current & Future	Indeter-minate	Current	Future	Current & Future
Mildly Constr. MD&As	Obs.	365	11442	490	244	365 (+0)	11446 (+4)	730 (+240)
	Share	2.97%	93.06%	3.97%		2.91%	91.27%	5.82%
Moderately Constr. MD&As	Obs.	1682	19058	2998	5083	1721 (+39)	19816 (+758)	7284 (+4286)
	Share	7.09%	80.28%	12.63%		5.97%	68.76%	25.27%
Severely Constr. MD&As	Obs.	4233	1592	1237	2389	4370 (+137)	1626 (+34)	3455 (+2218)
	Share	59.96%	22.52%	17.52%		46.24%	17.20%	36.56%
All Constr. MD&As	Obs.	6280	32092	4725	7716	6456 (+176)	32888 (+796)	11469 (+6744)
	Share	14.57%	74.46%	10.97%		12.71%	64.72%	22.57%

Panel A reports the distribution of firm-year observations by the number of decisive text segments. Panel B shows the distribution of firm-year observations assigned to a particular time horizon using the two-step classification described in the text. Numbers in parenthesis refer to the additional observations assigned to time horizon categories during step two.

5 Validating the Financial Constraints Measure

5.1 Firm Characteristics

The descriptive evidence in the top panel of Table 6 shows that our financial constraint measure captures firm characteristics commonly associated with financially constrained firms, aligning well with findings in the existing literature (e.g. Buehlmaier and Whited (2018)). As the severity of financial constraints tightens, firms tend to be smaller and younger, they have lower cash flow, higher indebtedness, reduced dividend payments, greater R&D intensity, and higher Tobin's Q. These patterns are consistent with diminished financial headroom and the differences between severely constrained and unconstrained firms are significant.

We go beyond the existing literature by studying the characteristics of firms constrained at present and those anticipating constraints in future. These results are shown in the middle panels of Table 6. The relationships identified for the full sample remain consistent when distinguishing between present and future financial constraints.[31] Notably, leverage increases with the severity of constraints across the full sample as well as within each time horizon subgroup. This contrasts with findings in Buehlmaier and Whited (2018), who report no clear relationship between leverage and financial constraint status – although they do note a sharp increase in net leverage driven by changes in cash holdings.

There are striking differences in firms' behavior depending on the time horizon of financial constraints. Firms expecting future financial constraints tend to raise their cash holdings as severity increases, whereas currently constrained firms, regardless of severity, hold less cash than their unconstrained counterparts. This suggests firms may accumulate cash preemptively as a precautionary measure in light of looming financial frictions, whereas those already constrained have likely depleted their excess reserves to navigate their financial diffi-

[31] To ensure a clear distinction between firms with constraints at different time horizons, this section focuses on firms that exclusively face either present or future constraints. Similar patterns are also observed among firms reporting constraints at both time horizons. Corresponding results for this group, analogous to Table 6, are provided in Appendix D.1.

culties. Recall from Panel B of Table 5 that as severity increases, the share of firms expecting future constraints declines and conversely the fraction of currently constrained firms rises. The seemingly counterintuitive inverse-U pattern for cash holdings observed for the full data set in Table 6 thus reflects that currently constrained firms dominate with rising severity. This underscores the importance of distinguishing financial constraints based on their time horizon.

The key insight is that the time horizon of financial constraints is linked to differences in firm characteristics extends beyond cash holdings. The bottom panel of Table 6 shows that firms currently facing financial constraints have significantly higher debt-to-asset ratios and greater leverage (total liabilities over total assets) than those expecting constraints in the future. Working capital declines with increasing constraint severity and is smaller for firms facing constraints at present relative to those anticipating constraints in the future. Notably, firms experiencing severe current constraints exhibit exceptionally low working capital, signaling potential liquidity issues. These relationships are statistically significant across all three levels of constraint severity. Additionally, R&D intensity and cash flow are higher for firms anticipating future constraints than for those constrained at present, though this difference is statistically significant for cash flow only in the case of severely constrained firms.

These patterns suggest that unconstrained firms, firms constrained at present, and firms constrained in the future exhibit distinct balance sheet profiles. Firms facing financial constraints generally have less financial headroom, with those currently constrained experiencing greater financial inflexibility than those anticipating constraints in the future. This aligns with the notion that the former are actively struggling with financial restrictions, whereas the latter are still in a preparatory phase, and attempt to mitigate expected future challenges. Supporting this conjecture, both groups of firms exhibit lower dividend payments in comparison to unconstrained firms, and no significant differences are observed between the two constrained groups in this regard.

Table 6: Firm Characteristics by Constraint Severity and Time Horizon

Full Data Set	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3297.28	2341.01	1566.74	164.42	-3132.86	0.00
Firm Age	20.84	15.79	14.14	11.87	-8.97	0.00
Cash/Lagged Total Assets	0.19	0.25	0.27	0.21	0.01	0.00
Cashflow/Lagged Total Assets	0.03	0.01	-0.24	-2.29	-2.33	0.00
Total Debt/Lagged Total Assets	0.28	0.29	0.43	1.24	0.96	0.00
R&D/Lagged Total Assets	0.07	0.11	0.19	0.34	0.27	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	-0.01	0.00
Tobin's Q	2.23	2.52	2.91	6.38	4.15	0.00
Working Capital	239.14	220.46	139.84	3.51	-235.63	0.00
Leverage	0.43	0.44	0.55	1.29	0.86	0.00
Kaplan & Zingales Index	-470.42	-412.10	-238.99	-28.97	441.45	0.00
Whited & Wu Index	-138.04	-101.52	-64.83	-7.09	130.95	0.00
Hadlock & Pierce Index	-3.78	-3.62	-3.23	-1.73	2.05	0.00
Hoberg & Maksimovic Index	-0.04	0.00	0.03	0.04	0.07	0.00

Current Constraints	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3297.28	2353.23	1275.21	187.25	-3110.02	0.00
Firm Age	20.84	17.34	16.31	12.54	-8.30	0.00
Cash/Lagged Total Assets	0.19	0.17	0.17	0.15	-0.04	0.00
Cashflow/Lagged Total Assets	0.03	-0.09	-0.37	-2.26	-2.29	0.00
Total Debt/Lagged Total Assets	0.28	0.40	0.52	1.32	1.03	0.00
R&D/Lagged Total Assets	0.07	0.08	0.13	0.30	0.23	0.00
Dividends/Lagged Total Assets	0.01	0.00	0.01	0.00	-0.01	0.00
Tobin's Q	2.23	2.45	2.70	6.38	4.15	0.00
Working Capital	239.14	179.98	112.37	1.32	-237.83	0.00
Leverage	0.43	0.52	0.65	1.35	0.92	0.00
Kaplan & Zingales Index	-470.42	-334.16	-168.85	-27.74	442.68	0.00
Whited & Wu Index	-138.04	-98.94	-54.89	-8.86	129.17	0.00
Hadlock & Pierce Index	-3.78	-3.39	-3.09	-1.71	2.08	0.00
Hoberg & Maksimovic Index	-0.04	-0.03	-0.02	0.02	0.05	0.00

Future Constraints	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3297.28	2313.53	1559.01	224.88	-3072.40	0.00
Firm Age	20.84	15.55	13.72	11.32	-9.52	0.00
Cash/Lagged Total Assets	0.19	0.26	0.30	0.35	0.16	0.00
Cashflow/Lagged Total Assets	0.03	0.01	-0.27	-1.52	-1.55	0.00
Total Debt/Lagged Total Assets	0.28	0.29	0.39	0.87	0.59	0.00
R&D/Lagged Total Assets	0.07	0.11	0.20	0.40	0.33	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	-0.01	0.00
Tobin's Q	2.23	2.53	2.97	5.48	3.25	0.00
Working Capital	239.14	219.23	153.33	27.80	-211.35	0.00
Leverage	0.43	0.43	0.51	0.93	0.50	0.00
Kaplan & Zingales Index	-470.42	-418.64	-252.99	-51.49	418.93	0.00
Whited & Wu Index	-138.04	-100.39	-64.14	-8.38	129.66	0.00
Hadlock & Pierce Index	-3.78	-3.61	-3.28	-2.12	1.66	0.00
Hoberg & Maksimovic Index	-0.04	0.00	0.04	0.07	0.10	0.00

	Mild: Future - Current		Moderate: Future - Current		Severe: Future - Current	
	Difference	P-Value	Difference	P-Value	Difference	P-Value
Total Assets	-39.70	0.93	283.81	0.05	37.63	0.37
Firm Age	-1.79	0.01	-2.59	0.00	-1.22	0.00
Cash/Lagged Total Assets	0.09	0.00	0.13	0.00	0.20	0.00
Cashflow/Lagged Total Assets	0.11	0.13	0.10	0.40	0.74	0.04
Total Debt/Lagged Total Assets	-0.12	0.00	-0.13	0.00	-0.44	0.00
R&D/Lagged Total Assets	0.03	0.07	0.07	0.00	0.09	0.00
Dividends/Lagged Total Assets	0.00	0.04	0.00	0.29	0.00	0.99
Tobin's Q	0.09	0.60	0.27	0.01	-0.90	0.00
Working Capital	39.25	0.14	40.96	0.00	26.48	0.00
Leverage	-0.09	0.00	-0.14	0.00	-0.42	0.00
Kaplan & Zingales Index	-84.48	0.55	-84.14	0.00	-23.75	0.00
Whited & Wu Index	-1.45	0.95	-9.25	0.16	0.48	0.81
Hadlock & Pierce Index	-0.22	0.00	-0.19	0.00	-0.42	0.00
Hoberg & Maksimovic Index	0.03	0.00	0.06	0.00	0.05	0.00

This table shows the t-test differences between the different time horizon groups, conditioning on severity. The P-Value to the right of each difference reports the t-test significance between the means of the corresponding groups. The four continuous financial constraint index variables are mapped into the unconstrained-mild-moderate-severe categories by applying the respective shares that we find for each category in our data set.

5.2 Relation to Existing Constraint Proxies

The literature has suggested various proxies to capture financial constraints. Table 6 shows our measure broadly aligns with the reduced form estimates of Kaplan and Zingales (1997), Whited and Wu (2006) and Hadlock and Pierce (2010) as well as the bag-of-words-based natural language processing approach of Hoberg and Maksimovic (2015). All these indices increase monotonically as our constraint severity measure tightens. However, the former three indices are based on reduced form equations with coefficient estimates corresponding to the sample period considered in the respective papers which limits their out-of-sample performance. We calculate the statistics in Table 6 for the Hoberg and Maksimovic (2015) index using their primary financial constraints variable 'delay investment score' on a restricted data set containing firm-year observations that overlap their sample (59,652 firm-year observations) to ensure direct comparability.

In Table 7 we deepen the comparison to Hoberg and Maksimovic (2015). Since they estimate a continuous proxy, we map their score into our discrete severity categories using two different methods. First, we sort firms in ascending order of the Hoberg and Maksimovic (2015) score and divide them into equal quartiles (25% unconstrained, 25% mild, 25% moderate, 25% severe). Alternatively, we sort firms according to their score, classifying them based on the distribution in our sample (47.22% unconstrained, 12.85% mild, 30.98% moderate, 8.95% severe). We refer to these as scheme one and scheme two, respectively.

Table 7 shows that firm characteristics implied by our measure align with those in Hoberg and Maksimovic (2015) in many dimensions but substantially diverge in some respects. Notably, there are distinctly different patterns in the size distribution. Our measure suggests that constrained firms are smaller than unconstrained ones, and a negative monotonic relationship between constraint severity and firm size. These patterns align with the literature's notion that smaller firms tend to be more constrained. In contrast, the equal-weighting approach (scheme one) of Hoberg and Maksimovic (2015) implies that constrained firms have larger total assets relative to their unconstrained counterparts. A similar pattern appears in scheme two, where only severely constrained firms have slightly smaller total assets than

unconstrained firms. The statistics in schemes one and two are consistent with the results reported in Hoberg and Maksimovic (2015), documenting a modest negative correlation (-3%) between the delay investment score index and total assets.

Furthermore, working capital declines with increasing severity for all measures, yet our classification indicates a substantially steeper decline for severely constrained firms. Previously, we noted the inverse-U relation between cash holdings and constraint severity. Our discussion shows this stems from differences in cash management behavior of firms anticipating future constraints and those constrained at present, together with changes in their relative distribution across severity categories. Conversely, both Hoberg and Maksimovic (2015) schemes exhibit a monotonic increase in cash holdings with constraint severity. Our patterns for cash holdings and working capital relate well to those suggested in the wider literature.[32]

5.3 Diagnostic Tests and External Validity

Diagnostic Tests. Farre-Mensa and Ljungqvist (2016) propose two diagnostic checks to identify firms that are plausibly constrained. We apply these in the following to validate our AI approach.

The first check characterizes constraints in terms of the capital supply curve's curvature. As the supply of capital becomes more inelastic, a firm's cost of raising an additional unit of capital increases. At the extreme, the supply curve becomes vertical and the firm is unable to raise funding in capital markets. Owing to the tax deductibility of interest payments, an increase in corporate tax rates raises the value of tax shields and a firm's demand for debt. In this instance, a firm facing an inelastic supply of debt should be unable to increase leverage, despite issuing debt being attractive. A valid financial constraints measure should thus pinpoint firms that are unable to issue debt, despite having incentives to do so. This incentive is captured by exogenous tax rate increases (Heider and Ljungqvist (2015)).

[32]Hoberg and Maksimovic (2015) apply a scheme where they split all firms into terciles. The findings of the discussion above is robust also to this scheme and we report results in Appendix D.1.

Table 7: Comparison of Firm Characteristics: Our Financial Constraints Measure vs. Hoberg & Maksimovic Delay Investment Score

Restricted Data Set	Our Financial Constraints Measure					
	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
	47.22%	*12.85%*	*30.98%*	*8.95%*	Difference	P-Value
Total Assets	2317.08	1596.80	1329.78	183.58	-2133.50	0.00
Firm Age	19.28	14.31	13.41	11.72	-7.56	0.00
Cash/Lagged Total Assets	0.20	0.26	0.26	0.18	-0.02	0.00
Cashflow/Lagged Total Assets	0.04	0.00	-0.26	-1.85	-1.89	0.00
Total Debt/Lagged Total Assets	0.26	0.27	0.43	1.07	0.81	0.00
R&D/Lagged Total Assets	0.07	0.11	0.18	0.31	0.24	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.00	0.00	-0.01	0.00
Tobin's Q	2.13	2.46	2.82	6.06	3.93	0.00
Working Capital	217.76	184.94	124.13	2.58	-215.18	0.00
Leverage	0.40	0.40	0.53	1.23	0.83	0.00
Kaplan & Zingales Index	-317.42	-273.42	-198.07	-31.85	285.57	0.00
Whited & Wu Index	-95.33	-67.53	-53.55	-7.63	87.70	0.00
Hadlock & Pierce Index	-3.69	-3.49	-3.19	-1.81	1.88	0.00

Restricted Data Set	Hoberg & Maksimovic (Scheme 1)					
	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
	25.00%	*25.00%*	*25.00%*	*25.00%*	Difference	P-Value
Total Assets	1558.15	1756.89	1932.59	1669.88	111.73	0.28
Firm Age	18.79	16.86	16.05	12.86	-5.93	0.00
Cash/Lagged Total Assets	0.19	0.20	0.22	0.28	0.10	0.00
Cashflow/Lagged Total Assets	-0.06	-0.11	-0.21	-0.53	-0.46	0.00
Total Debt/Lagged Total Assets	0.30	0.37	0.39	0.45	0.15	0.00
R&D/Lagged Total Assets	0.08	0.10	0.13	0.23	0.15	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.01	0.00	0.00
Tobin's Q	2.18	2.50	2.75	3.50	1.32	0.00
Working Capital	181.14	172.00	172.32	136.78	-44.36	0.00
Leverage	0.46	0.49	0.52	0.56	0.09	0.00
Kaplan & Zingales Index	-229.47	-262.97	-274.10	-237.57	-8.10	0.62
Whited & Wu Index	-64.86	-70.94	-81.37	-71.43	-6.58	0.14
Hadlock & Pierce Index	-3.55	-3.40	-3.36	-3.05	0.50	0.00

Restricted Data Set	Hoberg & Maksimovic (Scheme 2)					
	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
	47.22%	*12.85%*	*30.98%*	*8.95%*	Difference	P-Value
Total Assets	1662.07	1649.95	2051.73	1080.42	-581.65	0.00
Firm Age	17.92	16.60	14.87	10.58	-7.34	0.00
Cash/Lagged Total Assets	0.19	0.22	0.24	0.34	0.15	0.00
Cashflow/Lagged Total Assets	-0.09	-0.16	-0.31	-0.82	-0.74	0.00
Total Debt/Lagged Total Assets	0.33	0.36	0.43	0.45	0.12	0.00
R&D/Lagged Total Assets	0.09	0.11	0.16	0.30	0.21	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	-0.01	0.00
Tobin's Q	2.33	2.57	3.00	4.16	1.83	0.00
Working Capital	177.07	168.87	164.01	105.86	-71.21	0.00
Leverage	0.48	0.50	0.54	0.58	0.10	0.00
Kaplan & Zingales Index	-246.61	-242.65	-283.83	-172.54	74.07	0.00
Whited & Wu Index	-67.96	-68.88	-86.97	-45.90	22.06	0.00
Hadlock & Pierce Index	-3.48	-3.41	-3.27	-2.76	0.72	0.00

The restricted data set consists only of observations used in Hoberg and Maksimovic (2015). It is comprised of 59,652 firm-year observations.

Following Farre-Mensa and Ljungqvist (2016), we test this proposition by estimating

$$\Delta D_{i,j,t} = \alpha \Delta T^{+}_{i,j,t-1} + \beta \Delta X_{i,j,t-1} + \delta_{j,t} + \epsilon_{i,j,t},$$

where $D_{i,j,t}$ is long-term book leverage, defined as the ratio of total long-term debt to assets, for firm i in industry j during year t; $X_{i,j,t-1}$ is a vector of controls (the lagged change in ROA, tangibility, firm size and investment opportunities); $\delta_{j,t}$ denote firm-year fixed effects; $\epsilon_{i,j,t}$ is the error term. The key independent variable, $T^{+}_{i,j,t-1}$, is a weighted average of all the tax increases that have taken place in the states in which firm i operates. We retrieve firm-specific marginal tax rate data from Blouin et al. (2010) who report this information for Compustat firms.[33]

Table 8: Farre-Mensa and Ljungqvist Debt Test

	Unconstrained	Constraints Timing		
Dep var: Δ LT Debt/Total Assets		Current	Future	Current & Future
ΔT^{+}_{t-1}	0.1082***	-0.0999	0.0854	0.4161
	(0.01)	(0.87)	(0.60)	(0.13)
ΔROA$_{t-1}$	-0.0136	0.0055	0.0108	-0.0003
	(0.23)	(0.86)	(0.27)	(0.99)
ΔTangibility$_{t-1}$	-0.0800	-0.0249	-0.2113	-0.5219***
	(0.41)	(0.89)	(0.13)	(0.01)
ΔLog Total Assets$_{t-1}$	-0.3196***	-0.4254***	-0.3053***	-0.4650***
	(0.00)	(0.00)	(0.00)	(0.00)
ΔInvestment Opportunities$_{t-1}$	-0.0013	0.0094***	0.0009	0.0003
	(0.41)	(0.01)	(0.59)	(0.63)
Industry x Year FE	Yes	Yes	Yes	Yes
Observations	27,849	2,364	17,553	5,130
R^2	0.18	0.44	0.16	0.29

The 'Unconstrained' group contains all unconstrained firm-year observations. Standard errors clustered at the state level; p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Table 8 examines the tax sensitivity of leverage for different sub-samples. Unconstrained firms respond to an increase in the marginal tax rate by significantly increasing leverage. A one percentage point increase in the tax rate provokes a 0.11 percentage point increase in the long-term debt-to-asset ratio. In contrast, in column 2 currently constrained firms'

[33]Blouin et al. (2010) report annual firm-specific marginal tax rates between 1993 and 2016. The sample therefore excludes observations between 2017 and 2021. We use this source rather than constructing weighted-average firm-specific tax rates using sales and employment nexus following Farre-Mensa and Ljungqvist (2016) because National Enterprise Time Series data is unavailable.

leverage exhibits no significant reaction to tax increases. This is also the case throughout the remaining columns of the table when we partition the sample to include firms subject to future and current and future constraints. The debt test suggests, that the AI-classified constraints measures identify firms that face an inelastic supply of debt.

Farre-Mensa and Ljungqvist (2016) outline a second diagnostic check focusing on equity markets. Specifically, they estimate whether when subject to an inelastic supply of equity a firm engages in less equity recycling – the tendency of firms to simultaneously raise and pay out equity – because it requires funds for fixed investment. Firms classified as constrained should therefore pay out a smaller fraction, if any, of their issuance proceeds relative to those classified as unconstrained.

To test this conjecture, we follow Farre-Mensa and Ljungqvist (2016) and estimate

$$\Delta Payout_{i,j,t} = \beta \Delta EquityIssue_{i,j,t} + \delta \Delta OSF_{i,j,t} + \gamma \Delta Size_{i,j,t} + \alpha_{j,t} + \epsilon_{i,j,t},$$

where $Payout_{i,j,t}$ is the sum of total dividends and share repurchases over total assets; $EquityIssue_{i,j,t}$ is the ratio of firm initiated equity issuance to total assets; other sources of funds, $OSF_{i,j,t}$, captures operating cash flows, debt issues net of debt repurchases, the proceeds of stock option exercises and asset sales. We control for firm size, defined as log total assets, and include $\alpha_{j,t}$ industry-year fixed effects; $\epsilon_{i,j,t}$ is the error term.

The estimates in column 1 of Table 9 show unconstrained firms engage in significant equity recycling. The equity issuance proceeds coefficient estimate is 0.0018 and significant. Among constrained firms, it is only those who anticipate future constraints that engage in significant equity recycling although the economic magnitude is smaller relative to unconstrained firms. (coefficient 0.0011). In contrast, firms subject to current or current and future constraints exhibit no systematic tendency to recycle equity. Together, these patterns suggest that our AI-based financial constraints measure passes the test posed by Farre-Mensa and Ljungqvist (2016) and is able to accurately detect financially constrained firms.[34]

[34]These results are robust to additionally including firm fixed effects. For details see Appendix D.2.

Table 9: Farre-Mensa and Ljungqvist Equity Recycling Test

Dependent variable: Δ Total Dividends and Share Repurchases/Total Assets	Unconstrained	Constraints Timing		
		Current	Future	Current & Future
Δ Equity issuance proceeds	0.0018***	0.0028	0.0011***	0.0015
	(0.00)	(0.11)	(0.00)	(0.24)
Δ Other Sources of Funds	0.0314**	-0.0219	0.0097	-0.0002
	(0.02)	(0.17)	(0.56)	(0.55)
Δ Log Total Assets	-0.0572***	-0.1256**	-0.0479***	-0.0905***
	(0.00)	(0.04)	(0.00)	(0.00)
Industry × Year FE	Yes	Yes	Yes	Yes
Observations	12,473	440	8,008	1,447
R^2	0.121	0.284	0.148	0.258

The 'Unconstrained' group contains all unconstrained firm-year observations. Standard errors clustered at the firm (gvkey) level; p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

External Validity. As an external validity check, we assess whether our financial constraints measure aligns with narrative evidence suggesting that such constraints intensify during economic downturns in specific sectors. Our sample includes three distinct episodes: the burst of the dot-com bubble, which deeply impacted the IT sector, the financial crisis and the first Covid-19 lockdown period which both substantially affected firms' operations.

The top panel in Table 10 presents statistics on the share of technology firms that are unconstrained and constrained to varying degrees during the dot-com recession and outside all crisis periods. Constraints are more common and are more severe during the recession. Outside crises, 43% of technology companies are unconstrained compared to 34% amid the dot-com recession. Moreover, among constrained firms the share of moderately (severely) constrained firms rises substantially during the crisis, from 51% (19%) to 56% (23%). We uncover similar patterns of results for all sectors during the dot-com recession, financial crisis and first Covid lockdown period in the remainder of Table 10. In both recessions, the share of constrained firms rises and constraints are getting more severe.

Altogether the battery of multifaceted exercises spanning firm characteristics, existing constraint proxies, the diagnostic test of Farre-Mensa and Ljungqvist (2016), and the external validation exercise corroborate our financial constraints measure's validity.

Table 10: Financial Constraints during Recessionary Periods

Dot Com Crash: March 2000 - November 2001

Technology	non-recessionary			Dot Com Recession			column 5 − column 2	
(SIC 7370-7379)	Obs.	%	% const.	Obs.	%	% const.	Δ	p-value
Unconstrained	4042	43.01		485	34.13		-8.88	0.00
Mild	1639	17.44	30.60	199	14.00	21.26	-3.44	0.00
Moderate	2703	28.76	50.47	519	36.52	55.45	7.76	0.00
Severe	1014	10.79	18.93	218	15.34	23.29	4.55	0.00
All	non-recessionary			Dot Com Recession			column 5 − column 2	
Sectors	Obs.	%	% const.	Obs.	%	% const.	Δ	p-value
Unconstrained	39387	50.32		4372	46.74		-3.59	0.00
Mild	10141	12.96	26.08	982	10.50	19.71	-2.46	0.00
Moderate	21812	27.87	56.10	2979	31.85	59.80	3.98	0.00
Severe	6926	8.85	17.81	1021	10.92	20.49	2.07	0.00

Financial Crisis: October 2007 - June 2009

All	non-recessionary			Financial Crisis			column 5 − column 2	
Sectors	Obs.	%	% const.	Obs.	%	% const.	Δ	p-value
Unconstrained	39387	50.32		2006	41.56		-8.77	0.00
Mild	10141	12.96	26.08	601	12.45	21.30	-0.51	0.30
Moderate	21812	27.87	56.10	1639	33.95	58.10	6.09	0.00
Severe	6926	8.85	17.81	581	12.04	20.60	3.19	0.00

Covid-19 Pandemic: February 2020 - June 2020

All	non-recessionary			Covid-19			column 5 − column 2	
Sectors	Obs.	%	% const.	Obs.	%	% const.	Δ	p-value
Unconstrained	39387	50.32		1501	41.17		-9.16	0.00
Mild	10141	12.96	26.08	489	13.41	22.80	0.45	0.43
Moderate	21812	27.87	56.10	1187	32.56	55.34	4.69	0.00
Severe	6926	8.85	17.81	469	12.86	21.86	4.01	0.00

The table shows the number and share of firm-year observations falling into one of 3 recessionary periods, as well as outside of it. The recessionary periods are: a) the Dot Com Crash (March 2000 – November 2001), b) the Global Financial Crisis (October 2007 – June 2009) and c) the first Covid-19 recession (February 2020 – June 2020). A firm year is classified to belong to a recessionary date if at least 50% of its financial year leading up to its MD&A report date, falls within the period. Except for the first phase of the Covid-19 pandemic, where a firm year is counted if at least 30 days of its financial year falls within the period. For each recessionary and the general non-recessionary periods we report the number and share of firm-year observations, by severity of the constraint. Further, we report the distribution of severity of constraints among constraint firms, the difference Δ of the share relative to the non-recessionary periods, as well as the p-value of a t-test of this difference.

6 Revisiting the Cash Flow Sensitivity of Cash

In a seminal article, Almeida et al. (2004) outline a theoretical model of corporate liquidity demand where, as a precaution, firms anticipating future financing constraints hoard cash today. A constrained firm cannot undertake all of its positive net present value projects and thus, retains cash from cash flow allowing it to finance projects that might become available in future. In contrast, unconstrained firms can fund all their positive net present value investments by accessing the capital market and hence have no incentive to save cash from cash flow.[35] The model's key prediction is that future financial constraints relate to a firm's incentive to save cash from cash flow whereas unconstrained firms have no systematic propensity to do so.

We are the first who can test the theoretical model's prediction as our financial constraints measure can explicitly infer the time horizon in which financial constraints are binding. A vast empirical literature has taken the cash flow sensitivity of cash as a proxy for financial constraints. However, this work abstracts from the model's timing nuance and employs it as a general constraints proxy. Extant findings associate a positive and significant cash flow sensitivity of cash with financial constraints – disregarding the timing dimension – and insignificance with unconstrained status.

Using the specification in Almeida et al. (2004), we estimate

$$\Delta CashHoldings_{i,t} = \alpha_0 + \alpha_1 CashFlow_{i,t} + \alpha_2 Q_{i,t} + \alpha_3 Size_{i,t} + \varphi_i + \varepsilon_{i,t}, \qquad (1)$$

where $CashHoldings_{i,t}$ is the ratio of cash holdings and marketable securities to total assets for firm i in year t; $CashFlow_{i,t}$ is the ratio of earnings before extraordinary items and depreciation (minus dividends) to total assets; $Q_{i,t}$ is the market value divided by the book value of assets; $Size_{i,t}$ is the natural logarithm of total assets; φ_i denotes firm fixed effects; $\varepsilon_{i,t}$ is the error term. Following Almeida et al. (2004), we estimate equation (1) using subsamples containing unconstrained or constrained observations and use robust standard errors.

[35] Retaining cash out of cash flow is costly because it requires sacrificing returns from investing these funds.

Estimates in Table 11 test the theoretical model of Almeida et al. (2004). We first consider observations which our constraints measure labels as unconstrained. For unconstrained firms the cash flow parameter is economically close to zero and statistically insignificant. In contrast, firms anticipating constraints in future show a positive and significant cash flow sensitivity of cash. Increasing the cashflow to total assets ratio by 10 percentage points, raises cash holdings over assets by 0.12 percentage points. This is consistent with the Almeida et al. (2004) theoretical model's predictions which attributes differences in cash holding responses to cash flow to a precautionary savings motive of firms anticipating constraints in future. Notably, we find substantial heterogeneity across constrained firms: currently constrained firms do not show a significant cash flow sensitivity of cash. Their cash flow coefficient is economically almost zero.

While firms anticipating future constraints retain cash out of cash flow as a precaution to finance positive net present value projects that arise, currently constrained firms are unable to do so. Their constrained status limits contemporary investments. Rather than accumulating cash, currently constrained firms use cashflow to undertake alternative measures to gain financial headroom. Results in Appendix D.4 show they reduce current liabilities and increase working capital. In particular, they reduce short- and long-term debt holdings, as well as accounts payable and accrued expenses. They retain their level of dividend payments and total inventories, but use cashflow to stock up on raw materials. Firms reporting financial constraints at present and in future behave in similar fashion to their currently constrained counterparts. This suggests that current constraints are binding and restrict firm's ability to accumulate cash as a precaution.

The patterns emerging from Table 11 are robust to a number of sensitivity checks, including the addition of year fixed effects, clustered standard errors at the industry or firm level, restricting the sample to those firms with positive free cash flow, an augmented specification with additional expenditure variables, and various methodological checks. For details see Appendix D.3.

While our results confirm the predictions of the theoretical model, they call into question

the traditional use of the cash flow sensitivity of cash as a broad empirical indicator of financial constraints. Although theoretical models associate a high sensitivity of cash holdings to cash flow with firms expecting future financing difficulties, empirical research has often lacked the detail needed to verify this time-dependent dynamic. By distinguishing between firms that are currently constrained and those anticipating constraints down the line, we are able to empirically test a previously unexamined aspect of the theory. We find that only firms anticipating future funding limitations demonstrate meaningful cash flow sensitivity of cash, while those already facing constraints do not. This distinction reveals that the cash flow sensitivity is not a general signal of constraint but rather reflects expectations about future access to finance. Ignoring the timing of financial constraints can obscure important differences among firms, undermining both empirical accuracy and interpretive insight.

Table 11: Cashflow Sensitivity of Cash

	Unconstrained	**Constrained**		
Dep var: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0009	-0.0000	0.0120***	0.0015
	(0.20)	(0.99)	(0.00)	(0.22)
Tobin's Q	0.0004	0.0001	0.0014**	0.0029***
	(0.56)	(0.94)	(0.03)	(0.00)
Log Total Assets	-0.0037***	0.0015	-0.0014	0.0066
	(0.01)	(0.84)	(0.49)	(0.22)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,370	3,216	24,060	6,745
R^2	0.118	0.244	0.146	0.246

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

7 Conclusion

This paper introduces a new AI approach to identify financial constraints in U.S. public firms by leveraging state-of-the-art natural language processing techniques applied to the MD&A sections of 10-K filings. Through the fine-tuning of BERT models, we extract a semantically rich, context-sensitive signal of constraint-related disclosures that goes beyond

the limitations of existing keyword frequency approaches. Our model not only classifies whether a firm is financially constrained, but crucially distinguishes the timing of these constraints – current or future – thus enabling a more nuanced understanding of how firms perceive and respond to financial constraints.

The ability to disaggregate financial constraints by their time horizon reveals important heterogeneity in firm behavior and financial profiles. Firms that anticipate future constraints tend to engage in precautionary liquidity management, stockpiling cash and reducing dependence on external funding in advance of anticipated financing difficulties. In contrast, firms currently facing constraints show signs of financial distress, such as lower liquidity and elevated leverage, reflecting their diminished flexibility in responding to shocks. These behavioral differences illustrate the empirical value of our timing-aware classification framework.

Our findings challenge the conventional interpretation of the widely used cash flow sensitivity of cash as a proxy for financial constraints. While the underlying theoretical model explicitly links positive cash flow sensitivity of cash to the anticipation of future financial constraints, existing empirical applications have lacked the granularity to test this timing-dependent mechanism. Disentangling currently constrained firms from those expecting future constraints allows us to test theoretical predictions previously out of empirical reach: we show that only the latter exhibit significant cash flow sensitivity of cash while the former do not. Although the cash flow sensitivity is often treated as a general proxy for constraints, our results imply that it is in fact best understood as an indicator of expected, not current, financing constraints. Using it without regard to constraint timing risks conflating distinct firm types which diminishes empirical precision and interpretive clarity.

More broadly, our study demonstrates the transformative potential of artificial intelligence in finance and economics. Our methodology enables more precise measurement of firm-level phenomena and closer alignment between theory and data. It opens new avenues for empirical research on how firms respond to frictions, adapt to shocks, and allocate resources under constraints – core questions across corporate finance, macroeconomics, and industrial organization. More generally, the integration of AI into empirical research enhances

our ability to uncover hard-to-observe mechanisms, improve the realism of firm behavior models, and gain deeper insights into how firms make decisions in complex environments.

References

Acharya, V. V., Almeida, H., and Campello, M. (2007). Is Cash Negative Debt? A Hedging Perspective on Corporate Financial Policies. *Journal of Financial Intermediation*, 16(4):515–554.

Acharya, V. V., Almeida, H., and Campello, M. (2013). Aggregate Risk and the Choice Between Cash and Lines of Credit. *Journal of Finance*, 68(5):2059–2116.

Aggarwal, U., Popescu, A., and Hudelot, C. (2021). Minority Class Oriented Active Learning for Imbalanced Datasets. In *2020 25th International Conference on Pattern Recognition (ICPR)*, pages 9920–9927. IEEE.

Almeida, H., Campello, M., Laranjeira, B., and Weisbenner, S. (2012). Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis. *Critical Finance Review*, 1(1):3–58.

Almeida, H., Campello, M., and Weisbach, M. S. (2004). The Cash Flow Sensitivity of Cash. *Journal of Finance*, 59(4):1777–1804.

Almeida, H., Campello, M., Weisbach, M. S., et al. (2024). The Cash Flow Sensitivity of Cash: Replication, Extension, and Robustness. *Critical Finance Review*, 13(3-4):351–365.

Ash, E. and Hansen, S. (2023). Text Algorithms in Economics. *Annual Review of Economics*, 15(1):659–688.

Bao, D., Chan, K. C., and Zhang, W. (2012). Asymmetric Cash Flow Sensitivity of Cash Holdings. *Journal of Corporate Finance*, 18(4):690–700.

Bartram, S. M., Hou, K., and Kim, S. (2022). Real Effects of Climate Policy: Financial Constraints and Spillovers. *Journal of Financial Economics*, 143(2):668–696.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009). Why Do U.S. Firms Hold So Much More Cash than They Used To? *Journal of Finance*, 64(5):1985–2021.

Belo, F., Lin, X., and Yang, F. (2019). External Equity Financing Shocks, Financial Flows, and Asset Prices. *Review of Financial Studies*, 32(9):3500–3543.

Blouin, J., Core, J. E., and Guay, W. (2010). Have the tax benefits of debt been overestimated? *Journal of Financial Economics*, 98(2):195–213.

Bodnaruk, A., Loughran, T., and McDonald, B. (2015). Using 10-k text to gauge financial constraints. *Journal of Financial and Quantitative Analysis*, 50(4):623–646.

Bräuning, F., Fillat, J. L., and Joaquim, G. (2023). Firms' Cash Holdings and Monetary Policy Transmission. *Federal Reserve Bank of Boston Research Paper Series Current Policy Perspectives Paper*, (97115).

Buehlmaier, M. M. and Whited, T. M. (2018). Are Financial Constraints Priced? Evidence from Textual Analysis. *Review of Financial Studies*, 31(7):2693–2728.

Caggese, A., Cuñat, V., and Metzger, D. (2019). Firing the Wrong Workers: Financing Constraints and Labor Misallocation. *Journal of Financial Economics*, 133(3):589–607.

Calabrese, G., Falavigna, G., and Ippoliti, R. (2024). Financial Constraints Prediction to Lead Socio-Economic Development: An Application of Neural Networks to the Italian Market. *Socio-Economic Planning Sciences*, 95:101973.

Campello, M., Graham, J. R., and Harvey, C. R. (2010). The Real Effects of Financial Constraints: Evidence from a Financial Crisis. *Journal of Financial Economics*, 97(3):470–487.

Chava, S. and Roberts, M. R. (2008). How Does Financing Impact Investment? The Role of Debt Covenants. *Journal of Finance*, 63(5):2085–2121.

Chen, W., Yang, K., Yu, Z., Shi, Y., and Chen, C. (2024). A Survey on Iimbalanced Learning: Latest Research, Applications and Future Directions. *Artificial Intelligence Review*, 57(6):1–51.

Chu, K. K., Chen, S., and Leung, T. (2021). A novel algorithm for generating a gvkey-cik link table. *Journal of Information Systems*, 35(1):27–46.

Cooley, T. F. and Quadrini, V. (2001). Financial Markets and Firm Dynamics. *American Economic Review*, 91(5):1286–1310.

Denis, D. J. and Sibilkov, V. (2009). Financial constraints, investment, and the value of cash holdings. *Review of Financial Studies*, 23(1):247–269.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, pages 4171–4186.

Duchin, R. (2010). Cash Holdings and Corporate Diversification. *Journal of Finance*, 65(3):955–992.

Duong, H. N., Nguyen, J. H., Nguyen, M., and Rhee, S. G. (2020). Navigating through Economic Policy Uncertainty: The Role of Corporate Cash Holdings. *Journal of Corporate Finance*, 62:101607.

Erel, I., Jang, Y., and Weisbach, M. S. (2015). Do Acquisitions Relieve Target Firms' Financial Constraints? *Journal of Finance*, 70(1):289–328.

Farre-Mensa, J. and Ljungqvist, A. (2016). Do Measures of Financial Constraints Measure Financial Constraints? *Review of Financial Studies*, 29(2):271–308.

Fazzari, S. M., Hubbard, R. G., and Petersen, B. C. (1988). Financing Constraints and Corporate Investment. *Brookings Papers on Economic Activity*, 19(1):141–206.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, 57(3):535–574.

Gertler, M. and Gilchrist, S. (1994). Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms. *Quarterly Journal of Economics*, 109(2):309–340.

Gomes, J. F. (2001). Financing Investment. *American Economic Review*, 91(5):1263–1285.

Gomes, J. F., Yaron, A., and Zhang, L. (2006). Asset Pricing Implications of Firms' Financing Constraints. *Review of Financial Studies*, 19(4):1321–1356.

Görtz, C., Sakellaris, P., and Tsoukalas, J. D. (2023). Firms' Financing Dynamics Around Lumpy Capacity Adjustments. *European Economic Review*, 156(C).

Granja, J., Makridis, C., Yannelis, C., and Zwick, E. (2022). Did the Paycheck Protection Program Hit the Target? *Journal of Financial Economics*, 145(3):725–761.

Gürkaynak, R., Karasoy-Can, H. G., and Lee, S. S. (2022). Stock Market's Assessment of Monetary Policy Transmission: The Cash Flow Effect. *Journal of Finance*, 77(4):2375–2421.

Hadlock, C. J. and Pierce, J. R. (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Review of Financial Studies*, 23(5):1909–1940.

Han, S. and Qiu, J. (2007). Corporate Precautionary Cash Holdings. *Journal of Corporate Finance*, 13(1):43–57.

Hansen, S., McMahon, M., and Prat, A. (2017). Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach. *Quarterly Journal of Economics*, 133(2):801–870.

Harford, J., Mansi, S. A., and Maxwell, W. F. (2008). Corporate Governance and Firm Cash Holdings in the US. *Journal of Financial Economics*, 87(3):535–555.

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-Level Political Risk: Measurement and Effects. *Quarterly Journal of Economics*, 134(4):2135–2202.

Heider, F. and Ljungqvist, A. (2015). As certain as debt and taxes. *Journal of Financial Economics*, 118(3):684–712.

Hennessy, C. A. and Whited, T. M. (2007). How Costly is External Financing? Evidence from a Structural Estimation. *Journal of Finance*, 62(4):1705–1745.

Hoberg, G. and Maksimovic, V. (2015). Redefining Financial Constraints: A Text-Based Analysis. *Review of Financial Studies*, 28(5):1312–1352.

Howell, S. T. (2017). Financing Innovation: Evidence from RD Grants. *American Economic Review*, 107(4):1136–64.

Jegadeesh, N. and Wu, D. (2013). Word Power: A New Approach for Content Analysis. *Journal of Financial Economics*, 110(3):712–729.

Kaplan, S. and Zingales, L. (1997). Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics*, 112(1):169–215.

Kelly, B., Papanikolaou, D., Seru, A., and Taddy, M. (2021). Measuring Technological Innovation over the Long Run. *American Economic Review: Insights*, 3(3):303–20.

Kerr, W. R. and Nanda, R. (2010). Banking Deregulations, Financing Constraints and Firm Entry Size. *Journal of the European Economic Association*, 8(2/3):582–593.

Khurana, I. K., Martin, X., and Pereira, R. (2006). Financial Development and the Cash Flow Sensitivity of Cash. *Journal of Financial and Quantitative Analysis*, 41(4):787–808.

Kogan, S., Levin, D., Routledge, B. R., Sagi, J. S., and Smith, N. A. (2009). Predicting Risk from Financial Reports with Regression. In *Proceedings of human language technologies: the 2009 annual conference of the North American Chapter of the Association for Computational Linguistics*, pages 272–280.

Kölbel, J. F., Leippold, M., Rillaerts, J., and Wang, Q. (2024). Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks Affects the CDS Term Structure. *Journal of Financial Econometrics*, 22(1):30–69.

Li, F. et al. (2010). Textual Analysis of Corporate Disclosures: A Survey of the Literature. *Journal of Accounting Literature*, 29(1):143–165.

Lian, C. and Ma, Y. (2021). Anatomy of Corporate Borrowing Constraints. *Quarterly Journal of Economics*, 136(1):229–291.

Linn, M. and Weagley, D. (2024). Uncovering financial constraints. *Journal of Financial and Quantitative Analysis*, 59(6):2582–2617.

Loughran, T. and McDonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance*, 66(1):35–65.

Loughran, T. and McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, 54(4):1187–1230.

Nikolov, B., Schmid, L., and Steri, R. (2019). Dynamic Corporate Liquidity. *Journal of Financial Economics*, 132(1):76–102.

Ottonello, P. and Winberry, T. (2020). Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica*, 88(6):2473–2502.

Pfeifer, M. and Marohl, V. P. (2023). CentralbankRoBERTa: A Fine-Tuned Large Language Model for Central Bank Communications. *Journal of Finance and Data Science*, 9:100114.

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., and Liu, P. J. (2020). Exploring The Limits of Transfer Learning with a Unified Text-to-Text Transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Riddick, L. A. and Whited, T. M. (2009). The Corporate Propensity to Save. *Journal of Finance*, 64(4):1729–1766.

Rosa, G. J. (2010). The Elements of Statistical Learning: Data Mining, Inference, and Prediction by Hastie, T., Tibshirani, R., and Friedman, J. *Biometrics*, 66(4):1315.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance*, 62(3):1139–1168.

Whited, T. and Wu, G. (2006). Financial Constraints Risk. *Review of Financial Studies*, 19(2):531–559.

Appendix

A Data Sources, Cleaning, Pre-Processing and Matching

A.1 SEC 10-K Filings

The SEC deposits firms' 10-K filings in the SEC Edgar Database, which we download via the Notre Dame Software Repository for Accounting and Finance (SRAF) proposed by Loughran and McDonald (2016). The SRAF provides annual cleaned 10-X filings for the financial years 1993 to 2021, where extraneous characters have been removed. We focus on the filings relevant to our analysis, namely the filing types: 10-K, 10-K405, 10-KSB and 10-KSB40, henceforth simply referred to as 10-K.[36]

From each 10-K document, we extract identifying information: the Central Index Key (CIK) number, Filing Type and Filing Date. We further extract from the 10-K filing header, using regular expression techniques, the Company Conformed Name, the Conformed Period of Report, the Address, the SIC Classification Code, Former Company Name, and the Date of Name Change.[37] This information is used to match the 10-K document with firm-year observations in the Compustat Database. From each 10-K filing, we extract the Management's Discussion and Analysis (MD&A) section. The MD&A section generally appears as Item 7 in 10-K documents and as Item 6 in 10-KSB documents and its variants. Some MD&As are incorporated in the reference sections and we make use of regular expression techniques to detect these MD&A sections. We disregard all 10-K documents for which we cannot extract a valid MD&A section.[38]

[36] 10-K denotes the main filing type. The other three filing types we consider are variants of annual reports that companies file based on their size, reporting status, and compliance with specific rules. These variants of 10-K forms have now been phased out. Since December 2008, all firms are required to file a 10-K.

[37] There are a total of 1,281 reports which did not have a 'Conformed Period of Report' in their headers. Most of these reports include a statement 'for the fiscal/financial year ended (*date*)'. We extract this date as the 'Conformed Period of Report' for that particular document. The very few remaining reports without the fiscal/financial year statement, have a standalone date in the header of the report. We extract this date as the 'Conformed Period of Report' for that particular report.

[38] In a few instances, MD&A sections cannot be extracted as they do not appear under the conventional headers or, particularly for older reports, poor formatting impedes text extraction.

A.2 Compustat Data

We download Annual Compustat North America for the years 1993 to 2021. Variables used in our analysis are defined and cleaned as follows and deflated using the GDP deflator, except for Capital Expenditure (CAPX), which is deflated using the implicit price deflator for private, fixed non-residential investment.

A.2.1 Compustat Variable Construction

- Total Assets is the variable AT.
- Firm age is the number of years since the firm first appears in the Compustat database.
- Tobin's Q is is defined as (AT+(PRCC_F*CSHO)-CEQ)/AT, where PRCC_F is the Annual Price Close (fiscal year end), CSHO is Common Shares Outstanding, AT is Total Assets and CEQ is Common Equity.
- R&D Expenditure is the variable XRD.
- The R&D to lagged Total Asset ratio is constructed by taking R&D Expenditure (XRD), divided by lagged Total Assets (AT).
- Total Debt is the sum of Debt in Current Liabilities (DLC) and Total Long-Term Debt (DLTT).
- The Total Debt to Lagged Total Assets ratio is calculated by taking the ratio of Total Debt to lagged total assets (AT).
- Book Leverage is the ratio of Total Liabilities (LT) to Total Assets (AT).
- The Cash to (lagged) Total Assets ratio is the ratio of Cash and Short Term Investments (CHE) to (lagged) Total Assets (AT).
- Cashflow is constructed by adding Depreciation and Amortization (DP) to Income Before Extraordinary Items (IB).
- Cashflow to lagged Total Assets ratio is Cashflow over lagged AT.
- Cashflow to Total Assets ratio is Cashflow over AT.

- Working Capital is the difference between Current Assets (ACT) and Current Liabilities (LCT).
- Net (Non-Cash) Working Capital is defined as ACT-LCT-CHE.
- Cash dividends is the variable Cash Dividends (DV).
- Cash dividends to lagged Total Assets is the ratio of Cash Dividends to lagged Total Assets (AT).
- Total Dividends is the variable DVT.
- Capital expenditure is the variable CAPX.
- The investment rate is defined as the ratio of CAPX to lagged Net Property, Plant and Equipment (PPENT).
- Return on Asset (ROA) is defined as the ratio of Income Before Extraordinary Items (IB) to Total Assets (AT).
- Aquisitions is the variable AQC.
- Advertising Expense and Administrative Expenses are the variables XAD and XSGA, respectively.
- Employment is the variable EMP.
- Share repurchases is the variable PRSTKC.
- We use variables from Compustat Quarterly for the check proposed by Farre-Mensa and Ljungqvist (2016). These are SSTKY (Sale of Common and Preferred Stock), CSHOQ (Common Shares Outstanding (Quarterly) and PRCCQ (Closing Share Price). As outlined in Farre-Mensa and Ljungqvist (2016), these variables were used to create "New Firm Initiated Equity Issuance", or Equity Proceeds, as it appears in the regressions.
- Other Sources of Funds is defined as the sum of DLTIS (Long Term Debt Issuance), IBC (Income before extraordinary items), DPC (Depreciation and Amortization), SPPE (Sale of Property, Plant and Equipment), SIV (Sale of Investments) net of Equity Proceeds, scaled by Total Assets (AT).

- Bankrupt and liquidated firms are identified by the values of the variable DLRSN ('02' for bankruptcy and '03' for liquidation).

A.2.2 Variable Cleaning

We apply the general data selection criteria outlined in Section 3. These are:

- We include only firms which use the US Dollar as the reporting currency.
- We drop firms if sales or the sum of common and preferred stock is zero or negative.
- We drop firms whose reporting sector is SIC 4900-4999 or SIC 6000-6999.
- We exclude firm-year observations as soon as a firm is in financial distress. Specifically, if the variable DLRSN takes the value '02' or '03'.

In addition, we apply the cleaning criteria below to the following variables:

- We set negative values of long- and short-term debt (DLC and DLTT) and Stockholder's Equity (SEQ) to missing.
- We set values of AT, DLC, DLTT, ACT, LCT, CHE and SALE to missing for extreme changes in these variables. Specifically, values for these variables are replaced with missing in the top 1^{st} percentile of their growth rates.
- We replace negative values of DVC, DVT and DVPSP_F to missing. Additionally, the top 0.1 percentile of DVPSP_F is set to missing. For DLC/AT, Total Debt/Lagged Assets, Return on Assets, Return on Equity, Change in PPE (Gross), Change in PPE (Net) and R&D Spending to Assets we set the top 0.1 percentile to missing. Additionally, the bottom 0.1 percentile of Return on Assets is also set to missing.
- For Working Capital, Debt/Asset, Tobin's Q, Leverage (Book Value), Cash/Lagged Assets and R&D to Sales ratio, the top 1 percentile is set to missing.

A.3 Matching Compustat Data with the MD&A Information

This section describes how we match MD&A sections from 10-K filings to the corresponding firm-year observations in Compustat.

We begin by matching using exact Central Index Keys (CIK) and the report dates. The CIK is a unique identifier assigned by the U.S. Securities and Exchange Commission. It is provided in Compustat and the SEC Edgar Database. The report date is the Fiscal Period End Date in Compustat, and the Period of Report end date which we extract from the 10-K files. For matches by CIK, we classify the report dates as a match if these are no more than 14 days apart.

Occasionally, firms' CIK codes change, for example, due to mergers or organizational restructuring. A firm may thus have multiple historical CIK codes that differ from its most recent CIK code. By default, Compustat only provides the most recent CIK. We use historical CIK codes from Chu et al. (2021) and repeat the matching process described above for all remaining unmatched Compustat firms. The steps described above allow us to match the vast majority of firm-year observations (99%) of our final sample. The remaining matched observations in our final sample come from other matching approaches, described below.

For all remaining unmatched Compustat firm-year observations, we perform fuzzy matching on the company name. Prior to using this algorithm, we clean and simplify all company names. We remove non-essential terms and only keep alphanumeric characters, which removes, for example, special characters that sometimes appear in company names. We remove empty spaces, and change all letters to be lower case. For the fuzzy matching procedure, we adopt a cosine similarity threshold of 0.75 and proceed to fuzzy match Company Names in Compustat with the 'Company Conformed Name' and 'Former Company Conformed Name' from the 10-K documents. We discard the matches where the matched string is less than 6 characters long. Among observations for which company names were matched, we further match based on the report dates, that is, the Compustat Fiscal Period End Date and the 10-K Period of Report end date. Again, we retain matches if these dates fall within a 14

day interval. This fuzzy matching procedure on corporation name allows us to add another 0.06% of matched firm-year observations to the final data set.

Similar to the case of CIKs, companies may change their name over time, yet Compustat by default only records the most recent company name. We access historical company names for every corporate financial year from the CRSP database and link this information to the respective Compustat firm-year observations. This allows us to account for company name changes over time. We repeat the fuzzy company name matching and date matching step as documented in the previous paragraph which allows us to match an additional 0.05% of our final data set.

We further collect historical company names using the DISCERN 2.0 database provided by Arora et al. (2024a,b). The DISCERN 2.0 data set matches patent ownership to a particular company, and captures company name changes over time. Name changes in this data set are already linked to the Compustat firm and fiscal year end variables, 'gvkey' and 'fyear'. We repeat the fuzzy company name matching and date matching step as documented previously. We match an additional 0.89% of our final sample in this way.

Our matching procedures achieve a 73.3% matching rate for cleaned Compustat firm-year observations with MD&A sections. Figure 1 shows the matching rate over time. Since 1996, the matching rate is consistently above 80% (on average 82.1%) which is in line with previous studies.[39] Prior to the SEC's full implementation of the Edgar system in the early 1990s, filings were often submitted in paper format. For this reason, filings at the beginning of our sample may not be electronically available on the Edgar database which results in the substantially lower matching rates during the first three years. The decline in publicly listed firms evident from Figure 1 is well documented in the literature, see e.g. Kahle and Stulz (2017) or Doidge et al. (2017).

[39]Chu et al. (2021) for example achieve a match rate of 63.8% for their sample.

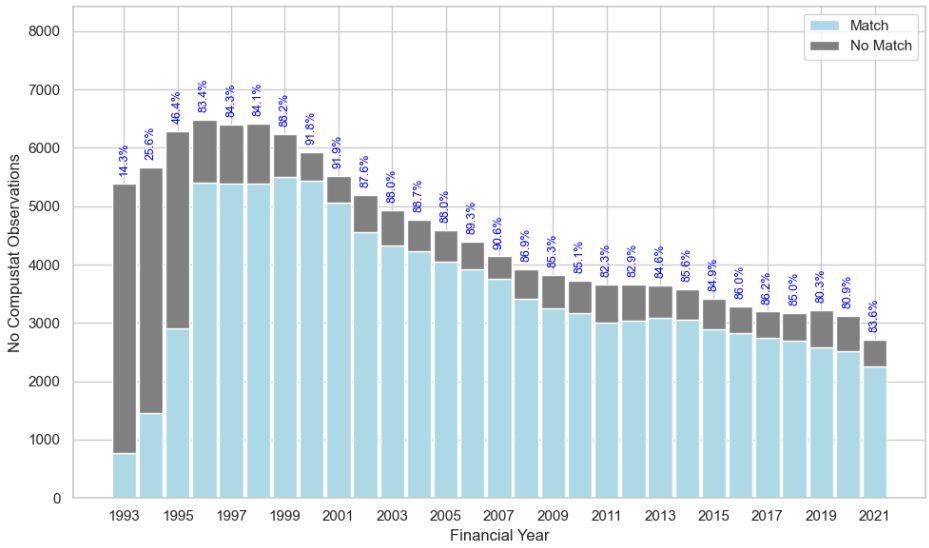


Figure 1: Compustat Firm-Year Observations and Matching Rates with MD&A Sections

B Training and Performance of BERT Models

B.1 Details on Generating Training Data Using Active Learning

Figure B1 provides a graphical overview of the model training steps for the Constraint Classifier model, including the Active Learning algorithm. Further details of these steps are described here.

Step 1: Initial Data Collection

Our first step is to collect an initial seed data set from the SEC filings. For this purpose we manually read a number of MD&A sections and extract and label text segments as constrained or unconstrained. These text segments typically have the length of a paragraph (see Section 3 for details). Our seed data set contains 251 text segments labeled 'constrained' and 2000 segments labeled 'unconstrained'.

Step 2: Fine-tuning a FinBERT model

We use the seed dataset of text segments from step one to fine-tune a BERT model based on the FinBERT pre-trained model. Fine-tuning involves replacing the output layer of the

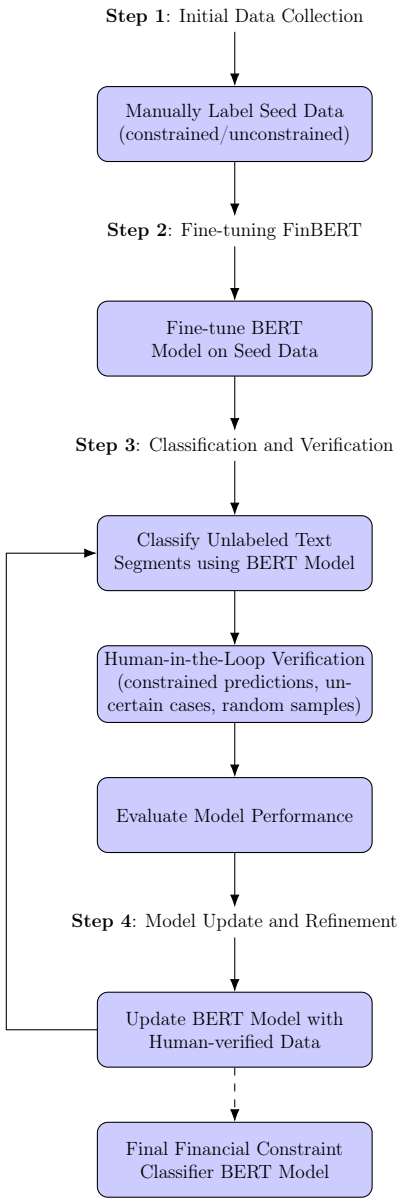


Figure B1: Active Learning Process for Financial Constraint Classification

pre-trained FinBERT model with a binary classification layer that can be trained to predict for a given text segment whether the text is suggestive of financial constraints or not.

For each input text segment, the trained model outputs a probability value for the estimated likelihood of the input sample being indicative of financial constraints. Throughout this training procedure, we refer to a sample as being labeled constrained by our model if the predicted probability is greater than 0.5 and unconstrainded if it is below 0.5. This cut-off is standard in the literature (for example, Rosa (2010) and Pang et al. (2002)). We train

our BERT models using all hand-labeled data available in each iteration. For more details on the specifics of the fine-tuning of a BERT model see section B.2. This appendix also shows that the predicted probabilities tend to be concentrated either near zero or near one, far away from the 0.5 cut-off threshold.

Step 3: Automated Classification and Human-in-the-Loop Verification

After completing the initial training phase, we employ our model to categorize a broader corpus of text segments outside our initial hand-labeled training sample. Its primary objective is to identify text segments and automatically annotate them based on the learned patterns. This process results in a pre-classified dataset, with predictions generated by our latest BERT model.

After the automated classification, expert readers begin a detailed verification process. This involves a strategic review of the pre-classified text segments. To ensure efficient utilization of the available human labor, we select three separate samples of text segments: a) Text segments classified as indicating financial constraints. This is to ensure we specifically monitor the examples that the algorithm indicates as containing financial constraints, in order to minimize the risk of false positives. b) Text segments that were classified as not indicating financial constraints, but where the predicted probability of financial constraints exceeds 10%. These are text segments, where the model is uncertain about the correctness of its classification, and therefore these cases are highly valuable for improving the model's performance in subsequent iterations. This also helps to reduce the risk of false negatives. c) A random subset of text segments where the model assigns a probability of being indicative of financial constraints of less than 10%. These are text segments likely to be correctly classified as not containing financial constraints, but we include a number of these segments in order to monitor overall model accuracy and ensure an adequate balance of constrained and unconstrained samples in future training runs.

This tripartite selection strategy is aimed at enhancing the robustness of our training data set, by not only capturing clear instances of financial constraints but also by considering edge

cases which are essential for improving the model's predictive capabilities. In each iteration of the human-in-the-loop process, we collect around 500 sample text segments of type a) and 500 type b) segments and add to this an equal number of type c) examples, resulting in a total addition to the training data set of roughly 2,000 text segments per iteration which are subsequently read and classified by the expert readers.

Step 4: Model Update and Refinement Loop

Using the approximately 2,000 text segments verified by the expert readers in step three, we update the model through training on the expanded dataset. This training is essential in enabling the model to correct its biases and improve performance over time. By letting the model pre-label examples and flagging those associated with high levels of uncertainty, we ensure that human attention is focused on high value examples. This allows us to collect a large number of diverse example text segments within a reasonable period of time. We perform several iterations of this refinement cycle, utilizing the progressively updated model to analyze fresh batches of text segments.

During each iteration, we monitor the model's performance metrics. One of these is the agreement rate between the model's predictions and the experts' judgments, which is defined as:

$$\text{Agreement Rate}_i = \frac{1}{N_i} \sum_{j=1}^{N_i} \mathbf{1}(D_{i,j}^h = D_{i,j}^m),$$

where N_i is the total number of text segments evaluated in one particular iteration $i = 1, \ldots, I$. $D_{i,j}^h$ and $D_{i,j}^m$ are the labels assigned to a particular text segment $j = 1, \ldots, N_i$ by the human expert and the model, respectively. $\mathbf{1}$ is the indicator function that equals 1 when $D_{i,j}^h = D_{i,j}^m$, showing agreement between the human and machine-based classification, and 0 otherwise. This metric serves as an indicator of the alignment between the model's assessments and the experts' judgments.

We further monitor the model's precision in identifying those text segments indicating

financial constraints. This metric, referred to as the 'Precision Rate Constrained', is calculated for each iteration as the share of correctly identified text segments indicating financial constraints (where both the model and the human experts agree that a constraint exists) of the total number of instances classified as constrained by the model. It can be expressed as

$$\text{Precision Rate Constrained}_i = \frac{\sum_{j=1}^{N_i} \mathbf{1}(D_{i,j}^m = 1 \text{ and } D_{i,j}^h = 1)}{\sum_{j=1}^{N_i} \mathbf{1}(D_{i,j}^m = 1)},$$

and helps to ensure that the model reliably detects actual constraints, minimizing the risk of overlooking critical financial conditions, as well as avoiding false positives (cases in which a text segment is incorrectly classified as indicative of financial constraints).

Analogously, we monitor the 'Precision Rate Unconstrained' which measures the model's success in identifying text segments indicating no notion of financial constraints. For each iteration, this metric is given by

$$\text{Precision Rate Unconstrained}_i = \frac{\sum_{j=1}^{N_i} \mathbf{1}(D_{i,j}^m = 0 \text{ and } D_{i,j}^h = 0)}{\sum_{j=1}^{N_i} \mathbf{1}(D_{i,j}^m = 0)},$$

tracking the share of text segments indicating no notion of financial constraints (identified in agreement by the human readers and the model) in the total number of such instances classified by the model.

Figure B2 illustrates the performance improvements of our BERT models over each iteration. The left panel shows the agreement rate, i.e. the share of BERT-classified text segments that are judged to be correct by the expert readers. The rate starts at around 84% in iteration one, which is encouraging given the small initial training data set, and increases to approximately 95% in iteration 10.

The right panel of Figure B2 shows the precision rate constrained and the unconstrained counterpart over the ten iterations. In iteration one, the model's ability to correctly identify cases of financial constraints is rather limited. Only about 50% of BERT-classified constrained examples were also judged to be constrained by the expert readers. This is indicative of the initial model's inability to generalize well, and a result of the limited rep-

resentativeness of the language used in the step-one training data for expressing financial constraints in a textual setting. Since the initial training data (step one) came from a non-random subset of all MD&A text segments, the model has learned to associate certain phrases and words with constraints without realizing that sometimes these can occur in unconstrained contexts. For example, the phrase 'raising additional funds', is likely to occur frequently in the initial examples, mostly in a negative context. However, since there are likely many cases, where the raising of funds is successful, the model initially mistakes these for incidences of constraints. As we provide feedback, the model learns from these mistakes and steadily improves its performance to correctly predict over 90% of constrained examples. We stop our Active Learning procedure after ten iterations when performance plateaus at a high level.

The right panel of Figure B2 shows that the model is very successful throughout all iterations at identifying text segments without any notion of financial constraints. The precision measure for recognizing unconstrained text segments is well above 90% across all iterations.

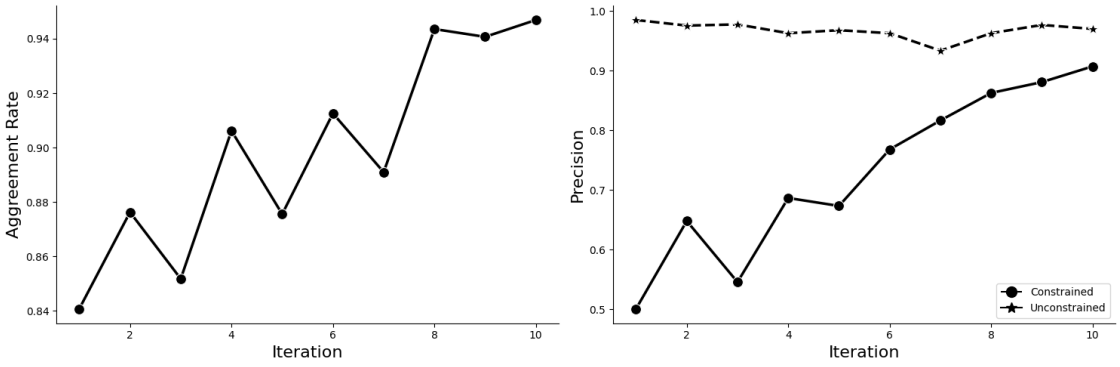


Figure B2: Trained BERT Model Performance over Active Learning Iterations

Table B1 provides additional details on the model's performance throughout the active learning iterations. All metrics are calculated based on the fully human-annotated pre-labeled dataset from Step 3. The false positive rate in the first iteration is almost 50%, resulting in a correspondingly low precision of 0.501. We take this as evidence of the presence of bias in the initial seed sample – the model has learned to associate certain patterns with

financially constrained text segments in the seed sample, but when extrapolating these to the wider universe of MD&A documents, it turns up a large number of false positives. Applying our Active Learning strategy alleviates the initial bias over time, although the improvements are not always monotonic. With respect to the rate of false positives, the model takes around 5 iterations to get to a point where the rate improves steadily between every iteration. This process mimics a form of explore-exploit pattern, where the model adapts its understanding of financial constraints based on human feedback. Once the rate of improvements begins to levels off, we terminate the Active Learning process.

Table B1: Active Learning Algorithm Performance Metrics

Iteration	Accuracy	Precision	Recall	F1 Score	True Positives	False Positives	True Negatives	False Negatives	Checked Samples
Iteration 1	0.841	0.501	0.934	0.652	313	312	1451	22	2098
Iteration 2	0.876	0.648	0.921	0.761	418	227	1445	36	2126
Iteration 3	0.852	0.546	0.909	0.682	341	284	1487	34	2146
Iteration 4	0.906	0.687	0.827	0.750	287	131	1558	60	2036
Iteration 5	0.876	0.673	0.906	0.772	441	214	1389	46	2090
Iteration 6	0.913	0.768	0.878	0.819	404	122	1454	56	2036
Iteration 7	0.891	0.817	0.876	0.845	628	141	1252	89	2110
Iteration 8	0.944	0.863	0.848	0.855	352	56	1637	63	2108
Iteration 9	0.941	0.881	0.958	0.918	688	93	1263	30	2074
Iteration 10	0.947	0.907	0.947	0.927	695	71	1266	39	2071

Each iteration corresponds to the evaluation of the model's performance on a new set of human-labeled data acquired through the Active Learning process described in Appendix B. Accuracy measures the overall proportion of correctly classified samples. Precision is the proportion of correctly classified constrained samples. Recall is the proportion of actual constrained samples correctly identified by the model. The F1 Score is the harmonic mean of precision and recall. True Positives and True Negatives represent correctly classified samples, while False Positives and False Negatives represent misclassifications.

B.2 Training the Constraints Classifier Model

We train the model over 10 epochs, using a learning rate of $2 \times e^{-5}$ and a weight decay of 0.01.[40] The training process minimizes the cross-entropy loss function, updating the model parameters using gradient descent.[41] Cross-entropy loss is commonly used in classification tasks to measure the difference between the true distribution of labels and the predicted

[40] An epoch in machine learning is a full pass through the entire training data set by the model. The learning rate controls the size of the parameter updates during gradient descent – smaller values lead to more gradual, stable convergence. Weight decay is a regularization method that penalizes large parameter values to help prevent overfitting.

[41] Gradient descent is an iterative optimization technique that adjusts the model parameters in the direction that most rapidly decreases the loss function.

probabilities output by a model. For a multi-class classification problem, it is defined as:[42]

$$L = -\sum_{c=1}^{C} y_{o,c} \log(p_{o,c}), \tag{2}$$

where C is the number of classes, $y_{o,c}$ is a binary indicator (0 or 1) that is unity if class label c is the correct classification for observation o, and $p_{o,c}$ is the predicted probability of observation o being of class c. The loss function penalizes the model more the greater the discrepancy between the actual and the predicted probabilities, effectively guiding the model to increase the probability of the true class label while decreasing the probabilities of the incorrect labels.

Table B2 shows that the Constraint Classifier Model is subject to low uncertainty when labeling text segments as either constrained or unconstrained. It assigns high probabilities (mostly >90%) to MD&As classified as constrained and low (mostly <0.1%) to those classified as unconstrained. This indicates that the applied threshold of 0.5 as a cut-off between constrained and unconstrained is not very binding.

Table B2: Average Probability Scores by MD&A Section

Average by Document	**Constrained MD&As**	**Unconstrained MD&As**
Mean (constrained sections)	0.9421	-
Maximum	0.9653	0.0364
Mean (unconstrained)	0.0022	0.0009
Variance	0.0326	0.0001

Note: The above statistics shows the average the BERT probabilities (confidence) on the categories assigned, per MD&A section. Note that MD&As classified as constrained include unconstrained and constrained text segments, while MD&As classified as unconstrained only include unconstrained text segments.

[42] Alternatively, since there are only two classes in this case, this could be considered a binary classification problem.

B.3 Training of the Time Horizon and Severity Classifier BERT Models

We fine-tune two additional BERT models for the classification tasks related to Time Horizon and Severity. Both models use as a starting point the off-the-shelf FinBERT model, trained on about 1,000 hand-labeled text segments for the respective category. The models are trained over 10 epochs with a learning rate of $2e^{-5}$ and a weight decay of 0.01. The training process employs specific loss functions tailored to each classification task, detailed below.

The Time Horizon Classifier relies on multi-label models, meaning they are designed to predict multiple labels simultaneously for a single instance. For example, a text segment might simultaneously reference both financial constraints at present and in future. The training process minimizes the binary cross-entropy loss, which treats the prediction for each label as an independent binary classification problem (i.e. "Does this label apply?"). Specifically, the loss function for the multi-label classification task is defined as:

$$L = -\frac{1}{M} \sum_{m=1}^{M} \left[y_{o,m} \log(p_{o,m}) + (1 - y_{o,m}) \log(1 - p_{o,m}) \right],$$

where M is the number of labels, $y_{o,m}$ is a binary indicator (0 or 1) indicating whether label m is true for observation o, and $p_{o,m}$ is the predicted probability for label m. For multi-label classification, the loss is computed for each label separately and then averaged across all labels. This ensures that the model learns to predict each label effectively without interference from others. By handling each label independently, the model is able to account for the complexity of our data where multiple aspects of financial constraints (e.g. frictions at present and anticipated in future) may be present simultaneously in a single text segment.

The Severity Classifier, in contrast, is a multi-class model, where each observation belongs to a single class. This model minimizes the categorical cross-entropy loss as given in equation (2). This loss penalizes discrepancies between the true class and predicted probabilities, guiding the model to maximize the probability of the correct class.

Table B3 shows that the Time Horizon and the Severity Classifier Model are subject to low uncertainty when labeling text segments. It assigns high probabilities (on average >95% with a low variance) to text segments. In case of these classifiers, there are four possible options, so for a category to be assigned, at least a probability score of 25% is required and the reported minimum is substantially above this value. This indicates that the model is highly certain about its classifications.

Table B3: Average Probability Scores for Severity and Time Horizon Classifiers

Severity Classifier				
	Average	Variance	Min	Max
Mild	0.9642	0.0088	0.3571	0.9999
Moderate	0.9805	0.0047	0.3494	0.9999
Severe	0.9879	0.0031	0.3783	0.9999
Time Horizon Classifier				
	Average	Variance	Min	Max
Current	0.9975	0.0003	0.5138	0.9997
Future	0.9980	0.0003	0.5022	0.9998
Current & Future	0.9481	0.0044	0.5331	0.9979

Note: The above statistics shows the average the BERT probabilities (confidence) on the categories assigned to each text segment.

C Classifying Financially Constrained Text Segments

C.1 Categorizing Financially Constrained Text Segments

This section provides further details on the classification of financial constraints in the time horizon and severity dimensions.

Time Horizon of Constraints. The time horizon dimension distinguishes between constraints that affect the firm in the current financial year and those expected to impact in the future. We allow text segments to be labeled as 'Current', 'Future', or 'Current & Future'. In addition, we allow segments to be labeled as 'unclear' if it cannot clearly be mapped into one of the former categories. Table C1 summarizes the detailed definitions for

each category.

Table C1: Definitions for Classifying the Time Horizon of Constraints

	Definition
Current	When financial constraints occur in the current financial year.
Future	When financial constraints are expected to occur in future (after the current financial year).
Current & Future	When financial constraints occur in the current financial year and are expected to occur in future financial years.
Unclear	Time horizon cannot be evaluated from the text.

Severity of Constraints. Severity measures the intensity of the financial constraints, classified as 'mild', 'moderate', or 'severe'. Mild constraints may cause minor operational frictions, while severe constraints threaten a firm's survival. These classifications are mutually exclusive. If a text segment discusses different constraints of varying severity, we select the most severe classification. Further, we allow for an additional label, 'unclear', if the segment cannot clearly be mapped to one of the three former categories. Table C2 summarizes the detailed definitions for each category.

Table C2: Definitions for Classifying the Severity of Constraints

Severity	**Definition**
Mild	When constraints may affect a firm's ability to finance investment projects. The lack of funds implies no direct risk to a firm's survival and continuation of ongoing operations.
Moderate	When constraints do affect a firm's ability to finance investment projects or to finance at least some ongoing operations. The inability to raise funds is no direct concern to a firm's survival.
Severe	When constraints affect a firm's ability to finance investment projects or ongoing operations, and this is a threat to firm survival.
Unclear	When severity of constraints cannot clearly be mapped to the above categories.

Using the training data set, we then train two BERT models, each specialized in predicting either the time horizon or severity dimension. Details about the training and performance of these models are provided in Appendices B.2 and B.3.

C.2 Details on the Performance Metrics for Non-Exclusive and Exclusive Multi-Label Classifiers

Owing to the non-exclusive, multi-label nature of the Time Horizon Classifier, we calculate the accuracy, precision, recall, and F1-score using micro-averaging methods suitable for multi-label classification. Specifically, accuracy is computed as the Hamming Accuracy, which measures the proportion of correctly predicted labels over the total number of labels. This is calculated by comparing the predicted and true labels for each class independently and averaging the correctness across all labels and samples.

For precision, recall, and F1-score, we aggregate the true positives (TP), false positives (FP), and false negatives (FN) across all labels and samples before computing the metrics. Using micro-averaging, these metrics are defined as:

$$\begin{aligned}
\text{Precision}_{\text{micro}} &= \frac{\sum_{\text{labels}} \text{TP}}{\sum_{\text{labels}} (\text{TP} + \text{FP})}, \\
\text{Recall}_{\text{micro}} &= \frac{\sum_{\text{labels}} \text{TP}}{\sum_{\text{labels}} (\text{TP} + \text{FN})}, \\
\text{F1}_{\text{micro}} &= 2 \times \frac{\text{Precision}_{\text{micro}} \times \text{Recall}_{\text{micro}}}{\text{Precision}_{\text{micro}} + \text{Recall}_{\text{micro}}}.
\end{aligned}$$

This approach treats each individual label prediction equally, effectively turning the multi-label problem into multiple binary classification problems, and provides an overall performance metric that accounts for all labels.

For the Severity Classifier, which operates as an exclusive multi-class classifier with mutually exclusive labels (mild, moderate, severe, unclear), accuracy, precision, recall, and F1-score are computed differently compared to a non-exclusive multi-label setup. Accuracy is defined as the proportion of correctly predicted labels to the total number of samples and provides an overall measure of the classifier's performance. Precision for a given class is calculated as the ratio of true positives to the sum of true positives and false positives, while recall is calculated as the ratio of true positives to the sum of true positives and false negatives. The F1-score combines precision and recall into a single metric using the harmonic

mean.

C.3 Examples of AI-Classified Text Segments

Table C3 shows examples of text segments classified using our trained AI models.

Table C3: Example Text segments

Text Segment	Labels
GLOBALNET CORP (31/12/2003)	
We anticipate that the full amount of the convertible debentures, together with accrued interest, will be converted into shares of our common stock, in accordance with the terms of the convertible debentures. If we are required to repay the convertible debentures, we would be required to use our limited working capital and raise additional funds. If we were unable to repay the debentures when required, the debenture holders could commence legal action against us and foreclose on all of our assets to recover the amounts due. Any such action would require us to curtail or cease operations.	future; severe
OTELCO INC (31/12/2008)	
There can be no assurance that we will have sufficient cash in the future to pay dividends on our Class A common stock at the historical rate or at all. If we do not generate sufficient cash from our operating activities in the future to pay dividends, we may have to reduce or eliminate dividends or rely on cash provided by financing activities in order to fund dividend payments, if such financing is available. However, if we use working capital or borrowings under our credit facility to fund dividends, we would have less cash available for future dividends and we may not have sufficient cash to pursue growth opportunities such as the introduction of new services and the acquisition of other telephone companies, or to respond to unanticipated events such as the failure of a portion of our switching or network facilities. If we do not have sufficient cash to finance growth opportunities or capital expenditures that would otherwise be necessary or desirable, and cannot find alternative sources of financing, our financial condition and our business will suffer. Our current dividend policy, our high indebtedness levels and related debt service requirements and our capital expenditure requirements will significantly limit any cash available from operations for other uses for the foreseeable future.	future; moderate
CELSION CORP (31/12/2017)	
If adequate funds are not available through either the capital markets, strategic alliances, or collaborators, we may be required to delay or, reduce the scope of, or terminate our research, development, clinical programs, manufacturing, or commercialization efforts, or effect additional changes to our facilities or personnel, or obtain funds through other arrangements that may require us to relinquish some of our assets or rights to certain of our existing or future technologies, product candidates, or products on terms not favorable to us.	future; moderate

Continued on next page

Text Segment	Labels
DOVER DOWNS GAMING & ENTMT INC (31/12/2016)	
The credit facility is classified as a current liability as of December 31, 2016 in our consolidated balance sheets as the facility expires on September 30, 2017. We will seek to refinance or extend the maturity of this obligation prior to its expiration date; however, there is no assurance that we will be able to execute this refinancing or extension or, if we are able to refinance or extend this obligation, that the terms of such refinancing or extension would be as favorable as the terms of our existing credit facility. These factors raise substantial doubt about our ability to continue as a going concern. The financial statements have been prepared assuming that we will continue as a going concern and do not include any adjustments that might result from the outcome of this uncertainty.	current; severe
OTELCO INC (31/12/2007)	
Both our credit facility and the senior subordinated notes have material covenants based upon Adjusted EBITDA, as defined in the indenture. In our credit facility, covenants relating to our senior leverage and fixed charge ratios are calculated based upon Adjusted EBITDA. In the indenture for the senior subordinated notes, our ability to pay dividends on our common stock is dependent in large part on our Adjusted EBITDA. In addition, our ability to incur debt under the indenture for the senior subordinated notes and the credit facility is based on our ability to meet a specified leverage ratio. If we are unable to meet the leverage ratio, our liquidity would be adversely affected to the extent that we intend to rely on additional debt to enhance our liquidity.	future; moderate
ENERGY FOCUS INC (31/12/2018)	
If we fail to obtain required additional financing to sustain our business before we are able to produce levels of revenue to meet our financial needs, we will need to delay, scale back or eliminate our business plan and further reduce our operating costs and headcount, each of which would have a material adverse effect on our business, future prospects, and financial condition. A lack of additional financing could also result in our inability to continue as a going concern and force us to sell certain assets or discontinue or curtain our operations and, as a result, investors in the Company could lose their entire investment.	future; severe
JAGUAR ANIMAL HEALTH INC (31/12/2015)	
We do not believe our current capital is sufficient to fund our operating plan through December 2016. We will need to seek additional funds sooner than planned, through public or private equity or debt financings or other sources, such as strategic collaborations. Such financing may result in dilution to stockholders, imposition of debt covenants and repayment obligations or other restrictions that may affect our business. In addition, we may seek additional capital due to favorable market conditions or strategic considerations even if we believe we have sufficient funds for our current or future operating plans. We may also not be successful in entering into partnerships that include payment of upfront licensing fees for our products and product candidates for markets outside the United States, where appropriate. If we do not generate upfront fees from any anticipated arrangements, it would have a negative effect on our operating plan.	future; mild

Continued on next page

Text Segment	Labels
RUDY NUTRITION (30/06/2005)	
At June 30, 2005, we had an accumulated deficit of 34,458,370. During the six months ended June 30, 2005, we completed two contracts to conduct private elections using our voting system with a value of 17,416; however, these contracts are not substantial and there is no assurance of additional future revenues at this time. Consequently, we will require substantial additional funding for continuing the development, obtaining regulatory approval, and commercialization of our product. There is no assurance that we will be able to obtain sufficient additional funds when needed or that such funds, if available, will be obtainable on satisfactory terms.	current & future; moderate
SEALED AIR CORP (31/12/2008)	
ANZ Facility The Company has a 170.0 million Australian dollar, dual-currency revolving credit facility, known as the ANZ facility, equivalent to U.S. 116.8 million at December 31, 2008, due March 2010. A syndicate of banks made this facility available to a group of the Company's Australian and New Zealand subsidiaries for general corporate purposes, including refinancing of previously outstanding indebtedness. The Company may re-borrow amounts repaid under the ANZ facility from time to time prior to the expiration or earlier termination of the facility. The Company plans to renew or replace the ANZ credit facility prior to its expiration date. However, there is no assurance that the syndicate of banks will renew or replace this facility. As of December 31, 2008, the Company had an outstanding balance of 9.4 million Australian dollars, which was equivalent to U.S. 6.5 million.	future; mild
ALBANY MOLECULAR RESEARCH INC (31/12/2011)	
As of September 30, 2011, we were not in compliance with one of the financial covenant requirements. As a result, the we received a waiver from the lenders and additionally amended the above credit agreement effective November 29, 2011. The amended credit agreement increased the effective interest rate, limited any further borrowings, required that we diligently seek refinancing of this debt agreement with a commitment for such to be obtained by March 31, 2012 and required the further repayment of 3.0 million in December 2011 and another 0.8 million of such obligations in the first quarter of 2012 with the remaining outstanding balance to be repaid in June 2012, on the loan s maturity date. In addition, certain of the restrictive covenants were revised and as of such date we are only required to comply with certain cash maintenance requirements and to limit our capital expenditures. As of December 31, 2011, the Company was in compliance with the existing financial covenant requirements.	current; moderate
RXBAZAAR INC (31/12/2003)	
We are not profitable. In the year ended December 31, 2003 we incurred a net loss of 4.7 million, and as of December 31, 2003, we had a stockholders' deficit of 5.7 million. We anticipate future losses and negative cash flow to continue for the foreseeable future, even though monthly sales have recently increased. Because of our history of operating losses and working capital deficit, our independent auditors have expressed doubt as to our ability to continue as a going concern. We can give no assurance that we will be able to operate profitably or produce a positive cash flow. In general, our ability to become profitable depends on our ability to generate and sustain substantially higher revenues while maintaining reasonable expense levels. If we were to achieve profitability, we cannot give any assurance that we would be able to sustain or increase profitability on a quarterly or annual basis in the future.	current & future; severe

Continued on next page

Text Segment	Labels
SALON MEDIA GROUP INC (31/12/2004)	
PricewaterhouseCoopers LLP, Salon's independent accountants through November 13, 2003 have included a paragraph in their report indicating that substantial doubt exists as to Salon's ability to continue as a going concern because of Salon's recurring operating losses, negative cash flow and an accumulated deficit for the for the years ended March 31, 2002 and March 31, 2003. Salon's current independent accountants, Burr, Pilger & Mayer LLP make the same assertions in their report for Salon's year ended March 31, 2004.	current; severe

D Additional Results

D.1 Additional Results on Firm Characteristics

Table D1 links to the discussion in Section 5.1 and shows characteristics of firms that indicate financial constraints at present and in future.

Table D1: Firm Characteristics by Constraint Severity and Time Horizon: Current & Future

	Current & Future					
Total Data Set	Unconstrained	Mild	Moderate	Severe	Severe-Unconstrained	
					Difference	P-Value
Total Assets	3297.28	2765.06	1657.16	106.83	-3190.44	0.00
Firm Age	20.84	18.70	14.76	11.28	-9.56	0.00
Cash/Lagged Total Assets	0.19	0.17	0.21	0.20	0.01	0.21
Cashflow/Lagged Total Assets	0.03	0.00	-0.14	-2.70	-2.73	0.00
Total Debt/Lagged Total Assets	0.28	0.35	0.52	1.32	1.04	0.00
R&D/Lagged Total Assets	0.07	0.06	0.15	0.34	0.27	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.00	0.00	-0.01	0.00
Tobin's Q	2.23	2.35	2.79	6.81	4.59	0.00
Working Capital	239.14	259.91	108.80	-5.44	-244.59	0.00
Leverage	0.43	0.52	0.63	1.38	0.95	0.00
Kaplan & Zingales Index	-470.42	-348.42	-216.81	-19.11	451.31	0.00
Whited & Wu Index	-138.04	-120.53	-69.00	-4.24	133.80	0.00
Hadlock & Pierce Index	-3.78	-3.77	-3.13	-1.57	2.21	0.00
Hoberg & Maksimovic Index	-0.04	-0.02	0.02	0.05	0.08	0.00

Table D2 links to the discussion of Table 7 in Section 5.1. It shows firm characteristics if we apply the scheme by Hoberg and Maksimovic (2015) to split the entire sample into terciles according to the presence of financial frictions.

D.2 Farre-Mensa Ljungqvist: Robustness Tests

Table D3 shows results for the equity recycling check proposed by Farre-Mensa and Ljungqvist (2016) with additional firm and industry-by-year fixed effects. Including firm fixed effects yields results that are fully consistent with the baseline results shown in the main body.

Table D2: Comparison of Firm Characteristics by Constraint Severity: Hoberg & Maksimovic Alternative Measure

Restricted Data Set	Low	Medium	High	High - Low Constraints	
	Constraints	Constraints	Constraints	Difference	P-Value
Total Assets	1578.17	1828.93	1780.11	201.93	0.04
Firm Age	18.42	16.52	13.49	-4.93	0.00
Cash/Lagged Total Assets	0.19	0.21	0.27	0.08	0.00
Cashflow/Lagged Total Assets	-0.09	-0.15	-0.45	-0.36	0.00
Total Debt/Lagged Total Assets	0.32	0.37	0.44	0.12	0.00
R&D/Lagged Total Assets	0.09	0.11	0.21	0.12	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	0.00
Tobin's Q	2.24	2.59	3.37	1.13	0.00
Working Capital	178.92	173.02	144.84	-34.08	0.00
Leverage	0.47	0.51	0.55	0.08	0.00
Kaplan & Zingales Index	-227.60	-274.44	-251.04	-23.43	0.11
Whited & Wu Index	-64.53	-75.95	-76.14	-11.62	0.01
Hadlock & Pierce Index	-3.52	-3.39	-3.11	0.41	0.00

Data is first sorted by the variable, delay investment score, in ascending order, and then broken down into 3 equal terciles to assign the groups low, medium and high constraints. Our sample is restricted to correspond to the one of Hoberg and Maksimovic (2015)

Table D3: Farre-Mensa and Ljungqvist Equity Recycling Test: Firm & Industry-Year fixed effects

Dependent variable:	Unconstrained	Constrained	Constraints Timing		
Δ Total Dividends and Share Repurchases/Total Assets			Current	Future	Current & Future
Δ Equity Proceeds	0.0019***	0.0007**	-0.0666	0.0006**	0.0016
	(0.00)	(0.02)	(0.24)	(0.02)	(0.35)
Δ Other Sources of Funds	0.0650***	0.0002	0.2224	0.0098	-0.0001
	(0.00)	(0.60)	(0.14)	(0.58)	(0.84)
Δ Log Total Assets	-0.0857***	-0.0568***	-0.8636*	-0.0432***	-0.1321
	(0.00)	(0.00)	(0.05)	(0.00)	(0.15)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	11,373	9,037	69	6,711	578
R^2	0.261	0.405	0.751	0.350	0.529

The 'Unconstrained' group contains all unconstrained firm-year observations. Standard errors clustered at the firm (gvkey) level; p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

D.3 Cashflow Sensitivity of Cash: Robustness Tests

We conduct a battery of robustness checks on the cashflow sensitivity of cash results following the literature. Each check supports the view in our baseline results that there are systematic differences between firms in the way they conduct their cash policies depending on the temporal nature of the financial constraints they face.

First, Table D4 reports estimates of equation (1) including year fixed effects. Consistent with the baseline results, the cashflow-to-assets coefficient is significant only for future constrained firms, and remains of similar magnitude to the baseline findings. The coefficient is approximately zero and insignificant for unconstrained firms, those constrained at present, and those constrained at present and anticipating constraints in future.

Table D4: Including Year Fixed Effects

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0010	0.0001	0.0120***	0.0015
	(0.19)	(0.97)	(0.00)	(0.22)
Tobin's Q	0.0004	-0.0001	0.0013**	0.0026***
	(0.52)	(0.92)	(0.05)	(0.01)
Log Assets	-0.0044***	0.0032	-0.0031	0.0066
	(0.01)	(0.69)	(0.17)	(0.23)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	37,370	3,216	24,060	6,745
R^2	0.128	0.259	0.157	0.259

This table reports estimates of equation (1) including year fixed effects. Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Second, Tables D5 and D6 report estimates of equation (1) using standard errors clustered either by NAICS 1-digit industry or by firm.[43] These alternative specifications do not alter the baseline results' significance.

Third, Table D7 shows results based on a restricted sample that includes only those firms with positive free cash flow, i.e. cash flows are strictly larger than required investment outlays. Following Almeida et al. (2004), we define free cash flow as the difference between

[43]Using 1-digit industries is the most conservative clustering approach, although this leads to a limited number of clusters. The findings endure when clustering at more granular industry levels.

Table D5: Industry Clustered Standard Errors

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0009	-0.0000	0.0120***	0.0015
	(0.47)	(0.99)	(0.00)	(0.29)
Tobin's Q	0.0004	0.0001	0.0014***	0.0029***
	(0.20)	(0.82)	(0.00)	(0.01)
Log Assets	-0.0037***	0.0015	-0.0014	0.0066
	(0.00)	(0.73)	(0.61)	(0.52)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,370	3,216	24,060	6,745
R^2	0.118	0.244	0.146	0.246

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. We cluster the standard errors by NAICS 1-digit industry. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Table D6: Firm Clustered Standard Errors

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0009	-0.0000	0.0120***	0.0015
	(0.31)	(0.99)	(0.00)	(0.26)
Tobin's Q	0.0004	0.0001	0.0014**	0.0029***
	(0.56)	(0.94)	(0.03)	(0.00)
Log Total Assets	-0.0037***	0.0015	-0.0014	0.0066
	(0.00)	(0.84)	(0.44)	(0.21)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,370	3,216	24,060	6,745
R^2	0.118	0.244	0.146	0.246

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. We cluster the standard errors by firm. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

cashflow and depreciation. This sample restriction addresses the concern that the observed positive sensitivity of cash to cashflow could be the result of a mechanical relationship. Specifically, that firms are simply forced to reduce cash holdings when operating income falls short of covering investment needs. In such cases, cash flows may appear to drive cash holdings because the firm must finance a shortfall. However, because investment levels are partly discretionary, a more telling test of precautionary savings behavior is to isolate cases where cash flows exceed non-discretionary investment requirements. We use depreciation as a proxy for such required investment outlays, thereby controlling for the possibility that the sensitivity is driven by financing deficits rather than intentional savings behavior. Our conclusions based on this restricted sample remain robust: only firms anticipating constraints in future display a positive and significant cashflow sensitivity of cash.

Table D7: Positive Free Cashflow Firms

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0009	-0.0000	0.0132***	0.0012
	(0.21)	(0.99)	(0.00)	(0.32)
Tobin's Q	0.0003	-0.0000	0.0017**	0.0027***
	(0.62)	(0.98)	(0.01)	(0.01)
Log Total Assets	-0.0033**	0.0017	0.0003	0.0086
	(0.03)	(0.84)	(0.90)	(0.16)
Firm FE	Yes	Yes	Yes	Yes
Observations	31,251	2,665	20,012	5,428
R^2	0.135	0.249	0.160	0.250

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. In addition, we restrict the 'Unconstrained' and 'Constrained' samples to contain only firm-year observations where a firm has positive free cashflow. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Fourth, Table D8 reports estimates of equation (1), extended to the specification in Table IV of Almeida et al. (2004). In particular, it includes Δ Net Non-Cash Working Capital (NWC), Δ Short Term Debt, Capital Expenditures, and Acquisitions as additional independent variables. This specification controls for additional sources and uses of funds and confirms the results of our baseline regression. The coefficient on future constrained firms remains positive and significant while the other coefficients are insignificant.

Table D8: Augmented Specification

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0057	-0.0030	0.0106**	0.0045
	(0.23)	(0.36)	(0.03)	(0.17)
Tobin's Q	0.0015**	-0.0013	0.0018***	0.0035***
	(0.04)	(0.39)	(0.01)	(0.00)
Log Total Assets	-0.0019	0.0052	0.0014	0.0098*
	(0.18)	(0.51)	(0.53)	(0.10)
Δ NWC	-0.0001***	-0.0001**	-0.0001***	-0.0001***
	(0.00)	(0.02)	(0.00)	(0.00)
Δ Short Term Debt	-0.0000***	-0.0001**	-0.0000***	-0.0000***
	(0.00)	(0.03)	(0.00)	(0.00)
CAPX	-0.0000***	0.0000	-0.0000***	-0.0000***
	(0.00)	(0.89)	(0.00)	(0.00)
Acquisitions	-0.0000***	-0.0000	-0.0000***	-0.0000*
	(0.00)	(0.22)	(0.00)	(0.07)
Firm FE	Yes	Yes	Yes	Yes
Observations	32051	2206	20435	5133
R^2	0.14	0.28	0.16	0.27

This table reports estimates of equation (1) with further controls for capital expenditures, acquisitions, the change in non-cash net working capital (NWC), and the change in short-term debt. Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Sixth, Almeida et al. (2024) point out that their baseline specification does not formally account for variations in the severity of financial constraints at a given point in time. To account for this, they suggest a variant of equation (1) that controls for an interaction term of cash over twice lagged total assets and cashflow. Table D9 reports estimates of this specification which are fully consistent with our baseline results. The coefficient on future constrained firms remains significant and is not substantially affected by the inclusion of the additional control variable. Coefficients for unconstrained firms and those constrained at present are close to zero and insignificant.

Seventh, Grieser and Hadlock (2019) challenge the widespread reliance on fixed-effects estimators in empirical corporate finance research. A central critique lies in the frequent neglect of testing for the strict exogeneity of explanatory variables, a key assumption underlying both estimators. They demonstrate that this assumption is often violated in standard applications, which can lead to significant distortions in inference and estimation reliability. To detect such violations, Grieser and Hadlock (2019) propose a simple yet powerful diag-

Table D9: Cash Dynamics

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0017	-0.0003	0.0118***	0.0018
	(0.13)	(0.85)	(0.00)	(0.23)
Tobin's Q	0.0015**	-0.0017	0.0013*	0.0027**
	(0.04)	(0.14)	(0.06)	(0.01)
Log Total Assets	-0.0075***	-0.0040	-0.0055**	0.0082
	(0.00)	(0.59)	(0.01)	(0.16)
Cash / Assets_{t-2}	-0.2259***	-0.1639***	-0.2259***	-0.1899***
	(0.00)	(0.00)	(0.00)	(0.00)
Cash / Assets_{t-2} × Cashflow	-0.0125**	-0.0024*	0.0025	-0.0003
	(0.01)	(0.07)	(0.68)	(0.21)
Firm FE	Yes	Yes	Yes	Yes
Observations	32,337	2,674	20,762	5,746
R^2	0.170	0.243	0.180	0.265

This table reports estimates of equation (1) with further controls for the twice-lagged level of firm cash holdings, and its interaction with the cash flow variable. Cashflow denotes the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

nostic tool: comparing coefficient estimates from fixed-effects and first-differences models. Divergences in these estimates typically signal potential issues with the exogeneity assumption. We follow this intuition by estimating equation (1) with first-differences methods and reporting the outcomes in Table D10. Across our tables, the results from fixed-effects and first-differences estimations provide consistent inferences. This holds in particular for the coefficients on unconstrained, future-constrained, and currently constrained firms. The coefficient for firms constrained at present and in future is significant, however it is an order of magnitude smaller than the coefficient for future constrained firms.

Eighth, Riddick and Whited (2009) highlight a potential concern that measurement error in Tobin's Q may distort the estimated cash flow sensitivities of cash holdings, particularly for financially constrained firms. To assess the extent of this issue in our analysis, we implement the corrective procedures outlined by Almeida et al. (2010). Their methodology addresses potential biases by employing two estimation strategies. First, we apply an OLS-IV approach to the first-differenced version of equation (1), using lagged values of Tobin's Q as instruments. Second, we utilize the Arellano-Bond GMM estimator, which also leverages lagged Tobin's Q to account for endogeneity and measurement error. The outcomes of

Table D10: First Difference Specification

	Unconstrained	**Constrained**		
Dependent variable: Δ (Δ Cash holdings)		Current	Future	Current & Future
Δ Cashflow	-0.0000	0.0007	0.0126***	0.0028**
	(1.00)	(0.58)	(0.01)	(0.04)
Δ Tobin's Q	0.0011	0.0002	0.0028***	0.0027**
	(0.33)	(0.86)	(0.00)	(0.02)
Δ Log Total Assets	0.0069	0.0058	0.0110*	0.0246***
	(0.23)	(0.58)	(0.07)	(0.00)
Firm FE	No	No	No	No
Observations	32,277	3,771	21,416	7,032
R^2	0.000	0.000	0.004	0.008

This table reports estimates of a first-differenced specification of equation (1). Δ Cashflow denotes the first difference of the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

these robustness checks are summarized in Tables D11 and D12. Across all specifications, we find consistent evidence that future-constrained firms exhibit significantly stronger cash flow sensitivities of cash. In contrast, the coefficients for unconstrained firms and firms constrained at present remain small and statistically indistinguishable from zero. The same holds for the the coefficient for firms constrained at present and in future based on OLS-IV. While it is significant using the Arellano-Bond GMM specification, it is economically very small, almost by an order of magnitude in comparison to the coefficient on future constrained firms. These findings suggest that our core results are not driven by biases due to measurement error in Tobin's Q.

Ninth, to address potential biases in our estimation strategy, we incorporate the methodological correction introduced by Welch (2021). Specifically, we estimate a differenced specification of equation (1) that omits firm fixed effects, as suggested by his framework. An additional refinement involves altering the way changes are computed: rather than using ratios of changes, we follow Almeida et al. (2024) and adopt the change-of-ratios approach to measure variations in both cash holdings and cash flow. Table D13 reveals consistent results with our baseline specification. In fact, the sensitivity of cash holdings to cash flow for firms anticipating future constraints appears to strengthen under this alternative specification, underscoring the robustness of our main findings.

Table D11: OLS-IV Model

	Unconstrained	**Constrained**		
Dep var: Δ(Δ Cash holdings)		Current	Future	Current & Future
Δ Cashflow	0.0262	0.0049	0.0334*	0.0105
	(0.27)	(0.85)	(0.09)	(0.29)
Δ Tobin's Q	0.1156	0.0232	0.0177	0.0443
	(0.26)	(0.89)	(0.60)	(0.34)
Δ Log Total Assets	0.1199	0.0739	0.0406	0.1318
	(0.25)	(0.89)	(0.41)	(0.26)
Firm FE	No	No	No	No
Observations	28,197	3,107	18,463	5,918

This table reports estimates equation (1) using the second lag of Tobin's Q to instrument Tobin's Q after taking first differences (OLS-IV). Δ Cashflow denotes the first difference of the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2024), the residuals are clustered by firm. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Table D12: Generalized Method of Moments Results

	Unconstrained	**Constrained**		
Dep var: Δ(Δ Cash holdings)		Current	Future	Current & Future
Δ Cashflow/Assets	0.0011	0.0007	0.0111**	0.0048**
	(0.19)	(0.73)	(0.04)	(0.02)
Δ Tobin's Q	0.0078***	0.0026	0.0054**	0.0074***
	(0.00)	(0.25)	(0.01)	(0.00)
Δ Log Total Assets	0.0120**	0.0054	0.0105	0.0315***
	(0.02)	(0.68)	(0.12)	(0.00)
Firm FE	No	No	No	No
Observations	32,277	3,771	21,416	7,032

This table reports estimates of equation (1) using an Arellano-Bond estimator in which we use all available lags of Tobin's Q to instrument Tobin's Q after taking first differences. Δ Cashflow denotes the first difference of the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is as constrained. Following Almeida et al. (2024), the residuals are clustered by firm. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Table D13: Welch Correction

	Unconstrained	**Constrained**		
Dep var: Δ (Δ Cash/Assets)		Current	Future	Current & Future
Δ COR Cashflow	0.0463	0.0144	0.0419***	0.0053
	(0.30)	(0.21)	(0.00)	(0.91)
Δ Tobin's Q	-0.0045	0.0099	0.0051	0.0237*
	(0.60)	(0.20)	(0.11)	(0.06)
Δ Log Total Assets	0.1658***	0.3667*	0.3438***	0.2714**
	(0.00)	(0.06)	(0.00)	(0.01)
Firm FE	No	No	No	No
Observations	32,277	3,771	21,416	7,032

This table reports estimates of equation (1) using the Welch correction. Δ COR Cashflow denotes the first difference of the change in the ratio of cashflow to assets. The 'Unconstrained' sample contains all unconstrained firm-year observations. The 'Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained. Following Almeida et al. (2004), we allow the residuals to be correlated within years (across firms) using the 'sandwich' (or Huber–White) variance/covariance matrix estimator. p-values are reported in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

D.4 Cash Flow Sensitivity, Constraint Status and Balance Sheet Items

We estimate equation (1), replacing the dependent variable with several balance sheet items, using subsamples. Table D14 reports results for a data set restricted to firm-year observations classified as currently constrained while Table D15 shows corresponding results for a data set containing firm-year observations classified as constrained at present and in future. The cashflow coefficient estimate indicates cash flow sensitivity on expenditure items.

We find that currently constrained firms use cashflow to reduce current liabilities and increase working capital. In particular, they reduce short- and long-term debt, accounts payable and accrued expenses. While they do not use additional cashflow to increase dividend payments or expand the stock of total inventories, they build up additional raw materials. A qualitatively similar picture emerges in the case of firms constrained at present and in future. The exceptions are that the cashflow coefficients in the long-term debt and raw materials regressions are insignificant.

Table D14: Constraints at Present: Cash Flow Sensitivity of Various Balance Sheet Items

	Liabilities / Assets	ST Debt / Assets	LT Debt / Assets	Acc. Pay. / Assets	Acr. Exp. / Assets	WC / Assets	Dividends / Assets	Inventories / Lag Sales	Raw Materials / Lag Sales
Cashflow	-0.0621***	-0.0302**	-0.0121*	-0.0144**	-0.0110**	0.0630***	-0.0000	0.0277	0.0202*
	(0.00)	(0.02)	(0.05)	(0.01)	(0.02)	(0.00)	(0.99)	(0.24)	(0.08)
Tobin's Q	0.1974***	0.0683***	0.0179**	0.0267***	0.0323***	-0.2016***	0.0000	0.1125**	0.0650
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.97)	(0.04)	(0.17)
Log Total Assets	-1.0489***	-0.2858***	-0.1701***	-0.2417***	-0.1897***	1.0279***	-0.0273***	1.5243**	0.8845
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.11)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,675	3,304	3,322	3,847	2,935	3,580	3,846	3,381	2,413
R^2	0.74	0.67	0.58	0.71	0.67	0.75	0.46	0.36	0.41

Acc. Pay. denotes Accounts Payables, Acr. Exp. is Accrued Expenses, WC stands for Working Capital, ST Debt for short term-debt and LT Debt for long-term debt. The 'Current Constrained' sample includes only the firm-year observations where an MD&A document is classified as constrained at present. Results show coefficients and the robust p-values in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively. The regressions above include firm (gvkey) fixed effects and robust standard errors.

Table D15: Current & Future Constraints: Cash Flow Sensitivity of Balance Sheet Items

	Liab / Assets	ST Debt / Assets	LT Debt / Assets	Acc. Pay. / Assets	Acr. Exp. / Assets	WC / Assets	Div / Assets	Inven. / Lag Sales	RM / Lag Sales
Cashflow	-0.1373***	-0.0828***	-0.0161	-0.0238**	-0.0176*	0.1386***	-0.0002	-0.0371	-0.0224
	(0.00)	(0.00)	(0.12)	(0.02)	(0.08)	(0.00)	(0.89)	(0.75)	(0.32)
Tobin's Q	0.1479***	0.0389***	0.0304***	0.0218***	0.0425***	-0.1511***	0.0019	-0.1439	-0.0971
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)	(0.21)	(0.19)
Log (Total Assets)	-0.5532***	-0.1465***	-0.0765***	-0.1380***	-0.0951***	0.5069***	-0.0174***	-0.3106	-0.0912
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.61)	(0.50)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	7,544	7,144	7,132	7,866	6,259	7,334	7,857	6,965	5,025
R^2	0.74	0.62	0.53	0.66	0.69	0.74	0.34	0.33	0.37

Acc. Pay. denotes Accounts Payables, Acr. Exp. is Accrued Expenses, WC stands for Working Capital, ST Debt for short term-debt, LT Debt for long-term debt, Div for Dividends, Inven. for Inventories and RM for Raw Materials

References in the Appendix

Almeida, H., Campello, M., and Galvao, A. F. (2010). Measurement Errors in Investment Equations. *Review of Financial Studies*, 23(9):3279–3328.

Almeida, H., Campello, M., and Weisbach, M. S. (2004). The Cash Flow Sensitivity of Cash. *Journal of Finance*, 59(4):1777–1804.

Almeida, H., Campello, M., Weisbach, M. S., et al. (2024). The Cash Flow Sensitivity of Cash: Replication, Extension, and Robustness. *Critical Finance Review*, 13(3-4):351–365.

Arora, A., Belenzon, S., Cioaca, L., Sheer, L., Shin, H. M., and Shvadron, D. (2024a). DISCERN 2.0: Duke Innovation & Scientific Enterprises Research Network [Dataset].

Arora, A., Belenzon, S., Cioaca, L., Sheer, L., and Shvadron, D. (2024b). Back to the Future: Are Big Firms Regaining their Scientific and Technological Dominance? Evidence from DISCERN 2.0. (available soon).

Chu, K. K., Chen, S., and Leung, T. (2021). A novel algorithm for generating a gvkey-cik link table. *Journal of Information Systems*, 35(1):27–46.

Doidge, C., Karolyi, G. A., and Stulz, R. M. (2017). The US Listing Gap. *Journal of Financial Economics*, 123(3):464–487.

Farre-Mensa, J. and Ljungqvist, A. (2016). Do Measures of Financial Constraints Measure Financial Constraints? *Review of Financial Studies*, 29(2):271–308.

Grieser, W. D. and Hadlock, C. J. (2019). Panel-Data Estimation in Finance: Testable Assumptions and Parameter (In)Consistency. *Journal of Financial and Quantitative Analysis*, 54(1):1–29.

Hoberg, G. and Maksimovic, V. (2015). Redefining Financial Constraints: A Text-Based Analysis. *Review of Financial Studies*, 28(5):1312–1352.

Kahle, K. M. and Stulz, R. M. (2017). Is the US Public Corporation in Trouble? *Journal of Economic Perspectives*, 31(3):67–88.

Loughran, T. and McDonald, B. (2016). Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research*, 54(4):1187–1230.

Pang, B., Lee, L., and Vaithyanathan, S. (2002). Thumbs up? sentiment classification using machine learning techniques. In *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (EMNLP 2002)*, pages 79–86. Association for Computational Linguistics.

Riddick, L. A. and Whited, T. M. (2009). The Corporate Propensity to Save. *Journal of Finance*, 64(4):1729–1766.

Rosa, G. J. (2010). The Elements of Statistical Learning: Data Mining, Inference, and Prediction by Hastie, T., Tibshirani, R., and Friedman, J. *Biometrics*, 66(4):1315.

Welch, I. (2021). Ratios of Changes: How Real Estate Shocks Did Not Affect Corporate Investment. *American Economic Review*, 111(10):3351–3387.