Defining Current and Expected Financial Constraints using AI*

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Abstract

We develop a novel annual measure of current and expected financial constraints for publicly listed US firms over 1993 to 2024. Applying artificial intelligence to 10-K filings' text enables more accurate and context-aware detection of financial constraints than traditional text classification techniques. Uniquely, we distinguish constraints affecting firms presently from those anticipated for the future. These constraint types are associated with distinct financial profiles and transition dynamics from which we distill three novel facts: (i) Expected constraints are seldom realized, instead, firms typically become unconstrained or postpone constraints further into the future. (ii) Firms frequently mitigate current constraints within a year, but persistence rises with severity. (iii) Firms prioritize resolving immediate over future constraints. Notably, timing-related heterogeneity impacts the practical application of the widely-used cash flow sensitivity of cash: while it identifies anticipated future financial constraints, it conflates distinct constraint types – unconstrained and currently constrained – and therefore fails to capture all financially constrained firms. A general implication of our work is that firms' observable financial decisions remain informative for identifying financial constraints as liability-cashflow sensitivities distinguish unconstrained from currently binding constraints.

Keywords: Financial Constraints, Expectations, Firm Dynamics, Artificial Intelligence.

JEL Classification: G31, G32, D22, D92.

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1 Introduction

Financial constraints shape firms' corporate decision making and inform broader debates in asset pricing, monetary policy, firm dynamics, and entrepreneurship.[1] Despite their foundational role, financial constraints are inherently difficult to observe, arising from sources such as limited pledgeability, asymmetric information, and contracting imperfections that do not appear directly in firms' balance sheets or market prices. Recent advances in text processing via artificial intelligence provide a new avenue for capturing how firms perceive and describe their financial limitations.

We develop a novel annual firm-level measure of financial constraints between 1993-2024 using text from publicly listed US firms' 10-K filings.[2] Leveraging recent innovations in natural language processing, we train Bidirectional Encoder Representations from Transformers (BERT) models which are particularly well suited tools to extract context-aware information from lengthy financial disclosures as they account for the semantic word environment, syntax and contextual nuance. This deep semantic understanding distinguishes our approach from previous dictionary-based classifications. Beyond the identification of constraints, a noticeable advance is that BERT's contextual awareness allows us to extract information on constraints' severity, and whether they bind contemporaneously or are anticipated to materialize in future.

We find that two thirds of constraints are expected to bind exclusively in future, and are associated with financial profiles distinct from currently binding constraints. We uncover three novel facts about transition dynamics showing how firms alleviate constraints over time by either becoming unconstrained or postponing them to the future. An important implication is that financial constraints are not a fixed firm characteristic.

[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), Gilchrist et al. (2017), 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 US public companies must 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.

Firms move in and out of constrained states, and managers rationally anticipate changes in future financing conditions and adjust their current liquidity in response. Our unique information on constraints' time horizon enables the first empirical test of the Almeida et al. (2004) cash flow sensitivity of cash (CFSC) model. Estimates support their model's predictions but highlight that the vast subsequent empirical literature's use of the CFSC conflates unconstrained and currently constrained observations. Notably, we show that firms' observable financial decisions remain informative about financial constraints. The CFSC captures anticipated constraints, while the sensitivity of liabilities to cash flow distinguishes unconstrained from current constraints.

Our approach sets a new standard for the identification and interpretation of financial constraints. We train BERT models using thousands of human-labeled examples to identify the presence, severity and time horizon of financial constraints in the Compustat universe.[3] Specifically, we apply our trained models on the Management Discussion and Analysis (MD&A) section of 10-K filings. Consistent with extant findings, relative to their unconstrained counterparts, financially constrained observations tend to be present among smaller and younger firms, those with lower cash flow and dividend payments, and higher indebtedness, R&D intensity and Tobin's Q. Our measure satisfies several further validation exercises and notably passes the diagnostic checks proposed by Farre-Mensa and Ljungqvist (2016) to identify observations that are plausibly constrained and which have proven challenging for many existing proxies.

A key innovation is to uncover economically meaningful heterogeneity that previous measures overlook by failing to capture the context in which constraints are discussed. Among constrained observations, only 12.1% are currently binding constraints, 21.5% bind at present and anticipated for the future, while 66.4% are anticipated exclusively for the future. Firms in these categories differ systematically not only in their observable financial positions, but also in their strategic responses. Those anticipating future constraints have cash-to-asset ratios beyond the level of unconstrained firms, and this

[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.

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 constraints. Conversely, currently constrained firms have substantially lower cash-to-asset ratios than their unconstrained peers, irrespective of constraint severity, suggesting that liquidity has already been drawn down to sustain operations during financial stress. Other balance sheet components exhibit similar patterns.

We establish three novel facts by studying transition dynamics between different states. First, anticipated future financial constraints are rarely realized during the next year; instead, firms typically transition to an unconstrained state or push the constraints further into the future, though the likelihood of doing so declines with severity. Second, firms facing currently binding financial constraints often alleviate them in the following year by either becoming unconstrained or postponing constraints to the future. Yet, the more severe the current constraints, the more likely they are to persist into the following year. Third, firms prioritize resolving immediate constraints over those that lie ahead. We show that observed changes in balance sheet items across states align with managerial strategies aimed at addressing financial constraints. These insights emphasize that it is critical not only to determine whether financial constraints exist, but also to recognize the substantial heterogeneity implied by their severity and timing.

Our work has fundamental implications for understanding the relation between firms' cash dynamics and financial constraints. In particular, with respect to interpreting the CFSC introduced by Almeida et al. (2004) as a means of capturing financial constraints. Their work is foundational in empirical corporate finance, influencing a wide range of debates, including studies on firm liquidity management, investment behavior, and monetary policy.[4] Almeida et al. (2004) demonstrate in a theoretical model 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

[4]The CFSC 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)).

and therefore exhibit no sensitivity of cash holdings to internal cash flows.

Our novel information on constraints' time horizon makes us the first to be able to test the theoretical model of Almeida et al. (2004). Confirming the model's predictions, we show that only firms anticipating financial constraints exhibit a positive CFSC, whereas unconstrained firms do not. However, we also find no significant CFSC among currently constrained firms. Instead, these firms use cash flow to reduce leverage and strengthen working capital rather than building cash buffers, whereas unconstrained firms have no need for costly precautionary cash accumulation since they can access external capital markets. While our findings validate the theoretical model's predictions, they also underscore that existing empirical applications – which abstract from the time dimension of constraints emphasized in the theoretical framework – risk misinterpreting the CFSC as a universal signal of financial constraints. We show that the CFSC serves as a valuable tool to identify future constraints. However, they call for a narrower interpretation of the CFSC than applied previously in the empirical literature, as it conflates distinct constraint types – unconstrained and currently constrained – and therefore fails to capture all financially constrained firms.

A general contribution of our work is to show how firms' observable financial decisions can identify different types of constraints. In addition to identifying future constraints via the CFSC, we can also disentangle currently constrained and unconstrained observations. Consistent with pecking order theory and dynamic trade-off models, when firms face currently binding constraints they use cashflow to reduce liabilities. In contrast, there is no such significant relationship when they are unconstrained, potentially because their unrestricted access to external funding means that cashflow realizations carry little incentive to repay liabilities.

A methodological contribution of our work lies in how we train language models that measure financial constraints. Training is essential because mentions of financial constraints are sparse within the voluminous MD&A texts — an untrained model could thus achieve high accuracy by ignoring this minority class and simply classifying all text segments as unconstrained. Our rigorous training procedure also ensures our BERT models capture the subtleties of constraint-specific language within MD&A sections. Training requires a large human-labeled training data set that is representative of the MD&A sections' language. Generating such a data set is often infeasible in settings like ours concerned with identification of a minority class. Our novel training methodology overcomes this issue by introducing an Active Learning strategy with human-in-the-loop-verification in Economics and Finance. This builds on best practice in computer science and yields a training data set containing 23,687 hand-labeled text segments. Human readers also label the severity of a constraint (mild, moderate, or severe) and its timing (current, future, or both time horizons) to train two additional models. The three trained BERT models that classify constraint status, severity and timing achieve convincing out-of-sample performance, including accuracy scores of 94%, 92% and 98%, respectively.[5]

Our methodological approach has four key advantages over existing strategies. First, it mitigates the sampling bias that arises when training data is selected purely through keyword filtering, a limitation affecting 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, our approach goes beyond simplistic frequency heuristics of dictionary-based approaches to determine the severity of constraints. Prior approaches often equate severity with the number of times particular terms appear, however, even a single sentence can reveal serious constraints, while repeated mentions of generic financial terms may mean little. Instead of relying on frequency, we extract information on severity directly from the textual discussion of constraints and show that the relation between severity and the number of constrained paragraphs is modest. Finally, artificial intelligence extracts information on constraint's severity and time horizon which uncovers meaningful economic patterns. Hence, our framework opens new avenues for empirical research on the origins, effects, and evolution of financial constraints.

[5] Accuracy is the proportion of correct classifications out of all classifications.

2 Literature

Our paper advances the literature that identifies 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)). They remain widely used, but lack external validation and firm-specific nuance.[6] Alternative methods, such as survey-based indicators (e.g. Campello et al. (2010)) offer additional insight but are typically limited in scope, representativeness and availability.

A strand of this literature focuses on firms' observable financial decisions as indirect proxies for constraints. A prominent example is the CFSC proposed by Almeida et al. (2004). They show theoretically that firms anticipating future financing constraints accumulate cash from internal cash flows while their unconstrained counterparts do not. Based on this insight the CFSC became a benchmark measure of financial constraints in corporate finance and macro-financial research.[7] We are the first to empirically test and confirm the Almeida et al. (2004) theoretical framework due to the availability of a measure that explicitly differentiates by constraints' time horizon. A key message from our analysis is to advocate for a narrower interpretation of the CFSC than typically applied in the vast empirical literature. While the CFSC reflects precautionary savings behavior in anticipation of future constraints, it is not well suited to identifying contemporaneously constrained firms and differentiating them from unconstrained companies.

These findings shed new light on a longstanding debate in the literature. While widely used, the interpretation of the CFSC 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, as predicted by the Almeida et al. (2004) model.

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

[7] 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).

Recent efforts to identify financial constraints have turned toward textual data as a scalable and complementary source of 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 bag-of-words approach by applying cosine similarity to compare the words in MD&A sections with those appearing in a training data set of manually classified filings. Buehlmaier and Whited (2018) construct a training sample to estimate a firm's probability of financial constrainedness as a function of the word count in its MD&A section, purely relying on word frequency but ignoring words' location in the text. They subsequently apply this fitted probability model to predict firm's financial constraints status across the whole sample and analyze the relation between 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 the technology available at the time 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 natural language processing beyond 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, but also enables us to distinguish between current and anticipated constraints as well as their severity, uncovering previously unobserved heterogeneity in constraint dynamics. Lastly, our data fills a gap by providing practitioners with a comprehensive financial constraints measure, spanning the Compustat universe over 1993-2024.[8]

Our work also adds to the large literature that uses machine learning on textual measures to which we cannot do full justice here. Key contributions have been made on various financial or macroeconomic dimensions such as risk (e.g. Hassan et al. (2019)),

[8] Previous contributions cover limited time periods (e.g. Hoberg and Maksimovic (2015) over 1997-2009), are based on early data so that reduced for regressions may not be representative for different time periods (Kaplan and Zingales (1997); Whited and Wu (2006); Hadlock and Pierce (2010)), or data is not made publicly available.

innovation (e.g. Kelly et al. (2021)), or monetary policy (e.g. Hansen et al. (2017)). For detailed surveys on the literature on textual analysis, see Loughran and McDonald (2016) and Ash and Hansen (2023).

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 2024.[9] To identify the presence and nature of financial constraints in these detailed textual disclosures, we focus on the Management's Discussion and Analysis (MD&A) section of each 10-K report. This is consistent with the practice in existing studies that use 10-K reports for this purpose, see e.g. Hoberg and Maksimovic (2015), Bodnaruk et al. (2015), and Buehlmaier and Whited (2018). 10-K filings must comply with the SEC's disclosure requirements which mandate a firm discusses its sources of financing as well as current and expected future liquidity needs in the MD&A section.[10]

We pre-process and clean the MD&A data in three steps. First, we remove non-narrative content such as tables, figures, and headings from the MD&A text. 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 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.[11] Third, some MD&A sections are very brief and therefore lack

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

[10] 10-K documents are signed by the company's CFO and CEO. Under Section 302 of the Sarbanes Oxley Act, they are directly responsible for the accuracy, documentation and submission of all financial reports as well as the internal control structure to the SEC. Section 906 of the the Sarbanes Oxley Act, addresses criminal penalties for certifying a misleading or fraudulent financial report and penalties can be upwards of $5 million in fines and 20 years in prison. There have been convictions for violations of this act. It is also a requirement in Section 13(a) of the Securities Exchange Act of 1934 that the form and content of the financial statements are examined by an independent accountant. For these reasons, it is highly likely that the content of 10-K filings is exhaustive and to the best of a corporation's knowledge and conscience, unlike in earnings calls where interviewees may choose not to answer a question and the content covered depends on the selection of questions.

[11] A text segment of 512 tokens consists of around 250-350 words. 3.2% of all paragraphs exceeded the 512 token limit.

sufficient information for our analysis. We thus exclude MD&A sections in the bottom percentile of the word count distribution, which contain 154 words or fewer. Online Appendix B.1 provides further details on how we extract and clean the MD&A sections.

The second data source we use is Compustat North America, from which we extract the Annual Financial Statements between 1993 and 2024. 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)), by excluding firms that do not use the US Dollar as their reporting currency, those in highly-regulated (SIC codes 4900-4999) or the financial (SIC codes 6000-6999) sectors. Following Hoberg and Maksimovic (2015) and Buehlmaier and Whited (2018), we exclude firm-year observations as soon as a firm is has filed for bankruptcy protection or is 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 Online Appendix B.2.

We match 83.65% 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 91.2%. Further details and statistics related to the matching process are provided in Online Appendix B.3. The final merged Compustat-MD&A data set contains 12,581 firms, 102,925 firm-year observations and 7,857,505 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 infers surrounding text from both the left and right of each word, thereby capturing nuanced meanings and context. Pre-trained on large text corpora, BERT can be trained further for various natural language processing tasks.[12]

[12]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. While AI offers a remedy, a BERT model's efficacy hinges on the diversity of its 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. Even constructing a representative solely hand-classified training sample within a reasonable time frame is infeasible since it must encompass a sufficiently diverse range of text passages. Training a model on a non-representative sample could lead to poor out of sample performance, resulting in unreliable predictions when applied to the broader corpus of text. We generate a comprehensive training data set by implementing an Active Learning methodology with human-in-the-loop verification in Section 4.1.1. We introduce this methodology of computer sciences into economics and finance. We train our BERT model on the training data set and evaluate model performance in Section 4.1.2.[13]

4.1.1 Generating the Training Data: Seed and Active Learning Samples

We create the training data set in four steps. First, multiple trained readers classify whether a text segment indicates financial constraints or not.[14] Once two independent readers agree on a constrained/unconstrained classification, a text segment becomes part of our *seed training sample* which in the end 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 to train a FinBERT model which allows us to capture the patterns and signals indicative of financial constraints within the text segments.[15] Active Learning is a supervised machine learning technique where the algorithm selectively queries a human annotator to

[13]This training, or 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).

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

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

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 (e.g. those classified to be financially constrained), the Active Learning approach efficiently expands 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, 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 is used to monitor the model's performance on data not used to train the model. Subsequently, we train 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.[16] In each iteration, the human readers manually evaluate the model's predictions 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 three.

[16]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.

An off-the-shelf FinBERT model is then trained 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 Online Appendix C.1.

Our Active Learning approach with human-in-the-loop verification is more effective than purely 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.[17] The ideal approach is to randomly select and label many text segments to obtain a training sample that is representative of the population. However, this approach is very time consuming and infeasible in most applications. In our case, it is particularly difficult to find text segments because mentions of constraints are exceptionally rare. The existing literature therefore often takes the faster and pragmatic approach of selecting a small sample, e.g. using external criteria identifying constraints, at the expense of being less likely to yield a representative training sample. In our case, Active Learning overcomes the issues inherent in the two approaches and is key to generating a comprehensive data set that includes a sufficiently large number of constrained text segments.

In the context of 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 labels inconsistent with humans annotations that may occur in previous

[17]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).

training iterations. After ten iterations, the final training data set consists of 23,687 labeled text segments. Of these 5,102 (18,585) 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 described how we generate an informative training data set. Next, we use 70% of the training data set's text segments for training and retain 15% each for validation and testing samples.[18] We first train a binary classifier that identifies whether or not a text segment indicates 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 Online Appendix C.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.[19] 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.

Evaluating the Constraint Classifier Model's performance on the test data set uses a set of standard metrics. Accuracy measures the proportion of correct predictions out of all predictions made. The model's accuracy is 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 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 constrained text segments, a high share of 86% are correctly identified as having financial constraints.

[18] 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.

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

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.[20] 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.[21] 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 reliable ability to discriminate between the two outcomes, regardless of where the decision boundary is set.[22]

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

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

[21] 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.

[22] 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 Online Appendix C.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). Online Appendix C.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.

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 Constraints' Severity and Time Horizon

Beyond the binary classification of text segments' constrained status, the richness of our textual data also provides insights into their severity and timing. 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 constraints bind in the current financial year and in future, we classify the time horizon as Current & Future. Online Appendix D.1 provides further information on the two classifiers and their labels.

To train the two additional BERT models, we extract a subset of financially constrained text segments from the training sample developed in Section 4.1.1. 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 1,314 and 1,169 text segments for severity and time horizon classification dimensions, respectively. We 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.[23]

Table 2 summarizes each classification model's performance. The metrics for the Time Horizon and Severity classifiers indicate strong model performance across all dimensions.[24] The Time Horizon Classifier Model's accuracy is 98%. The F1 score of 98%

[23]Further information on the training of classification-specific BERT models is provided in Online Appendix C.3.

[24]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 Online Appendix D.2.

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.[25, 26]

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 %

We evaluate performance using the 15% test sample. The Time Horizon metrics are calculated using micro-averaging suitable for non-exclusive multi-label classification. See Online Appendix D.2 for details.

4.3 Descriptive Statistics on Text Segments

This section describes the distribution of text segments in our data set. Table 3 overviews the text segments in MD&A sections classified as constrained or unconstrained by the binary Constraint Classifier Model. MD&A documents are lengthy, containing 76.34 text segments and 7,517 words, on average. The mean (90th percentile) segment comprises 102 (151) words. Many companies do not mention financial constraints: at the median, one text segment per MD&A section is classified as constrained. However, at the 90th (95th) percentile firms discuss the matter in 3 (5) text segments, encompassing roughly 6% (9%) of the MD&A section.

We classify 1.50% of all text segments as financially constrained. Among those constrained text segments, 21.73% are classified as mildly, 60.27% moderately, and 16.20% severely constrained. 1.81% are classified as unclear by the Severity Classifier Model.[27]

[25]BERT models are purpose built for classification while Large Language Models (LLMs) excel in reasoning. Online Appendix D.4 shows our trained BERT model substantially outperforms GPT-type LLMs.

[26]Examples of text segments and their classifications by the BERT models are provided in Online Appendix D.5.

[27]As discussed in Online Appendix D, not all text segments can be clearly mapped to a severity level or time horizon. These cases are identified by our human reviewers and labeled accordingly. The model is trained to recognize these cases.

We classify 15.50% of all constrained text segments as constrained at present, 67.98% as anticipating constraints in future and 14.13% facing constraints at both time horizons. 2.39% are classified as unclear by the Time Horizon Classifier Model. In the following analysis, we disregard any text segments that are labeled as unclear by either the Severity or the Time Horizon Classifier Model.[28]

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	7,517.05	1,963	3,602	6,644	10,377	14,167	16,816	22,864
Total Number of Text Segments within MD&A	76.34	23	38	63	100	147	181	264
Words per Text Segment within MD&A	102.35	69.08	80.34	95.23	118.89	150.81	164.16	180.67
Number of Constrained Text Segments within MD&A	1.18	0	0	1	2	3	5	8
% of Constrained Text Segments within MD&A	2.06	0.00	0.00	0.67	2.70	5.88	8.70	16.67

Mean, p10, p25, $\cdots$, p99 denote the mean, 10^{th} percentile, 25^{th} percentile, $\cdots$, 99^{th} percentile value of the variable in the left column, respectively.

4.4 Aggregating Text Segment Classifications to the Firm-Year Level

In this section, we aggregate the individual text segment classifications to the firm-year level, i.e. the MD&A section level. First, we discuss this aggregation in the context of severity before turning to the time dimension.

4.4.1 The Severity of Firms' Financial Constraints

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 the overall severity of financial constraints, we show below that there is by no means a one-to-one mapping between our severity measure and frequency counts. For instance, some firms may express acute financial distress in a single text segment, flagging

[28] Online Appendix D.3 shows the distribution of the share of constrained text segments per MD&A section, by constraint severity and time horizon, respectively.

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 overcome these limitations. Our classification goes beyond the count-based metrics applied in previous literature, because the AI model detects context-dependent nuances within text segments on constraint severity. The information on text segment severity enables us to synthesize text-level information to the firm-year level.

We argue the content of a text segment discussing tougher constraints refers to matters that supersede weaker constraints discussed in the same MD&A document as they limit managerial actions to a greater degree. Therefore, 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*.[29]

Following aggregation to the firm-year level, 52% of firm-year observations mention, even if briefly, that they are in some way financially constrained, while the remaining 48% are unconstrained. 11.0% of firm-year observations contain at least one mention of severe financial constraints. A further 29.1% are classified as moderately constrained, and 12.0% as mildly constrained.[30]

[29]In the example above, these decisive segments would be the one or more text segments in an MD&A section mentioning severe financial constraints. Similarly, firms are 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).

[30]This is broadly in line with previous studies' findings. For example, Hadlock and Pierce (2010)

Relation to Count-Based Measures. Next we turn to the relation between our severity classification and the incidence of constraint mentions, the latter being often used in the literature as a proxy to capture severity of financial constraints. If we sort the MD&A documents by their share of constrained text segments from lowest to highest, a count-based metric would for example associate the top 20% (10%) [5%] of these MD&A documents with severe financial constraints. However, we find that 45.5% (36.1%) [31.0%] of these documents, that contain a large number of constrained text segments, do not include a single segment classified as severely constrained. Count-based approaches to measuring financial constraints therefore have limited efficacy, because simply equating the constraint frequency/share with constraint severity results in an indicator containing non-negligible measurement error. Appendix A.1 shows further corroborative statistics indicating companies dedicate a relatively large part of their MD&A section to discussing constraints without these constraints necessarily being a critical threat to their operations.

4.4.2 The Time Horizon of Firms' Financial Constraints

Classifying the time horizon of an MD&A document relies on the timing of constraints mentioned in its decisive text segments. 33.8% of MD&A documents contain only one decisive text segment and 95.0% of them contain no more than three decisive text segments.[31] The limited number of decisive text segments within constrained MD&A documents helps with the identification of their time horizon. However, ambiguity surrounding the time horizon may exist if an MD&A document contains multiple decisive text segments. For example, in an MD&A document with four decisive text segments, if all four segments discuss financial constraints in future, the associated time horizon is clear. In case one decisive text segment is associated with constraints in future and three in the present however, the classification of the time horizon of the MD&A document is less clear. We therefore proceed in two steps to determine the time horizon of an MD&A

report 37% of firms are to some extent financially constrained. Using survey data, Campello et al. (2010) find 40% of firms are somewhat affected and about 20% 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), Buehlmaier and Whited (2018)).

[31] For details see Online Appendix D.3.

document's financial constraints.

In the first step, we handle the unambiguous cases. 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. The left hand side of Table 4 reports the distribution of firm-year observations that are classified using the unambiguous step one procedure. The time horizon of the vast majority of MD&A documents can be classified unambiguously. Given the low number of decisive text segments per MD&A document, they often point towards the same time horizon and only a minority (15.4% 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 Table 4 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.[32]

A key contribution of our work is to differentiate financial constraints by time horizon and severity. Table 4 shows that most constraints pertain to the future (66.4%), while 12.1% of the constrained observations relate to currently binding constraints and the remaining 21.5% to both both current and future. Accounting for the severity of financial constraints shows that an increase in severity shifts the distribution towards firms experiencing current constraints. Among severely constrained firms, Current comprises

[32]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. They are also robust to setting the threshold of step two to 0.67%. Results are available upon request.

43.4%, Current & Future 39.1% while only 17.5% 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 4: Distributions of Decisive Text Segments and Time Horizon Classifications

		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 Constrained MD&As	Obs	226	11,590	335	207	226 (+0)	11,593 (+3)	539 (+204)
	Share	1.86%	95.38%	2.76%		1.83%	93.81%	4.36%
Moderately Constrained MD&As	Obs	1,306	21,245	2,459	4,909	1,332 (+26)	22,034 (+789)	6,553 (+4,094)
	Share	5.22%	84.95%	9.83%		4.45%	73.65%	21.90%
Severely Constrained MD&As	Obs	4,733	1,947	1,448	3153	4,899 (+166)	1,973 (+26)	4,409 (+2,961)
	Share	58.23%	23.95%	17.81%		43.43%	17.49%	39.08%
All Constrained MD&As	Obs	6,265	34,782	4,242	8,269	6,457 (+192)	35,600 (+818)	11,501 (+7,259)
	Share	13.83%	76.80%	9.37%		12.06%	66.47%	21.47%

This table shows the distribution of firm-year observations assigned to a particular time horizon using the two-step classification described in the text. Obs denotes the number of observations. Share denotes the share of constrained observations. Numbers in parenthesis refer to the additional observations assigned to time horizon categories during step two.

5 Firm Characteristics

Existing literature often validates constraints proxies using characteristics commonly associated with financially constrained firms (e.g. Buehlmaier and Whited (2018)). The descriptive evidence in Panel A of Table 5 shows our measure aligns with these: 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 observations are significant. Additional validation exercises of our measure, including its relation to existing constraint proxies, are discussed in Section 8.

We go beyond the existing literature by studying the characteristics of those constrained at present and those anticipating constraints for the future which uncovers interesting heterogeneity and commonalities across these groups. The relationships identified for the full sample, shown in Panels B of Table 5, remain consistent when distinguishing between present and future financial constraints.[33] Notably, leverage increases with the

[33]To ensure a clear distinction between constraints at different time horizons, this section focuses

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. Those expecting future financial constraints have higher cash holdings than unconstrained firms and this gap widens when severity increases. In contrast, currently constrained firms hold cash balances that, depending on constraint severity, are comparable to or lower than those of unconstrained firms. In light of looming financial constraints firms may accumulate cash preemptively as a precautionary measure, whereas those facing currently binding constraints have likely depleted their excess reserves to navigate their financial difficulties. Recall from Table 4 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 Panel A of Table 5 thus reflects that currently constrained firms dominate with rising severity. This underscores the importance of distinguishing financial constraints based on their time horizon.

Constraints' time horizon notably extends to balance sheet components beyond cash holdings. Panel D of Table 5 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, also relative to total assets (not shown), and is smaller for firms facing constraints at present relative to those anticipating constraints in the future. Notably, firms experiencing severe current constraints exhibit particularly low working capital, signaling potential liquidity issues. Additionally, R&D intensity and cash flow are higher for firms anticipating future constraints than for those constrained at present. These relationships are statistically significant for all three constraint severity levels, with

on those that exclusively face either present or future constraints. The same patterns are also observed among firms reporting constraints at both time horizons. Corresponding results for this group, analogous to Table 5, are provided in Appendix A.2.

only a few exceptions.

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 less financial flexibility 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.

6 New Facts from Transition Dynamics

In this section, we analyze transition dynamics between states, conditional on time horizon and severity. Subsequently, we explore the concomitant balance sheet movements, shedding light on how managerial actions may coincide with transitions. Table 6 shows a transition matrix from a multinomial logit model documenting firms' movements between states.[34] Each row represents a firm's initial state in period t, while the corresponding columns indicate the probability of transitioning to a particular state in period $t+1$. The diagonal entries show the probability of a firm remaining in the same state, while off-diagonal elements reflect movements between states.

Firms Anticipating Future Constraints at Time t. Rows five, six, and seven of Table 6 show transition probabilities for firms anticipating future financial constraints at time t. Regardless of severity, these firms are unlikely to transition to Current & Future (columns eight-ten) and are even less likely to be currently constrained at $t+1$

[34]The table presents the conditional transition probabilities from a multinomial logit model that estimates the probability of transitioning to a certain state in the following period. The model controls for firm characteristics (log total assets, Tobin's Q), year and industry fixed effects. We estimate $\Pr(Y_{i,t+1} = j \mid X_{i,t}) = \exp(X'_{i,t}\beta_j)/\sum_k \exp(X'_{i,t}\beta_k)$, where $Y_{i,t+1}$ denotes the categorical outcome for constraint status at $t+1$, and $X_{i,t}$ is the vector of covariates at time t, including a vector of dummy coefficients for the current constraint status of the firm. Unconstrained in period $t+1$ is the base outcome and normalized to zero. The conditional transition probabilities in Table 6 show the average predicted probability of a firm being in each constraint category at $t+1$, given the initial constraint status and additional covariates. Each value reflects the mean estimated probability after averaging over all control variables.

Table 5: Balance Sheet Characteristics by Constraint Severity and Time Horizon

Panel A: Full Data Set	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3,932.41	2,665.45	1,799.87	247.96	-3,684.45	0.00
Firm Age	20.13	15.16	13.20	10.61	-9.52	0.00
Cash/Lagged Total Assets	0.20	0.26	0.31	0.26	0.05	0.00
Cashflow/Lagged Total Assets	0.03	0.00	-0.25	-1.87	-1.90	0.00
Total Debt/Lagged Total Assets	0.28	0.28	0.43	1.22	0.94	0.00
R&D/Lagged Total Assets	0.07	0.10	0.17	0.32	0.25	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	-0.01	0.00
Tobin's Q	2.60	2.89	3.34	7.17	4.57	0.00
Working Capital	241.59	217.83	150.60	9.29	-232.30	0.00
Leverage	0.45	0.45	0.57	1.32	0.87	0.00
Kaplan & Zingales Index	-633.97	-454.55	-277.24	-37.26	596.70	0.00
Whited & Wu Index	-165.85	-113.18	-72.74	-10.60	155.25	0.00
Hadlock & Pierce Index	-3.77	-3.58	-3.23	-1.75	2.02	0.00
Hoberg & Maksimovic Index	-0.04	0.00	0.03	0.04	0.07	0.00

Panel B: Current Constrained	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3,932.41	1,767.96	1,434.37	274.38	-3,658.03	0.00
Firm Age	20.13	15.42	15.54	11.23	-8.90	0.00
Cash/Lagged Total Assets	0.20	0.22	0.16	0.20	-0.01	0.30
Cashflow/Lagged Total Assets	0.03	-0.13	-0.27	-1.95	-1.97	0.00
Total Debt/Lagged Total Assets	0.28	0.31	0.53	1.33	1.04	0.00
R&D/Lagged Total Assets	0.07	0.07	0.10	0.27	0.20	0.00
Dividends/Lagged Total Assets	0.01	0.00	0.00	0.00	-0.01	0.00
Tobin's Q	2.60	3.09	3.19	7.46	4.86	0.00
Working Capital	241.59	122.64	99.09	6.09	-235.50	0.00
Leverage	0.45	0.48	0.66	1.37	0.92	0.00
Kaplan & Zingales Index	-633.97	-158.37	-168.05	-33.98	599.99	0.00
Whited & Wu Index	-165.85	-74.57	-58.70	-12.17	153.68	0.00
Hadlock & Pierce Index	-3.77	-3.03	-2.99	-1.68	2.09	0.00
Hoberg & Maksimovic Index	-0.04	-0.02	-0.02	0.02	0.06	0.00

Panel C: Future Constrained	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
					Difference	P-Value
Total Assets	3,932.41	2,666.22	1,824.67	389.58	-3,542.83	0.00
Firm Age	20.13	15.12	12.88	10.34	-9.79	0.00
Cash/Lagged Total Assets	0.20	0.27	0.34	0.43	0.22	0.00
Cashflow/Lagged Total Assets	0.03	0.00	-0.23	-1.26	-1.29	0.00
Total Debt/Lagged Total Assets	0.28	0.28	0.39	0.79	0.50	0.00
R&D/Lagged Total Assets	0.07	0.11	0.19	0.38	0.31	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	-0.01	0.00
Tobin's Q	2.60	2.89	3.38	5.76	3.16	0.00
Working Capital	241.59	221.10	166.94	35.08	-206.51	0.00
Leverage	0.45	0.45	0.54	0.94	0.48	0.00
Kaplan & Zingales Index	-633.97	-462.98	-297.71	-63.77	570.20	0.00
Whited & Wu Index	-165.85	-113.69	-75.19	-15.94	149.90	0.00
Hadlock & Pierce Index	-3.77	-3.59	-3.30	-2.17	1.60	0.00
Hoberg & Maksimovic Index	-0.04	0.00	0.03	0.07	0.10	0.00

Panel D: Comparison across	Mild: Future - Current		Moderate: Future - Current		Severe: Future - Current	
Time Horizon and Severity	Difference	P-Value	Difference	P-Value	Difference	P-Value
Total Assets	898.26	0.34	390.30	0.09	115.19	0.08
Firm Age	-0.30	0.74	-2.66	0.00	-0.89	0.00
Cash/Lagged Total Assets	0.05	0.08	0.18	0.00	0.23	0.00
Cashflow/Lagged Total Assets	0.13	0.03	0.04	0.52	0.68	0.00
Total Debt/Lagged Total Assets	-0.03	0.33	-0.14	0.00	-0.54	0.00
R&D/Lagged Total Assets	0.04	0.04	0.09	0.00	0.11	0.00
Dividends/Lagged Total Assets	0.01	0.02	0.00	0.19	0.00	0.55
Tobin's Q	-0.19	0.45	0.20	0.17	-1.71	0.00
Working Capital	98.46	0.00	67.85	0.00	28.99	0.00
Leverage	-0.04	0.12	-0.12	0.00	-0.44	0.00
Kaplan & Zingales Index	-304.61	0.15	-129.66	0.00	-29.78	0.00
Whited & Wu Index	-39.12	0.37	-16.49	0.10	-3.78	0.23
Hadlock & Pierce Index	-0.56	0.00	-0.30	0.00	-0.49	0.00
Hoberg & Maksimovic Index	0.02	0.01	0.06	0.00	0.05	0.00

Panels A, B and C report the mean of each variable for unconstrained, mild, moderate, and severe observations (columns two to five). Columns six and seven in these panels show the results of t-tests on the equality of the mean between severe and unconstrained observations. Difference is the difference in mean values between the groups. P-Value is the t-test's p-value. Panel D reports the results of t-tests on the equality of the mean between mild future and mild current (columns two and three), moderate future and moderate current (columns four and five), severe future and severe current (columns six and seven). The continuous financial constraint index variables (Kaplan & Zingales, Whited & Wu, Hadlock & Pierce, and Hoberg & Maksimovic) are mapped into the unconstrained-mild-moderate-severe categories by applying the respective shares that we find for each category in our data set.

(columns two-four). Instead, they are more likely to avoid binding constraints at time $t+1$ by either remaining in the future-constraints category (columns five-seven) or by transitioning to an unconstrained state (column one). Among firms continuing to expect future constraints at $t+1$, these constraints are likely to remain at the same severity level – although the degree of persistence declines from 61% and 64% for mild and moderate, respectively, to 39% for severe financial constraints. This suggests that firms anticipating future financial constraints may take proactive steps to avoid constraints binding at $t+1$, resulting in either a transition to unconstrained (13% for mild, 12% for moderate and 11% for severe), or to a future category.

Currently Constrained Firms at Time t. Firms that are mildly, moderately or severely current-constrained at time t (rows two, three and four) remain so at time $t+1$ with a probability of 24%, 24%, 42% (sum of columns two-four), respectively. There is a high probability that these firms alleviate their constraints in $t+1$: they either become unconstrained (46%, 40%, 23%, respectively; column one), or attempt to create financial headroom by postponing constraints to the future (19%, 20%, 20%, respectively; sum of columns five-seven). These patterns suggests that firms may actively take measures to relax or defer their financial constraints, but this becomes increasingly difficult as constraint severity toughens.

Firms Constrained at Present & Future at Time t. Firms that simultaneously face financial constraints at present and in future are likely to remain in the same state at $t+1$ (30%, 40%, 48% for mild, moderate and severe at time t, respectively; sum of columns eight-ten). However, they may actively take steps to mitigate their financial constraints: many are able to relax them in $t+1$, either by becoming unconstrained (24%, 17%, 17%, respectively; column one) or by resolving current constraints while still facing future pressures (39%, 36%, 22%, respectively; sum of columns five to seven). Resolving financial constraints at present seems more important than alleviating those in future since the probability of becoming constrained at present only is rather low at (6%, 7%, 13%, respectively; sum of columns two to four).

Firms Transitioning to Unconstrained. A similar notion is apparent when considering the probabilities of transitioning to being unconstrained in period $t+1$ (column one). Firms that face constraints at present (Current and Current & Future) are more likely to become unconstrained than those anticipating constraints to bind in future only, for any given constraint severity. This suggests that firms take greater remedial measures when constraints are currently binding, compared to companies anticipating future constraints. However, more severe constraints inhibit this process.

Table 6: Transition Probabilities

	Unconstr. at $t+1$	Current at $t+1$			Future at $t+1$			Current & Future at $t+1$		
		Mild	Moderate	Severe	Mild	Moderate	Severe	Mild	Moderate	Severe
Unconstrained at t	84.3***	0.2***	1.0***	1.4***	3.4***	5.6***	0.3***	0.3***	2.6***	0.9***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Current, Mild at t	46.4***	15.7***	5.0***	3.0***	8.7***	8.1***	1.9**	5.1***	5.3***	0.9
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.15)
Current, Moderate at t	39.8***	0.4**	19.4***	4.4***	9.2***	10.8***	0.4**	1.3***	13.1***	1.2***
	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)
Current, Severe at t	23.2***	0.1*	1.9***	40.0***	4.2***	13.9***	1.4***	0.3**	6.3***	8.7***
	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
Future, Mild at t	13.2***	0.1***	1.1***	2.0***	60.5***	16.6***	0.6***	1.0***	3.7***	1.1***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Future, Moderate at t	11.8***	0.1***	0.6***	2.7***	8.3***	64.0***	1.6***	0.3***	8.2***	2.5***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Future, Severe at t	11.0***	0.0***	0.5**	4.2***	3.3***	22.4***	38.8***	0.2	7.2***	12.4***
	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.32)	(0.00)	(0.00)
Current & Future, Mild at t	24.4***	2.4***	1.3**	2.2***	23.2***	16.3***	0.0***	21.5***	7.2***	1.5**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)
Current & Future, Moderate at t	17.1***	0.1**	3.1***	4.2***	6.3***	28.1***	1.5***	0.6***	35.4***	3.6***
	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Current & Future, Severe at t	17.4***	0.0***	1.4***	11.7***	2.6***	14.3***	5.0***	0.1	8.7***	38.8***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.32)	(0.00)	(0.00)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,066	81,066	81,066	81,066	81,066	81,066	81,066	81,066	81,066	81,066

The table reports average transition probabilities derived from a multinominal logit model of a firm's constraint status in t+1. Unconstrained in t+1 is the base category. The unreported firm control variables are the log of total assets, Tobin's Q, and 1-digit SIC industry and year fixed effects. Coefficients indicate the probability that a firm in a specific constraint status at t transitions to another status in t+1 accounting conditional on the covariates. Heteroskedasticity robust p-values are in parentheses. *, ** and *** indicate statistical significance the at 1%, 5% and 10% level, respectively.

Summary and Adjustments in Balance Sheet Items. The discussion above shows that financial constraints are not a fixed firm characteristic, see Appendix A.4 for further corroborative evidence. This insight matters because much of the existing literature treats financial constraints as either a static firm characteristic or a highly persistent condition, largely due to the fact that commonly used proxies are constructed from variables that exhibit strong persistence over time. We now distill three stylized facts from this analysis and examine how balance sheet variables evolve as firms transition between states.

We track the evolution of firms' balance sheet items across different transition paths.

First, we report simple averages for each path, providing a descriptive picture of how firms on different trajectories adjust. Next, we complement these raw differences with propensity-score-matched estimates that compare firms with observationally equivalent time t characteristics across different states at time $t+1$.[35] For every observed mean in state $S_{t+1} = i \neq j$, we mark whether it is significantly higher or lower relative to that of the matched base group firms in state $S_{t+1} = j$, indicating these differences with "+" or "–" superscripts. This approach does not assign causal meaning to the balance sheet movements across time transitions, but it highlights which movements are systematically different across $t+1$ outcomes, while accounting for firms' financial structure and operating environment.

Fact one: Firms that anticipate future financial constraints rarely experience immediately binding constraints in the following year. Instead, they either tend to become unconstrained or stay in the future-constrained category. The probability of these transitions falls as constraint severity increases.

This suggests these firms may take proactive steps, and are often successful, in preventing anticipated future constraints from becoming binding. While our data only contains outcomes rather than information on managerial incentives, balance sheet movements provide a first step into understanding potential managerial strategies. The bottom-left panel of Table 7 shows balance sheet adjustments in line with this notion for firms anticipating future constraints at time t. Those remaining in the future-constrained category maintain markedly higher cash-to-asset ratios (0.28) and keep leverage stable and substantially lower than firms ending up in a constrained state at $t+1$, this is consistent with precautionary strategy that helps prevent anticipated constraints from being realized. A similar pattern is evident for firms that successfully transition to an unconstrained state, albeit they exhibit a somewhat lower cash-to-asset ratio (0.20), consistent with either reduced precautionary needs or the use of cash reserves to remove potential constraints.[36]

[35] We use kernel matching with propensity scores estimated from log total assets, cash-to-assets, leverage, and Tobin's Q, with industry, year, and severity fixed effects. Further details, including evidence on the quality of the matching, are provided in Appendix A.3. For the sake of brevity and implementability, we base the results on balance sheet items on a transition table differentiating by time horizon only.

[36] Appendix A.3.4 documents that firms remaining future constrained or transition to unconstrained, constraint severity correlates positively with $t+1$ levels of cash-to-asset ratios and leverage. The most

In sharp contrast, firms that move from anticipating future constraints to experiencing binding constraints (Current or Current & Future) show signs of immediate financial pressure – high levels of, and increases in, leverage, accounts payable and accruals, and the strongest declines in, and lower levels of, working capital and cash-to-assets (relative to the Future and Unconstrained groups). As indicated by the plus and minus superscripts, all discussed movements of variables and their levels differ significantly from those of otherwise comparable firms that remain in the future-constrained base state.

Fact two: Firms facing current financial constraints often relax these in the following year by becoming unconstrained or shifting to a future-constrained category. However, the more severe the current constraints are, the more likely they are to carry over into the next year.

Evidence from balance sheet items aligns with the notion that managers attempt to ease or postpone immediately binding financial constraints – albeit with diminishing success as severity increases. The top-right panel of Table 7 reports that firms transitioning from Current to Unconstrained or Future states raise their cash-to-asset ratios – both in absolute terms, and relative to the Current subsample as evident from the superscripts. In particular, those firms transitioning to Future show a higher $t+1$ level of cash-to-assets than those in Current or Unconstrained, consistent with a precautionary motive. Relative to those remaining currently constrained at time $t+1$, the two groups that alleviate constraints – Future and Unconstrained – reduce (increase), rather than increase (reduce), leverage and accounts payable (working capital) and report a lower (higher) level for these variables. These relations are significant relative to firms facing current $t+1$ constraints when matching on covariates. Remarkably, there are almost no significant differences in balance sheet variables between the two groups that face currently binding constraints – Current and Current & Future – indicative of their largely aligned behavior.[37]

severely constrained of these firms exhibit lower working capital and higher accounts payable and accruals relative to the corresponding mildly and moderately constrained firms. These patterns are consistent with forward-looking managerial behavior: more severely future-constrained firms appear to proactively hold larger cash buffers, secure more debt financing in advance of the looming constraints, and compress working capital to mitigate expected tightening of financial conditions.

[37] We show in Appendix A.3.4 that remaining in one of the two states implying currently binding constraints results in higher $t+1$ levels of leverage, accruals and accounts payable and lower working capital as severity increases. This pattern is consistent with reactive managerial behavior: as constraints

Table 7: Balance Sheet Movements for Firm Transitions by Time Horizon

	Unconstrained at **t**				Current at **t**			
Variables at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	$-0.00^{\mathbf{b}}$	-0.02^{---}	-0.02^{---}	-0.02^{---}	0.02^{+++}	$-0.00^{\mathbf{b}}$	0.02^{+++}	-0.01
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.52)
Cash / Assets	$0.17^{\mathbf{b}}$	0.14^{---}	0.18	0.15^{---}	0.17^{++}	$0.17^{\mathbf{b}}$	0.23^{+++}	0.18
	-	(0.00)	(0.11)	(0.00)	(0.02)	-	(0.00)	(0.37)
$\Delta_{t,t+1}$ Leverage	$0.02^{\mathbf{b}}$	0.15^{+++}	0.04^{+++}	0.11^{+++}	-0.06^{---}	$0.28^{\mathbf{b}}$	-0.08^{---}	0.26
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.84)
Leverage	$0.44^{\mathbf{b}}$	0.73^{+++}	0.49^{+++}	0.61^{+++}	0.63^{---}	$1.50^{\mathbf{b}}$	0.71^{---}	1.28
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.87)
$\Delta_{t,t+1}$ Working Capital / Assets	$-0.01^{\mathbf{b}}$	-0.15^{---}	-0.03^{---}	-0.09^{---}	0.02^{+++}	$-0.23^{\mathbf{b}}$	0.03^{+++}	-0.21
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.62)
Working Capital / Assets	$0.26^{\mathbf{b}}$	-0.03^{---}	0.22^{---}	0.09^{---}	0.10^{+++}	$-0.73^{\mathbf{b}}$	0.09^{+++}	-0.51
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.94)
$\Delta_{t,t+1}$ Accounts Payable / Assets	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{+++}	0.01^{+++}	0.00^{--}	$0.04^{\mathbf{b}}$	0.00^{---}	0.03
	-	(0.00)	(0.00)	(0.00)	(0.02)	-	(0.00)	(0.33)
Accounts Payable / Assets	$0.07^{\mathbf{b}}$	0.12^{+++}	0.07	0.09^{+++}	0.10^{---}	$0.24^{\mathbf{b}}$	0.11^{---}	0.19^{-}
	-	(0.00)	(0.97)	(0.00)	(0.00)	-	(0.00)	(0.06)
$\Delta_{t,t+1}$ Accruals / Assets	$0.00^{\mathbf{b}}$	0.01^{+++}	0.00^{+++}	0.01^{+++}	0.01^{-}	$0.03^{\mathbf{b}}$	0.00^{---}	0.03
	-	(0.00)	(0.00)	(0.00)	(0.09)	-	(0.00)	(0.91)
Accruals / Assets	$0.06^{\mathbf{b}}$	0.09^{+++}	0.06	0.08^{+++}	0.09	$0.18^{\mathbf{b}}$	0.09^{---}	0.15
	-	(0.00)	(0.24)	(0.00)	(0.17)	-	(0.00)	(0.95)

	Future at **t**				Current & Future at **t**			
Variables at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	-0.00	-0.03^{---}	$-0.01^{\mathbf{b}}$	-0.03^{---}	0.01^{+++}	-0.00	0.01^{+++}	$-0.01^{\mathbf{b}}$
	(0.95)	(0.00)	-	(0.00)	(0.00)	(0.87)	(0.00)	-
Cash / Assets	0.20^{--}	0.20^{---}	$0.28^{\mathbf{b}}$	0.24^{---}	0.18^{++}	0.18	0.25^{+++}	$0.21^{\mathbf{b}}$
	(0.04)	(0.00)	-	(0.00)	(0.03)	(0.41)	(0.00)	-
$\Delta_{t,t+1}$ Leverage	0.01^{---}	0.22^{+++}	$0.04^{\mathbf{b}}$	0.13^{+++}	-0.03^{---}	0.22	0.02^{---}	$0.17^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.83)	(0.00)	-
Leverage	0.50^{---}	0.84^{+++}	$0.53^{\mathbf{b}}$	0.70^{+++}	0.57^{---}	1.17	0.62^{---}	$1.12^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.96)	(0.00)	-
$\Delta_{t,t+1}$ Working Capital / Assets	0.00^{+++}	-0.20^{---}	$-0.03^{\mathbf{b}}$	-0.11^{---}	0.03^{+++}	-0.16	-0.01^{+++}	$-0.13^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.56)	(0.00)	-
Working Capital / Assets	0.23^{++}	-0.12^{---}	$0.26^{\mathbf{b}}$	0.05^{---}	0.17^{+++}	-0.42	0.14^{+++}	$-0.31^{\mathbf{b}}$
	(0.01)	(0.00)	-	(0.00)	(0.00)	(0.95)	(0.00)	-
$\Delta_{t,t+1}$ Accounts Payable / Assets	0.00^{---}	0.03^{+++}	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{---}	0.02	0.00^{---}	$0.02^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.95)	(0.00)	-
Accounts Payable / Assets	0.07^{-}	0.14^{+++}	$0.07^{\mathbf{b}}$	0.10^{+++}	0.09^{---}	0.17	0.09^{---}	$0.17^{\mathbf{b}}$
	(0.06)	(0.00)	-	(0.00)	(0.00)	(0.60)	(0.00)	-
$\Delta_{t,t+1}$ Accruals / Assets	0.00^{---}	0.03^{+++}	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{---}	0.03	0.01^{---}	$0.02^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.67)	(0.00)	-
Accruals / Assets	0.07	0.11^{+++}	$0.07^{\mathbf{b}}$	0.10^{+++}	0.08^{--}	0.14	0.09^{--}	$0.14^{\mathbf{b}}$
	(0.31)	(0.00)	-	(0.00)	(0.03)	(0.37)	(0.03)	-

Each cell reports the mean value of a balance sheet variables for firms' transitioning between states from t to t+1. Superscripts "+" ("–") denote that the reported mean is significantly higher (lower) than that of the matched control firms in the base group, indicated by 'b'. These differences are ATT estimates obtained via kernel propensity-score matching; +(-), ++(- -), +++(- - -) indicate significance at the 10%, 5%, and 1% levels, respectively. P-values in parentheses. Matching covariates include log total assets, cash-to-assets, leverage, and Tobin's Q, with SIC 1-digit industry, year, and severity fixed effects.

Fact three: Firms are more likely to resolve currently binding financial constraints rather than those anticipated in the future. Firms experiencing both current and future constraints prioritize resolving current constraints over alleviating prospective ones.

Firms simultaneously facing constraints at present and in future rarely transition into the current-only state. In these cases, it is evident from the bottom-right panel of Table 7 that there are no significantly different movements in balance sheet identities between Current and Current & Future, again indicative of the groups' largely aligned behavior.

tighten, managers draw on remaining debt capacity, rely more heavily on supplier and accrual-based financing, and compress working capital to generate liquidity.

More often, firms either remain in the Current & Future category or relax constraints by transitioning to unconstrained or future-constrained. Relative to Unconstrained and Future-constrained, firms in Current & Future increase leverage, accounts payable and accruals, and reduce – rather than raise – their cash- and working capital-to-asset ratios. Differences between firms that cannot relax current constraints (Current and Current & Future) relative to those that can (Unconstrained and Future) also show the former have relatively higher (lower) levels of leverage, accruals and accounts payable (working capital). These differences relative to Current & Future are statistically significant. Our observations align with managers prioritizing mitigating immediate financial pressure rather than constraints that lie in the future, underscoring the relevance of distinguishing financial constraints by their time horizon.

The discussion in this section underscores the need not only to identify whether firms face financial constraints, but also to distinguish how intense these constraints are and when they arise. In the next section, we demonstrate that differentiating constraints – particularly along the time dimension – has substantial implications for our understanding of how internal financial pressures translate into broader balance sheet re-balancing.

7 Revisiting the Cash Flow Sensitivity of Cash

In a seminal article, Almeida et al. (2004) outline a theoretical model of corporate liquidity with two types of firms. Firms anticipating future financing constraints accumulate cash today as a precaution. A future 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 capital markets and hence have no incentive to save cash from cash flow.[38]

We are the first who are able to test the theoretical model's prediction as our AI measure can explicitly differentiate a constraint's time horizon. Following the work of

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

Almeida et al. (2004), a vast empirical literature has taken the CFSC as a proxy for financial constraints. However, this literature abstracts from the model's timing nuance and employs it as a general constraints proxy. Extant findings associate a positive and significant CFSC with financial constraints – disregarding the theoretical model's 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 sub-samples containing unconstrained or constrained observations and use Huber-White robust standard errors.

Table 8 reports estimates of equation (1). Among unconstrained firms, shown in column one, the cash flow parameter is economically close to zero and statistically insignificant. In contrast, firms anticipating constraints in future show a positive and significant CFSC. Increasing the cash flow to total assets ratio by 10 percentage points, raises the change in cash holdings over assets by 0.118 percentage points, equivalent to a 0.55% increase relative to the mean. 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 exhibit a significant CFSC and 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, firms that are constrained at present are unable to do so. Their constraint status limits contemporary investments. Rather than accumulating cash, currently constrained firms use cashflow to undertake alternative measures to gain financial headroom. Results in Appendix A.6 show they reduce liabilities and increase working capital. In particular, they reduce short-term debt holdings, as well as accounts payable and accrued expenses. They maintain their level of dividend payments and long-term debt. Firms reporting financial constraints at present and in future behave in similar fashion to their currently constrained counterparts in reducing liabilities. This suggests that current constraints are binding and restrict a firm's ability to accumulate cash as a precaution.[39]

Table 8: Cashflow Sensitivity of Cash

	Unconstrained	**Constrained**		
Dep var: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0068	-0.0006	0.0118***	0.0011
	(0.11)	(0.78)	(0.00)	(0.48)
Tobin's Q	0.0008	0.0002	0.0017***	0.0016**
	(0.12)	(0.75)	(0.00)	(0.01)
Log Total Assets	-0.0039***	0.0055	0.0007	0.0047
	(0.00)	(0.42)	(0.68)	(0.29)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,876	2,931	25,810	6,338
R^2	0.12	0.26	0.14	0.26

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Although the Almeida et al. (2004) model links high cash–flow sensitivity of cash to anticipated financing difficulties, extant empirical studies are unable to test this dynamic directly. By distinguishing between firms that are currently constrained and those anticipating future constraints, we are able to empirically test a previously unexamined aspect of the theory. We find that only firms anticipating future funding limitations demonstrate meaningful CFSC, while those already facing constraints do not. This distinction reveals that the cash flow sensitivity is not a general signal of constraints, but rather reflects expectations about limited future access to finance. Ignoring the timing of financial constraints can obscure important differences among firms, undermining both empirical accuracy and interpretive insight.

Our analysis shows, that a significant CFSC can be used to distinguish firms expecting

[39]The patterns emerging from Table 8 are robust to various sensitivity checks, including the addition of year fixed effects, clustered standard errors at the industry or firm level, differentiating by constraint severity, restricting the sample to those firms with positive free cash flow, an augmented specification with additional expenditure variables, and additional methodological checks. For details see Appendix A.5.

financial constraints from those that do not, but it cannot differentiate between unconstrained and currently constrained observations. To resolve this issue arising from our findings, we propose an additional test that enables researchers to differentiate between these groups using balance-sheet data.

Theory points to mechanisms that may help to distinguish unconstrained and currently constrained observations. Credit constraints fundamentally change how firms use cashflow because external finance is costly and fragile. Our previous insights document that firms facing currently binding constraints use cashflow to reduce their liabilities. The literature also suggests it is optimal to use extra internal funds to reduce dependence on outside credit, by reducing debt, accounts payable, and accruals. Pecking order theory, in which internal funds dominate, documents that financing surpluses translate into debt retirement rather than new borrowing. Similarly, dynamic trade-off models, in which recapitalization is costly and the marginal benefit of moving away from distress/covenant 'cliffs' is high, especially for constrained firms, suggest that cashflow windfalls are deployed to delever and restore future borrowing capacity. Finally, agency-based arguments further support the reduction of liabilities as a commitment and credibility device that lowers lender concerns about risk shifting and improves access to future finance.

The negative link between cashflow and liabilities is a pattern in our data. We build on the specification of equation (1) and investigate the sensitivity of liability growth to cashflow. Table 9 documents that firms facing binding constraints at present – Current, and Current & Future – use cash flow to reduce liabilities. Unconstrained firms show no such behavior as their cashflow coefficient is insignificant, potentially because their unrestricted access to external funding means that cashflow realizations carry little incentive to repay liabilities. Appendix A.7 documents our results are robust to a wide range of specifications. Importantly, they carry general implications for identifying financial constraints. Anticipated financial constraints can be identified via the CFSC. Among the remaining observations, currently binding constraints can be distinguished from unconstrained observations via the sensitivity of liabilities growth to cashflow.

Table 9: Cashflow and Liability Growth

	Unconstrained	Constrained		
Dep var: Δ Log Total Liabilities		Current	Future	Current & Future
Cashflow	-0.0174	-0.0240***	-0.0130	-0.0114**
	(0.28)	(0.00)	(0.24)	(0.04)
Tobin's Q	0.0112***	0.0054**	0.0100***	0.0063***
	(0.00)	(0.03)	(0.00)	(0.00)
Log Total Assets	0.0887***	0.1554***	0.0983***	0.1328***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	38,349	3,154	26,332	6,638
R^2	0.20	0.34	0.20	0.34

This table reports estimates of equation (1) where the dependent variable is the growthr ate of total liabilities. Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

8 Further Validation of Our Constraint Measure

Section 5 assesses our financial constraints measure against characteristics typically associated with financially constrained firms. In this section, we consider additional validation exercises.

Relation to Plausibly Constrained Firms. We validate our AI approach using the two diagnostic tests Farre-Mensa and Ljungqvist (2016) propose to identify firms that are plausibly constrained. They show that existing constraints proxies fail these checks. The first test characterizes constraints in terms of the curvature of the capital supply curve. 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. Following Farre-Mensa and Ljungqvist (2016), we estimate

$$\Delta D_{i,j,t} = \alpha T^{+}_{i,t-1} + \beta \Delta X_{i,t-1} + \delta_{j,t} + \epsilon_{i,j,t}, \tag{2}$$

where $D_{i,j,t}$ the ratio of long-term debt to total assets, for firm i in industry j during year t; $X_{i,t-1}$ is a vector of controls (the lagged change in return on assets, tangibility, firm size and investment opportunities); $\delta_{j,t}$ denote industry-year fixed effects; $\epsilon_{i,j,t}$ is the error term. $T^{+}_{i,t-1}$ is the percentage point increase in a firm's headquarter state corporate tax rate, and 0 otherwise.[40] In line with Farre-Mensa and Ljungqvist (2016), we restrict the sample to firms headquartered in states that raise in the corporate tax rate and firms headquartered in adjacent states that do not, and we drop firm-year observations that face a zero marginal tax rate based on the data provided by John Graham.[41]

Table 10: Farre-Mensa and Ljungqvist Debt Test

	Unconstrained	Constraints Timing		
Dep var: Δ Long-Term Debt/Total Assets		Current	Future	Current & Future
$T_{t-1}{}^{+}$	0.0072**	-0.0874	-0.0125	0.0006
	(0.03)	(0.51)	(0.24)	(0.99)
Δ ROA_{t-1}	0.0014	0.0024	0.0098	-0.0117
	(0.86)	(0.91)	(0.37)	(0.19)
Δ $Tangibility_{t-1}$	-0.0426*	0.1890	-0.0028	-0.1439
	(0.08)	(0.52)	(0.96)	(0.28)
Δ Log Total $Assets_{t-1}$	-0.0085	0.0150	-0.0154*	-0.0823**
	(0.25)	(0.75)	(0.09)	(0.01)
Δ Investment $Opportunities_{t-1}$	-0.0040	-0.0005	-0.0007	-0.0043***
	(0.17)	(0.63)	(0.33)	(0.01)
Industry x Year FE	Yes	Yes	Yes	Yes
Observations	18,484	852	10,734	2,073
R^2	0.15	0.29	0.12	0.23

The table reports estimates of equation (2). Following Farre-Mensa and Ljungqvist (2016), we restrict the sample to firms headquartered in US states which raise the state corporate tax rate during the sample period and adjacent states with no state corporate tax rate revisions. We cluster standard errors at the state level and report p-values in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10 examines the tax sensitivity of leverage for different subsamples. 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 0.07 percentage point increase in the change of the long-term debt-to-asset ratio. In contrast, in the remaining columns, constrained firms' leverage exhibits no significant reaction to tax increases ir-

[40] Annual state-level corporate tax rate data is taken from The Tax Foundation. Data availability precludes us from following the approach Farre-Mensa and Ljungqvist (2016) use to proxy firm-level marginal tax rate increases by weighting exposures to state-level revisions to marginal tax rates based on a firm's sales and employment in each state which they retrieve from the National Establishment Time Series data set. We therefore follow Schandlbauer (2017) who shows that a firm's tax nexus is largely determined by its headquarter location.

[41] The results are robust to removing these sample restrictions, i.e. keeping firms headquartered in any state; or keeping firm-year observations that face zero marginal tax rates. John Graham's tax data is available at https://people.duke.edu/ jgraham/taxform.html and we impute missing values using the approach taken in Graham and Mills (2008).

respective of whether they face constraints currently or in the future. The test suggests that our AI-classified constraints measure identifies those firms facing or anticipating an inelastic supply of capital.

Farre-Mensa and Ljungqvist (2016) outline a second diagnostic check focusing on equity markets. They argue a firm engages in less equity recycling – the tendency of firms to simultaneously raise and pay out equity – when subject to an inelastic supply of 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

$$\Delta Payout_{i,j,t} = \beta \Delta EquityIssue_{i,j,t} + \delta \Delta OSF_{i,j,t} + \gamma \Delta Size_{i,j,t} + \alpha_{j,t} + \epsilon_{i,j,t}, \quad (3)$$

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.

Estimates in column 1 of Table 11 show unconstrained firms engage in significant equity recycling. The equity issuance proceeds' coefficient estimate is 0.0014 and significant. Among constrained firms, it is only those anticipating future constraints that engage in significant equity recycling although the economic magnitude is smaller relative to unconstrained firms (coefficient 0.0009).[42] In contrast, firms subject to Current or Current & Future constraints exhibit no systematic tendency to recycle equity. Together, these patterns suggest that our AI-based financial constraints measure passes the Farre-Mensa and Ljungqvist (2016) tests and accurately detects financially constrained observations.[43]

Relation to Existing Constraints Proxies. As a second validation exercise, we evaluate our measure in relation to the proxies of Kaplan and Zingales (1997), Whited and

[42] A test of coefficient equality pools observations in both states and estimates a fully interacted version of equation (3) strongly rejects the null hypothesis (p<0.001).

[43] Our results on the two Farre-Mensa and Ljungqvist (2016) debt and equity recycling tests are robust to additionally including firm fixed effects. For details see Appendix A.8.1.

Table 11: 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	0.0014**	0.0033	0.0009***	0.0008
	(0.04)	(0.41)	(0.00)	(0.50)
Δ Other Sources of Funds	0.0474	-0.0007*	0.0250***	0.0008**
	(0.11)	(0.05)	(0.00)	(0.02)
Δ Log Total Assets	-0.0779***	-0.1999*	-0.0610***	-0.0818***
	(0.00)	(0.08)	(0.00)	(0.01)
Industry $\times$ Year FE	Yes	Yes	Yes	Yes
Observations	11,300	279	7,924	1,097
R^2	0.178	0.305	0.195	0.251

The table reports estimates of equation (3). We cluster standard errors at the firm level. P-values are in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Wu (2006) and Hadlock and Pierce (2010), based on reduced form estimates, as well as the natural language processing approach of Hoberg and Maksimovic (2015). Panel A in Table 5 shows our measure broadly aligns with the three reduced-form indices and the text-based index of Hoberg and Maksimovic (2015). We calculate the statistics in Table 5 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 (59,354 firm-year observations) to ensure direct comparability. 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. While we observe broad correspondence between our measure and the four alternatives in the full data set, Panels B and C show somewhat weaker relations when considering currently and future constrained firms. This is to be expected because our deep learning models can extract context-aware information that earlier measures, e.g. those based on dictionaries, cannot access.

A deeper comparison with Hoberg and Maksimovic (2015) is documented in Appendix A.8.2 and shows agreement across many firm characteristics but notable differences in size and working capital. In particular, our measure implies that constrained firms are smaller – while Hoberg and Maksimovic (2015) document a modest negative correlation (-3%) between their index and total assets – and exhibit a sharper decline in working capital, results that are more consistent with the broader financial constraints literature.

External Validity. As an external validity check, we assess whether our financial constraints measure aligns with narrative evidence suggesting that 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.

We find that financial constraints become both more prevalent and more severe during economic downturns. During the dot-com recession, the share of unconstrained firms declines in the Information Technology sector, while the fraction of moderately and severely constrained firms increases markedly. Similar patterns hold across all sectors and appear during the financial crisis and the initial COVID-19 lockdown, indicating that constraints systematically intensify in recessions. Detailed results are shown in Appendix A.8.3.

Altogether, the battery of multifaceted exercises spanning firm characteristics (see Section 5), existing constraint proxies, the diagnostic test of Farre-Mensa and Ljungqvist (2016), and the external validation exercise corroborate our financial constraints measure's validity.

9 Conclusion

We introduce a state-of-the-art natural language processing technique to identify financial constraints, and apply it to the MD&A sections of 10-K filings by US publicly listed firms. A key contribution is that our AI model can distinguish the timing of these constraints – current or future – and their severity, thus enabling a more nuanced understanding of how firms perceive and respond to financial constraints.

Current and future financial constraints exhibit sharply contrasting financial profiles and transition dynamics from which we distill three novel facts: First, anticipated future constraints are seldom realized, instead, firms typically become unconstrained or postpone constraints further into the future. Second, firms frequently mitigate current constraints within a year, but persistence rises with severity. Third, firms prioritize resolving immediate over future constraints. Notably, timing-related heterogeneity impacts our understanding and practical application of the widely-used CFSC: while it identifies firms that anticipate future financial constraints, it conflates distinct firm types – unconstrained and currently constrained – and therefore fails to capture all financially constrained firms. To resolve this issue arising from our findings, we propose an additional test that enables researchers to differentiate between these groups using balance-sheet data. Currently constrained firms exhibit a negative link between cashflow and liabilities while unconstrained do not.

More broadly, our study demonstrates the transformative potential of AI 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 constraints, 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.

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Appendix

A Additional Results

A.1 Additional Results on the Relation to Count-Based Measures.

Panel A of Appendix Table D1 tabulates the severity of financial constraints (measured as ratio of constrained observations by severity to all constrained firm-year observations) conditional on the number of constrained segments within an MD&A document. For example, among documents containing one constrained text segment (data column one), 41.2% are classified as mild, 51.5% moderate and 7.4% as severe. As the number of constrained text segments increases, the severity distribution skews towards substantial constraints which is consistent with more severely constrained firms, dedicating more space in their MD&A section to discussion of constraints. However, 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 to ten constrained segments (column four), only 61.2% are classified as severely constrained, illustrating that for the remaining 38.8% of firms the content of these discussions is not a critical threat to their operations. Count-based approaches to measuring financial constraints therefore have limited efficacy, because simply equating the constraint frequency/share with constraint severity results in an indicator containing measurement error. As an illustration, a document with more than ten constrained text segments would likely be classified as severe on a purely count-based measure, despite column five in Panel A revealing that only 74.6% of these firm-year observations are classified as severely constrained. Panel B shows this argument extends to considering the share of constrained segments in the entire MD&A document. 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.

Table D1: Percentage Share of Constraint Text Segments by Severity within an MD&A

Panel A: Distribution of constraint severity among firm-year observations, conditional on number of constrained text segments						
Number of Constrained Segments	1	2	3-5	6-10	>10	≥ 1
Mildly Constrained	41.17	11.57	1.29	0.00	0.00	23.07
Moderately Constrained	51.47	67.53	57.39	38.83	25.36	55.86
Severely Constrained	7.36	20.90	41.32	61.17	74.64	21.06
Total by Column	100.00	100.00	100.00	100.00	100.00	100.00

Panel B: Distribution of constraint severity among firm-year observations, conditional on share constrained quintile					
Constrained Share Quintile	0–20	20–40	40–60	60–80	80–100
Mildly Constrained	42.99	31.57	23.75	12.36	4.16
Moderately Constrained	53.66	61.51	62.62	59.83	41.33
Severely Constrained	3.35	6.92	13.63	27.81	54.50
Total by Column	100.00	100.00	100.00	100.00	100.00

The column headers in Panel A denote the number of constrained text segments within an MD&A section. Each cell reports the share of MD&As that are classified as mild, moderate or severe conditional on the number of constrained text segments within an MD&A section. Panel B reports the share of constrained text segments within MD&A sections. This is conditional on the quintile share shown in the column headers. Each cell shows the share of MD&As that are classified as mild, moderate or severe conditional on the quintile share.

A.2 Additional Results on Firm Characteristics

Appendix Table D2 links to the discussion in Section 5 and shows characteristics of firms that indicate financial constraints at present and in future.

Table D2: 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	3,932.41	3,023.33	1,791.00	155.60	-3,776.81	0.00
Firm Age	20.13	15.94	13.80	10.04	-10.09	0.00
Cash/Lagged Total Assets	0.20	0.17	0.22	0.25	0.04	0.00
Cashflow/Lagged Total Assets	0.03	-0.03	-0.29	-2.06	-2.08	0.00
Total Debt/Lagged Total Assets	0.28	0.36	0.53	1.30	1.02	0.00
R&D/Lagged Total Assets	0.07	0.06	0.14	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	2.60	2.74	3.25	7.50	4.90	0.00
Working Capital	241.59	186.73	105.33	1.16	-240.43	0.00
Leverage	0.45	0.51	0.65	1.44	0.98	0.00
Kaplan & Zingales Index	-633.97	-393.98	-230.32	-28.59	605.38	0.00
Whited & Wu Index	-165.85	-117.06	-67.42	-6.54	159.30	0.00
Hadlock & Pierce Index	-3.77	-3.51	-3.05	-1.64	2.13	0.00
Hoberg & Maksimovic Index	-0.04	-0.02	0.01	0.05	0.08	0.00

This table shows the mean of each balance sheet item for firms that are Unconstrained or Current & Future constrained, conditioning on severity. Columns six and seven report the results of a t-test on equality of means between severe and unconstrained observations.

A.3 Details and Additional Results on the Transition Dynamics and Propensity Score Matching

A.3.1 Additional Transition Dynamic Tables

Appendix Tables D3 and D4 correspond to Table 6 in the main body and show transition probabilities by time horizon and severity, respectively.

Table D3: Transition Probabilities of Firms by Time Horizon of Constraint

	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	Current & Future at **t+1**
Unconstrained at **t**	84.1***	2.7***	9.2***	4.0***
	(0.00)	(0.00)	(0.00)	(0.00)
Current at **t**	27.9***	37.3***	18.8***	16.0***
	(0.00)	(0.00)	(0.00)	(0.00)
Future at **t**	12.0***	3.2***	75.3***	9.5***
	(0.00)	(0.00)	(0.00)	(0.00)
Current & Future at **t**	16.2***	8.5***	31.7***	43.5***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	81,066	81,066	81,066	81,066

The table reports average transition probabilities derived from a multinominal logit model of a firm's constraint status one period ahead. Unconstrained in t+1 is the base category. The unreported firm control variables are the log of total assets, and Tobin's Q. Coefficients indicate the probability that a firm in a specific constraint status transitions to another status in t+1, conditional on the covariates. Heteroskedasticity robust p-values are reported in parentheses. *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table D4: Transition Probabilities of Firms by Severity of Constraint

	Unconstrained at **t+1**	Mild at **t+1**	Moderate at **t+1**	Severe at **t+1**
Unconstrained at **t**	84.3***	4.0***	9.2***	2.6***
	(0.00)	(0.00)	(0.00)	(0.00)
Mild at **t**	14.1***	60.7***	21.4***	3.8***
	(0.00)	(0.00)	(0.00)	(0.00)
Moderate at **t**	13.8***	8.3***	70.7***	7.2***
	(0.00)	(0.00)	(0.00)	(0.00)
Severe at **t**	18.5***	3.7***	24.3***	53.6***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	81,066	81,066	81,066	81,066

The table reports average transition probabilities derived from a multinominal logit model of a firm's constraint status one period ahead. Unconstrained in t+1 is the base category. The unreported firm control variables are the log of total assets, and Tobin's Q. Coefficients indicate the probability that a firm in a specific constraint status transitions to another status in t+1, conditional on the covariates. Heteroskedasticity robust p-values are reported in parentheses. *, ** and *** denote statistical significance at the 1%, 5% and 10% levels, respectively.

A.3.2 Details and Robustness on the Propensity Score Matching

Our empirical strategy to generate Table 7 in Section 6 proceeds in two steps. First, for each origin status, we classify firms into four transition groups according to their destination status at time $t+1$, i.e. firms with $S_t \in \{\text{Unconstrained}, \text{Current}, \text{Future}, \text{Current \& Future}\}$ transition to $S_{t+1} \in \{\text{Unconstrained}, \text{Current}, \text{Future}, \text{Current \& Future}\}$. For each balance sheet variable, we then compute the raw mean change between t and $t+1$ within each transition group, providing a descriptive comparison of how firms on different paths evolve.

In the second step, we complement the raw differences with statistics derived using propensity score matching. Firms transitioning from $S_t = j$ into alternative statuses $S_{t+1} = i, i \in \neg j$ are matched with a set of firms that remain in the same state $S_{t+1} = j$, using a set of predetermined covariates to ensure comparability in observable characteristics. Propensity scores are estimated separately for each destination state i using a logit specification that contrasts firms transitioning from $S_t = j$ to $S_{t+1} = i$ with firms that remain in their original state ($S_{t+1} = j$):

$$\Pr(S_{t+1} = i \mid S_t = j, X_{i,t}) = \frac{\exp(X'_{i,t}\beta_{ij})}{1 + \exp(X'_{i,t}\beta_{ij})}.$$

The covariate vector $X_{i,t}$ consists of the predetermined balance sheet characteristics used for matching. The estimated propensity scores are used to form kernel-weighted averages of outcomes for firms that remain in $S_{t+1} = j$, thereby producing counterfactual outcomes against which the observed outcomes of transitioning firms ($S_{t+1} = i$) are compared. This yields average treatment effect on the treated (ATT) estimates for each transition path.

We estimate the ATTs, using a kernel matching procedure. Matched observations provide a close comparison group in terms of predetermined balance sheet variables which we document in detail below. We interpret outcomes in state $S_{t+1} = i$ relative to matched firms in the base category $S_{t+1} = j$ not as causal effects, but as covariate-adjusted differences that highlight which balance sheet movements (relative to $S_{t+1} = j$) systematically accompany a given transition path between firms that were initially similar but follow different trajectories. We indicate statistically significant positive (negative) differences relative to matched firms using superscript plus (minus) signs.

For each transition-base combination, we obtain propensity scores from a logit specification that includes a set of predetermined covariates chosen to ensure comparability across firms. In particular, we include the following time t control variables: log total assets, the cash-to-assets ratio, the leverage ratio, and Tobin's Q. These variables capture the firm's liquidity and debt position, overall size, and investment opportunities in the period prior to the transition. Additionally, the specification incorporates year and industry (SIC 1-digit) fixed effects, and indicators for the severity of the constraint status at time t, thereby purging aggregate, sectoral, and severity-specific sources of heterogeneity in transition probabilities. Together, these covariates allow the kernel matching estimator to construct counterfactual comparisons among firms that are similar in their financial structure, size, and economic environment.[44]

We assess the sensitivity of the matching results to several alternative specifications. First, we augment the baseline covariate set by including lags of the financing ratios, allowing the matching procedure to condition more flexibly on firms' recent financial histories. Second, we replace log total assets with log employment to verify that the findings do not depend on the particular proxy used for firm size. Third, we incorporate an alternative measure for borrowing, namely short- and long-term debt-to-asset ratios instead of leverage. Finally, we extend the covariate set to include both contemporaneous and lagged cash flow and return on assets, thereby controlling for recent profitability and operating shocks. Across all of these variations, the estimated effects shown in the main body remain similar in magnitude and sign, indicating that the observed adjustment patterns are not sensitive to the choice of matching specification. Results for the specification including cash flow and return on assets are shown in Appendix Table D5. Results on the other specifications are available upon request.

[44] Results are robust to using nearest-neighbor matching or local linear regression matching instead of kernel matching.

A.3.3 Balance Tests related to the the Propensity Score Matching

To evaluate the performance of the matching procedure we examine balance tables. Appendix Table D6 summarizes the covariate balance achieved after kernel matching. For each transition type, the table reports the mean of each covariate for treated firms, the corresponding kernel-weighted mean of the matched control group, and the resulting standardized mean difference (SMD).

A successful matching procedure should substantially reduce discrepancies between treated and control groups, aligning covariate distributions so that remaining differences are small in magnitude. Conventionally, absolute SMD values smaller than 0.1 are viewed as indicating very good balance, while absolute values between 0.1 and 0.25 are considered acceptable, and absolute values between 0.25 and 0.5 (indicated by * in the table) indicate considerable imbalance. As the table shows, kernel matching delivers close correspondence across most variables, bringing treated and control means into close alignment.

Additionally, we can see that beyond the variables explicitly targeted by the matching process, there is close correspondence of treated firms and their matched controls between a range of non-targeted balance sheet variables. This arises even though these variables do not enter the propensity score model, indicating that kernel matching implicitly balances related dimensions of firms' financial structure. In practice, this suggests that the covariates selected for matching capture underlying patterns strongly correlated with other financial characteristics, allowing the procedure to generate more comprehensive covariate alignment than what was specified by the matching procedure.

A.3.4 Additional Results on Balance Sheet Movements during Transitions

Appendix Table D7 shows balance sheet items for selected transitions of firms anticipating future constraints at time t. Importantly, these transition dynamics are differentiated by severity of constraints at t and show only selected outcome states at $t+1$ – Current and Current & Future are omitted to ease readability. The superscripts indicate statistical significance relative to the corresponding Future category of a particular constraint severity. Comparisons of significance across different levels of severity are not valid, since they use different control populations. The same holds for Appendix Table D8.

Appendix Table D7 documents that the constraint severity of firms remaining future constrained or transition to unconstrained correlates positively with $t+1$ levels of cash-to-asset ratios and leverage. For example for transitions to Future $t+1$, leverage increases from 0.45 (mild) and 0.54 (moderate) to 0.95 (severe) for future-constrained firms. The most severely constrained firms exhibit lower working capital and higher accounts payable and accruals relative to the corresponding mildly and moderately constrained firms.

Appendix Table D8 shows balance sheet items for selected transitions of currently constrained firms at time t. Transition dynamics are differentiated by constraint severity at t and the table shows selected outcome states at time $t+1$ – Unconstrained and Future are omitted to ease readability. Appendix Table D8 shows that remaining in one of the two states implying currently binding constraints results in higher $t+1$ levels of leverage, accruals and accounts payable and lower working capital as severity increases. For example, leverage increases from 0.53 (mild) and 0.78 (moderate) to 1.48 (severe) for Current & Future-constrained firms.

Table D5: Balance Sheet Movements for Firm Transitions by Time Horizon – Extended Specification Robustness Test

Variables at **t+1**	Unconstrained at **t**				Current at **t**			
	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	$-0.00^{\mathbf{b}}$	-0.02^{---}	-0.02^{---}	-0.02^{---}	0.02^{+++}	$-0.00^{\mathbf{b}}$	0.02^{+++}	-0.01
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.80)
Cash / Assets	$0.17^{\mathbf{b}}$	0.14^{---}	0.18^{-}	0.15^{---}	0.17^{++}	$0.17^{\mathbf{b}}$	0.23^{+++}	0.18
	-	(0.00)	(0.08)	(0.00)	(0.03)	-	(0.01)	(0.65)
$\Delta_{t,t+1}$ Leverage	$0.02^{\mathbf{b}}$	0.15^{+++}	0.04^{+++}	0.11^{+++}	-0.06^{---}	$0.28^{\mathbf{b}}$	-0.08^{---}	0.26
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.93)
Leverage	$0.44^{\mathbf{b}}$	0.73^{+++}	0.49^{+++}	0.61^{+++}	0.63^{---}	$1.50^{\mathbf{b}}$	0.71^{---}	1.28
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.90)
$\Delta_{t,t+1}$ Working Capital / Assets	$-0.01^{\mathbf{b}}$	-0.15^{---}	-0.03^{---}	-0.09^{---}	0.02^{+++}	$-0.23^{\mathbf{b}}$	0.03^{+++}	-0.21
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.82)
Working Capital / Assets	$0.26^{\mathbf{b}}$	-0.03^{---}	0.22^{---}	0.09^{---}	0.10^{+++}	$-0.73^{\mathbf{b}}$	0.09^{+++}	-0.51
	-	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.82)
$\Delta_{t,t+1}$ Accounts Payable / Assets	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{++}	0.01^{+++}	0.00^{--}	$0.04^{\mathbf{b}}$	0.00^{---}	0.03
	-	(0.00)	(0.04)	(0.00)	(0.05)	-	(0.00)	(0.24)
Accounts Payable / Assets	$0.07^{\mathbf{b}}$	0.12^{+++}	0.07	0.09^{+++}	0.10^{---}	$0.24^{\mathbf{b}}$	0.11^{---}	0.19^{--}
	-	(0.00)	(0.17)	(0.00)	(0.01)	-	(0.00)	(0.01)
$\Delta_{t,t+1}$ Accruals / Assets	$0.00^{\mathbf{b}}$	0.01^{+++}	0.00^{+++}	0.01^{+++}	0.01^{-}	$0.03^{\mathbf{b}}$	0.00^{---}	0.03
	-	(0.00)	(0.01)	(0.00)	(0.08)	-	(0.00)	(0.99)
Accruals / Assets	$0.06^{\mathbf{b}}$	0.09^{+++}	0.06	0.08^{+++}	0.09^{-}	$0.18^{\mathbf{b}}$	0.09^{---}	0.15
	-	(0.00)	(0.34)	(0.00)	(0.10)	-	(0.00)	(0.90)

Variables at **t+1**	Future at **t**				C & F at **t**			
	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**	Unconstrained at **t+1**	Current at **t+1**	Future at **t+1**	C & F at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	-0.00	-0.03^{---}	$-0.01^{\mathbf{b}}$	-0.03^{---}	0.01^{+++}	-0.00	0.01^{+++}	$-0.01^{\mathbf{b}}$
	(0.71)	(0.00)	-	(0.00)	(0.00)	(1.00)	(0.00)	-
Cash / Assets	0.20	0.20^{---}	$0.28^{\mathbf{b}}$	0.24^{---}	0.18^{++}	0.18	0.25^{+++}	$0.21^{\mathbf{b}}$
	(0.16)	(0.00)	-	(0.00)	(0.04)	(0.42)	(0.00)	-
$\Delta_{t,t+1}$ Leverage	0.01^{---}	0.22^{+++}	$0.04^{\mathbf{b}}$	0.13^{+++}	-0.03^{---}	0.22	0.02^{---}	$0.17^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.88)	(0.00)	-
Leverage	0.50^{---}	0.84^{+++}	$0.53^{\mathbf{b}}$	0.70^{+++}	0.57^{---}	1.17	0.62^{---}	$1.12^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.99)	(0.00)	-
$\Delta_{t,t+1}$ Working Capital / Assets	0.00^{+++}	-0.20^{---}	$-0.03^{\mathbf{b}}$	-0.11^{---}	0.03^{+++}	-0.16	-0.01^{+++}	$-0.13^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.29)	(0.00)	-
Working Capital / Assets	0.23^{++}	-0.12^{---}	$0.26^{\mathbf{b}}$	0.05^{---}	0.17^{+++}	-0.42	0.14^{+++}	$-0.31^{\mathbf{b}}$
	(0.03)	(0.00)	-	(0.00)	(0.00)	(0.66)	(0.00)	-
$\Delta_{t,t+1}$ Accounts Payable / Assets	0.00^{--}	0.03^{+++}	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{---}	0.02	0.00^{---}	$0.02^{\mathbf{b}}$
	(0.02)	(0.00)	-	(0.00)	(0.00)	(0.64)	(0.00)	-
Accounts Payable / Assets	0.07	0.14^{+++}	$0.07^{\mathbf{b}}$	0.10^{+++}	0.09^{---}	0.17^{-}	0.09^{---}	$0.17^{\mathbf{b}}$
	(0.29)	(0.00)	-	(0.00)	(0.00)	(0.10)	(0.00)	-
$\Delta_{t,t+1}$ Accruals / Assets	0.00^{---}	0.03^{+++}	$0.00^{\mathbf{b}}$	0.02^{+++}	0.00^{---}	0.03	0.01^{---}	$0.02^{\mathbf{b}}$
	(0.00)	(0.00)	-	(0.00)	(0.00)	(0.80)	(0.00)	-
Accruals / Assets	0.07	0.11^{+++}	$0.07^{\mathbf{b}}$	0.10^{+++}	0.08^{--}	0.14	0.09^{--}	$0.14^{\mathbf{b}}$
	(0.80)	(0.00)	-	(0.00)	(0.03)	(0.46)	(0.01)	-

The table reports the mean of balance sheet variables for transition paths between constraint states from t to t+1. Each mean corresponds to firms making the indicated transition. Superscripts '+' ('–') denote that the reported mean is significantly higher (lower) than that of the matched control firms in the base group, indicated by 'b'. These differences are the average treatment on the treated (ATT) estimates obtained via kernel propensity-score matching; +(-), ++(- -), +++(- - -) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. P-values are in parentheses. The matching covariates are log total assets, cash-to-assets, leverage, Tobin's Q, lagged and contemporaneous cashflow to assets, return on assets, 1-digit SIC industry, year, and severity fixed effects.

Table D6: Covariate Balance After Kernel Matching by Time Horizon

Panel A: Unconstrained at **t**	Current at **t+1**			Future at **t+1**			C & F at **t+1**		
Matching Variables	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD
Cash / Assets	0.1477	0.1661	-0.0967	0.1980	0.1895	0.0394	0.1785	0.1765	0.0097
Leverage	0.5824	0.4662	0.2063	0.4673	0.4269	0.1131	0.5099	0.4368	0.1639
Log Total Assets	4.4177	5.4546	-0.4208*	5.6296	5.8046	-0.0777	4.9763	5.6067	-0.2677*
Tobin's Q	3.2969	2.7102	0.1146	2.8593	2.6418	0.0608	2.8760	2.5581	0.0778
Additional Variables									
Working Capital / Assets	0.1024	0.2207	-0.2121	0.2357	0.2712	-0.0982	0.1908	0.2527	-0.1515
Accounts Payable / Assets	0.1041	0.0809	0.1965	0.0718	0.0723	-0.0057	0.0827	0.0759	0.0722
Accruals / Assets	0.0749	0.0672	0.0892	0.0625	0.0628	-0.0048	0.0679	0.0646	0.0503
Panel B: Current at t	**Unconstrained at t+1**			**Future at t+1**			**C & F at t+1**		
Matching Variables	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD
Cash / Assets	0.1443	0.1480	-0.0194	0.2075	0.2013	0.0251	0.1945	0.1866	0.0337
Leverage	0.7493	0.7322	0.0202	0.8551	0.8519	0.0030	1.1268	1.0710	0.0408
Log Total Assets	4.2506	4.2902	-0.0152	3.8769	3.9527	-0.0294	2.8350	3.0442	-0.0841
Tobin's Q	3.5766	3.2523	0.0526	4.7894	4.3817	0.0545	6.2904	5.7314	0.0579
Additional Variables									
Working Capital / Assets	-0.0659	-0.0566	-0.0113	-0.1152	-0.1380	0.0234	-0.3758	-0.3545	-0.0170
Accounts Payable / Assets	0.1143	0.1258	-0.0712	0.1289	0.1413	-0.0679	0.1683	0.1760	-0.0351
Accruals / Assets	0.0904	0.0862	0.0374	0.1024	0.1080	-0.0434	0.1226	0.1224	0.0010
Panel C: Future at t	**Unconstrained at t+1**			**Current at t+1**			**C & F at t+1**		
Matching Variables	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD
Cash / Assets	0.2028	0.2116	-0.0381	0.2251	0.2513	-0.1031	0.2626	0.2732	-0.0389
Leverage	0.4956	0.4868	0.0225	0.6490	0.5655	0.1069	0.6057	0.5327	0.1048
Log Total Assets	5.7889	5.7968	-0.0036	3.9027	4.5470	-0.2740*	4.6624	4.8267	-0.0724
Tobin's Q	2.8383	2.8614	-0.0062	4.2862	3.7557	0.0835	3.6373	3.4681	0.0328
Additional Variables									
Working Capital / Assets	0.2254	0.2290	-0.0103	0.0438	0.1547	-0.1403	0.1557	0.2106	-0.0856
Accounts Payable / Assets	0.0726	0.0731	-0.0061	0.1145	0.0913	0.1536	0.0871	0.0811	0.0509
Accruals / Assets	0.0652	0.0638	0.0237	0.0869	0.0796	0.0689	0.0795	0.0751	0.0478
Panel D: C & F at t	**Unconstrained at t+1**			**Current at t+1**			**Future at t+1**		
Matching Variables	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD	Treated	Matched Ctrl	SMD
Cash / Assets	0.1645	0.1633	0.0061	0.1785	0.1753	0.0144	0.2406	0.2402	0.0018
Leverage	0.6155	0.6334	-0.0299	1.0758	1.0297	0.0337	0.6574	0.6432	0.0183
Log Total Assets	5.0553	5.0845	-0.0116	3.0935	3.3538	-0.1074	4.6237	4.7358	-0.0447
Tobin's Q	2.8136	2.6694	0.0318	4.8228	4.4400	0.0546	3.7389	3.5361	0.0328
Additional Variables									
Working Capital / Assets	0.1086	0.0894	0.0375	-0.3449	-0.3005	-0.0351	0.0837	0.1129	-0.0411
Accounts Payable / Assets	0.0934	0.1005	-0.0617	0.1582	0.1609	-0.0132	0.0968	0.0980	-0.0086
Accruals / Assets	0.0793	0.0786	0.0080	0.1331	0.1308	0.0134	0.0870	0.0863	0.0067

The table reports treated means, kernel-weighted matched control means, and standardized mean differences (SMD). Thresholds: $*0.25 < |SMD| \leq 0.5$ (indicating some imbalance), $**0.5 < |SMD|$ (indicating problematic imbalance). Kernel balancing uses Epanechnikov kernels with bandwidth 0.06. Unreported variables are year, industry (SIC 1-digit) and severity fixed effects.

Table D7: Selected Balance Sheet Movements for Firm Transitions from Future

Variables at **t+1**	Future, Mild at **t**		Future, Moderate at **t**		Future, Severe at **t**	
	Unconstrained at **t+1**	Future at **t+1**	Unconstrained at **t+1**	Future at **t+1**	Unconstrained at **t+1**	Future at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	-0.00	-0.01$^{\mathbf{b}}$	0.00	-0.01$^{\mathbf{b}}$	0.01	-0.00$^{\mathbf{b}}$
	(0.71)	-	(0.70)	-	(0.75)	-
Cash / Assets	0.19	0.23$^{\mathbf{b}}$	0.20	0.30$^{\mathbf{b}}$	0.33	0.41$^{\mathbf{b}}$
	(0.14)	-	(0.25)	-	(0.60)	-
$\Delta_{t,t+1}$ Leverage	0.01	0.02$^{\mathbf{b}}$	0.01^{---}	0.04$^{\mathbf{b}}$	-0.13^{---}	0.16$^{\mathbf{b}}$
	(0.70)	-	(0.00)	-	(0.00)	-
Leverage	0.48	0.45$^{\mathbf{b}}$	0.51^{---}	0.54$^{\mathbf{b}}$	0.56^{---}	0.95$^{\mathbf{b}}$
	(0.72)	-	(0.00)	-	(0.00)	-
$\Delta_{t,t+1}$ Working Capital / Assets	-0.02	-0.03$^{\mathbf{b}}$	0.00^{+++}	-0.05$^{\mathbf{b}}$	-0.21	-0.34$^{\mathbf{b}}$
	(0.45)	-	(0.00)	-	(0.90)	-
Working Capital / Assets	0.24	0.28$^{\mathbf{b}}$	0.23^{++}	0.26$^{\mathbf{b}}$	0.24^{++}	-0.03$^{\mathbf{b}}$
	(0.61)	-	(0.02)	-	(0.03)	-
$\Delta_{t,t+1}$ Accounts Payable / Assets	0.00	0.00$^{\mathbf{b}}$	0.00^{---}	0.01$^{\mathbf{b}}$	0.05	0.07$^{\mathbf{b}}$
	(0.20)	-	(0.00)	-	(0.84)	-
Accounts Payable / Assets	0.07	0.07$^{\mathbf{b}}$	0.08	0.09$^{\mathbf{b}}$	0.17	0.26$^{\mathbf{b}}$
	(0.88)	-	(0.19)	-	(0.82)	-
$\Delta_{t,t+1}$ Accruals / Assets	0.00	0.00$^{\mathbf{b}}$	0.00^{---}	0.01$^{\mathbf{b}}$	-0.03^{--}	0.06$^{\mathbf{b}}$
	(0.63)	-	(0.00)	-	(0.02)	-
Accruals / Assets	0.07	0.07$^{\mathbf{b}}$	0.07	0.08$^{\mathbf{b}}$	0.09^{---}	0.22$^{\mathbf{b}}$
	(0.27)	-	(0.17)	-	(0.00)	-

The table reports the mean of balance sheet variables by firms' transition paths between states from t to t+1. Each mean corresponds to firms making the indicated transition. Superscripts '+' ('–') denote that the reported mean is significantly higher (lower) than that of the matched control firms in the base group, indicated by 'b'. These differences are ATT estimates obtained via kernel propensity-score matching; +(-), ++(- -), +++(- - -) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. P-values in parentheses. The matching covariates are log total assets, cash-to-assets, leverage, and Tobin's Q, with SIC 1-digit industry and year fixed effects.

Table D8: Selected Balance Sheet Movements for Firm Transitions from Current

Variables at **t+1**	Current, Mild at **t**		Current, Moderate at **t**		Current, Severe at **t**	
	Current at **t+1**	C & F at **t+1**	Current at **t+1**	C & F at **t+1**	Current at **t+1**	C & F at **t+1**
$\Delta_{t,t+1}$ Cash / Assets	-0.02$^{\mathbf{b}}$	-0.03	-0.00$^{\mathbf{b}}$	-0.01	-0.00$^{\mathbf{b}}$	-0.01
	-	(0.29)	-	(0.68)	-	(0.13)
Cash / Assets	0.25$^{\mathbf{b}}$	0.13	0.14$^{\mathbf{b}}$	0.16	0.17$^{\mathbf{b}}$	0.19
	-	(0.42)	-	(0.36)	-	(0.33)
$\Delta_{t,t+1}$ Leverage	0.02$^{\mathbf{b}}$	0.08^{+}	0.09$^{\mathbf{b}}$	0.15	0.32$^{\mathbf{b}}$	0.31
	-	(0.07)	-	(0.22)	-	(0.87)
Leverage	0.57$^{\mathbf{b}}$	0.53	0.73$^{\mathbf{b}}$	0.78	1.65$^{\mathbf{b}}$	1.48
	-	(0.57)	-	(0.38)	-	(0.92)
$\Delta_{t,t+1}$ Working Capital / Assets	-0.41$^{\mathbf{b}}$	-0.09	-0.61$^{\mathbf{b}}$	-0.09	-1.44$^{\mathbf{b}}$	-0.89
	-	(0.42)	-	(0.35)	-	(0.49)
Working Capital / Assets	0.11$^{\mathbf{b}}$	0.21	-0.04$^{\mathbf{b}}$	-0.04	-0.87$^{\mathbf{b}}$	-0.70
	-	(0.57)	-	(0.67)	-	(0.96)
$\Delta_{t,t+1}$ Accounts Payable / Assets	0.02$^{\mathbf{b}}$	0.00	0.04$^{\mathbf{b}}$	0.02	0.22$^{\mathbf{b}}$	0.19
	-	(0.32)	-	(0.80)	-	(0.12)
Accounts Payable / Assets	0.13$^{\mathbf{b}}$	0.13	0.18$^{\mathbf{b}}$	0.15	0.96$^{\mathbf{b}}$	0.54^{--}
	-	(0.43)	-	(0.90)	-	(0.01)
$\Delta_{t,t+1}$ Accruals / Assets	-0.00$^{\mathbf{b}}$	-0.00	0.06$^{\mathbf{b}}$	0.02	0.23$^{\mathbf{b}}$	0.19
	-	-	-	(0.68)	-	(0.34)
Accruals / Assets	0.06$^{\mathbf{b}}$	0.05	0.28$^{\mathbf{b}}$	0.13	0.78$^{\mathbf{b}}$	0.60
	-	(.)	-	(0.86)	-	(0.97)

The table reports the mean of balance sheet variables by firms' transition paths between states from t to t+1. Each mean corresponds to firms making the indicated transition. Superscripts '+' ('–') denote that the reported mean is significantly higher (lower) than that of the matched control firms in the base group, indicated by 'b'. These differences are ATT estimates obtained via kernel propensity-score matching; +(-), ++(- -), +++(- - -) indicate statistical significance at the 10%, 5%, and 1% levels, respectively. P-values in parentheses. The matching covariates are log total assets, cash-to-assets, leverage, and Tobin's Q, with SIC 1-digit industry and year fixed effects.

A.4 Constraint Spell Length

In extant research, a firm's constraint status is often a highly persistent firm characteristic as it is proxied by statistics such as size, age, or balance sheet composition which vary little through time (Whited and Wu (2006), Hadlock and Pierce (2010)). Farre-Mensa and Ljungqvist (2016) raise the concern that these constraint measures largely capture latent firm characteristics rather than binding financing constraints. To gain deeper insights into the transitional nature of financial constraints, we analyze constrained spells. We define a constrained spell as a sequence of consecutive years in which a firm is classified as constrained, bounded on either side by unconstrained observations or by the beginning or end of the sample.

Appendix Figure D1 shows the distribution of spell durations. The left hand side reports the distribution of all constrained spells of any time horizon. The modal spell length is one year, 55% of spells last at most two years, and the incidence of longer spells declines rapidly in with duration. Financial constraints are therefore often a transitory rather than permanent phenomenon. However, the long right tail highlights that a non-trivial subset of firms experience prolonged periods of financial constraints.

The right hand side of Appendix Figure D1 differentiates between spells of currently constrained (Current and Current & Future) and Future constrained firms. We observe similar distributions when differentiating by time horizon. However, Future is more right-skewed, indicating somewhat shorter spell length than the currently constrained firms.

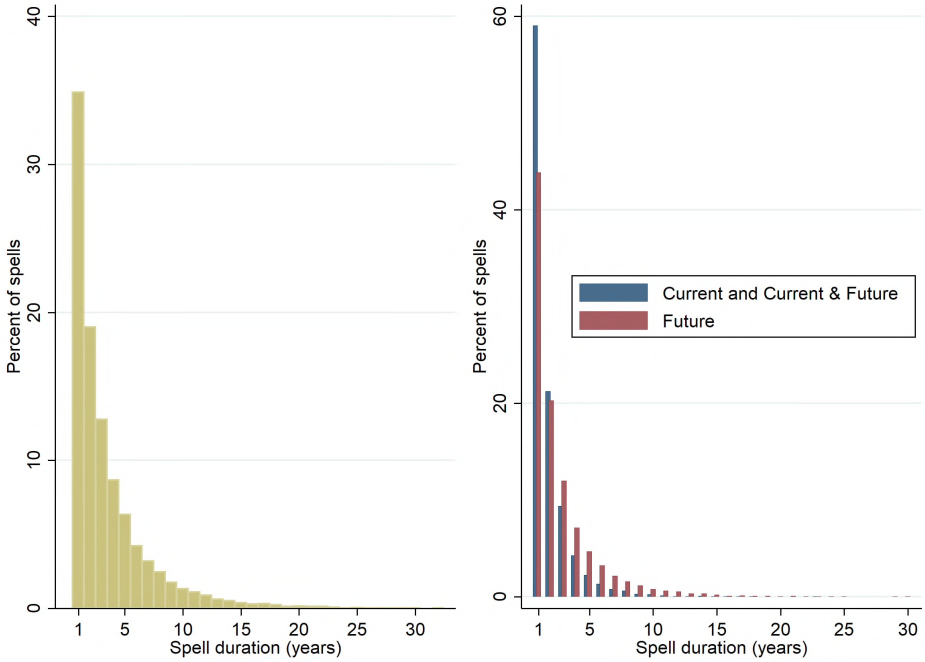

Figure D1: Spell duration distribution

The left panel plots the distribution of spell durations, where a spell is defined as a sequence of consecutive years in which a firm is financially constrained. The right panel differentiates by constraint time horizon. In this panel, spells are defined as sequences of consecutive years within the same constraint timing category: Current (or Current & Future) constraints and Future constraints. Durations are measured in years. Bars represent within-category percentages.

A.5 Cashflow Sensitivity of Cash: Robustness Tests

Following guidance in the literature, we conduct a battery of robustness checks on the cashflow sensitivity of cash results presented in Section 7. 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 time horizon of the financial constraints they face.

First, Appendix Table D9 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 substantially smaller and insignificant for unconstrained firms, those constrained at present, and those constrained at present and anticipating constraints in future.

Second, Appendix Tables D10 and D11 report estimates of equation (1) using standard

Table D9: Including Year Fixed Effects

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0082	-0.0010	0.0117***	0.0006
	(0.14)	(0.64)	(0.00)	(0.68)
Tobin's Q	0.0010	-0.0001	0.0016***	0.0013*
	(0.12)	(0.90)	(0.00)	(0.06)
Log Total Assets	-0.0043***	0.0067	0.0000	0.0056
	(0.00)	(0.40)	(0.99)	(0.24)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	37,876	2,931	25,810	6,338
R^2	0.13	0.28	0.16	0.28

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

errors clustered either by SIC-1-digit industry or by firm.[45] These alternative specifications do not alter the baseline result.

Table D10: Industry Clustered Standard Errors

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0068	-0.0006	0.0118**	0.0011
	(0.22)	(0.85)	(0.02)	(0.61)
Tobin's Q	0.0008	0.0002	0.0017***	0.0016***
	(0.17)	(0.85)	(0.01)	(0.01)
Log Total Assets	-0.0039***	0.0055	0.0007	0.0047
	(0.00)	(0.25)	(0.69)	(0.37)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,876	2,931	25,810	6,338
R^2	0.12	0.26	0.14	0.26

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. We cluster the standard errors at the 1-digit SIC industry level. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Third, Appendix Table D12 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 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,

[45]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 like SIC-2-digit and SIC-3-digit.

Table D11: Firm Clustered Standard Errors

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0068	-0.0006	0.0118***	0.0011
	(0.15)	(0.80)	(0.00)	(0.47)
Tobin's Q	0.0008	0.0002	0.0017***	0.0016***
	(0.14)	(0.74)	(0.00)	(0.01)
Log Total Assets	-0.0039***	0.0055	0.0007	0.0047
	(0.00)	(0.39)	(0.63)	(0.30)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,876	2,931	25,810	6,338
R^2	0.12	0.26	0.14	0.26

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. We cluster the standard errors at the firm level. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

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 flow exceeds 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 D12: Positive Free Cashflow Firms

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0069	-0.0006	0.0115***	0.0011
	(0.12)	(0.77)	(0.00)	(0.48)
Tobin's Q	0.0008	0.0002	0.0016***	0.0018***
	(0.12)	(0.83)	(0.00)	(0.01)
Log Total Assets	-0.0030**	0.0055	0.0022	0.0059
	(0.02)	(0.44)	(0.22)	(0.22)
Firm FE	Yes	Yes	Yes	Yes
Observations	34,354	2,690	22,810	5,483
R^2	0.13	0.26	0.15	0.26

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Fourth, Appendix Table D13 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 cashflow coefficient on future constrained firms remains positive and significant while the other cashflow coefficients are insignificant.

Table D13: Augmented Specification

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0076	-0.0026	0.0112***	0.0028
	(0.11)	(0.18)	(0.00)	(0.14)
Tobin's Q	0.0007	0.0005	0.0015***	0.0017**
	(0.20)	(0.45)	(0.00)	(0.01)
Log Total Assets	-0.0014	0.0102	0.0023	0.0087*
	(0.29)	(0.13)	(0.23)	(0.08)
Δ NWC	-0.0001***	-0.0001***	-0.0001***	-0.0000***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ Short Term Debt	-0.0000***	-0.0001**	-0.0000***	-0.0000
	(0.00)	(0.01)	(0.00)	(0.53)
CAPX	-0.0000***	-0.0001**	-0.0000***	-0.0001***
	(0.00)	(0.05)	(0.00)	(0.00)
Acquisitions	-0.0000***	-0.0000*	-0.0000***	-0.0000***
	(0.00)	(0.07)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	33,531	2,543	23,118	5,561
R^2	0.14	0.28	0.16	0.26

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. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Fifth, Almeida et al. (2004) 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 the twice lagged level of cash holdings and cashflow. Appendix Table D14 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 insignificant.

Since we identify information on constraint severity directly from the MD&A text, we can utilize this information for an additional robustness test on the role of constraint severity. We estimate a variant of equation (1), where we include additional dummy variables for the severity level of the constraint. Appendix Table D15 shows the corresponding estimation results are consistent with our baseline estimates.

Table D14: Cash Dynamics

	Unconstrained	**Constrained**		
Dependent variable: Δ Cash holdings		Current	Future	Current & Future
Cashflow	0.0059	-0.0030	0.0127***	0.0007
	(0.19)	(0.39)	(0.00)	(0.79)
Cashflow × $Cash_{t-2}$	-0.0000	0.0001	-0.0000*	-0.0000
	(0.34)	(0.26)	(0.08)	(0.85)
$Cash_{t-2}$	-0.0000**	0.0000	-0.0000	-0.0000**
	(0.05)	(0.20)	(0.85)	(0.05)
Tobin's Q	0.0014**	0.0000	0.0017***	0.0018**
	(0.02)	(0.96)	(0.00)	(0.02)
Log Total Assets	-0.0042***	0.0055	0.0016	0.0095*
	(0.00)	(0.50)	(0.39)	(0.06)
Firm FE	Yes	Yes	Yes	Yes
Observations	32,332	2,336	21,843	5,184
R^2	0.12	0.23	0.13	0.26

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. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Sixth, 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 diagnostic tool: comparing coefficient estimates from fixed-effects and first-difference models. Divergences in these estimates typically signal potential issues with the exogeneity assumption. We follow this intuition by estimating equation (1) with first-difference methods and reporting the outcomes in Appendix Table D16. Overall, the results from fixed-effects and first-difference estimations are consistent.

Seventh, 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. (2024). 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

Table D15: Severity Specification

Dep variable: Δ Cash holdings	Unconstrained	Constrained: Current	Constrained: Future	Constrained: Current & Future
Cashflow	0.0068	-0.0006	0.0115***	0.0011
	(0.11)	(0.78)	(0.00)	(0.50)
Tobin's Q	0.0008	0.0002	0.0016***	0.0015**
	(0.12)	(0.78)	(0.00)	(0.02)
Log Total Assets	-0.0039***	0.0049	0.0004	0.0023
	(0.00)	(0.48)	(0.80)	(0.60)
Moderate Severity		0.0039	0.0057**	0.0060
		(0.87)	(0.02)	(0.59)
Severe Severity		-0.0051	-0.0091	-0.0193
		(0.85)	(0.25)	(0.17)
Firm FE	Yes	Yes	Yes	Yes
Observations	37,876	2,931	25,810	6,338
R^2	0.12	0.26	0.14	0.26

This table reports estimates of equation (1) with additional controls for the severity of the constraint. Mild Severity is the base category. Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table D16: First Difference Specification

Dependent variable: Δ (Δ Cash holdings)	Unconstrained	Constrained: Current	Constrained: Future	Constrained: Current & Future
Δ Cashflow	-0.0024	-0.0000	0.0119***	0.0016
	(0.52)	(0.99)	(0.00)	(0.33)
Δ Tobin's Q	0.0015*	0.0007	0.0022***	0.0019**
	(0.08)	(0.49)	(0.00)	(0.02)
ΔLog Total Assets	0.0067	0.0304**	0.0303***	0.0446***
	(0.19)	(0.01)	(0.00)	(0.00)
Firm FE	No	No	No	No
Observations	33,229	3,410	22,941	6,630
R^2	0.00	0.00	0.01	0.01

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. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

also leverages lagged values of Tobin's Q to account for endogeneity and measurement error. The outcomes of these robustness checks are summarized in Appendix Tables D17 and D18. Across all specifications, we find consistent evidence that future-constrained firms exhibit significant cash flow sensitivities of cash. In contrast, the coefficients for unconstrained firms and firms constrained at present or at present and in the future remain statistically indistinguishable from zero. These findings suggest that our core results are not driven by biases due to measurement error in Tobin's Q.

Eighth, to address potential biases in our estimation strategy, we incorporate the methodological correction introduced by Welch (2021). Specifically, we estimate a dif-

Table D17: OLS-IV Model

	Unconstrained	Constrained		
Dep var: Δ(Δ Cash holdings)		Current	Future	Current & Future
Δ Cashflow	0.0392	0.0306	0.0303***	0.0669
	(0.22)	(0.57)	(0.01)	(0.64)
Δ Tobin's Q	0.0754	0.0236	0.0255*	0.1020
	(0.15)	(0.57)	(0.09)	(0.67)
Δ Log Total Assets	0.0537	0.0685	0.0655***	0.2916
	(0.18)	(0.32)	(0.00)	(0.61)
Firm FE	No	No	No	No
N	28,131	2,645	19,007	5,281

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. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table D18: Generalized Method of Moments Results

	Unconstrained	Constrained		
Dep var: Δ(Δ Cash holdings)		Current	Future	Current & Future
Δ Cashflow	-0.0044	-0.0004	0.0138***	0.0029
	(0.13)	(0.89)	(0.00)	(0.14)
Δ Tobin's Q	0.0025*	-0.0004	0.0048***	0.0041***
	(0.07)	(0.80)	(0.00)	(0.01)
Δ Log Total Assets	0.0091**	0.0144	0.0249***	0.0413***
	(0.05)	(0.21)	(0.00)	(0.00)
Firm FE	No	No	No	No
Observations	33,229	3,410	22,941	6,630

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.
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. Following Almeida et al. (2004), we use Huber-White robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

ferenced 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 changes of ratios, we follow Almeida et al. (2024) and adopt the ratios-of-changes approach to measure variations in both cash holdings and cash flow. Appendix Table D19 reveals consistent results with our baseline specification.

Table D19: Welch Correction

	Unconstrained	**Constrained**		
Dep var: RoC (Δ Cash/Assets)		Current	Future	Current & Future
RoC Cashflow	0.0689	0.0180	0.0720**	0.0038
	(0.36)	(0.12)	(0.02)	(0.38)
Δ Tobin's Q	0.0092	0.0037	0.0078***	0.0199**
	(0.12)	(0.59)	(0.00)	(0.02)
Δ Log Total Assets	0.1524**	0.5727**	0.3419***	0.0056
	(0.03)	(0.05)	(0.00)	(0.96)
Firm FE	No	No	No	No
Observations	33,366	3,514	23,147	6,787
R^2	0.04	0.04	0.09	0.01

This table reports estimates of equation (1) using the Welch correction. RoC (Δ Cash/Assets) is defined as the first difference of cash minus the lagged first difference of cash scaled by current assets. RoC Cashflow denotes the first difference of cashflow scaled by current assets. Following Almeida et al. (2004), we use robust standard errors. P-values are reported in parentheses. *, ** and *** reflect statistical significance levels at the 10%, 5% and 1% level, respectively.

A.6 Cash Flow Sensitivity, Constraint Status and Balance Sheet Items

We estimate equation (1), replacing the dependent variable with several balance sheet items, using subsamples. Appendix Table D20 reports results for a data set restricted to firm-year observations classified as currently constrained, while Appendix Table D21 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-term debt, accounts payable and accrued expenses. They do not use additional cashflow to increase dividend payments. A qualitatively similar picture emerges in the case of firms constrained at present and in future, although these also reduce long-term debt.

Table D20: Currently Constrained Firms: Cash Flow Sensitivity of Various Balance Sheet Items

	$\Delta\frac{\text{Liabilities}}{\text{Assets}}$	$\Delta\frac{\text{ST Debt}}{\text{Assets}}$	$\Delta\frac{\text{LT Debt}}{\text{Assets}}$	$\Delta\frac{\text{Acc. Pay.}}{\text{Assets}}$	$\Delta\frac{\text{Acr. Exp.}}{\text{Assets}}$	$\Delta\frac{\text{WC}}{\text{Assets}}$	$\Delta\frac{\text{Dividends}}{\text{Assets}}$
Cashflow	-0.2842***	-0.0913***	-0.0083	-0.0166***	-0.0126***	0.1024***	-0.0014
	(0.01)	(0.01)	(0.15)	(0.00)	(0.00)	(0.00)	(0.12)
Tobin's Q	0.0842***	0.0335***	-0.0007	-0.0008	-0.0009	0.0015	-0.0003
	(0.00)	(0.00)	(0.76)	(0.29)	(0.22)	(0.66)	(0.60)
Log Total Assets	-0.4958***	-0.2882***	-0.0824***	-0.0217***	-0.0283***	0.1558***	-0.0090*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,888	2,991	2,976	2,679	1,989	2,427	3,034
R^2	0.53	0.46	0.29	0.43	0.46	0.53	0.24

The table reports estimates of $\Delta Y_{i,t} = \alpha + \beta X_{i,t-1} + \varphi_i + \varepsilon_{i,t}$, where $\Delta Y_{i,t}$ is the annual change in an outcome, Y; $X_{i,t-1}$ is a vector of control variables; φ_i denotes firm fixed effects; $\varepsilon_{i,t}$ is the error term. Acc. Pay. denotes Accounts Payables, Acr. Exp. is Accrued Expenses, WC stands for Working Capital, ST Debt represents short term-debt and LT Debt indicates long-term debt. The sample includes only the firm-year observations where an MD&A document is classified as constrained in the current period. Heteroskedasticity robust p-values are in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

Table D21: Current & Future Constrained Firms: Cash Flow Sensitivity of Various Balance Sheet Items

	$\Delta\frac{\text{Liabilities}}{\text{Assets}}$	$\Delta\frac{\text{ST Debt}}{\text{Assets}}$	$\Delta\frac{\text{LT Debt}}{\text{Assets}}$	$\Delta\frac{\text{Acc. Pay.}}{\text{Assets}}$	$\Delta\frac{\text{Acr. Exp.}}{\text{Assets}}$	$\Delta\frac{\text{WC}}{\text{Assets}}$	$\Delta\frac{\text{Dividends}}{\text{Assets}}$
Cashflow	-0.3966***	-0.0806***	-0.0117**	-0.0094***	-0.0079***	0.0951***	-0.0005
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.69)
Tobin's Q	0.0592***	0.0243***	-0.0011	-0.0002	-0.0000	0.0023	0.0001
	(0.00)	(0.00)	(0.59)	(0.67)	(0.98)	(0.41)	(0.90)
Log Total Assets	-0.2428***	-0.1202***	-0.0259**	-0.0185***	-0.0190***	0.0879***	-0.0038
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.21)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,228	6,372	6,363	6,082	4,692	5,597	6,460
R^2	0.59	0.39	0.30	0.41	0.44	0.49	0.24

The table reports estimates of $\Delta Y_{i,t} = \alpha + \beta X_{i,t-1} + \varphi_i + \varepsilon_{i,t}$, where $\Delta Y_{i,t}$ is the annual change in an outcome, Y; $X_{i,t-1}$ is a vector of control variables; φ_i denotes firm fixed effects; $\varepsilon_{i,t}$ is the error term. Acc. Pay. denotes Accounts Payables, Acr. Exp. is Accrued Expenses, WC stands for Working Capital, ST Debt represents short term-debt and LT Debt indicates long-term debt. The sample includes only the firm-year observations where an MD&A document is classified as constrained both currently and in future. Heteroskedasticity robust p-values are in parentheses. *, ** and *** reflect significance levels at 10%, 5% and 1% respectively.

A.7 Liability Growth and Cashflow: Robustness

This section provides robustness tests on the relation between liability growth and cashflow shown in Table 9 in the main body.

Appendix Tables D22 to D26 show the results reported in the main body are robust to using industry or firm clustered standard errors, including firm and year fixed effects, adding additional control variables, and accounting for the severity of constraints. In all these specifications, currently constrained observations (Current, and Current & Future) have a significant negative coefficient estimate while the relation between liability growth and cashflow is insignificant for unconstrained observations.

Appendix Table D27 further 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 cashflow and depreciation. This sample restriction addresses the concern that the observed negative sensitivity of liability growth to cashflow could be the result of a mechanical relationship. Specifically, that firms are simply forced to increase liabilities when operating income falls short of covering investment needs. In such cases, cash flows may appear to drive liabilities because the firm must finance a shortfall. However, because investment levels are partly discretionary, a more telling test is to isolate cases where cash flows exceed non-discretionary investment requirements. We use depreciation as a proxy for such required investment outlays, thereby eliminating the possibility that the sensitivity is driven by financing deficits rather than intentional deleveraging behavior. Our conclusions based on this restricted sample remain robust: currently constrained firms display a negative and significant sensitivity of liability growth to cashflow while unconstrained firms do not.

Table D22: Industry Clustered Standard Errors

	Unconstrained	**Constrained**		
Dependent variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0174	-0.0240***	-0.0130	-0.0114**
	(0.53)	(0.00)	(0.54)	(0.02)
Tobin's Q	0.0112***	0.0054***	0.0100***	0.0063***
	(0.00)	(0.01)	(0.00)	(0.00)
Log Total Assets	0.0887***	0.1554***	0.0983***	0.1328***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	38,349	3,154	26,332	6,638
R^2	0.20	0.34	0.20	0.34

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. Standard errors are clustered at the SIC-1-digit level. P-values are reported in parentheses. *, ** and *** reflect statistical significance at the 10%, 5% and 1% level, respectively.

A.8 Further Validation Exercises

A.8.1 Farre-Mensa Ljungqvist: Robustness Test

Appendix Table D28 shows results for the debt test proposed by Farre-Mensa and Ljungqvist (2016) are robust to including firm and industry-by-year fixed effects. The results of the specification are consistent with the baseline results shown in the main

Table D23: Firm Clustered Standard Errors

	Unconstrained	Constrained		
Dependent variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0174	-0.0240***	-0.0130	-0.0114**
	(0.33)	(0.00)	(0.28)	(0.04)
Tobin's Q	0.0112***	0.0054**	0.0100***	0.0063***
	(0.00)	(0.03)	(0.00)	(0.00)
Log Total Assets	0.0887***	0.1554***	0.0983***	0.1328***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	38,349	3,154	26,332	6,638
R^2	0.20	0.34	0.20	0.34

This table reports estimates of equation (1). Cashflow denotes the ratio of cashflow to assets. Standard errors are clustered at the firm level. P-values are reported in parentheses. *, ** and *** reflect statistical significance at the 10%, 5% and 1% level, respectively.

Table D24: Including Year Fixed Effects

	Unconstrained	Constrained		
Dependent variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0389	-0.0232***	-0.0261	-0.0122***
	(0.12)	(0.00)	(0.25)	(0.00)
Tobin's Q	0.0081***	0.0054***	0.0068***	0.0058***
	(0.00)	(0.00)	(0.00)	(0.00)
Log Total Assets	0.1334***	0.1514***	0.1363***	0.1298***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	38,349	3,154	26,332	6,638
R^2	0.22	0.35	0.23	0.35

This table reports estimates of equation (1) including year fixed. Cashflow denotes the ratio of cashflow to assets. Standard errors are clustered at the SIC-1-digit level. P-values are reported in parentheses. *, ** and *** reflect statistical significance at the 10%, 5% and 1% level, respectively.

Table D25: Augmented Specification

	Unconstrained	Constrained		
Dependent variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0062	-0.0139**	-0.0150	-0.0188***
	(0.70)	(0.01)	(0.14)	(0.00)
Tobin's Q	0.0115***	0.0055**	0.0099***	0.0060***
	(0.00)	(0.03)	(0.00)	(0.00)
Log Total Assets	0.0759***	0.1152***	0.0944***	0.1179***
	(0.00)	(0.00)	(0.00)	(0.00)
Δ NWC	-0.0000***	-0.0002**	-0.0001***	-0.0001**
	(0.00)	(0.03)	(0.00)	(0.04)
CAPX	-0.0000***	0.0006**	-0.0000**	-0.0000
	(0.00)	(0.02)	(0.01)	(0.83)
Acquisitions	0.0002***	0.0003***	0.0002***	0.0002***
	(0.00)	(0.01)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	33,811	2,621	23,412	5,710
R^2	0.23	0.35	0.23	0.35

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. Following Almeida et al. (2004), we use robust standard errors and firm fixed effects. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table D26: Severity Specification

	Unconstrained	Constrained		
Dep variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0174	-0.0241***	-0.0143	-0.0114**
	(0.28)	(0.00)	(0.20)	(0.04)
Tobin's Q	0.0112***	0.0055**	0.0098***	0.0063***
	(0.00)	(0.03)	(0.00)	(0.00)
Log Total Assets	0.0887***	0.1582***	0.0967***	0.1334***
	(0.00)	(0.00)	(0.00)	(0.00)
Moderate Severity		-0.1340	-0.0077	-0.0351
		(0.11)	(0.40)	(0.48)
Severe Severity		-0.0883	-0.0595**	-0.0275
		(0.33)	(0.04)	(0.62)
Firm FE	Yes	Yes	Yes	Yes
Observations	38,349	3,154	26,332	6,638
R^2	0.20	0.34	0.20	0.34

This table reports estimates of equation (1) with additional controls for the severity of the constraint. Mild Severity is the base category. Following Almeida et al. (2004), we use robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table D27: Positive Free Cashflow Firms

	Unconstrained	Constrained		
Dependent variable: Δ Log Total Liab		Current	Future	Current & Future
Cashflow	-0.0173	-0.0237***	-0.0127	-0.0111**
	(0.29)	(0.00)	(0.26)	(0.04)
Tobin's Q	0.0105***	0.0058**	0.0097***	0.0059***
	(0.00)	(0.02)	(0.00)	(0.00)
Log Total Assets	0.0832***	0.1577***	0.0966***	0.1308***
	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Observations	34,776	2,912	23,272	5,772
R^2	0.21	0.34	0.21	0.34

This table reports estimates of equation (1) restricted to a subset of firms with positive free cashflow. Cashflow denotes the ratio of cashflow to assets. Following Almeida et al. (2004), we use robust standard errors. P-values are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

body for unconstrained firms, with the estimated coefficient being very close to the effect estimated in the baseline specification. Current and Current & Future constrained firms show no statistically significant tendency to increase debt in response to a tax hike. The coefficient for future constrained firms is marginally significant at the 10% level, but the estimated coefficient is negative. Firms anticipating future constraints are in an ambiguous situation with respect to tax increases. On then one hand, tax increases raise the value of debt as a tax shield, while on the other hand it might signal reduced future profits and cashflow which might make debt less sustainable in the long run. As a response firms anticipating future constraints might plausibly try and reduce their long term liabilities in response to a tax hike.

Table D28: Farre-Mensa and Ljungqvist Debt Test: Firm fixed effects

	Unconstrained	Constraints Timing		
Dep var: Δ Long-Term Debt/Total Assets		Current	Future	Current & Future
T_{t-1}^{+}	0.0071*	0.0971	-0.0199*	0.0498
	(0.08)	(0.25)	(0.10)	(0.70)
Δ ROA_{t-1}	-0.0058	-0.0289	0.0102	-0.0248
	(0.35)	(0.53)	(0.14)	(0.27)
Δ $Tangibility_{t-1}$	-0.0395	-0.5769	-0.0294	-0.2540
	(0.15)	(0.33)	(0.52)	(0.36)
Δ Log Total $Assets_{t-1}$	-0.0142	-0.1717*	0.0037	-0.1019**
	(0.24)	(0.10)	(0.70)	(0.02)
Δ Investment $Opportunities_{t-1}$	-0.0060	-0.0022	-0.0004	-0.0078*
	(0.24)	(0.52)	(0.67)	(0.06)
Firm FE	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes
Observations	17,420	312	9,523	1,039
R^2	0.33	0.72	0.34	0.58

The table shows estimates of equation (2) including firm fixed effects. The sample is restricted to firms headquartered in US states that increase the state corporate tax rate during the sample period and adjacent states where state corporate tax rates do not change. Standard errors are clustered at the state level. P-values are reported in parentheses. *, ** and *** reflect statistical significance at the 10%, 5% and 1% level, respectively.

Appendix Table D29 shows results for the equity recycling test 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 findings shown in the main body.

Table D29: Farre-Mensa and Ljungqvist Equity Recycling Test: Firm & Industry-Year fixed effects

Dependent variable:	Unconstrained	Constraints Timing		
Δ Total Dividends and Share Repurchases/Total Assets		Current	Future	Current & Future
Δ Equity issuance proceeds	0.0013**	-0.0122	0.0004***	-0.0000
	(0.04)	(0.84)	(0.00)	(1.00)
Δ Other Sources of Funds	0.1076***	0.1594	0.0229**	0.0002
	(0.00)	(0.59)	(0.02)	(0.72)
Δ Log Total Assets	-0.1251***	-0.9162	-0.0593***	-0.0220
	(0.00)	(0.34)	(0.00)	(0.60)
Constant	0.0141***	0.1028	0.0077***	0.0154***
	(0.00)	(0.51)	(0.00)	(0.00)
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Observations	10,161	35	6,703	384
R^2	0.323	0.764	0.379	0.588

The table reports estimates of (3) including firm fixed effects. Standard errors clustered at the firm level. P-values are reported in parentheses. *, ** and *** reflect statistical significance at the 10%, 5% and 1% level, respectively.

A.8.2 Relation to Existing Constraint Proxies

In this section, we deepen the comparison to Hoberg and Maksimovic (2015). We continue to calculate statistics 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 (59,354 firm-year observations) to ensure direct comparability. Since they estimate a continuous proxy, we map their score into our discrete severity categories using two different methods. Scheme one sorts 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, scheme two sorts firms according to their score, classifying them based on the distribution in our restricted sample (46.32% unconstrained, 12.48% mild, 31.17% moderate, 10.03% severe).

Appendix Table D30 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 there is 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 scheme one equal-weighting approach implies that constrained firms have larger total assets relative to their unconstrained counterparts. A similar pattern appears using scheme two, where only severely constrained firms have substantially 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 of constrained firms is, for both the Hoberg and Maksimovic (2015) and our measures, lower than for their unconstrained counterparts. Yet our classification indicates a strict decline with increasing severity, which is not the case in Hoberg and Maksimovic (2015) scheme one, and a substantially steeper decline for severely constrained firms. Previously, in Section 5, we noted the inverse-U relation between cash holdings and constraint severity. Our discussion in Section 5 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, schemes one and two 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. Hoberg and Maksimovic (2015) apply a scheme where they split all firms into terciles. The findings of the discussion above are robust also to this scheme and we report results in Appendix Table D31.

A.8.3 External Validity

The top panel in Appendix Table D32 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, 41.3% of technology companies are unconstrained compared to 33.1% amid the dot-com recession. Moreover, among constrained firms the share of moderately (severely) constrained firms rises substantially during the crisis, from 53.4% (20.0%) to 57.6% (24.5%). We uncover similar patterns of results for all sectors during the dot-com recession, financial crisis and first Covid-19 lockdown period in the remainder of Appendix Table D32. In both recessions, the share of constrained firms rises and constraints become more severe.

Table D30: 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	
	46.32%	*12.48%*	*31.17%*	*10.03%*	Difference	P-Value
Total Assets	2,474.55	1,604.93	1,429.69	264.36	-2,210.19	0.00
Firm Age	18.10	13.10	12.31	10.59	-7.51	0.00
Cash/Lagged Total Assets	0.21	0.28	0.30	0.21	0.00	0.86
Cashflow/Lagged Total Assets	0.03	-0.01	-0.24	-1.64	-1.68	0.00
Total Debt/Lagged Total Assets	0.26	0.26	0.43	1.10	0.85	0.00
R&D/Lagged Total Assets	0.07	0.11	0.18	0.31	0.23	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.00	0.00	-0.01	0.00
Tobin's Q	2.58	2.98	3.42	7.21	4.63	0.00
Working Capital	209.58	174.58	124.58	7.55	-202.02	0.00
Leverage	0.41	0.39	0.53	1.26	0.85	0.00
Kaplan & Zingales Index	-357.77	-272.08	-205.67	-36.79	320.98	0.00
Whited & Wu Index	-98.37	-64.38	-53.62	-10.67	87.70	0.00
Hadlock & Pierce Index	-3.63	-3.41	-3.15	-1.79	1.84	0.00
Hoberg & Maksimovic Index	-0.04	0.00	0.03	0.04	0.07	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	1,590.52	1,833.43	2,053.53	1,809.60	219.08	0.11
Firm Age	17.57	15.66	14.80	11.65	-5.92	0.00
Cash/Lagged Total Assets	0.19	0.22	0.25	0.34	0.14	0.00
Cashflow/Lagged Total Assets	-0.06	-0.12	-0.19	-0.51	-0.45	0.00
Total Debt/Lagged Total Assets	0.31	0.37	0.41	0.48	0.17	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	2.61	3.03	3.32	4.40	1.79	0.00
Working Capital	174.96	163.04	163.22	133.43	-41.53	0.00
Leverage	0.47	0.50	0.54	0.59	0.11	0.00
Kaplan & Zingales Index	-237.11	-275.04	-301.13	-264.63	-27.51	0.22
Whited & Wu Index	-64.34	-71.28	-80.80	-73.71	-9.37	0.09
Hadlock & Pierce Index	-3.49	-3.34	-3.29	-2.96	0.53	0.00
Hoberg & Maksimovic Index	-0.12	-0.04	0.02	0.12	0.24	0.00

Restricted Data Set	Hoberg & Maksimovic (Scheme 2)					
	Unconstrained	Mild	Moderate	Severe	Severe - Unconstrained	
	46.32%	*12.48%*	*31.17%*	*10.03%*	Difference	P-Value
Total Assets	1,716.88	1,698.75	2,223.43	1,207.55	-509.34	0.00
Firm Age	16.75	15.28	13.79	9.54	-7.21	0.00
Cash/Lagged Total Assets	0.20	0.23	0.27	0.40	0.20	0.00
Cashflow/Lagged Total Assets	-0.09	-0.14	-0.27	-0.78	-0.69	0.00
Total Debt/Lagged Total Assets	0.34	0.37	0.44	0.52	0.18	0.00
R&D/Lagged Total Assets	0.09	0.11	0.15	0.30	0.21	0.00
Dividends/Lagged Total Assets	0.01	0.01	0.01	0.00	0.00	0.00
Tobin's Q	2.81	3.08	3.61	5.27	2.46	0.00
Working Capital	170.32	158.99	158.91	103.97	-66.35	0.00
Leverage	0.48	0.52	0.56	0.62	0.13	0.00
Kaplan & Zingales Index	-255.94	-252.74	-319.26	-196.95	58.99	0.01
Whited & Wu Index	-67.89	-68.29	-87.67	-50.23	17.66	0.00
Hadlock & Pierce Index	-3.42	-3.33	-3.20	-2.68	0.74	0.00
Hoberg & Maksimovic Index	-0.09	-0.01	0.06	0.18	0.26	0.00

The table reports the mean of balance sheet variables and continuous financial constraints measures. Columns two to five report values for unconstrained, mild, moderate, and severe constraints. Columns six and seven report the results of t-tests on the equality of means between severe and unconstrained observations. Difference is the difference in means. P-value is the p-value from the t-test. Throughout the table, we use a restricted data set containing only observations used in Hoberg and Maksimovic (2015). It comprises 59,354 firm-year observations.

Table D31: Comparison of Firm Characteristics by Constraint Severity: Hoberg & Maksimovic Alternative Measure

Restricted Data Set	Low Constraints	Medium Constraints	High Constraints	High - Low Constraints Difference	P-Value
Total Assets	1637.05	1836.25	1992.99	355.94	0.01
Firm Age	17.20	15.27	12.29	-4.91	0.00
Cash/Lagged Total Assets	0.20	0.23	0.32	0.12	0.00
Cashflow/Lagged Total Assets	-0.07	-0.15	-0.44	-0.37	0.00
Total Debt/Lagged Total Assets	0.32	0.38	0.46	0.14	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	2.70	3.13	4.19	1.50	0.00
Working Capital	173.11	162.91	139.97	-33.15	0.00
Leverage	0.48	0.52	0.58	0.10	0.00
Kaplan & Zingales Index	-238.85	-282.44	-287.49	-48.64	0.02
Whited & Wu Index	-65.86	-71.85	-80.22	-14.36	0.01
Hadlock & Pierce Index	-3.46	-3.32	-3.03	0.43	0.00
Hoberg & Maksimovic Index	-0.10	-0.01	0.10	0.21	0.00

The table reports the mean of balance sheet variables and continuous financial constraints measures. Columns two to four report values for low, medium and high constraint observations. Columns five and six report the results of t-tests on the equality of means between high and low constraints observations. Difference is the difference in means. P-value is the p-value from the t-test. Throughout the table, we use a restricted data set containing only observations used in Hoberg and Maksimovic (2015). It comprises 59,354 firm-year observations. 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 D32: Financial Constraints during Recessionary Periods

Dot Com Crash								
Information Technology	Non-Recessionary			Dot Com Recession			Column 5 − Column 2	
	Obs.	%	% Constr.	Obs.	%	% Constr.	Δ	P-value
Unconstrained	5,428	41.28		623	33.07		-8.22	0.00
Mild	2,049	15.58	26.54	226	12.00	17.92	-3.59	0.00
Moderate	4,124	31.37	53.42	726	38.54	57.57	7.17	0.00
Severe	1,547	11.77	20.04	309	16.40	24.50	4.64	0.00
All Sectors	Non-Recessionary			Dot Com Recession			Column 5 − Column 2	
	Obs.	%	% Constr.	Obs.	%	% Constr.	Δ	P-value
Unconstrained	40,744	48.94		4,273	45.22		-3.72	0.00
Mild	10,210	12.26	24.02	999	10.57	19.30	-1.69	0.00
Moderate	23,632	28.39	55.60	3,081	32.61	59.52	4.22	0.00
Severe	8,663	10.41	20.38	1,096	11.60	21.17	1.19	0.00

Financial Crisis								
All Sectors	Non-Recessionary			Financial Crisis			Column 5 − Column 2	
	Obs.	%	% Constr.	Obs.	%	% Constr.	Δ	P-value
Unconstrained	40,744	48.94		1,972	40.71		-8.23	0.00
Mild	10,210	12.26	24.02	576	11.89	20.06	-0.37	0.44
Moderate	23,632	28.39	55.60	1,627	33.59	56.65	5.20	0.00
Severe	8,663	10.41	20.38	669	13.81	23.29	3.40	0.00

Covid-19 Pandemic								
All Sectors	Non-Recessionary			Covid-19			Column 5 − Column 2	
	Obs.	%	% Constr.	Obs.	%	% Constr.	Δ	P-value
Unconstrained	40,744	48.94		2,378	44.18		-4.77	0.00
Mild	10,210	12.26	24.02	573	10.64	19.07	-1.62	0.00
Moderate	23,632	28.39	55.60	1,579	29.33	52.55	0.95	0.14
Severe	8,663	10.41	20.38	853	15.85	28.39	5.44	0.00

The table shows the number and share of firm-year observations falling into one of three recessions and non-recessionary periods. 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). Information Technology sectors are SIC 4810-4899 and 7370-7377. A firm-year observation is classified as belonging to a recession if at least 50% of its financial year falls within the recession. The exception is 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. Δ is the difference between the percentage values in columns five and two. The P-value is from a t-test where the null hypothesis is that Δ equals zero.