Are Financial Constraints Priced? Evidence from Textual Analysis

Matthias M. M. Buehlmaier
Toni M. Whited*

First version: August 15, 2014
This revision: November 5, 2017

Abstract

We construct novel measures of financial constraints using textual analysis of firms' annual reports and investigate their impact on stock returns. Our three measures capture access to equity markets, debt markets, and external financial markets in general. In all cases, constrained firms earn higher returns, which move together and cannot be explained by the Fama and French (2015) factor model. A trading strategy based on financial constraints is most profitable for large, liquid stocks. Our results are strongest when we consider debt constraints. A portfolio based on this measure earns an annualized risk-adjusted excess return of 6.5%.

Keywords: Financial constraints, textual analysis, market efficiency.

JEL Codes: G14, G32

*Buehlmaier is at the Faculty of Business and Economics, The University of Hong Kong, Pokfulam Road, Hong Kong; telephone: +852 2219 4177, E-Mail: buehl@hku.hk. Whited is at the Ross School of Business, University of Michigan, 701 Tappan St., Ann Arbor, MI 48109; telephone: +1 734 764 1269, E-Mail: twhited@umich.edu, and the NBER. The authors thank two anonymous referees, Andrew Karolyi (the editor), John Campbell, Gerard Hoberg, Jonathan Kalodimos, Kewei Hou, Tim Loughran, Bill McDonald, Alexandra Niessen-Ruenzi (EFA discussant), Tao Shu (WFA discussant), Lu Zhang, and participants at the 2014 EFA and 2015 WFA conferences for valuable suggestions. The authors thank members of the research seminars at Technical University of Munich, University of Hong Kong, and University of Mannheim for valuable suggestions. The research assistance of Yunhao He, Ka Wai Huang, Cheuk Yin Lau, Zhaoying Lu, Ni Ma, Jiyuan Qian, Shan Tang, Cong Shen, Yilei Wu, Ruiyi Xu, and Ke Zhai is greatly appreciated. The work described in this paper was substantially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (project no. HKU 741311B). This paper previously circulated under the title, "Looking for Risk in Words: A Narrative Approach to Measuring the Pricing Implications of Financial Constraints"

Financial constraints arise from frictions such as information asymmetries that make external funds more costly than internal funds, sometimes prohibitively so. Although financial constraints are easy to understand on this conceptual level, it remains an empirical challenge to *quantify* them and to thus understand their implications. As pointed out by Farre-Mensa and Ljungqvist (2016), many popular measures based on accounting data are likely flawed. We contribute to the literature on measuring and understanding financial constraints by developing a novel measure of financial constraints based on textual analysis. We then revisit the question posed by Lamont, Polk, and Saá-Requejo (2001) and Whited and Wu (2006) of whether financial constraints affect stock returns.

Textual analysis looks for evidence of financial constraints where they are *directly* discussed—in firms' annual reports. In intuitive terms, the process proceeds in three stages. First, we isolate training samples, that is, firm-years in which a firm appears to be either financially constrained or financially unconstrained. Second, we use these training samples to estimate the probability that a firm is financially constrained as a function of the words in the annual report. Third, we use this fitted probability model to predict the financial constraints status for the whole sample.

Because financial constraints are not unidimensional, that is, because a company might face constraints when securing one type of external finance but not another, we employ three different training samples and thus three different measures of financial constraints. The first measure is based on a training sample constructed from manual searches of news articles that feature financially constrained firms. Thus, it captures financial constraints in a general way, without being specific about the source of the constraints. In contrast, the second and third measures capture specific sources of financing frictions. Following and extending Hoberg and Maksimovic (2015), we construct two additional constraints indices that measure financial frictions that interfere with issuing either debt or equity.

We find that all three of our financial constraints measures do a good job of capturing the firm characteristics that are typically associated with financial constraints. For example, constrained firms are small, have low cash flow, and pay out fewer dividends. Moreover, our measures appear to capture characteristics that differ from those captured by the widely used measures from Lamont, Polk, and Saá-Requejo (2001) and Whited and Wu (2006). These results make sense, inasmuch as textual analysis is fundamentally different from other approaches to measuring financial constraints, which are based on accounting data. By nature, accounting data only provide an *indirect* way of gauging financial constraints because the variables in financial statements must be used in conjunction with economic theory to create proxies either for financial constraints themselves or for the market frictions that lead to financial constraints. We circumvent this problem by looking for relevant information where it is directly available.

After our measures pass these initial sanity checks, we investigate their relation to stock returns. To this end, we build portfolios by sorting on our financial constraints measures. For all measures, we find that excess returns are higher for financially constrained firms, suggesting that investors need compensation for taking on financial constraints risk. This result has the same flavor as a similar finding in Whited and Wu (2006). However, our results are robust to filtering out the firms classified as constrained by the Whited-Wu index (WW index hereafter). More importantly, our results have more texture. We find that firms constrained in debt markets have the highest stock returns. To bolster these simple results, we then regress these portfolios on well-known risk factors, finding significant alphas that increase in financial constraints.

Next, we examine whether this risk premium is only concentrated in small stocks. We find that this is not the case. Instead, the largest and most liquid stocks are the ones most affected by financial constraints risk. In particular, when double-sorting portfolios on financial constraints and firm size, we find the largest excess returns for constrained mid-cap stocks and constrained large-cap stocks, but not for constrained small-cap stocks. Thus, illiquid stocks do not drive our results. This result is particularly important because it means that trading strategies that implement our results should not be prohibitively costly to construct.

To investigate financial constraints risk further, we construct a zero-cost financial constraints factor portfolio. We then average out size quantiles to ensure that we are detecting variation in financial constraints and not size (Fama and French, 1993; Whited and Wu, 2006). Regressing this portfolio on the Fama-French five factors yields an annualized alpha of 7.2% for our debt-based financial constraints measure for the top market capitalization percentile (Fama and French, 2015).

Of all three measures, the constraints measure for debt appears to be the most important for financial constraints risk. The annualized risk-adjusted excess stock returns for a zero-cost arbitrage portfolio are 6.5% for the debt constraints measure, 3.7% for the general constraints measure, and 3.0% for the equity constraints measure. These results imply that the equity market is not overly concerned about a firm's capacity to raise money through the stock market and instead prices its ability to raise money in debt markets. This finding is also one of our main contributions above and beyond the extant research on the risk from financial constraints, which does not distinguish between frictions in markets for different securities.

This result makes intuitive sense for two reasons. First, as documented in DeAngelo, DeAngelo, and Stulz (2010), equity issuances are rare events. Second, the model in Belo, Lin, and Yang (2016) shows that the least risky firms are those that can issue debt easily in times when equity issuance is costly. These firms have lower returns because they use this financial flexibility to smooth their real investment policies, thereby lowering systematic risk. Strictly speaking, in Belo, Lin, and Yang (2016), debt issuance is constrained by collateral. More generally, our result of higher returns for debt-constrained firms can be justified by an analogous argument based on any friction that limits debt issuance.

In the asset pricing literature, our paper is most closely related to Lamont, Polk, and Saá-Requejo (2001), Gomes, Yaron, and Zhang (2006), Whited and Wu (2006), Livdan, Sapriza, and Zhang (2009), and Li (2011), who also explore the impact of financial constraints on stock returns. Two key differences separate this earlier work from our study. The first is our use of constraints measures that are based on textual analysis of SEC filings. The second difference lies in our analysis of constraints based on different sources of external finance.[1]

Finally, our paper builds upon and extends the literature on the textual analysis of firms' official corporate disclosures. Textual analysis of these disclosures is not a panacea for the measurement problems that arise with the use of accounting data, as it faces several empirical challenges of its own. For example, traditional word lists from psychological dictionaries have limited power to capture the content of these disclosures (Loughran and McDonald, 2011), and the disclosures themselves sometimes suffer from low readability (Loughran and McDonald, 2014). Nontheless, corporate disclosures are useful for understanding issues in corporate finance. They contain valuation-relevant information during initial public offerings (Jegadeesh and Wu, 2013; Loughran and McDonald, 2013), as well as information about financial constraints (Bodnaruk, Loughran, and McDonald, 2015; Hoberg and Maksimovic, 2015). In addition, tone extracted from text dominates earnings surprises as a predictor of cumulative abnormal returns (Price, Doran, Peterson, and Bliss, 2012).

Our paper is most closely related to Hoberg and Maksimovic (2015) and Bodnaruk, Loughran, and McDonald (2015) in that textual analysis is used in both papers to obtain measures of financial constraints. Bodnaruk, Loughran, and McDonald (2015) measure financial constraints simply by developing a list of constraining words and then examining the percentage of these words in the 10-K. Our approach improves upon this method, as constraining words can isolate many negative outcomes unrelated to financial constraints. In contrast, we estimate a probability model on three different training samples and then impute constraint status on the rest of the sample using the fitted model. Our method builds upon Hoberg and Maksimovic (2015) in three dimensions. First, our training samples exploit the difference between constrained and unconstrained firms, while theirs simply isolate constrained firms. Second, our textual analysis examines a larger fraction of each 10-K. Third, Hoberg and Maksimovic (2015) use their measures of financial constraints to study investment

[1] This literature is distinct from studies of financial distress and stock returns (Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Campbell, Hilscher, and Szilagyi, 2008; Chava and Purnanandam, 2010; Garlappi and Yan, 2011). Financial constraints typically occur in firms that have good investment projects but struggle to find funding. In contrast, financially distressed firms typically are often near bankruptcy and struggle because they lack good investment projects.

and security issuance, while we use our closely related measures to understand stock returns.

1. Data

1.1 Data Sources and Data Screens

We combine data from three sources: Compustat, the Center for Research in Security Prices (CRSP), and the EDGAR database from the U.S. Securities and Exchange Commission (SEC). For Compustat, we begin with all observations in the Compustat North America Fundamentals Quarterly database between January 1, 1994 and December 31, 2010. Following Whited and Wu (2006), we apply the following exclusion criteria. We omit regulated firms with SIC classifications between 4900 and 4999, as well as financial firms with SIC classifications between 6000 and 6999. To eliminate coding errors, we delete firms that report smaller total debt than short-term debt ($DLCQ > DLTTQ$). If a firm undergoes a merger that accounts for more than 15% of the book value of its assets ($AQCQ > 0.15 \times ATQ$), we delete it. Finally, we exclude firm-quarters for which total assets (ATQ), book equity ($PSTKQ + CSTKQ$) or sales ($SALEQ$) are zero or negative. For all firms that survive these screens, we obtain monthly stock market data from the CRSP Monthly Stock File. We then merge the CRSP data with Compustat data, following the protocol in Fama and French (1993) that avoids look-ahead bias. Specifically, to each firm-month in CRSP, we match the most recent Compustat observation from the past.

From the EDGAR database we download all filings of Form 10-K from 1994 to 2010. Following Li (2010), Hoberg and Maksimovic (2015), and Bodnaruk, Loughran, and McDonald (2015), from each 10-K filing we extract the MD&A section, which contains a narrative explanation of the past performance of the firm, its financial condition, and its future prospects. As such, the MD&A material contains the textual information we want. We focus on the MD&A section because SEC Regulation S-K requires firms to discuss their liquidity needs and sources, and this discussion is always contained in the MD&A section. In this regard, we depart from Loughran and McDonald (2011), which examines the whole 10-K. However, their intent is to pick up word tone, which can appear anywhere in a 10-K, and our intent is to pick up specific discussions of financial frictions.

1.2 The Textual Financial Constraints Measure

The construction of the textual financial constraints measure proceeds in three steps: preprocessing each MD&A, classifying each MD&A, and selecting appropriate training samples. We discuss each step in detail below.

1.2.1. Preprocessing

After extracting the MD&A section from each 10-K filing, we preprocess each MD&A (Feinerer, Hornik, and Meyer, 2008; Li, 2010). The preprocessing steps are all standard and their goal is to make the textual analysis more precise by reducing unnecessary noise in the text. We remove all characters that are not alphanumeric, we convert all letters to lowercase, we remove all stop words (e.g., "am" or "and"), and we stem each document. Stemming means that we reduce inflected or derived words to their stem, which is a standard procedure from computational linguistics to conflate related words. Consider for example the following sentence:

> Diamond is the latest in a line of U.S. oil companies that have cut its contract prices over the last two days citing weak oil markets.

After stemming, this sentence becomes:

> Diamond is the latest in a line of U.S. oil compani that have cut it contract price over the last two day cit weak oil market.

Finally, we remove all words that do not occur in at least 99% of the MD&A statements. The purpose of this step is to remove words that appear so infrequently that their meaning cannot easily be detected by our textual analysis. Because there is a remote possibility these words have a greater impact, we are careful to set the threshold high enough to remove only the *very* infrequent words, while keeping the rest.

1.2.2. Classifying

For the text classification, we employ the naïve Bayes algorithm, which is one of the oldest and most well-established tools in computational linguistics, and which often outperforms more sophisticated alternatives (Lewis, 1998; Hastie, Tibshirani, and Friedman, 2001). Specifically, using this algorithm, we model the probability of being financially constrained as a function of the word count in each MD&A. That is, for each MD&A, we count how often each word appears, and relate this word count to the financial constraints status as follows:

$$P(\text{financially constrained}) = f(w_1, w_2, \ldots, w_n), \tag{1}$$

where P is a probability measure, the function f represents the naïve Bayes model, w_i represents how often word i appears, and $(w_1, w_2, \ldots, w_n)$ is the word count for a given MD&A. Following this model, for each MD&A (that is, each firm-year), we obtain a text classification score that indicates the probability that a given firm-year is financially constrained.[2]

Note that we model each MD&A as a bag of words, disregarding grammar and word order. The only relevant information is how often a word appears, whereas the location of the word within the text document is ignored. This bag-of-words approach follows common practice in computational linguistics (e.g., Bird, Klein, and Loper, 2009).

The application of the naïve Bayes model consists of three steps. In the first step, we construct a small, relatively homogeneous, training sample to obtain reliable observations on financial constraint status. In the second step, we estimate model (1) on this sample to obtain the relation between financial constraints and MD&A word counts. As has been well established in the computational linguistics literature, this relation is stable (McCallum and Nigam, 1998; Rish, 2001; Zhang, 2005), that is, it predicts well out-of-sample. Thus, in the third step, we can extrapolate this information to the whole sample consisting of all MD&As. Specifically, for each MD&A, we input the word count into the right-hand side of the fitted model (1) and thus obtain the probability that this firm-year is financially constrained, based

[2]Note we assume that the probability distribution used by naïve Bayes is time-invariant. Thus, any variation over time in the incidence of words indicating constraints would make our constraints measures noisier. In this case, it would be more difficult to find results, thus raising the bar for our research design.

on the textual content of the MD&A from that firm-year. This extrapolation underscores the importance of obtaining a highly representative training sample, which is essential for reliably capturing financial constraints. We turn to this problem next.

1.2.3. Training

The main challenge in constructing high-quality training samples is finding informative ways to measure the left-hand side of (1), that is, whether a firm is financially constrained or not. In contrast, observations on the right-hand side of (1) are readily available by counting the words in the MD&As. In turn, the character and informational content of the training sample quality depend strongly on the methods used to identify financially constrained firms, which we detail below. To allay concerns about the robustness and interpretability of our results, we create three different types of training samples.

For our first training sample, we search the Dow Jones Factiva database during our sample period for news articles that document cases in which a firm is financially constrained.[3] We manually read all articles identified in this search. To isolate financially constrained firms, we first discard cases in which we deem the firm to be financially distressed instead of financially constrained. We then drop observations for which we cannot find a matching 10-K filing with the MD&A section mentioning the financial constraints status of the firm, thus further dropping 40% of the cases. Our final sample contains 120 financially constrained firms, which we call the Factiva training sample. As documented in Brain and Webb (1999) via a variance decomposition and in Beleites, Neugebauer, Bocklitz, Krafft, and Popp (2013) via cross-validation, this number of observations in a training sample is sufficient for the naïve Bayes algorithm to provide accurate classifications.

While this method for obtaining a training sample produces the desired observations needed to populate the left-hand side of (1), it might be viewed as subjective. Although we cross-check the Factiva articles by using at least two different human readers per article, human judgment

[3] The following is an example of a search string we use to find firms: "((unable* or fail* or difficult* or problem* or trouble or cannot or unsuccessful* or challeng*) same (rais* Near5 (financ* or capital* or money or cash or fund*))) and "Securities and Exchange Commission"."

cannot be avoided when searching and reading the press articles. Using humans is necessary because the alternative would be to download all articles from Factiva and analyze them computationally to identify constrained firms. Unfortunately, this alternative is not possible because of download limits imposed by Factiva. Therefore, we also consider additional ways of obtaining training samples that are more directly tied to the MD&As.

For our second and third methods for constructing a training sample, we follow Hoberg and Maksimovic (2015) to find firm-years that are financially constrained or unconstrained. Specifically, Hoberg and Maksimovic (2015) contains lists of keywords that refer to the delay of investment projects, as well as to the issuance of equity and debt. The basic idea is that if investment is delayed because of difficulties with issuing securities (that is, financing problems), then in the MD&A, keywords that refer to these delays should show up in proximity to keywords that refer to security issuance.

Specifically for the second training sample, we use the two delay lists with the equity focused list from Hoberg and Maksimovic (2015) to find an equity training sample where investments are delayed because of difficulties with issuing equity. Briefly, the delay lists juxtapose words related to delay with words related to projects, and the equity list contains phrases related to the issuance of external equity. To ensure that the delay pertains to equity, we count how often words from the delay lists are within a twelve-word distance of a word from the equity focused list. The top 250 MD&As are used as financially constrained for the training sample, while the bottom 1,000 MD&As are used as financially unconstrained for the training sample. We choose a larger unconstrained set because most firms appear to be unconstrained, so the possibility of including constrained firms in this group is remote. The large sample size thus provides more precision. Further, the results are robust to choosing a different ratio of constrained firms versus unconstrained firms for the training sample. In the end, this classification scheme produces a training sample that captures financial constraints relating to equity issuance. We call it the equity training sample.

Finally, for the third training sample, called the debt training sample, we use the keywords from the delay lists and the debt focused list from Hoberg and Maksimovic (2015) in an analogous manner. In total, we have three different training samples.

Using these three training samples, as well as the methods discussed in Section 1.2.2, we obtain three measures of financial constraints: one that captures general financial constraints (using the Factiva training sample), one that captures financial constraints relating to the delay of investment due to problems issuing equity (using the equity training sample), and one that is about investment delays due to problems issuing debt (using the debt training sample). Because these measures are probability scores, they run between zero and one, with zero indicating an unconstrained firm, and one indicating the most constrained firm in our whole sample.

Note that these financial constraints measures are largely based on an out-of-sample performance of model (1) because the training sample makes up only 1% of the whole sample of MD&As. In other words, 99% of the observations on the financial constraints measures are obtained from data outside the training (estimation) sample. As such, there are no overfitting concerns, which only occur when a model is applied in-sample.

However, there might be a concern about out-of-sample prediction. To address this issue, we perform a five-fold cross-validation to assess the performance of the model on a new sample. Specifically, we divide each training sample into five parts, estimate the model on four of these parts, and test its out-of-sample performance on the fifth part. We then repeat this procedure for all permutations of the five parts. We find that the naïve Bayes model correctly classifies observations 77% of the time for the Factiva training sample, while the numbers for the equity and debt samples are markedly higher at 91% and 82%, respectively. Note that these numbers are high, inasmuch as anything above 50% means that the model has learned something from the data and does better than throwing a coin. Our naïve Bayes model also performs better than the examples in Li (2010), which reports success rates between 63% and 67%. In sum, for the vast majority of observations, the model provides predictive power for financial constraints out-of-sample.

Figure 1 shows histograms of the textual financial constraints measures corresponding to the three training samples. The most important result can be seen in the peak at zero (Panels A–C), which indicates that most of the time, firms are classified as being financially unconstrained. This result is unsurprising for a large developed economy such as the United States, and it confirms a similar result in Hadlock and Pierce (2010). Despite the high incidence of unconstrained firms, a nontrivial fraction of our sample experiences some degree of financial constraints, and there are still times with stringent binding constraints, consistent with episodes where outside financing opportunities dry up, such as during the recent financial crisis. Nonetheless, there are relatively few extremely constrained firms with financial constraints measures close to one. The other prominent finding in Figure 1 is the higher incidence of firms that appear constrained when classified using our debt training sample. Overall, Figure 1 provides a more textured description of distributional properties of firms' financial constraints status beyond the results in Hadlock and Pierce (2010) or Hoberg and Maksimovic (2015).

To further investigate whether our financial constraints measures are capturing constrained firms, we randomly choose ten large firms (top size octile) from the most constrained set of observations (top constraints octile) for a random set of five years. We then look for discussions in the 10-K reports that provide evidence that these firms indeed are financially constrained. For illustration, we focus on the debt financial constraints measure because, as shown below, it has the strongest influence on stock prices. All of the excerpts are in the Internet Appendix. Here, we provide two examples. The first one is from CONSOL Energy in 2006:

> CONSOL Energy was no longer able to participate as a seller of commercial paper due to Standard and Poor's lowering its rating of our short-term debt. ... There can be no assurance that additional capital resources, including debt financing, will be available to CONSOL Energy on terms which CONSOL Energy finds acceptable, or at all. ... We may choose to defer certain capital projects in light of operating results and the availability of financing.

The second excerpt is from Micrel in 2001:

> Additionally, the cost of any investment we may have to make to expand our manufacturing capacity is expected to be funded through ... additional debt ... We may not be able to obtain the additional financing necessary to fund the construction and completion of any new manufacturing facility.

All of the excerpts reported in the Internet Appendix contain similar evidence that these firms faced significant challenges raising external finance. Although this evidence is anecdotal, it does make the textual analysis more tangible.

1.3 Summary Statistics

Figure 2 plots the financial constraints scores in each year as a function of time. Several interesting patterns are evident. First, Panel A shows that the median scores are all quite low, reflecting the general level of financial development of the U.S. economy. Also apparent in Panel A is the lack of information in the medians. For example, one would expect an uptick in the severity of financial constraints with the 2007-2009 financial crisis, yet we only see a sharp increase for the equity score and a slight increase for the debt score. This result is not surprising, given that the medians reflect largely unconstrained firms. In contrast, Panel B shows that the mean score increases during the crisis in all three cases. Moreover, the means are higher than the medians, indicating incidence of some very constrained firms in the sample.

Table 1 shows summary statistics from our sample, which we stratify by our measures of financial constraints, as well as by other prominent measures in the literature. Panels A–C show the results for our textual measures of financial constraints, while Panels D and E show results for the KZ index (Kaplan and Zingales, 1997; Lamont, Polk, and Saá-Requejo, 2001) and the WW index (Whited and Wu, 2006). To construct each panel, we sort the sample by the relevant index of financial constraints and then calculate the means of several variables for each tercile of the index in question.

Two prominent results emerge from Table 1. First, we find that our financial constraints measures are indeed consistent with characteristics typically associated with financially constrained firms. For example, we find that for all three textual measures, highly constrained firms have markedly lower cash flows, higher cash balances, higher R&D intensity, and higher Tobin's qs than unconstrained firms, with these differences all highly significant. The constrained firms are also smaller in size and pay fewer dividends than their unconstrained counterparts, although this relation is neither always monotonic nor always significant. Interestingly, for the constraints measures based on the Factiva and equity training samples, the most constrained firms invest the least, despite having the highest levels of Tobin's q, and both of these results are strongly significant. These results are consistent with situations in which financially constrained firms are small and have good investment opportunities that they cannot exploit unless they hoard cash because their current cash flow is insufficient. Naturally, these constrained firms are less likely to pay dividends. Finally, leverage appears to be unrelated to financial constraints status, regardless of how we measure constraints, although the differences in cash balances indicate sharp differences in net leverage.

Our second main result in Table 1 is that all of the textual measures of financial constraints produce sample characteristics that are quite similar to one another. However, these characteristics differ sharply from those for the KZ index and differ slightly from those for the WW index. As show in Table A33 in the Internet Appendix, the rank correlations between our three measures range from 0.24 to 0.64. In contrast, the highest correlation between the KZ index and our measures is 0.07 in absolute value. Similarly, the correlation between our measures and the WW index is highest for the Factiva measure but only marginally higher at 0.13.

To add texture to these results, we turn to Panel D, where we find that while some of the patterns in the data sorted by our measures are shared by the sample sorted by the KZ index, many are not. Panel D in Table 1 shows that more constrained firms pay fewer dividends and have higher levels of Tobin's q. In sharp contrast, according to the KZ index, the least constrained firms are the most R&D intensive, have the lowest cash flow, while the most constrained firms have the highest leverage and lowest cash balances. These differences are all statistically significant and are more consistent with a scenario in which the firms labeled as constrained have ample cash flows and use both these cash flows and debt to fund projects. The high leverage in particular is consistent with firms that have easy access to debt markets and that may be more likely to experience financial distress than financial constraints.

Finally, the characteristics of the subsamples stratified by the WW index (Panel E in Table 1) are largely consistent with the characteristics of the subsamples stratified by our three textual constraints measures (Panels A–C in Table 1). The one important exception is that the WW index appears to load heavily on firm size, as the most constrained firms are 60 times smaller on average than the unconstrained firms. In contrast, we find no strong patterns in size across the samples split by our measures of financial constraints.

For a final reality check on whether our financial constraints measures are actually isolating financially constrained firms, we investigate whether financially constrained firms issue fewer securities than their unconstrained counterparts. To this end, we compute net debt and net equity issuance (i.e., issuance minus repurchases) over the year following the 10-K release, where we scale both of these variables by lagged total assets. We then compare these measures of security issuance between the top and bottom 30% of firms sorted by our three measures of financial constraints. For the debt (equity) financial constraints measure, we find that constrained firms issue 27.4% (20.4%) less net debt (net equity) than unconstrained firms. These differences are statistically significant, with t-statistics of 3.9 and 4.1, respectively. For the Factiva measure, we find that constrained firms issue 23.9% less debt and 7.7% less net equity than unconstrained firms. In this case, only the difference in debt issuance is significant, with a t-statistic of 2.8. The totality of this evidence leads us to conclude that high levels of our financial constraints measures predict that ex-post issuance of debt and equity will be lower.

2. Results

We now turn to the central portion of our analysis, which aims to estimate the relation between financial constraints and stock returns.

2.1 Baseline Results

We first examine whether the returns of portfolios of the stocks of constrained firms earn high risk-adjusted returns. We begin by forming three portfolios sorted on approximate terciles of the textual financial constraints measures (top-30%, middle-40%, and bottom-30%) based on NYSE breakpoints. As a first step, in Table 2, we present the raw excess returns on the resulting portfolios. We find that these excess portfolio returns increase with financial constraints. This trend is particularly strong for the portfolios based on the debt training sample (Panel C), although the difference between the returns on the most and least constrained portfolios is not statistically significant. We also find that the book-to-market ratio declines with increasing financial constraints, indicating that portfolios of more financially constrained firms also contain more growth stocks.

Next, to understand whether the dependence of returns on financial constraints persists if we control for known risk factors, in Table 3, we show the results from regressing financial constraints-sorted portfolios on the Fama-French five factors (Fama and French, 2015). To construct the portfolios, we sort stocks on the financial constraints measures and build three long-only portfolios corresponding to the top, middle, and bottom cutoffs used to construct the portfolios shown in Table 2. Additionally, in the last column of the table, we present the result of an investigation of a long-short portfolio (high minus low) that is long the top financial constraints percentile and short the bottom percentile. In a regression of these portfolios on the Fama-French factors, the intercepts or alphas of these regressions, shown in the rows labeled α, indicate the risk-adjusted annualized returns.[4]

Panels A–C in Table 3 show that for all training samples, the alphas are significantly higher when financial constraints are more severe. On an annualized basis, risk-adjusted portfolio returns increase to 2.9% from −0.9% for the Factiva training sample (Panel A), to 3.9% from 0.9% for the equity training sample (Panel B), and to 4.1% from −2.4% for the debt training sample (Panel C). Likewise, the high minus low portfolios have significantly positive alphas, with the annualized alpha for the debt training sample being 6.5% (Panel C), followed by 3.7% and 3.0% for the Factiva (Panel A) and equity (Panel B) samples.

[4]It is worth noting that a trading strategy based on Table 3 might have been difficult to implement over the sample period. Nonetheless, it would not have been completely impossible. Naïve Bayes has been used for more than half a century in information retrieval (Lewis, 1998). Furthermore, early versions of search engines, which are necessary to construct word lists, date back at least to the early 1990s, that is, before the start of our sample in 1994.

Recently, Harvey, Liu, and Zhu (2016) have emphasized that in a data set as extensively examined as stock returns in the Unites States, asymptotic critical values for t-tests are likely too conservative, producing unwarranted rejections of null hypotheses. They suggest a rule-of-thumb critical value of 3. Interestingly, for the debt training sample (Panel C), the t-statistic on the intercept does exceed this higher critical value. Also of interest is the result that the long-short portfolio returns are mainly driven by the long side, as seen in the mostly insignificant alphas of the low FC portfolios, which constitute the short side in a long-short portfolio. This result stands in contrast to much of the anomalies literature, in which anomalies are often driven by the short side, and short positions can be prohibitively costly to trade (Novy-Marx and Velikov, 2016). We further investigate the issue of trading costs below in Section 3.3.

In the remaining rows of Table 3, we examine the relation between our financial constraints portfolios and the Fama-French five factors. First, while the low-FC portfolios load positively on SMB (small minus big), the high-FC and high minus low portfolios load mostly negatively. Further, none of the corresponding t-statistics exceed a critical value of three, indicating that the relation of firm size with financial constraints is ambiguous and likely insignificant at the portfolio level. In contrast, financial constraints load negatively on HML (high minus Low), indicating that constrained firms tend to be growth stocks. Next, for the debt and equity training samples, the FC factor loads significantly negatively on the RMW (robust minus weak) factor. This result makes sense in that one would imagine that financially constrained firms are not likely to be robustly profitable. Finally, the loadings on the CMA (conservative minus aggressive) factor are largely insignificant, except for the factor based on the debt training sample, where we find a positive loading for financially unconstrained firms and a negative loading for financially constrained firms. This result also makes sense, as one would expect financially constrained firms to be trying to invest more than unconstrained firms in a later stage of their life cycle.

The last two results regarding the RMW and CMA factors are of interest relative to the results in Whited and Wu (2006), as these factors had not been identified in 2006. Moreover, when we recompute Table 3 with a portfolio based on the WW index, as shown in Table A34 in the Internet Appendix, we find that the results are qualitatively similar, but they are quantitatively weaker and of marginal significance, with the *t*-statistic on the high-minus-low alpha just less than the 10% critical value. Finally, profitability and investment are intuitively important components of any firm's desire and ability to tap financial markets, so understanding the relation between these newer factors and our financial constraints factors is important.

Next, although our results for the debt-based measure differ notably from those for the equity-based measure, the question arises whether the debt and equity constraints measures are actually capturing different firm risk factors. To investigate this possibility, we compute Spearman's rank correlation between the equity and debt FC portfolios, with the results in Table A33 in the Internet Appendix. At 32%, this correlation demonstrates that the two measures indeed capture different aspects of financial constraints. We also regress the debt and equity FC portfolios on each other, controlling for the Fama-French five factors. We find that the debt FC portfolio cannot fully be explained by the equity FC portfolio and control variables, resulting in a significantly positive annualized risk-adjusted return (alpha) of 4.5% with a *t*-statistic of 3.3. This finding suggests that the debt financial constraints measure indeed captures something unique that is not already encompassed by the equity measure.

Figure 3 depicts the pricing results in Table 3 by plotting the long-short cumulative portfolio returns from the rightmost column (high minus low) in Table 3 for all three training samples. Panels A–C show how financial constraints risk is priced by the market, and how these prices evolve over time. Consistent with the results from Table 3, the cumulative returns for the financial constraints portfolios exhibit a consistent upward trend over time. All samples exhibit peaks with subsequent declines during the dot-com bust, suggesting that stock returns were particularly sensitive to financial constraints risk during that time. In contrast, during the financial crisis of 2007-08, we see a rise in returns only for the equity-constrained portfolio, which parallels the results for the equity score in Figure 2. This finding does not necessarily mean that financial constraints were unimportant during the financial crisis. It only means that portfolio returns did not decline substantially during that period. Although our sample does not cover the entire episode of post-crisis quantitative easing, we speculate that one possible explanation is loose monetary policy, which may have influenced risk preferences towards financial constraints. Overall, the plots show a consistent overall upward trend, confirming that the results in Table 3 are not due to a few isolated outliers.

The contrast between the statistically insignificant spread in raw returns from Table 2 and the statistically significant alphas in Table 3 at first appears inconsistent. However, this contrast is consistent with the following three empirical facts. First, the financial constraints portfolio is strongly and significantly negatively correlated with HML, RMW, and CMA. Second, the raw returns of HML, RMW, and CMA over our sample period are on average positive. Third, the financial constraints portfolio has on average strictly positive raw returns.

The first two facts alone are consistent with an α that is significantly positive. For example, if we demean the financial constraints portfolio's returns and thus shut down the third fact, we still obtain a positive α with a t-statistic of 2.05 for the debt training sample. Intuitively, one is compensated for holding a portfolio that has a negative correlation with HML, RMW, and CMA, yet still has on average a nonnegative raw return. As such, the financial constraints portfolio is very different from a short version of HML, RMW, or CMA, which would be negatively correlated with these factors but would also have a strictly negative return. This negative correlation combined with a nonnegative return makes the financial constraints portfolio a valuable addition to an investor holding HML, RMW, and CMA, as it allows an expansion of the investment opportunity set by diversifying risk via the negative correlation with HML, RMW, and CMA.

The third fact is also consistent with the strictly positive raw return on the financial constraints portfolio, as an investor holding HML, RMW, and CMA can expand his investment frontier further, all of which implies a larger and more significant risk-adjusted return on the financial constraints portfolio.

2.2 Financial Constraints versus Size

Next, we ask whether the relation between portfolio returns and financial constraints holds up in different size percentiles. This exercise is of interest given that firm size is widely used as a measure of firm financial constraints (e.g., Gilchrist and Himmelberg, 1995; Erickson and Whited, 2000; Hadlock and Pierce, 2010). To this end, we double-sort firms based on size and textual financial constraints into top-30%, middle-40%, and bottom-30% based on the NYSE breakpoints for size (Fama and French, 1993; Whited and Wu, 2006). This double-sorting produces nine groups.

For our first test, for each group, we form a long-only portfolio and present its raw excess returns in Table 4. We find that for the constraints measures based on the Factiva (Panel A) and debt (Panel C) training samples, the impact of financial constraints on portfolio returns becomes *stronger* as the firms get larger. This result at first appears counterintuitive, as large firms seem less likely to face financial frictions. However, as illustrated by the annual report excerpts in Section 1.2.3 and in the Internet Appendix, some large firms do indeed face financial constraints, and these large, financially constrained firms are the ones driving our results. This result that large constrained firms earn higher returns is important, as it shows that this effect is not concentrated in small stocks, whose returns can contain illiquidity premia. Moreover, many anomalies are concentrated in stocks that are difficult to trade in large quantities (Novy-Marx and Velikov, 2016). In contrast, here we find the opposite. The return effects of financial constraints are concentrated in stocks that are easy to trade.

Next, we examine in Table 5 whether the concentration of high financial constraints returns in large firms is also evident on a risk-adjusted basis. To this end, we form portfolios that go long the high-constraints percentile and short the low-constraints percentile and examine the performance of these long-short portfolios on our different size subsamples. Specifically, for each size subsample, we regress these high minus low portfolio returns on the Fama-French five factors and calculate the resulting risk-adjusted returns (i.e., the alphas).

Table 5 shows that for the portfolios based on the Factiva and debt constraints measures, the alphas increase with financial constraints and become significantly positive in the medium and big size subsamples if one uses conventional *t*-test critical values. Using a critical value of 3, as suggested by Harvey, Liu, and Zhu (2016), leaves us with two significant alphas for the medium and large firms that are financially constrained according to the debt training sample (Panel C). On an annualized basis, the large/constrained portfolio has a risk-adjusted return of 6.7% when we define financial constraints according to the debt training sample (Panel C). When we use the equity and Factiva training samples, this double-sorted portfolio has a risk-adjusted return of 4.5% and 2.7%, respectively (Panels A and B). These results are consistent with the results on raw excess returns in Table 4.

One final result of interest in Table 5 is the significant alpha for the portfolio of small firms when we sort by the constraints measure based on the equity training sample. This result means that frictions related to equity issuance are relevant for small firms, to the extent that these small constrained firms earn a significant risk-adjusted premium of 4.1%.

2.3 Comovement and Factor Models

We next test for a source of common variation in the returns of constrained firms. Intuitively, this test is based on the idea that if financial constraints are completely idiosyncratic to the firm, then constrained firms' returns should not move together, controlling for other sources of common variation among asset returns. We test for comovement following Lamont, Polk, and Saá-Requejo (2001) and Whited and Wu (2006). Specifically, we regress the returns of all nine double-sorted portfolios on three reference portfolio returns. These reference portfolios consist of a proxy for the market factor (*BIG*), a proxy for the size factor (*SMALL*), and a financial constraints factor. Let portfolios starting with S/M/B denote those belonging to the small/medium/big percentile. Similarly, portfolios ending with L/M/H belong to the low/mid/high financial constraints index percentile. We then define *BIG* and *SMALL* as $BIG = (BM + BL + MM + ML)/4$ and $SMALL = (SL + SM)/2$. The financial constraints FC portfolio is then defined as $FC = HIGHFC - LOWFC$, where $HIGHFC = (SH + MH +$

$BH)/3$, and $LOWFC = (SL + ML + BL)/3$.

In words, the proxy for the market (BIG) consists of the less constrained medium-size and large-cap firms. The proxy for size ($SMALL$) consists of the less-constrained small-cap firms. In all regressions, we exclude the left-hand side portfolio from the construction of the right-hand side variables in order to avoid spurious results.

The results are given in Table 6. Panels A, B, and C show that for each financial constraints measure, the returns of firms classified as financially constrained covary with one another. Specifically, for each size category, the loading on FC increases when the portfolio contains more constrained firms. The coefficient on FC increases when moving from the SL portfolio to the SH portfolio, from the ML portfolio to the MH portfolio, and from the BL portfolio to the BH portfolio. Furthermore, regardless of which training sample we use, the FC loading is significantly positive for the high-constrained portfolios. Consistent with Whited and Wu (2006), these results show that financially constrained firms' returns covary positively with the returns of other firms that are also constrained, even if we condition on proxies for the market and size.

Next, we examine whether our FC portfolios are related to other factors such as size, book-to-market, profitability, and corporate investment and whether they are correctly priced relative to these other factors. To this end, we regress each of our three financial constraints portfolios on the factors from Fama and French (2015), with the results in Table 7. If the FC portfolios are correctly priced, the intercepts of these regressions should be zero, and the R^2 should be high.

For the portfolios constructed from all three training samples, we find that the intercepts are positive and significant. In the case of the debt training sample, the annualized risk-adjusted value-weighted return is 5.7%, followed by 3.1% and 3.0% for the Factiva and equity samples, respectively. The five-factor model thus cannot correctly price any of our FC portfolios. In fact, this finding is stronger than the one reported by Whited and Wu (2006), even though they control for fewer factors (and therefore are more likely to find higher risk-adjusted returns). For comparison, the annualized risk-adjusted return reported in Whited and Wu for their value-weighted FC factor is 2.4% when controlling for the Fama-French three factors and momentum.

The average R^2 for all specifications is 64%, leaving a significant portion of the variation of the FC portfolios unexplained. This piece of evidence, combined with the significantly positive intercepts, leads us to conclude that our FC portfolios constitute an anomaly that cannot be explained by the other known empirical factors.

Consistent with our findings above, all three of our FC portfolios are uncorrelated with SMB, indicating that constrained firms can be either large or small. The correlations of the FC portfolios with the book-to-market (HML) and profitability (RMW) factors are highly negative, confirming that financially constrained firms are growth firms with weaker operating profitability. This result is of interest because it is consistent with the notion that constrained firms have high growth potential but insufficient internal and external funds to meet all their investment opportunities. The loadings on the (CMA) investment portfolio are positive and significant for the FC portfolio based on the Factiva training sample, indicating that financially constrained firms invest *less*. These loadings on CMA are insignificant in the cases of the debt and equity training samples.

In general, the results in Table 7 are of note because they produce the first evidence investigating the correlation of a financial constraints portfolio with the new RMW and CMA factors from Fama and French (2015). Moreover, because the FC portfolio is not subsumed by the new RMW and CMA factors, we conclude that stock prices are moved by a separate financial constraints channel going beyond profitability and investment. This result makes sense, inasmuch as financial constraints occur when firms have insufficient profitability to finance all of their desired projects, and when frictions in capital markets prevent these firms from obtaining the necessary funds externally. As such, if financial constraints matter for returns, they are unlikely to be subsumed entirely by measures of profitability and investment.

3. Robustness Checks

3.1 Investment and Equity/Debt Issuance

It is well known that firms with low investment, low stock issuance, or low debt issuance have higher stock returns.[5] Given the construction of our textual financial constraints measures, it is possible that we are picking up this type of variation instead of financial constraints. Specifically, by construction, two of our three textual financial constraints measures capture textual content about delays in investment and the issuance of equity and debt, as described in Section 1.2.3. We therefore validate whether our results are driven by investment, equity issuance, or debt issuance, or whether our measures contain novel information about financial constraints that goes beyond investment and debt/equity issuance.

We run Fama-MacBeth (Fama and MacBeth, 1973) regressions of stock returns on our measures of financial constraints and controls, as in Novy-Marx (2013). We take a slight departure from the usual regression setup by specifying, for each firm-month, the dependent variable as the average monthly excess return over the following two quarters. Because we forward average the dependent variable, the resulting regression is still predictive and there is no look-ahead bias.[6] If markets are efficient and information about financial constraints is quickly incorporated into stock prices, this setup makes it more difficult for us to detect a significant result.

After estimating the basic model with financial constraints and the usual controls, we add investment (*capex*), stock issuance (*stk*), and debt issuance (*dbt*) to the right-hand side of the regression equation. If our results are only driven by investment and equity/debt issuance alone, and not by financial constraints, then the addition of these three variables should make the financial constraints coefficient insignificant. However, Table 8 shows that the inclusion

[5] See, for example, Hou, Xue, and Zhang (2015) for investment; Ritter (1991), Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Daniel and Titman (2006), Fama and French (2008), Pontiff and Woodgate (2008), McLean, Pontiff, and Watanabe (2009), and Greenwood and Hanson (2012) for stock issuance; and Lee and Loughran (1998), Spiess and Affleck-Graves (1999), and Baker and Wurgler (2000) for debt issuance.

[6] In this regard, it is also worth noting that the average (median) year-over-year rank autocorrelation of the financial constraints scores are 2%/10%/17% (5%/19%/23%) for the Factiva/equity/debt training samples.

of these additional variables leaves the financial constraints measures significant. In fact, the constraints coefficients and test statistics increase for the Factiva and debt training samples. In other words, our financial constraints measure is *not* subsumed by investment, stock issuance, or bond issuance and therefore contains novel information about financial constraints.

3.2 Hoberg and Maksimovic Text Classification

In this section we analyze an alternative method proposed by Hoberg and Maksimovic (2015) for extracting textual financial constraints from company filings. Both this method and our method are based on the Hoberg-Maksimovic keyword lists, so they are in principle related. However, to better understand their potentially differing empirical properties, we start out by reviewing their key conceptual differences.

The first difference is that we analyze the whole Management's Discussion and Analysis (MD&A) section, while Hoberg and Maksimovic (2015) inspect the Liquidity and Capital Resources section, which is a subsection of the MD&A. The reason why we focus on the whole MD&A section is that based on manual reading of a subsample of firm filings, we find that issues related to financial constraints are sometimes mentioned in the MD&A outside the Liquidity and Capital Resources section. By analyzing the whole MD&A, we offer more comprehensive data to the textual learning algorithm.

Second, an important difference between our analysis and the analysis in Hoberg and Maksimovic (2015) is that they consider whether a given MD&A has *any* match in their word lists, while we go further and count *how often* a word match occurs for a given MD&A. Thus, our training set contains only those MD&As that score highest on the Hoberg-Maksimovic keyword lists, while Hoberg and Maksimovic (2015) include all text documents that have a strictly positive score (no matter how high or low, as long as it is larger than zero). Our approach results in a more fine-grained analysis and allows us to obtain more precise training samples according to the ranking of the word match counts.

Third and last, another important difference lies in the manner in which we extract information about financial constraints from the training sets. Briefly, Hoberg and Maksimovic

(2015) only use financially constrained firms to train their model, while our model uses both constrained and unconstrained firms. To better understand this difference, we provide a brief overview of the models and how they differ conceptually.

As discussed in detail in Section 1.2.2, we use naïve Bayes, which is a simple statistical model that calculates Bayes' rule, that is, given the word count of the MD&A, it tells us the probability that this text document is from a financially constrained firm. If the resulting number is close to one, it means that the MD&A is from a firm similar to the constrained firms in the training set, while a number close to zero means it is similar to the unconstrained firms in the training set. Importantly, to estimate this statistical model, we need observations from constrained as well as unconstrained firms in the training set.

In contrast, Hoberg and Maksimovic (2015) use the cosine similarity measure, which is a geometric method based on the (cosine of the) angle between two word count vectors. With this method, no statistical estimation is necessary. Instead, one calculates the cosine distance between the text document that needs to be classified according to its financial constraints status and the average word count vector of a training set consisting of constrained firms. If the distance is close to one, it means that this document is from a firm that is very similar to other firms we know are constrained (because they are in the training set). If the cosine distance is close to zero on the other hand, the document is very dissimilar to constrained firms. Importantly, this measure is calculated based on a training set consisting only of constrained (but not of unconstrained) firms.

As emphasized above, the most important difference is that we use both constrained and unconstrained firms in the training set, while Hoberg and Maksimovic (2015) only use constrained firms. To isolate this effect, we shut down the other two differences when replicating the Hoberg-Maksimovic measures on our sample. Specifically, we use the whole MD&A (and not only the Liquidity and Capital Resources section), and for the training sample we use the same constrained firms that are also in the training sample for naïve Bayes.

To understand whether these different textual analysis choices matter for our results, we rerun the analysis in Tables 2–7 using the Hoberg-Maksimovic debt and equity constraints measures. These results are in Tables A1–A6 in the Internet Appendix. Briefly, we find that the return spreads between constrained and unconstrained firms are statistically insignificant. When we compare large and small firms, we find insignificant spreads for the former and borderline significant spreads for the latter. These results stand in sharp contrast to those from our measures (especially those based on the Factiva and debt training samples), which exhibit significantly positive return spreads. We therefore build upon the analysis in Hoberg and Maksimovic (2015) by demonstrating the importance of providing not only positive examples of financially constrained firms when training the textual analysis model, but also negative examples of unconstrained firms.

3.3 Accounting for Trading Costs

Trading costs are important because portfolio turnover and trading in potentially illiquid stocks can significantly erode net returns. To assess the effect of trading costs, we follow Novy-Marx and Velikov (2016) by calculating trading costs using the data from Hasbrouck (2009) and then repeating the tests from Tables 2, 3, 4, 5, and 7 with portfolio returns net of trading costs.[7] The data on trading costs in Hasbrouck (2009) come from the estimation of a random-walk model of stock prices in the spirit of Roll (1984), augmented for the presence of trading costs.

The results are in the Internet Appendix in Tables A7–A11. Briefly, we find that trading costs decrease risk-adjusted excess returns only marginally. For example, when comparing the alphas in Table 3 and the corresponding Table A8, which provides net-of-trading-costs results, we find that the long-short risk-adjusted excess returns of the Factiva/equity/debt training samples are 3.6%/2.8%/6.3% after trading costs, while they are 3.7%/3.0%/6.5% before trading costs. Similarly, a comparison of Tables 7 and A11 again reveals small decreases in net returns. This result follows intuitively because although we use quarterly data from

[7]These data end in 2009, while our data set ends in 2010. To extend the Hasbrouck data, we simply roll the 2009 data forward to 2010 for each firm in the data set. This procedure overestimates trading costs, as Novy-Marx and Velikov (2016) show that trading costs peaked in the financial crisis and fell thereafter.

Compustat and EDGAR to obtain the most recent fundamental and textual data, we form portfolios once a year to better mimic the construction of the Fama-French factors. Thus, except for minor rebalancing each month to keep the portfolio at its target allocation, we only have a single major rebalancing event each year. Thus, the overall portfolio performance is not materially affected by transaction costs.

One final interesting result can be found in a comparison of the alphas in Table 5 and the corresponding Table A10. We find that the spread between returns before and after trading costs is largest for small stocks, consistent with the notion that small stocks have lower liquidity and are therefore more costly to trade because of higher transaction costs and market impact. Specifically, for the Factiva/equity/debt training samples, the spreads before-and-after trading costs are 0.39/0.40/0.38 percentage points for small stocks, while they narrow down to 0.14/0.15/0.13 percentage points for large stocks. This result further emphasizes the importance of our earlier finding that our financial constraints measures have the biggest impact on large stocks, which are easier to trade.

3.4 Other Robustness Checks

One concern with our results is that they may be unduly influenced by micro cap stocks, which have a small market capitalization (less than $300 million) and are thus difficult to trade for institutional investors. However, micro caps are also likely to dominate the set of financially constrained firms. To examine whether our results persist if micro caps are eliminated from the sample, we rerun our earlier tests from Tables 2–7 with micro caps removed, and present the results in the Internet Appendix in Tables A12–A17. Interestingly, we find that our results are nearly unchanged and even become slightly stronger when we remove the micro caps. This result makes sense inasmuch as many of our results are concentrated in large firms.

Next, inspecting Figure 3, we notice a distinctive spike in the cumulative returns over the boom and bust of the dot-com bubble. To examine whether our results are driven by this time period, we repeat the regressions from Tables 2–7 on the sample that excludes July 1999 to June 2001. Tables A18–A23 in the Internet Appendix show that while the risk-adjusted returns decrease, they are still economically and statistically significant for the debt training sample. For example, the annualized risk-adjusted excess return of the long-short portfolio sorted on debt financial constraints is 4.8% in Table A19 and 5.0% for the big firms in Table A21.

Our next robustness check involves the alternative factor model in Hou, Xue, and Zhang (2015) that accounts for size, investment, and profitability. To investigate whether our results endure when we control for these alternative risk factors, we repeat similar regressions as previously in Tables 3 and 5 by replacing the Fama-French five factors with the Hou-Xue-Zhang factors.

These results are in Tables A24–A25 in the Internet Appendix. To summarize, our results become stronger when we use this alternative factor model. For example, controlling for the HXZ factors produces larger and more significant risk-adjusted returns. Importantly, this increase in returns comes mostly from the long side of the portfolio, which is much easier to trade than the short side.

Next, we ask whether the inclusion of the illiquidity factor from Pástor and Stambaugh (2003) affects our results. As before, we recompute Tables 3 and 5, except that we add the illiquidity factor to the Fama-French factors. Tables A26–A27 in the Internet Appendix show that our results are nearly identical when we add this extra factor, and this result bolsters our set of conclusions that the effects of financial constraints are concentrated in liquid stocks.

Finally, we explore whether our results in Tables 4 and 5 are robust to double sorting on the WW index instead of on firm size. The results are in Tables A28 and A29 in the Internet Appendix. For the debt-based measure, the highest raw returns and most significant alphas are concentrated in the low-WW and mid-WW ranges. This result makes sense because our results are strongest in large firms and the WW index is negatively correlated with size, as can be seen from Table 1. Taken together, subsampling on the WW index helps identify those firms where our results are strongest anyway.

One further concern with our analysis and results is that managers might want to manipulate the information in their 10-Ks, and the costs of massaging MD&As are heterogeneous across firms. This issue could drive our results if we only classify as constrained firms that are indeed constrained and that also have high manipulation costs. As such, we could be picking up manipulation cost risk instead of financial constraints risk.

To address this issue, in the regressions reported in Table 8, we control for several variables that are likely correlated with manipulation costs. The first variable is the number of analysts covering the firm, and the second is the number of outside board members. Both of these variables are indicative of independent oversight and thus positively correlated with manipulation costs. The third variable addresses the possibility that firms on the verge of financial distress might attract more scrutiny from large lenders and thus have different incentives to disclose. To capture this scenario, we include measures of the tightness of current ratio and net worth covenants, as in Chava and Roberts (2008), where we also include leverage and interact these tightness measures with our financial constraints measures. Including covenants also helps disentangle our financial constraints story from a financial distress story.

The results from including these variables are in Table A30. We find that even with the inclusion of covenant tightness measures, the financial constraints coefficients stay significant. Only the net-worth tightness measure is significant. When we interact the covenant tightness measures with our financial constraints indicators, we find that the coefficient on financial constraints loses significance only for the measure based on the equity training sample, and only when we use the net worth tightness measure. Leverage is negatively significant, so firms with high leverage have lower returns. The number of analysts is significantly positively associated with future returns, while the fraction of outside directors is insignificant.

Next, we consider the possibility that our results are driven by information disclosure instead of financial constraints. Specifically, to the regressions reported in Table 8, we add two measures of disclosure. The first is a word-count of the 10-K, and the second is a widely-used measure of earnings persistence from Dechow, Ge, and Schrand (2010), which is defined as the AR(1) coefficient of annual earnings divided by total assets. The idea behind this measure is that earnings manipulation in one period eventually has to be reversed, so more manipulation can lead to low or negative serial correlation. Relatedly, to address the possibility from Dutta and Nezlobin (2017) that disclosure quality depends nonlinearly on growth, we interact the disclosure measures with average sales growth over the previous twelve quarters.

The results are in Table A31. We find that two of the three financial constraints measures stay significant after the addition of the information disclosure variables, with the measure based on the equity training sample losing significance.[8]

These results make intuitive sense for two reasons. First, if managers manipulate 10-Ks to push up stock prices, they would have to state that they are financially constrained. Yet managers usually have strong incentives to state the opposite, that is, that their first-rate management skills make it easy for them to obtain outside financing. Second, if managers of unconstrained firms mimic managers of constrained firms in their disclosures, and if this mimicking is successful, as in some sort of pooling equilibrium, then we ought to observe minimal investor response to these disclosures. However, our evidence points to large differences in the returns of firms whose annual reports indicate financial constraints and those whose annual reports do not.

4. Conclusion

We construct three novel textual measures of financial constraints and then use these measures to revisit the question of whether financial constraints affect stock returns. The first measure captures a general notion of restricted access to external financial markets of any kind. The second and third capture frictions specifically related to access to external debt and equity markets. Reassuringly, we find that all three of our measures consistently capture firm characteristics that are typically associated with financial constraints.

As in Whited and Wu (2006), we generally find that our financial constraints measures are able to capture priced financial constraints risk in stock returns. Specifically, like Whited

[8]It is also possible to measure disclosure via investor relations activities as in Karolyi and Liao (2017). However, these measures typically have insufficient time-series or cross-sectional coverage for our purposes.

and Wu (2006) but unlike Lamont, Polk, and Saá-Requejo (2001), we find that financially constrained firms have higher stock returns. Like both of these studies, we find that the returns of constrained firms covary positively with the returns of other constrained firms.

However, our results go beyond these earlier studies in several important dimensions. First, these higher returns are evident especially for those firms that have limited access to debt markets, as opposed to equity markets. The risk-adjusted returns on portfolios that are long financially constrained firms and short financially unconstrained firms are 6.5%, 3.8%, and 3.0%, depending on whether we measure financial constraints using our debt, Factiva, or equity training samples, respectively. Financial constraints risk is therefore significantly priced, with debt-related risk the most important and equity-constraints risk the least important. One important exception is evident in portfolios of small firms, in which equity-constraints risk matters. While some inroads have been made towards understanding the relative importance of debt constraints on a theoretical basis (Belo, Lin, and Yang, 2016), we conjecture that further work in this direction would be interesting. Second, we find that a significant portion of the variation in factor portfolios based on our three financial constraints measures cannot be explained by the five-factor model from Fama and French (2015). Third, we find that high returns are not concentrated in small and illiquid firms. Instead, they are most prevalent in large firms with liquid stocks. This last result is particularly important because it means that one can easily form a trading strategy based on financial constraints, without the negative market impact typically associated with small, illiquid stocks.

In the end, our ability to find more definitive and richer results on the relation between financial constraints and returns can be attributed to using a better measure of financial constraints. This measure is essentially based on new data, where these data are words. Given that finance is a highly data-driven field, using textual analysis promises to enrich many different areas of inquiry. Moreover, using textual analysis in combination with traditional analysis of accounting variables may also prove useful for the measurement of difficult-to-observe corporate characteristics.

References

Baker, M., and J. Wurgler. 2000. The equity share in new issues and aggregate stock returns. *Journal of Finance* 55:2219–57.

Beleites, C., U. Neugebauer, T. Bocklitz, C. Krafft, and J. Popp. 2013. Sample size planning for classification models. *Analytica Chimica Acta* 760:25–33.

Belo, F., X. Lin, and F. Yang. 2016. External equity financing shocks, financial flows, and asset prices. Manuscript, University of Minnesota.

Bird, S., E. Klein, and E. Loper. 2009. *Natural language processing with python*. Sebastopol: O'Reilly Media.

Bodnaruk, A., T. Loughran, and B. McDonald. 2015. Using 10-K text to gauge financial constraints. *Journal of Financial and Quantitative Analysis* 50:623–46.

Brain, D., and G. I. Webb. 1999. On the effect of data set size on bias and variance in classification learning. In *Proceedings of the Fourth Australian Knowledge Acquisition Workshop*, 117–28. Sydney: University of New South Wales.

Campbell, J. Y., J. Hilscher, and J. Szilagyi. 2008. In search of distress risk. *Journal of Finance* 63:2899–939.

Chava, S., and A. Purnanandam. 2010. Is default risk negatively related to stock returns? *Review of Financial Studies* 23:2523–59.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? The role of debt covenants. *Journal of Finance* 63:2085–121.

Daniel, K., and S. Titman. 2006. Market reactions to tangible and intangible information. *Journal of Finance* 61:1605–43.

DeAngelo, H., L. DeAngelo, and R. M. Stulz. 2010. Seasoned equity offerings, market timing, and the corporate lifecycle. *Journal of Financial Economics* 95:275–95.

Dechow, P., W. Ge, and C. Schrand. 2010. Understanding earnings quality: A review of the proxies, their determinants and their consequences. *Journal of Accounting and Economics* 50:344–401.

Dutta, S., and A. Nezlobin. 2017. Information disclosure, firm growth, and the cost of capital. *Journal of Financial Economics* 123:415–31.

Erickson, T., and T. M. Whited. 2000. Measurement error and the relationship between investment and q. *Journal of Political Economy* 108:1027–57.

Fama, E. F., and K. R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

———. 2008. Dissecting anomalies. *Journal of Finance* 63:1653–78.

———. 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116:1–22.

Fama, E. F., and J. D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81:607–36.

Farre-Mensa, J., and A. Ljungqvist. 2016. Do measures of financial constraints measure financial constraints? *Review of Financial Studies* 29:271–308.

Feinerer, I., K. Hornik, and D. Meyer. 2008. Text mining infrastructure in R. *Journal of Statistical Software* 25:1–54.

Garlappi, L., and H. Yan. 2011. Financial distress and the cross-section of equity returns. *Journal of Finance* 66:789–822.

Gilchrist, S., and C. P. Himmelberg. 1995. Evidence on the role of cash flow for investment. *Journal of Monetary Economics* 36:541–72.

Gomes, J. F., A. Yaron, and L. Zhang. 2006. Asset pricing implications of firms' financing constraints. *Review of Financial Studies* 19:1321–56.

Greenwood, R., and S. G. Hanson. 2012. Share issuance and factor timing. *Journal of Finance* 67:761–98.

Griffin, J. M., and M. L. Lemmon. 2002. Book-to-market equity, distress risk, and stock returns. *Journal of Finance* 57:2317–36.

Hadlock, C. J., and J. R. Pierce. 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies* 23:1909–40.

Harvey, C. R., Y. Liu, and H. Zhu. 2016. . . . and the cross-section of expected returns. *Review of Financial Studies* 29:5–68.

Hasbrouck, J. 2009. Trading costs and returns for U.S. equities: Estimating effective costs from daily data. *Journal of Finance* 64:1445–77.

Hastie, T., R. Tibshirani, and J. Friedman. 2001. *The elements of statistical learning: Data mining, inference, and prediction*. New York: Springer.

Hoberg, G., and V. Maksimovic. 2015. Redefining financial constraints: A text-based analysis. *Review of Financial Studies* 28:1312–52.

Hou, K., C. Xue, and L. Zhang. 2015. Digesting anomalies: An investment approach. *Review of Financial Studies* 28:650–705.

Ikenberry, D., J. Lakonishok, and T. Vermaelen. 1995. Market underreaction to open market share repurchases. *Journal of Financial Economics* 39:181–208.

Jegadeesh, N., and D. Wu. 2013. Word power: A new approach for content analysis. *Journal of Financial Economics* 110:712–29.

Kaplan, S. N., and L. Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112:169–215.

Karolyi, G. A., and R. C. Liao. 2017. The economic consequences of investor relations: A global perspective. Manuscript, Cornell University.

Lamont, O., C. Polk, and J. Saá-Requejo. 2001. Financial constraints and stock returns. *Review of Financial Studies* 14:529–54.

Lee, I., and T. Loughran. 1998. Performance following convertible bond issuance. *Journal of Corporate Finance* 4:185–207.

Lewis, D. D. 1998. Naïve (Bayes) at forty: The independence assumption in information retrieval. In C. Nédellec and C. Rouveirol, eds., *Machine Learning: ECML-98*, no. 1398 in Lecture Notes in Computer Science, 4–15. Berlin: Springer.

Li, D. 2011. Financial constraints, R&D investment, and stock returns. *Review of Financial Studies* 24:2974–3007.

Li, F. 2010. The information content of forward-looking statements in corporate filings: A naïve Bayesian machine learning approach. *Journal of Accounting Research* 48:1049–102.

Livdan, D., H. Sapriza, and L. Zhang. 2009. Financially constrained stock returns. *Journal of Finance* 64:1827–62.

Loughran, T., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66:35–65.

———. 2013. Ipo first-day returns, offer price revisions, volatility, and form S-1 language. *Journal of Financial Economics* 109:307–26.

———. 2014. Measuring readability in financial disclosures. *Journal of Finance* 69:1643–71.

Loughran, T., and J. R. Ritter. 1995. The new issues puzzle. *Journal of Finance* 50:23–51.

McCallum, A., and K. Nigam. 1998. A comparison of event models for naïve Bayes text classification. In *ICML/AAAI-98 Workshop on Learning for Text Categorization*, vol. 752, 41–8. Madison: AAAI Press.

McLean, R. D., J. Pontiff, and A. Watanabe. 2009. Share issuance and cross-sectional returns: International evidence. *Journal of Financial Economics* 94:1–17.

Novy-Marx, R. 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics* 108:1–28.

Novy-Marx, R., and M. Velikov. 2016. A taxonomy of anomalies and their trading costs. *Review of Financial Studies* 29:104–47.

Pástor, Ľ., and R. F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111:642–85.

Pontiff, J., and A. Woodgate. 2008. Share issuance and cross-sectional returns. *Journal of Finance* 63:921–45.

Price, S. M., J. S. Doran, D. R. Peterson, and B. A. Bliss. 2012. Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking and Finance* 36:992–1011.

Rish, I. 2001. An empirical study of the naïve Bayes classifier. In *Proceedings of IJCAI-2001 Workshop on Empirical Methods in AI*, vol. 3, 41–6. Seattle.

Ritter, J. R. 1991. The long-run performance of initial public offerings. *Journal of Finance* 46:3–27.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39:1127–39.

Spiess, D. K., and J. Affleck-Graves. 1999. The long-run performance of stock returns following debt offerings. *Journal of Financial Economics* 54:45–73.

Vassalou, M., and Y. Xing. 2004. Default risk in equity returns. *Journal of Finance* 59:831–68.

Whited, T. M., and G. Wu. 2006. Financial constraints risk. *Review of Financial Studies* 19:531–59.

Zhang, H. 2005. Exploring conditions for the optimality of naïve Bayes. *International Journal of Pattern Recognition and Artificial Intelligence* 19:183–98.

Table 1: Summary Statistics
This table shows summary statistics of firm characteristics sorted on textual financial constraints measures, the KZ index (Kaplan and Zingales, 1997), and the WW index (Whited and Wu, 2006). Details of the construction of the training samples are described in Section 1.2.3. The first three columns show unconstrained, mid-constrained, and constrained values while the last column shows the difference (constrained minus unconstrained) and the corresponding t statistics.

Panel A: Sorted by Textual FC Index (Factiva Training Sample)

	Unconstrained Low FC	Mid FC	Constrained High FC	Difference	(t statistic)
Cash Flow/Total Assets	0.0161	0.0142	0.0007	−0.0154	(−9.4)
Total Assets	2627.9615	1584.7648	2293.8812	−334.0804	(−2.1)
Debt/Total Assets	0.2159	0.2183	0.2048	−0.0111	(−2.9)
Dividends/Total Assets	0.0027	0.0027	0.0023	−0.0005	(−2.4)
Cash/Total Assets	0.1408	0.1468	0.2035	0.0626	(10.8)
R&D/Sales	0.1063	0.1315	0.3340	0.2274	(11.9)
Capex/Total Assets	0.0162	0.0157	0.0134	−0.0027	(−5.5)
Tobin's q	1.7612	1.7601	2.0448	0.2836	(6.1)
KZ Index	0.8997	0.8896	0.8520	−0.0477	(−2.3)
Whited/Wu Index	−0.2910	−0.2765	−0.2736	0.0174	(5.5)
Text-based FC Index	0.0647	0.1086	0.4181	0.3534	(27.7)

Panel B: Sorted by Textual FC Index (Equity Training Sample)

	Unconstrained Low FC	Mid FC	Constrained High FC	Difference	(t statistic)
Cash Flow/Total Assets	0.0161	0.0172	−0.0032	−0.0193	(−8.5)
Total Assets	1926.3548	2490.6825	1794.0020	−132.3528	(−1.0)
Debt/Total Assets	0.2230	0.2276	0.1854	−0.0376	(−8.9)
Dividends/Total Assets	0.0026	0.0028	0.0023	−0.0003	(−1.2)
Cash/Total Assets	0.1365	0.1288	0.2317	0.0952	(13.5)
R&D/Sales	0.0910	0.0853	0.3589	0.2675	(11.9)
Capex/Total Assets	0.0159	0.0161	0.0133	−0.0025	(−6.5)
Tobin's q	1.7149	1.6878	2.1804	0.4655	(9.4)
KZ Index	0.9102	0.9242	0.7941	−0.1161	(−5.5)
Whited/Wu Index	−0.2781	−0.2912	−0.2671	0.0110	(3.6)
Text-based FC Index	0.0990	0.1251	0.4535	0.3544	(24.9)

Panel C: Sorted by Textual FC Index (Debt Training Sample)

	Unconstrained Low FC	Mid FC	Constrained High FC	Difference	(t statistic)
Cash Flow/Total Assets	0.0160	0.0135	0.0018	−0.0142	(−8.0)
Total Assets	2363.6129	2035.9876	1960.8807	−402.7322	(−3.3)
Debt/Total Assets	0.2171	0.2174	0.2050	−0.0121	(−2.9)
Dividends/Total Assets	0.0028	0.0028	0.0021	−0.0007	(−4.7)
Cash/Total Assets	0.1390	0.1484	0.2031	0.0640	(12.6)
R&D/Sales	0.1163	0.1452	0.3254	0.2087	(11.5)
Capex/Total Assets	0.0152	0.0151	0.0153	0.0002	(0.3)
Tobin's q	1.7389	1.7960	2.0158	0.2769	(6.5)
KZ Index	0.8954	0.8882	0.8594	−0.0360	(−1.7)
Whited/Wu Index	−0.2872	−0.2778	−0.2758	0.0114	(4.2)
Text-based FC Index	0.1051	0.1785	0.6370	0.5319	(38.6)

Panel D: Sorted by KZ Index

	Unconstrained Low FC	Mid FC	Constrained High FC	Difference	(t statistic)
Cash Flow/Total Assets	0.0000	0.0191	0.0111	0.0111	(4.9)
Total Assets	893.1475	2630.9180	2257.7642	1364.6167	(16.0)
Debt/Total Assets	0.0346	0.1796	0.4295	0.3950	(90.4)
Dividends/Total Assets	0.0049	0.0019	0.0012	−0.0037	(−13.2)
Cash/Total Assets	0.3031	0.1148	0.0831	−0.2201	(−37.7)
R&D/Sales	0.2898	0.1202	0.1627	−0.1270	(−6.6)
Capex/Total Assets	0.0119	0.0168	0.0171	0.0052	(9.9)
Tobin's q	1.6224	1.7513	2.1925	0.5701	(10.5)
KZ Index	−0.0229	0.8541	1.8235	1.8464	(71.1)
Whited/Wu Index	−0.2523	−0.2959	−0.2849	−0.0326	(−12.0)
Text-based FC Index	0.3251	0.2825	0.2807	−0.0444	(−5.0)

Panel E: Sorted by WW Index

	Unconstrained Low FC	Mid FC	Constrained High FC	Difference	(t statistic)
Cash Flow/Total Assets	0.0257	0.0193	−0.0050	−0.0307	(−25.2)
Total Assets	6226.8404	547.8237	98.0555	−6128.7849	(−25.5)
Debt/Total Assets	0.2361	0.2018	0.1762	−0.0599	(−11.7)
Dividends/Total Assets	0.0039	0.0028	0.0008	−0.0031	(−21.9)
Cash/Total Assets	0.0996	0.1620	0.2087	0.1091	(19.8)
R&D/Sales	0.0582	0.1189	0.2905	0.2322	(14.3)
Capex/Total Assets	0.0163	0.0163	0.0127	−0.0036	(−9.3)
Tobin's q	1.7837	1.7293	1.8866	0.1029	(3.0)
KZ Index	0.9740	0.8117	0.7709	−0.2031	(−9.4)
Whited/Wu Index	−0.3889	−0.2771	−0.1756	0.2133	(90.7)
Text-based FC Index	0.2898	0.2774	0.3078	0.0180	(2.1)

Table 2: Portfolio Characteristics

This table shows value-weighted portfolio characteristics when sorting on the textual financial constraints measures. Each panel shows the average values of the financial constraints measures (FC), excess returns ($r - r_f$, long-only, annualized), size (that is, market equity), book-to-market ratio (B/M), and the average number of stocks in the portfolio. The values are split according to the percentiles of the constraints measures. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.06	6.78	37342	0.367	551
Mid FC	0.09	8.22	50319	0.352	880
High FC	0.59	7.93	87456	0.319	879
High-Low	0.54	1.15	50114	-0.048	1430
t-statistic	69.46	0.52	17.58	-14.12	

Panel B: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.13	7.02	65413	0.324	700
Mid FC	0.14	7.58	59479	0.378	755
High FC	0.38	8.23	69609	0.317	855
High-Low	0.25	1.21	4196	-0.007	1555
t-statistic	34.02	0.63	1.83	-2.35	

Panel C: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.11	6.17	48036	0.357	579
Mid FC	0.20	7.77	57238	0.343	932
High FC	0.79	8.60	82105	0.329	800
High-Low	0.68	2.43	34069	-0.028	1379
t-statistic	93.24	1.05	14.77	-6.97	

Table 3: Portfolios Sorted on Textual Financial Constraints Measures
This table shows regression results for value-weighted portfolios sorted on the textual financial constraints measures. The different panels correspond to the training samples, described in Section 1.2.3. Columns one to three are long-only portfolios for different financial constraints percentiles. Column four shows results for a portfolio that is long the constrained and short the unconstrained percentile. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	-0.85 (-0.60)	0.49 (0.45)	2.87 (2.34)**	3.72 (1.93)*
$r_{mkt} - r_f$	102.00 (35.24)***	103.51 (46.77)***	98.47 (39.22)***	-3.54 (-0.90)
SMB	6.62 (1.77)*	8.93 (3.13)***	-2.99 (-0.93)	-9.61 (-1.89)*
HML	12.54 (2.51)**	-1.68 (-0.44)	-26.04 (-6.01)***	-38.58 (-5.68)***
RMW	13.85 (2.47)**	18.74 (4.38)***	1.85 (0.38)	-12.01 (-1.57)
CMA	-0.46 (-0.07)	2.78 (0.52)	-6.06 (-0.99)	-5.60 (-0.58)
R^2	0.90	0.94	0.93	0.36
Num. obs.	200	200	200	200
# Stocks	551	880	879	1430

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	0.90 (0.60)	-0.70 (-0.54)	3.86 (2.95)***	2.95 (1.55)
$r_{mkt} - r_f$	100.17 (32.64)***	100.83 (38.30)***	99.38 (37.12)***	-0.79 (-0.20)
SMB	9.57 (2.42)**	0.74 (0.22)	-1.38 (-0.40)	-10.95 (-2.19)**
HML	-12.11 (-2.29)**	8.85 (1.95)*	-26.38 (-5.71)***	-14.28 (-2.13)**
RMW	11.97 (2.02)**	24.36 (4.78)***	-14.64 (-2.83)***	-26.60 (-3.54)***
CMA	-15.40 (-2.06)**	11.68 (1.83)*	-5.44 (-0.84)	9.96 (1.06)
R^2	0.90	0.90	0.93	0.17
Num. obs.	200	200	200	200
# Stocks	700	755	855	1555

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	-2.35 (-1.85)*	0.97 (0.89)	4.13 (2.80)***	6.48 (3.28)***
$r_{mkt} - r_f$	101.78 (39.27)***	102.40 (46.09)***	97.16 (32.18)***	-4.62 (-1.14)
SMB	8.11 (2.43)**	-1.94 (-0.68)	0.80 (0.21)	-7.31 (-1.40)
HML	2.97 (0.66)	-16.23 (-4.24)***	-12.66 (-2.43)**	-15.63 (-2.24)**
RMW	23.02 (4.59)***	13.88 (3.23)***	-8.02 (-1.37)	-31.04 (-3.97)***
CMA	16.13 (2.56)**	7.15 (1.32)	-19.59 (-2.67)***	-35.71 (-3.63)***
R^2	0.91	0.94	0.91	0.38
Num. obs.	200	200	200	200
# Stocks	579	932	800	1379

Table 4: Excess Returns of Double Sorts on Size and Textual Financial Constraints
This table shows annualized excess returns of value-weighted long-only portfolios that are double sorted on the textual financial constraints measures and size. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	11.41	10.64	11.36	-0.06	-0.02
Medium	8.52	10.81	9.15	0.62	0.24
Big	6.19	7.62	8.18	2.00	0.84

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	10.19	11.04	11.20	1.01	0.34
Medium	10.23	9.23	9.75	-0.48	-0.23
Big	6.81	7.25	8.09	1.28	0.61

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.84	11.03	11.72	1.88	0.72
Medium	8.05	9.98	10.42	2.36	0.91
Big	5.82	7.45	8.52	2.69	1.11

Table 5: Risk-Adjusted Returns: Size versus Textual Financial Constraints
This table shows regressions of value-weighted portfolios that are double sorted on the textual financial constraints measures and size (that is, market equity). Each column shows results for a portfolio that is long the constrained and short the unconstrained percentile (indicated by FCHML), and different columns correspond to different size subgroups. The different panels correspond to the training samples, which are explained in Section 1.2.3. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	1.40 (0.68)	3.56 (2.13)**	4.48 (2.07)**
$r_{mkt} - r_f$	2.79 (0.66)	−4.38 (−1.28)	−2.87 (−0.65)
SMB	7.85 (1.44)	2.76 (0.63)	−7.75 (−1.36)
HML	−47.75 (−6.56)***	−46.88 (−7.96)***	−36.37 (−4.78)***
RMW	−34.03 (−4.16)***	−48.93 (−7.41)***	−9.96 (−1.17)
CMA	30.71 (2.99)***	26.83 (3.23)***	−9.89 (−0.92)
R^2	0.50	0.65	0.30
Num. obs.	200	200	200
# Stocks	846	371	211

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	4.07 (2.05)**	2.09 (1.33)	2.70 (1.23)
$r_{mkt} - r_f$	−3.24 (−0.80)	1.19 (0.37)	0.22 (0.05)
SMB	13.28 (2.54)**	2.50 (0.60)	−12.42 (−2.15)**
HML	−29.78 (−4.26)***	−17.06 (−3.08)***	−11.38 (−1.47)
RMW	−70.07 (−8.93)***	−44.83 (−7.22)***	−19.17 (−2.21)**
CMA	26.23 (2.66)***	0.56 (0.07)	6.39 (0.59)
R^2	0.63	0.53	0.08
Num. obs.	200	200	200
# Stocks	973	382	200

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	4.23 (2.13)**	6.24 (3.58)***	6.73 (3.10)***
$r_{mkt} - r_f$	3.19 (0.79)	−0.26 (−0.07)	−4.69 (−1.06)
SMB	4.92 (0.94)	1.83 (0.40)	−6.98 (−1.22)
HML	−27.45 (−3.93)***	−20.65 (−3.36)***	−13.09 (−1.71)*
RMW	−50.31 (−6.43)***	−60.64 (−8.80)***	−27.02 (−3.14)***
CMA	15.11 (1.54)	−6.56 (−0.76)	−42.12 (−3.90)***
R^2	0.52	0.62	0.32
Num. obs.	200	200	200
# Stocks	807	362	208

Table 6: Covariance Tests of Portfolios

This table shows the regression results of nine value-weighted portfolios formed by double-sorting on size and the textual financial constraints measures. Portfolios starting with S/M/B belong to the small/medium/big percentile, while portfolios ending with L/M/H belong to the low/mid/high financial constraints index percentile. The excess returns of each portfolio are regressed on three reference portfolios: a market proxy (*BIG*), a size factor proxy (*SMALL*), and the financial constraints factor (*FC*). *BIG* is the portfolio of less-constrained medium-size and large firms, $BIG = (BM + BL + MM + ML)/4 - r_f$. *SMALL* consists of less-constrained small firms, $SMALL = (SM + SL)/2 - r_f$. *FC* is the financial constraints factor, $FC = HIGHFC - LOWFC$, where $HIGHFC = (SH + MH + BH)/3$, $LOWFC = (SL + ML + BL)/3$. In each regression, we omit the portfolio on the left-hand side from the portfolios on the right-hand side. Furthermore, for *FC*, the matching portfolio on the short side is omitted. The different panels correspond to the training samples, which are explained in Section 1.2.3. Numbers in parentheses are *t*-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Factiva Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	0.00	−0.00	−0.02	−0.02	0.01	−0.02	−0.01	0.02	0.02
	(0.31)	(−0.07)	(−1.00)	(−1.11)	(1.12)	(−1.31)	(−0.45)	(0.91)	(0.95)
BIG	0.08	0.27***	−0.03	0.70***	0.60***	0.62***	1.11***	1.14***	1.19***
	(1.44)	(5.93)	(−0.51)	(15.29)	(16.73)	(11.15)	(18.14)	(17.88)	(17.30)
SMALL	0.96***	0.74***	1.13***	0.41***	0.46***	0.49***	−0.27***	−0.34***	−0.33***
	(21.83)	(21.83)	(22.45)	(11.97)	(17.00)	(11.35)	(−5.35)	(−6.30)	(−6.03)
FC	0.02	0.10**	0.74***	−0.12**	0.04	0.72***	−0.13**	0.15***	0.45***
	(0.35)	(2.09)	(11.74)	(−2.47)	(0.95)	(13.00)	(−2.47)	(2.81)	(7.37)
R^2	0.93	0.94	0.93	0.93	0.95	0.93	0.83	0.82	0.80
Num. obs.	200	200	200	200	200	200	200	200	200

Panel B: Equity Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.01	0.01	−0.01	0.01	−0.01	−0.02	−0.00	0.01	0.01
	(−0.44)	(0.75)	(−0.42)	(0.41)	(−0.44)	(−1.01)	(−0.13)	(0.58)	(0.48)
BIG	0.30***	0.20***	−0.05	0.59***	0.58***	0.78***	1.03***	1.00***	1.25***
	(5.49)	(3.40)	(−0.53)	(12.89)	(11.82)	(13.45)	(10.88)	(13.64)	(16.08)
SMALL	0.75***	0.80***	1.17***	0.47***	0.49***	0.36***	−0.20**	−0.24***	−0.32***
	(17.05)	(17.05)	(14.44)	(13.11)	(12.91)	(7.87)	(−2.51)	(−3.77)	(−5.16)
FC	0.20***	−0.08	0.95***	0.14***	0.02	0.81***	0.19**	−0.26***	0.37***
	(2.95)	(−1.12)	(8.12)	(2.79)	(0.43)	(14.17)	(2.48)	(−4.42)	(5.55)
R^2	0.92	0.91	0.86	0.93	0.92	0.94	0.71	0.76	0.80
Num. obs.	200	200	200	200	200	200	200	200	200

Panel C: Debt Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.01	0.01	−0.01	−0.01	0.01	−0.02	−0.00	0.01	0.01
	(−0.95)	(1.08)	(−0.82)	(−0.86)	(0.75)	(−1.03)	(−0.28)	(0.72)	(0.75)
BIG	0.10**	0.16***	−0.02	0.69***	0.58***	0.70***	1.02***	1.23***	1.15***
	(2.11)	(3.83)	(−0.40)	(15.66)	(14.90)	(13.91)	(18.10)	(16.80)	(17.24)
SMALL	0.95***	0.83***	1.12***	0.40***	0.45***	0.46***	−0.18***	−0.42***	−0.28***
	(26.69)	(26.69)	(23.66)	(12.31)	(15.74)	(12.18)	(−3.90)	(−6.92)	(−5.27)
FC	−0.03	0.11**	0.68***	−0.13***	0.08*	0.72***	−0.23***	0.28***	0.44***
	(−0.56)	(2.51)	(11.21)	(−2.64)	(1.82)	(14.23)	(−4.48)	(4.38)	(6.86)
R^2	0.95	0.95	0.94	0.92	0.94	0.94	0.83	0.78	0.81
Num. obs.	200	200	200	200	200	200	200	200	200

Table 7: Financial Constraints Portfolios and the Fama-French Five Factors

This table presents the results of regressions of the value-weighted (VW) and equal-weighted (EW) financial constraints portfolio *FC* on the Fama-French five factors. The different training samples (Factiva, equity, and debt) for constructing FC are explained in Section 1.2.3. The α's display the annualized risk-adjusted returns of the *FC* portfolios. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

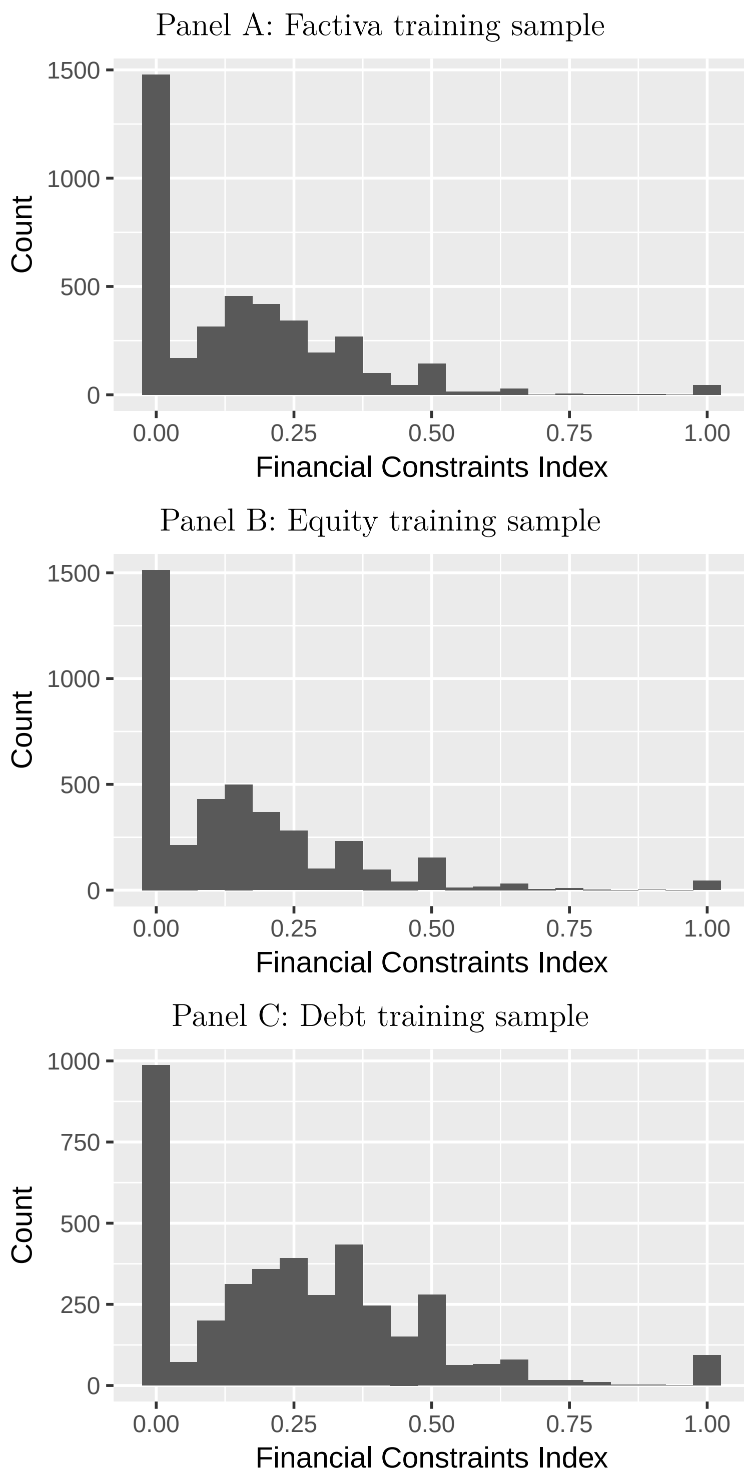
	Factiva FC (VW)	Factiva FC (EW)	Equity FC (VW)	Equity FC (EW)	Debt FC (VW)	Debt FC (EW)
α	3.14^{**}	3.65^{***}	2.95^{**}	3.55^{***}	5.73^{***}	5.48^{***}
	(2.25)	(2.64)	(2.36)	(2.97)	(3.92)	(3.62)
$r_{\text{Mkt}} - r_f$	-1.49	-0.19	-0.61	4.56^{*}	-0.59	1.81
	(-0.52)	(-0.07)	(-0.24)	(1.86)	(-0.20)	(0.59)
SMB	0.95	-0.03	1.12	2.88	-0.08	-2.73
	(0.26)	(-0.01)	(0.34)	(0.92)	(-0.02)	(-0.68)
HML	-43.67^{***}	-41.81^{***}	-19.41^{***}	-21.12^{***}	-20.40^{***}	-28.09^{***}
	(-8.88)	(-8.57)	(-4.40)	(-5.01)	(-3.96)	(-5.27)
RMW	-30.97^{***}	-31.88^{***}	-44.69^{***}	-48.26^{***}	-45.99^{***}	-46.49^{***}
	(-5.62)	(-5.82)	(-9.04)	(-10.21)	(-7.96)	(-7.77)
CMA	15.88^{**}	19.01^{***}	11.06^{*}	1.96	-11.19	-1.86
	(2.29)	(2.76)	(1.78)	(0.33)	(-1.54)	(-0.25)
R^2	0.64	0.63	0.62	0.72	0.61	0.63
Num. obs.	200	200	200	200	200	200

Table 8: Investment, New Stock Issues, and New Bond Issues

This table shows the results for Fama-MacBeth regressions of monthly stock returns on individual firm characteristics. The columns are grouped by the training samples ("TS" in the column headers below) used for the construction of the financial constraints (FC) measure. The training samples are described in Section 1.2.3. The dependent variable is, for each firm-month, the average monthly excess return over the following two quarters. Independent variables are the financial constraints measure (FC, described in Section 1.2), the book-to-market ratio (log(b/m)), size (log(me)), past stock return performance measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$), capital expenditures ($capex$=$CAPXQ$/lag(ATQ)), net cash raised from stock issues (stk=($SSTKQ-PRSTKCQ$)/lag(ATQ)), and net new long-term debt (dbt=($DLTISQ-DLTRQ$)/lag(ATQ)). Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Factiva TS	Factiva TS	Equity TS	Equity TS	Debt TS	Debt TS
FC	0.32^{**}	0.37^{***}	-1.45^{*}	-1.35	0.35^{***}	0.38^{***}
	(2.48)	(3.13)	(−1.68)	(−1.59)	(3.46)	(3.87)
log(b/m)	0.14^{**}	0.13^{**}	0.18^{***}	0.17^{***}	0.14^{**}	0.14^{**}
	(2.55)	(2.20)	(3.88)	(3.56)	(2.41)	(2.30)
log(me)	-0.12^{***}	-0.11^{***}	-0.10^{***}	-0.10^{***}	-0.12^{***}	-0.12^{***}
	(−3.59)	(−3.37)	(−3.61)	(−3.34)	(−3.66)	(−3.45)
$r_{1,0}$	0.29	0.02	0.19	−0.08	0.28	−0.00
	(1.14)	(0.09)	(0.80)	(−0.31)	(1.10)	(−0.01)
$r_{12,2}$	0.30^{**}	0.43^{***}	0.27^{**}	0.42^{***}	0.29^{**}	0.42^{***}
	(2.43)	(3.35)	(2.36)	(3.41)	(2.45)	(3.34)
capex		-4.51^{***}		-4.59^{***}		-5.62^{***}
		(−2.63)		(−2.79)		(−3.12)
stk		-7.41^{***}		-7.87^{***}		-7.75^{***}
		(−4.59)		(−5.03)		(−4.94)
dbt		-5.83^{***}		-5.66^{***}		-5.74^{***}
		(−9.96)		(−10.07)		(−9.61)
Num. obs.	360985	288824	361154	288963	361202	288816

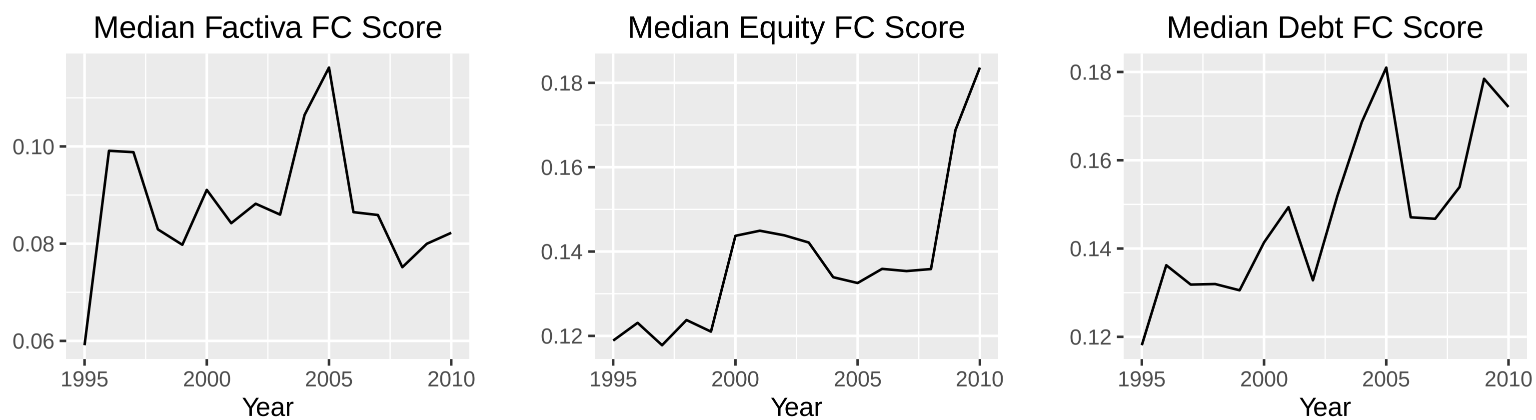
Figure 1
Histograms of textual financial constraints measures



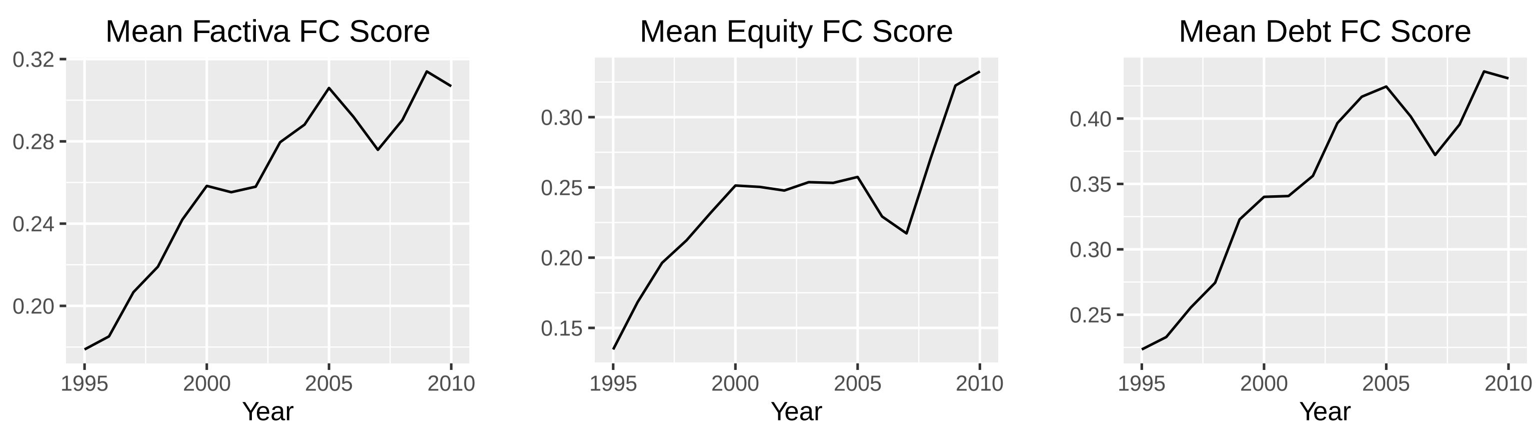
This figure shows histograms of textual financial constraints measures on the date level. The training samples are explained in detail in Section 1.2.3. Values closer to one (zero) mean that the firm is more (less) financially constrained.

Figure 2
Financial constraints measures over time

Panel A: Medians



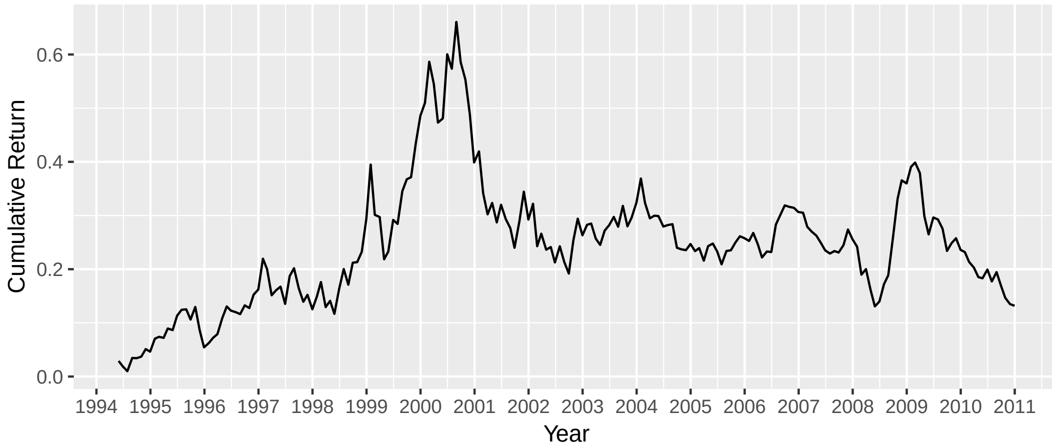
Panel B: Means



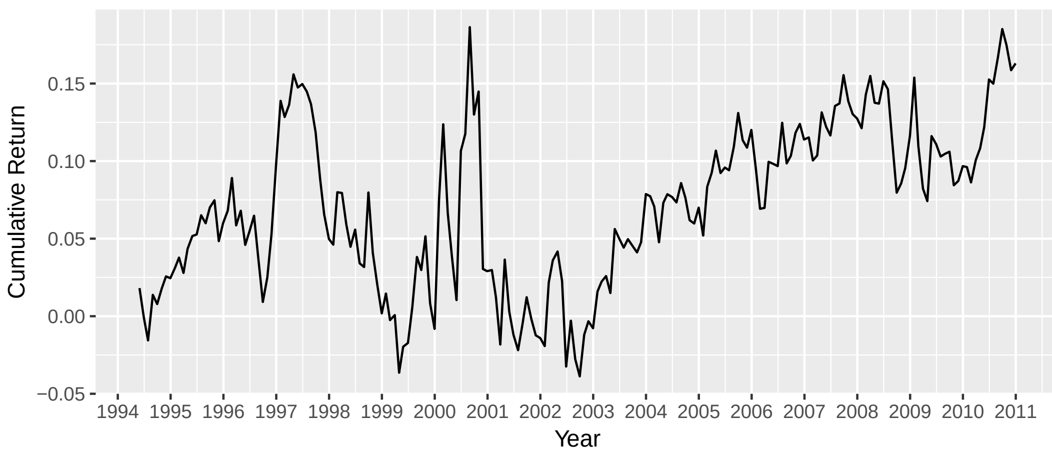
This figure shows the median and mean financial constraints scores as a function of time for each of our training samples: the Factiva sample, the equity sample, and the debt sample. These training samples are explained in detail in Section 1.2.3. Values closer to one (zero) mean that the firm is more (less) financially constrained.

Figure 3
Financial constraints portfolios

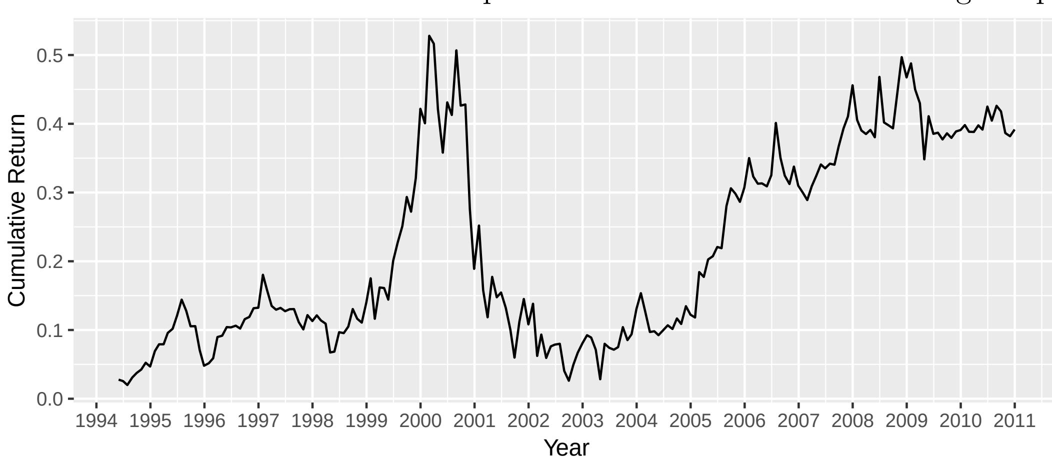
Panel A: Cumulative returns of the portfolio based on the Factiva training sample



Panel B: Cumulative returns of the portfolio based on the equity training sample



Panel C: Cumulative returns of the portfolio based on the debt training sample



These plots show cumulative returns of long-short value-weighted portfolios sorted on the financial constraints measures, going long the top constraints percentile and short the bottom percentile. Section 1.2.3 details the construction of the financial constraints measures based on the *Factiva* training sample, the *equity* training sample, and the *debt* training sample.

Internet Appendix to "Are Financial Constraints Priced? Evidence from Textual Analysis"

This appendix contains three sections. Section A contains all of the tables referred to in Section 3 in the main text. Section B contains excerpts from the financial reports of a randomly selected sample of firms classified as financially constrained according to our debt-based criterion. Section C contains miscellaneous results that have been omitted from the main text.

A. Additional Robustness Checks

This section contains Tables related to the robustness checks reported in Section 3.4. Section A.1 repeats Tables 2–7 with the text classification from Hoberg and Maksimovic (2015). Section A.2 repeats the tests from Tables 2, 3, 4, 5, and 7 with portfolio returns net of trading costs. Section A.3 repeats Tables 2–7 with the sample screened of micro cap stocks. Section A.4 repeats Tables 2–7 with the dot-com bubble removed from the sample. Section A.5 repeats Tables 3 and 5 with the factors from Hou, Xue, and Zhang (2015) substituted in for the factors from Fama and French (2015). Section A.6 repeats Tables 3 and 5 with the illiquidity factor from Pástor and Stambaugh (2003) included in addition to the factors from Fama and French (2015). Section A.7 repeats Tables 4 and 5, except that we replace size with the Whited-Wu index. Section A.8 repeats Table 8, with two extra sets of controls. The first includes the covenant tightness measure from Chava and Roberts (2008), leverage, the number of analysts, and the fraction of outside directors. The second includes 10-K word counts, a widely-used measure of earnings persistence from Dechow, Ge, and Schrand (2010), and the interaction of these disclosure measures with sales growth.

A.1 Hoberg and Maksimovic Text Classification

Table A1: Portfolio Characteristics (Hoberg-Maksimovic Classification)
This table presents results analogous to those in Table 2, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. Each panel shows the average values of the financial constraints measures, excess returns (long-only, annualized), size (that is, market equity), book-to-market ratio, and the average number of stocks in the portfolio. The values are split according to the percentiles of the constraints measures.

Panel A: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.55	5.24	93960	0.283	1150
Mid FC	0.67	5.23	63078	0.385	803
High FC	0.74	6.55	40429	0.389	574
High-Low	0.19	1.31	-53530	0.105	1724
t-statistic	112.51	0.37	-25.14	25.86	

Panel B: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.54	7.43	83807	0.330	838
Mid FC	0.62	5.40	67508	0.342	861
High FC	0.67	7.64	61057	0.349	793
High-Low	0.14	0.20	-22751	0.019	1631
t-statistic	28.58	0.06	-7.61	2.43	

Table A2: Single-Sorted Portfolios Using the Hoberg-Maksimovic Measures

This table presents regressions analogous to those in Table 3, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. Columns one to three are long-only portfolios for different financial constraints percentiles. Column four shows results for a portfolio that is long the constrained and short the unconstrained percentile. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	3.07 (2.18)**	−0.68 (−0.46)	−1.66 (−0.90)	−4.73 (−1.79)*
$r_{mkt} - r_f$	99.05 (35.12)***	101.20 (33.78)***	108.57 (29.31)***	9.52 (1.80)*
SMB	−3.38 (−0.93)	6.63 (1.71)*	20.97 (4.38)***	24.35 (3.56)***
HML	−29.16 (−5.98)***	5.83 (1.13)	8.56 (1.34)	37.72 (4.13)***
RMW	−12.92 (−2.34)**	24.22 (4.12)***	48.71 (6.71)***	61.63 (5.95)***
CMA	−7.93 (−1.19)	0.81 (0.11)	3.95 (0.45)	11.88 (0.95)
R^2	0.94	0.91	0.88	0.53
Num. obs.	164	164	164	164
# Stocks	1150	803	574	1724

Panel B: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	4.65 (2.65)***	−0.09 (−0.06)	0.17 (0.10)	−4.48 (−1.56)
$r_{mkt} - r_f$	104.77 (30.21)***	95.02 (35.74)***	105.13 (30.37)***	0.36 (0.06)
SMB	1.63 (0.36)	5.02 (1.44)	1.50 (0.33)	−0.13 (−0.02)
HML	−8.62 (−1.43)	−6.85 (−1.48)	−11.35 (−1.88)*	−2.72 (−0.28)
RMW	−2.56 (−0.38)	10.34 (1.98)**	26.90 (3.96)***	29.46 (2.64)***
CMA	−39.00 (−4.62)***	9.87 (1.52)	31.04 (3.68)***	70.04 (5.06)***
R^2	0.91	0.92	0.87	0.32
Num. obs.	176	176	176	176
# Stocks	838	861	793	1631

Table A3: Excess Returns of Double Sorts on Size and Textual Financial Constraints (Hoberg-Maksimovic Classification)

This table presents results analogous to those in Table 4, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. This table shows annualized excess returns of value-weighted long-only portfolios that are double sorted on the Hoberg and Maksimovic financial constraints measures and size.

Panel A: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	11.90	11.79	11.07	-0.82	-0.15
Medium	9.96	9.83	9.08	-0.88	-0.21
Big	4.70	4.59	5.77	1.07	0.30

Panel B: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	11.57	12.15	9.37	-2.21	-0.67
Medium	10.29	8.79	9.22	-1.07	-0.28
Big	7.40	4.82	7.40	-0.00	-0.00

Table A4: Double-Sorted Portfolios Using the Hoberg-Maksimovic Measures

This table presents regressions analogous to those in Table 5, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	-5.68 $(-1.94)^{*}$	-5.74 $(-2.66)^{***}$	-4.56 (-1.55)
$r_{mkt} - r_f$	15.34 $(2.61)^{***}$	2.59 (0.60)	6.52 (1.10)
SMB	-20.02 $(-2.64)^{***}$	-2.55 (-0.46)	22.12 $(2.90)^{***}$
HML	62.80 $(6.19)^{***}$	48.04 $(6.44)^{***}$	29.25 $(2.87)^{***}$
RMW	98.87 $(8.59)^{***}$	84.71 $(10.02)^{***}$	58.00 $(5.01)^{***}$
CMA	-17.54 (-1.26)	-2.90 (-0.28)	18.30 (1.31)
R^2	0.74	0.78	0.43
Num. obs.	164	164	164
# Stocks	1103	409	212

Panel B: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	-4.54 $(-1.65)^{*}$	-5.20 $(-1.79)^{*}$	-4.75 (-1.50)
$r_{mkt} - r_f$	-8.62 (-1.59)	-2.18 (-0.38)	0.58 (0.09)
SMB	-20.33 $(-2.85)^{***}$	-22.69 $(-3.00)^{***}$	2.50 (0.30)
HML	2.58 (0.27)	6.34 (0.63)	-4.38 (-0.40)
RMW	35.55 $(3.33)^{***}$	61.78 $(5.46)^{***}$	25.76 $(2.10)^{**}$
CMA	35.72 $(2.70)^{***}$	38.48 $(2.74)^{***}$	74.20 $(4.87)^{***}$
R^2	0.40	0.52	0.27
Num. obs.	176	176	176
# Stocks	1032	394	203

Table A5: Covariance Tests of Portfolios (Hoberg-Maksimovic Classification)

This table presents results analogous to those in Table 6, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. Portfolios starting with S/M/B belong to the small/medium/big percentile, while portfolios ending with L/M/H belong to the low/mid/high financial constraints index percentile. The excess returns of each portfolio are regressed on three reference portfolios: a market proxy (*BIG*), a size factor proxy (*SMALL*), and the financial constraints factor (*FC*). *BIG* is the portfolio of less-constrained medium-size and large firms, $BIG = (BM + BL + MM + ML)/4 - r_f$. *SMALL* consists of less-constrained small firms, $SMALL = (SM + SL)/2 - r_f$. *FC* is the financial constraints factor, $FC = HIGHFC - LOWFC$, where $HIGHFC = (SH + MH + BH)/3$, $LOWFC = (SL + ML + BL)/3$. In each regression, we omit the portfolio on the left-hand side from the portfolios on the right-hand side. Furthermore, for *FC*, the matching portfolio on the short side is omitted. Numbers in parentheses are *t*-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Equity Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.01	0.02	0.01	−0.00	0.01	−0.00	−0.00	−0.01	0.00
	(−0.38)	(1.11)	(0.25)	(−0.14)	(0.56)	(−0.14)	(−0.17)	(−0.69)	(0.07)
BIG	−0.11	0.47***	0.44***	0.65***	0.57***	0.73***	1.26***	0.99***	0.94***
	(−1.24)	(10.05)	(6.68)	(11.74)	(13.65)	(17.08)	(14.52)	(17.01)	(12.56)
SMALL	1.16***	0.54***	0.62***	0.52***	0.45***	0.33***	−0.45***	−0.17***	−0.08
	(16.42)	(16.42)	(12.28)	(12.81)	(14.11)	(9.70)	(−6.11)	(−3.41)	(−1.27)
FC	−0.92***	0.61***	0.64***	−0.41***	0.44***	0.60***	−0.25***	0.34***	0.37***
	(−15.00)	(13.97)	(13.26)	(−9.72)	(14.03)	(20.38)	(−5.16)	(9.99)	(8.20)
R^2	0.92	0.93	0.90	0.94	0.94	0.95	0.80	0.86	0.78
Num. obs.	164	164	164	164	164	164	164	164	164

Panel B: Debt Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.01	0.02	−0.01	−0.01	−0.01	0.01	0.02	−0.01	0.02
	(−0.76)	(1.15)	(−0.67)	(−0.33)	(−0.48)	(0.70)	(0.81)	(−0.43)	(0.74)
BIG	0.06	0.22***	0.10*	0.55***	0.61***	0.94***	1.43***	0.95***	1.01***
	(1.02)	(4.71)	(1.93)	(10.69)	(14.23)	(17.53)	(15.74)	(16.70)	(13.72)
SMALL	1.00***	0.77***	0.84***	0.57***	0.45***	0.13***	−0.53***	−0.20***	−0.12**
	(24.41)	(24.41)	(21.34)	(16.52)	(15.16)	(3.31)	(−7.26)	(−4.23)	(−2.15)
FC	−0.39***	0.32***	0.47***	−0.28***	0.38***	0.71***	−0.17**	0.27***	0.44***
	(−8.31)	(7.74)	(10.10)	(−5.40)	(8.43)	(14.00)	(−2.50)	(5.51)	(6.87)
R^2	0.96	0.95	0.93	0.94	0.94	0.91	0.80	0.83	0.75
Num. obs.	176	176	176	176	176	176	176	176	176

Table A6: Relating the Financial Constraints Factor to the Fama-French Five Factors (Hoberg-Maksimovic Classification)

This table presents results analogous to those in Table 7, except that firms are sorted according to the Hoberg-Maksimovic financial constraints measures described in Section 3.2. This table presents the results of regressions of the value-weighted (VW) and equal-weighted (EW) financial constraints factor *FC* on the Fama-French five factors. The α's display the annualized risk-adjusted returns of the *FC* factor. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Equity FC (VW)	Equity FC (EW)	Debt FC (VW)	Debt FC (EW)
α	-5.33^{***}	-7.48^{***}	-4.83^{**}	-5.00^{**}
	(-2.68)	(-3.75)	(-2.07)	(-2.28)
$r_{\text{Mkt}} - r_f$	8.15^{**}	3.40	-3.41	-8.18^{*}
	(2.04)	(0.85)	(-0.74)	(-1.89)
SMB	-0.15	3.36	-13.50^{**}	-12.99^{**}
	(-0.03)	(0.65)	(-2.23)	(-2.28)
HML	46.70^{***}	50.02^{***}	1.51	2.81
	(6.77)	(7.24)	(0.19)	(0.37)
RMW	80.53^{***}	73.60^{***}	41.03^{***}	36.47^{***}
	(10.30)	(9.39)	(4.53)	(4.28)
CMA	-0.71	-1.60	49.47^{***}	43.16^{***}
	(-0.08)	(-0.17)	(4.40)	(4.08)
R^2	0.78	0.77	0.49	0.51
Num. obs.	164	164	176	176

A.2 Trading Costs

Table A7: Portfolio Characteristics with After-Trading-Cost Returns
This table presents results analogous to those in Table 2, except that the portfolio returns are net of trading costs. Each panel shows the average values of the financial constraints measures, excess returns (long-only, annualized, net of trading costs), size (that is, market equity), book-to-market ratio, and the average number of stocks in the portfolio. The values are split according to the percentiles of the constraints measures. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.06	6.71	37342	0.367	551
Mid FC	0.09	8.15	50319	0.352	880
High FC	0.59	7.85	87456	0.319	879
High-Low	0.54	0.99	50114	-0.048	1430
t-statistic	69.46	0.45	17.58	-14.12	

Panel B: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.13	6.92	65413	0.324	700
Mid FC	0.14	7.52	59479	0.378	755
High FC	0.38	8.16	69609	0.317	855
High-Low	0.25	1.04	4196	-0.007	1555
t-statistic	34.02	0.54	1.83	-2.35	

Panel C: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.11	6.10	48036	0.357	579
Mid FC	0.20	7.69	57238	0.343	932
High FC	0.79	8.51	82105	0.329	800
High-Low	0.68	2.28	34069	-0.028	1379
t-statistic	93.24	0.99	14.77	-6.97	

Table A8: Single-Sorted Portfolio Performance After Trading Costs

This table presents regressions analogous to those in Table 3, except that the financial constraints portfolio returns are net of trading costs. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios after trading costs. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−0.92 (−0.65)	0.42 (0.38)	2.80 (2.28)**	3.58 (1.86)*
$r_{mkt} - r_f$	102.01 (35.23)***	103.50 (46.74)***	98.47 (39.23)***	−3.53 (−0.90)
SMB	6.60 (1.77)*	8.90 (3.12)***	−3.06 (−0.95)	−9.69 (−1.91)*
HML	12.51 (2.51)**	−1.65 (−0.43)	−26.03 (−6.01)***	−38.60 (−5.68)***
RMW	13.83 (2.47)**	18.70 (4.37)***	1.78 (0.37)	−12.10 (−1.59)
CMA	−0.46 (−0.07)	2.78 (0.52)	−6.12 (−1.00)	−5.66 (−0.59)
R^2	0.90	0.94	0.93	0.36
Num. obs.	200	200	200	200
# Stocks	551	880	879	1430

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	0.82 (0.55)	−0.77 (−0.60)	3.79 (2.89)***	2.80 (1.47)
$r_{mkt} - r_f$	100.17 (32.66)***	100.85 (38.30)***	99.36 (37.08)***	−0.82 (−0.21)
SMB	9.51 (2.41)**	0.74 (0.22)	−1.42 (−0.41)	−11.04 (−2.20)**
HML	−12.08 (−2.28)**	8.85 (1.95)*	−26.38 (−5.71)***	−14.25 (−2.12)**
RMW	11.87 (2.00)**	24.37 (4.78)***	−14.68 (−2.83)***	−26.75 (−3.56)***
CMA	−15.47 (−2.08)**	11.69 (1.83)*	−5.50 (−0.84)	9.82 (1.04)
R^2	0.90	0.90	0.93	0.17
Num. obs.	200	200	200	200
# Stocks	700	755	855	1555

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−2.41 (−1.90)*	0.90 (0.83)	4.05 (2.74)***	6.34 (3.20)***
$r_{mkt} - r_f$	101.78 (39.24)***	102.40 (46.11)***	97.16 (32.17)***	−4.62 (−1.14)
SMB	8.09 (2.42)**	−2.01 (−0.70)	0.79 (0.20)	−7.35 (−1.41)
HML	2.98 (0.67)	−16.20 (−4.23)***	−12.70 (−2.44)**	−15.66 (−2.25)**
RMW	22.97 (4.58)***	13.77 (3.21)***	−7.99 (−1.37)	−31.06 (−3.97)***
CMA	16.12 (2.56)**	7.08 (1.31)	−19.60 (−2.67)***	−35.73 (−3.63)***
R^2	0.91	0.94	0.91	0.38
Num. obs.	200	200	200	200
# Stocks	579	932	800	1379

Table A9: Excess Net Returns of Double Sorts on Size and Textual Financial Constraints
This table presents results analogous to those in Table 4, except that the portfolio returns are net of trading costs. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	11.24	10.48	11.12	-0.47	-0.17
Medium	8.43	10.74	9.05	0.42	0.16
Big	6.12	7.55	8.10	1.85	0.78

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.97	10.90	11.00	0.60	0.20
Medium	10.13	9.14	9.66	-0.66	-0.31
Big	6.71	7.19	8.02	1.12	0.53

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.67	10.86	11.49	1.48	0.57
Medium	7.96	9.91	10.31	2.17	0.84
Big	5.76	7.37	8.44	2.55	1.05

Table A10: Double-Sorted Portfolio Performance After Trading Costs

This table presents regressions analogous to those in Table 5, except that the financial constraints portfolio returns are net of trading costs. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	1.01 (0.49)	3.37 (2.02)**	4.34 (2.01)**
$r_{mkt} - r_f$	2.72 (0.64)	−4.40 (−1.29)	−2.85 (−0.65)
SMB	7.70 (1.42)	2.74 (0.62)	−7.83 (−1.38)
HML	−47.73 (−6.56)***	−46.85 (−7.97)***	−36.39 (−4.78)***
RMW	−34.26 (−4.20)***	−49.07 (−7.44)***	−10.04 (−1.18)
CMA	30.69 (2.99)***	26.78 (3.23)***	−9.95 (−0.93)
R^2	0.50	0.65	0.30
Num. obs.	200	200	200
# Stocks	846	371	211

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.67 (1.85)*	1.92 (1.22)	2.55 (1.17)
$r_{mkt} - r_f$	−3.28 (−0.81)	1.18 (0.37)	0.19 (0.04)
SMB	13.20 (2.53)**	2.44 (0.59)	−12.50 (−2.16)**
HML	−29.80 (−4.27)***	−17.03 (−3.08)***	−11.36 (−1.47)
RMW	−70.24 (−8.98)***	−44.98 (−7.25)***	−19.31 (−2.23)**
CMA	26.17 (2.66)***	0.53 (0.07)	6.24 (0.57)
R^2	0.64	0.53	0.08
Num. obs.	200	200	200
# Stocks	973	382	200

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.85 (1.95)*	6.05 (3.47)***	6.60 (3.03)***
$r_{mkt} - r_f$	3.13 (0.78)	−0.28 (−0.08)	−4.69 (−1.06)
SMB	4.75 (0.91)	1.80 (0.39)	−7.00 (−1.22)
HML	−27.36 (−3.93)***	−20.62 (−3.36)***	−13.13 (−1.71)*
RMW	−50.63 (−6.49)***	−60.80 (−8.82)***	−27.03 (−3.14)***
CMA	15.04 (1.53)	−6.61 (−0.76)	−42.13 (−3.90)***
R^2	0.52	0.62	0.32
Num. obs.	200	200	200
# Stocks	807	362	208

Table A11: Financial Constraints Factor After Trading Costs

This table presents regressions analogous to those in Table 7, except that the financial constraints portfolio returns are net of trading costs for both value-weighted (VW) and equal-weighted (EW) portfolio formation. The α's display the annualized risk-adjusted returns of the FC factors. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Factiva FC (VW)	Factiva FC (EW)	Equity FC (VW)	Equity FC (EW)	Debt FC (VW)	Debt FC (EW)
α	2.91^{**}	1.79	2.71^{**}	1.65	5.50^{***}	3.59^{**}
	(2.09)	(1.31)	(2.17)	(1.40)	(3.76)	(2.39)
$r_{\text{Mkt}} - r_f$	−1.51	−0.31	−0.64	4.46^{*}	−0.61	1.66
	(−0.53)	(−0.11)	(−0.25)	(1.85)	(−0.21)	(0.54)
SMB	0.87	−0.58	1.05	2.44	−0.15	−3.21
	(0.24)	(−0.16)	(0.32)	(0.79)	(−0.04)	(−0.81)
HML	-43.66^{***}	-41.30^{***}	-19.40^{***}	-20.71^{***}	-20.37^{***}	-27.61^{***}
	(−8.90)	(−8.59)	(−4.40)	(−4.99)	(−3.96)	(−5.22)
RMW	-31.12^{***}	-32.66^{***}	-44.84^{***}	-48.97^{***}	-46.15^{***}	-47.29^{***}
	(−5.65)	(−6.06)	(−9.07)	(−10.52)	(−7.99)	(−7.97)
CMA	15.84^{**}	17.87^{***}	10.98^{*}	0.83	−11.24	−2.95
	(2.29)	(2.64)	(1.77)	(0.14)	(−1.55)	(−0.40)
R^2	0.64	0.63	0.62	0.73	0.61	0.63
Num. obs.	200	200	200	200	200	200

A.3 Screening Micro Cap Stocks

Table A12: Portfolio Characteristics (Micro Caps Screened)
This table presents results analogous to those in Table 2, except that micro cap stocks have been removed from the sample. Each panel shows the average values of the financial constraints measures, excess returns (long-only, annualized), size (that is, market equity), book-to-market ratio, and the average number of stocks in the portfolio. The values are split according to the percentiles of the constraints measures. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.06	6.89	37674	0.361	286
Mid FC	0.09	7.84	51740	0.339	423
High FC	0.60	7.97	89279	0.314	382
High-Low	0.54	1.08	51605	-0.047	668
t-statistic	70.66	0.48	18.02	-14.44	

Panel B: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.13	6.95	66126	0.318	314
Mid FC	0.14	7.52	62506	0.365	386
High FC	0.38	8.08	70451	0.311	390
High-Low	0.25	1.13	4326	-0.007	704
t-statistic	33.84	0.59	1.93	-2.55	

Panel C: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.11	6.12	49291	0.348	296
Mid FC	0.20	7.69	57994	0.333	427
High FC	0.80	8.52	84330	0.324	368
High-Low	0.69	2.40	35039	-0.024	664
t-statistic	95.08	1.03	15.02	-6.23	

Table A13: Single-Sorted Portfolios (Micro Caps Screened)

This table presents regressions analogous to those in Table 3, except that micro cap stocks have been removed from the sample. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	-0.91 (-0.62)	0.30 (0.27)	2.91 (2.31)**	3.82 (1.95)*
$r_{mkt} - r_f$	102.04 (34.09)***	103.59 (45.81)***	98.84 (38.38)***	-3.19 (-0.80)
SMB	4.78 (1.24)	5.23 (1.79)*	-5.83 (-1.76)*	-10.61 (-2.06)**
HML	12.65 (2.45)**	-2.60 (-0.67)	-25.94 (-5.84)***	-38.59 (-5.59)***
RMW	16.94 (2.93)***	18.65 (4.26)***	3.59 (0.72)	-13.36 (-1.73)*
CMA	1.14 (0.16)	1.61 (0.29)	-6.55 (-1.05)	-7.70 (-0.79)
R^2	0.89	0.94	0.93	0.37
Num. obs.	200	200	200	200
# Stocks	286	423	382	668

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	0.97 (0.63)	-0.48 (-0.38)	3.44 (2.55)**	2.48 (1.28)
$r_{mkt} - r_f$	99.65 (31.74)***	99.17 (37.75)***	101.59 (36.73)***	1.94 (0.49)
SMB	7.58 (1.87)*	-2.46 (-0.73)	-4.91 (-1.38)	-12.49 (-2.45)**
HML	-11.73 (-2.17)**	7.72 (1.70)*	-26.26 (-5.51)***	-14.53 (-2.13)**
RMW	11.63 (1.92)*	23.12 (4.55)***	-9.45 (-1.77)*	-21.08 (-2.76)***
CMA	-16.10 (-2.11)**	12.15 (1.90)*	-5.88 (-0.87)	10.22 (1.06)
R^2	0.89	0.90	0.93	0.14
Num. obs.	200	200	200	200
# Stocks	314	386	390	704

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	-2.35 (-1.83)*	0.91 (0.82)	4.10 (2.71)***	6.45 (3.20)***
$r_{mkt} - r_f$	101.88 (38.84)***	102.95 (45.37)***	97.21 (31.45)***	-4.67 (-1.13)
SMB	4.95 (1.46)	-4.53 (-1.55)	-2.16 (-0.54)	-7.11 (-1.34)
HML	3.56 (0.79)	-17.29 (-4.42)***	-12.60 (-2.36)**	-16.16 (-2.28)**
RMW	23.27 (4.59)***	15.56 (3.55)***	-6.47 (-1.08)	-29.73 (-3.74)***
CMA	16.36 (2.57)**	6.75 (1.22)	-20.28 (-2.70)***	-36.63 (-3.67)***
R^2	0.91	0.94	0.90	0.37
Num. obs.	200	200	200	200
# Stocks	296	427	368	664

Table A14: Excess Returns of Double Sorts on Size and Textual Financial Constraints (Micro Caps Screened)

This table presents results analogous to those in Table 4, except that micro cap stocks have been removed from the sample. This table shows annualized excess returns of value-weighted long-only portfolios that are double sorted on the textual financial constraints measures and size. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	7.67	10.14	8.70	1.03	0.37
Medium	7.64	10.13	8.68	1.03	0.36
Big	6.33	7.23	8.35	2.02	0.82

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	10.05	9.54	7.93	-2.12	-0.87
Medium	9.07	8.85	9.23	0.16	0.06
Big	6.79	7.24	8.09	1.30	0.60

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.05	8.64	9.27	0.22	0.08
Medium	8.77	9.20	8.81	0.04	0.02
Big	5.60	7.43	8.73	3.13	1.26

Table A15: Double-Sorted Portfolios Without Micro Cap Stocks

This table presents regressions analogous to those in Table 5, except that micro cap stocks have been removed from the sample. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.63 (1.66)*	4.55 (2.27)**	4.58 (2.04)**
$r_{mkt} - r_f$	0.50 (0.11)	−5.95 (−1.45)	−1.71 (−0.37)
SMB	2.18 (0.38)	2.36 (0.45)	−7.32 (−1.24)
HML	−39.84 (−5.16)***	−47.35 (−6.70)***	−36.54 (−4.63)***
RMW	−45.64 (−5.26)***	−52.84 (−6.66)***	−11.54 (−1.30)
CMA	18.80 (1.73)*	20.70 (2.08)**	−11.70 (−1.05)
R^2	0.48	0.59	0.30
Num. obs.	200	200	200
# Stocks	253	252	162

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	−1.11 (−0.53)	4.52 (2.28)**	2.14 (0.94)
$r_{mkt} - r_f$	11.10 (2.60)**	−3.00 (−0.74)	3.42 (0.73)
SMB	4.35 (0.79)	−0.51 (−0.10)	−13.98 (−2.33)**
HML	−20.50 (−2.79)***	−13.41 (−1.92)*	−13.28 (−1.65)
RMW	−35.02 (−4.24)***	−58.97 (−7.54)***	−12.25 (−1.36)
CMA	12.56 (1.21)	−19.50 (−1.98)**	10.10 (0.89)
R^2	0.39	0.51	0.07
Num. obs.	200	200	200
# Stocks	292	258	154

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.60 (1.62)	4.89 (2.40)**	7.00 (3.11)***
$r_{mkt} - r_f$	3.16 (0.69)	−4.07 (−0.98)	−3.98 (−0.87)
SMB	−8.51 (−1.45)	2.12 (0.39)	−6.05 (−1.02)
HML	−14.84 (−1.89)*	−24.86 (−3.46)***	−13.76 (−1.73)*
RMW	−49.74 (−5.65)***	−65.55 (−8.14)***	−25.06 (−2.81)***
CMA	−9.10 (−0.82)	−15.44 (−1.52)	−41.55 (−3.71)***
R^2	0.38	0.59	0.31
Num. obs.	200	200	200
# Stocks	255	249	160

Table A16: Covariance Tests of Portfolios (Micro Caps Screened)
This table presents results analogous to those in Table 6, except that micro cap stocks have been removed from the sample. Portfolios starting with S/M/B belong to the small/medium/big percentile, while portfolios ending with L/M/H belong to the low/mid/high financial constraints index percentile. The excess returns of each portfolio are regressed on three reference portfolios: a market proxy (BIG), a size factor proxy ($SMALL$), and the financial constraints factor (FC). BIG is the portfolio of less-constrained medium-size and large firms, $BIG = (BM + BL + MM + ML)/4 - r_f$. $SMALL$ consists of less-constrained small firms, $SMALL = (SM+SL)/2-r_f$. FC is the financial constraints factor, $FC = HIGHFC - LOWFC$, where $HIGHFC = (SH + MH + BH)/3$, $LOWFC = (SL + ML + BL)/3$. In each regression, we omit the portfolio on the left-hand side from the portfolios on the right-hand side. Furthermore, for FC, the matching portfolio on the short side is omitted. The different panels correspond to the training samples, which are explained in Section 1.2.3. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Factiva Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.02	0.02	−0.02	−0.02	0.02	−0.02	−0.00	0.01	0.02
	(−1.48)	(1.48)	(−1.15)	(−0.98)	(1.59)	(−1.18)	(−0.15)	(0.42)	(0.81)
BIG	0.25***	0.19***	0.14**	0.66***	0.58***	0.58***	1.07***	1.12***	1.23***
	(4.77)	(3.51)	(2.03)	(12.25)	(15.16)	(9.35)	(16.43)	(16.91)	(17.92)
SMALL	0.80***	0.80***	0.96***	0.45***	0.46***	0.55***	−0.25***	−0.30***	−0.36***
	(18.65)	(18.65)	(17.48)	(10.60)	(14.99)	(10.91)	(−4.41)	(−5.18)	(−6.33)
FC	−0.10**	0.19***	0.75***	−0.00	0.09**	0.83***	−0.15***	0.12**	0.41***
	(−2.07)	(4.05)	(13.09)	(−0.07)	(2.38)	(15.74)	(−3.22)	(2.48)	(7.97)
R^2	0.92	0.92	0.92	0.91	0.94	0.92	0.82	0.83	0.82
Num. obs.	200	200	200	200	200	200	200	200	200

Panel B: Equity Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	0.01	−0.00	−0.03	0.00	−0.00	−0.00	0.01	0.01	0.02
	(0.46)	(−0.17)	(−1.61)	(0.01)	(−0.12)	(−0.24)	(0.23)	(0.66)	(1.02)
BIG	0.28***	0.24***	0.22***	0.58***	0.64***	0.56***	1.02***	0.95***	1.29***
	(5.04)	(4.03)	(2.80)	(12.23)	(12.97)	(7.62)	(11.68)	(13.22)	(18.93)
SMALL	0.72***	0.80***	0.93***	0.48***	0.43***	0.57***	−0.19***	−0.21***	−0.37***
	(16.21)	(16.21)	(14.78)	(13.08)	(11.17)	(9.61)	(−2.62)	(−3.32)	(−6.67)
FC	0.23***	−0.15**	0.67***	0.18***	0.09	0.82***	0.37***	−0.19***	0.47***
	(3.71)	(−2.20)	(8.08)	(3.06)	(1.44)	(9.82)	(4.77)	(−2.91)	(7.52)
R^2	0.90	0.90	0.89	0.92	0.91	0.89	0.74	0.74	0.84
Num. obs.	200	200	200	200	200	200	200	200	200

Panel C: Debt Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	0.00	−0.00	−0.01	0.00	0.01	−0.02	−0.01	0.01	0.02
	(0.11)	(−0.10)	(−0.67)	(0.19)	(0.65)	(−1.15)	(−0.71)	(0.64)	(1.22)
BIG	0.19***	0.19***	0.19***	0.71***	0.54***	0.56***	0.98***	1.28***	1.15***
	(3.66)	(3.91)	(2.84)	(17.03)	(14.14)	(8.69)	(15.83)	(17.70)	(17.46)
SMALL	0.87***	0.78***	0.93***	0.38***	0.49***	0.59***	−0.17***	−0.44***	−0.28***
	(20.25)	(20.25)	(16.98)	(12.11)	(16.74)	(11.70)	(−3.26)	(−7.19)	(−5.29)
FC	−0.10**	0.18***	0.51***	−0.07*	0.09**	0.79***	−0.16***	0.27***	0.47***
	(−2.06)	(4.07)	(8.82)	(−1.67)	(2.18)	(13.16)	(−3.12)	(4.70)	(8.26)
R^2	0.92	0.93	0.91	0.94	0.94	0.92	0.81	0.81	0.83
Num. obs.	200	200	200	200	200	200	200	200	200

Table A17: Relating the Financial Constraints Factor to the Fama-French Five Factors (Micro Caps Screened)

This table presents results analogous to those in Table 7, except that micro cap stocks have been removed from the sample. This table presents the results of regressions of the value-weighted (VW) and equal-weighted (EW) financial constraints factor *FC* on the Fama-French five factors. The different training samples (Factiva, equity, and debt) for constructing FC are explained in Section 1.2.3. The α's display the annualized risk-adjusted returns of the *FC* factors. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Factiva FC (VW)	Factiva FC (EW)	Equity FC (VW)	Equity FC (EW)	Debt FC (VW)	Debt FC (EW)
α	4.25^{***}	2.70^{*}	1.85	1.56	5.16^{***}	4.39^{***}
	(2.77)	(1.83)	(1.37)	(1.24)	(3.42)	(3.02)
$r_{\text{Mkt}} - r_f$	−2.39	1.73	3.84	6.55^{**}	−1.63	1.46
	(−0.76)	(0.57)	(1.40)	(2.56)	(−0.53)	(0.49)
SMB	−0.93	−0.95	−3.38	0.22	−4.15	−6.21
	(−0.23)	(−0.24)	(−0.95)	(0.07)	(−1.04)	(−1.62)
HML	-41.25^{***}	-42.12^{***}	-15.73^{***}	-13.47^{***}	-17.82^{***}	-24.03^{***}
	(−7.64)	(−8.07)	(−3.32)	(−3.05)	(−3.34)	(−4.68)
RMW	-36.67^{***}	-32.84^{***}	-35.41^{***}	-39.89^{***}	-46.78^{***}	-46.75^{***}
	(−6.05)	(−5.61)	(−6.66)	(−8.05)	(−7.83)	(−8.12)
CMA	9.27	16.49^{**}	1.06	−2.79	-22.03^{***}	−11.35
	(1.22)	(2.24)	(0.16)	(−0.45)	(−2.93)	(−1.57)
R^2	0.61	0.61	0.50	0.61	0.60	0.63
Num. obs.	200	200	200	200	200	200

A.4 Removing the Dot-Com Bubble

Table A18: Portfolio Characteristics (Dot-Com Bubble Removed)
This table presents results analogous to those in Table 2, except that the time period of the dot-com bubble has been removed from the sample. Each panel shows value-weighted portfolio characteristics when sorting on the textual financial constraints measures. Each panel shows the average values of the financial constraints measures, excess returns (long-only, annualized), size (that is, market equity), book-to-market ratio, and the average number of stocks in the portfolio. The values are split according to the percentiles of the constraints measures. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.06	9.57	38292	0.371	518
Mid FC	0.09	9.79	48944	0.366	856
High FC	0.57	9.98	81187	0.333	824
High-Low	0.52	0.41	42895	-0.037	1342
t-statistic	58.26	0.18	15.50	-11.75	

Panel B: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.13	9.90	59727	0.338	670
Mid FC	0.14	9.34	58411	0.391	734
High FC	0.36	9.68	63256	0.331	795
High-Low	0.23	-0.22	3529	-0.007	1465
t-statistic	32.71	-0.14	1.49	-1.86	

Panel C: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
Low FC	0.11	8.07	45403	0.366	546
Mid FC	0.21	9.82	56906	0.352	901
High FC	0.78	10.77	76068	0.346	752
High-Low	0.67	2.71	30665	-0.020	1298
t-statistic	76.82	1.46	13.26	-5.07	

Table A19: Single-Sorted Portfolios (Dot-Com Bubble Removed)
This table presents regressions analogous to those in Table 3, except that the time period of the dot-com bubble has been removed from the sample. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	0.39 (0.26)	0.56 (0.51)	3.19 (2.66)***	2.79 (1.35)
$r_{mkt} - r_f$	100.82 (32.25)***	103.43 (45.06)***	97.87 (38.96)***	−2.94 (−0.68)
SMB	11.12 (2.52)**	10.30 (3.17)***	−4.52 (−1.27)	−15.64 (−2.55)**
HML	5.54 (1.02)	−4.06 (−1.02)	−27.15 (−6.23)***	−32.69 (−4.34)***
RMW	12.06 (1.76)*	13.60 (2.70)***	−6.46 (−1.17)	−18.52 (−1.95)*
CMA	8.60 (1.14)	7.77 (1.41)	−7.18 (−1.19)	−15.79 (−1.51)
R^2	0.90	0.95	0.94	0.26
Num. obs.	176	176	176	176
# Stocks	518	856	824	1342

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	1.84 (1.33)	0.40 (0.31)	3.08 (2.40)**	1.25 (0.75)
$r_{mkt} - r_f$	98.99 (34.33)***	100.46 (37.77)***	98.80 (36.75)***	−0.19 (−0.05)
SMB	13.61 (3.34)***	−1.25 (−0.33)	0.08 (0.02)	−13.53 (−2.74)***
HML	−17.63 (−3.52)***	2.39 (0.52)	−22.58 (−4.84)***	−4.95 (−0.82)
RMW	5.15 (0.81)	12.63 (2.16)**	−15.84 (−2.69)***	−21.00 (−2.74)***
CMA	0.60 (0.09)	8.26 (1.29)	−6.52 (−1.01)	−7.12 (−0.85)
R^2	0.92	0.92	0.93	0.10
Num. obs.	176	176	176	176
# Stocks	670	734	795	1465

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−0.73 (−0.62)	1.21 (1.04)	4.05 (2.81)***	4.77 (2.50)**
$r_{mkt} - r_f$	101.12 (41.16)***	100.80 (41.56)***	96.60 (32.09)***	−4.52 (−1.13)
SMB	10.32 (2.97)***	2.15 (0.63)	−0.89 (−0.21)	−11.21 (−1.98)**
HML	−8.10 (−1.90)*	−13.17 (−3.13)***	−12.56 (−2.40)**	−4.46 (−0.64)
RMW	7.25 (1.35)	9.87 (1.85)*	−10.10 (−1.53)	−17.35 (−1.98)**
CMA	12.70 (2.15)**	9.64 (1.65)	−12.47 (−1.72)*	−25.16 (−2.62)***
R^2	0.94	0.94	0.91	0.11
Num. obs.	176	176	176	176
# Stocks	546	901	752	1298

Table A20: Excess Returns of Double Sorts on Size and Textual Financial Constraints (Dot-Com Bubble Removed)

This table presents results analogous to those in Table 4, except that the time period of the dot-com bubble has been removed from the sample. Each panel shows annualized excess returns of value-weighted long-only portfolios that are double sorted on the textual financial constraints measures and size. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	11.23	8.95	8.03	-3.21	-1.38
Medium	9.16	10.73	8.16	-1.00	-0.53
Big	9.34	9.45	10.55	1.20	0.50

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.22	11.13	7.48	-1.74	-0.85
Medium	10.20	9.60	9.05	-1.15	-0.72
Big	10.17	9.11	9.89	-0.28	-0.15

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Small	9.63	9.45	8.17	-1.46	-0.64
Medium	8.57	10.22	9.45	0.87	0.44
Big	7.85	9.90	11.03	3.18	1.59

Table A21: Double-Sorted Portfolios (Dot-Com Bubble Removed)
This table presents regressions analogous to those in Table 5, except that the time period of the dot-com bubble has been removed from the sample. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	−1.18 (−0.56)	1.71 (1.09)	3.45 (1.49)
$r_{mkt} - r_f$	4.61 (1.05)	−2.11 (−0.64)	−2.08 (−0.43)
SMB	−1.98 (−0.32)	−3.11 (−0.67)	−14.99 (−2.18)**
HML	−41.56 (−5.47)***	−38.61 (−6.77)***	−30.08 (−3.56)***
RMW	−40.59 (−4.23)***	−42.02 (−5.83)***	−16.24 (−1.52)
CMA	15.61 (1.48)	11.19 (1.42)	−19.71 (−1.69)*
R^2	0.33	0.42	0.21
Num. obs.	176	176	176
# Stocks	795	348	200

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	0.21 (0.11)	0.74 (0.50)	1.17 (0.60)
$r_{mkt} - r_f$	5.67 (1.47)	4.56 (1.48)	−1.21 (−0.30)
SMB	−5.75 (−1.05)	−6.28 (−1.44)	−11.87 (−2.06)**
HML	−22.20 (−3.31)***	−3.00 (−0.56)	−3.92 (−0.56)
RMW	−48.51 (−5.73)***	−36.29 (−5.37)***	−18.24 (−2.04)**
CMA	16.33 (1.76)*	−15.19 (−2.05)**	−9.90 (−1.01)
R^2	0.32	0.29	0.06
Num. obs.	176	176	176
# Stocks	923	352	189

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	1.44 (0.72)	4.37 (2.60)**	4.96 (2.36)**
$r_{mkt} - r_f$	3.30 (0.79)	1.24 (0.35)	−4.74 (−1.08)
SMB	0.87 (0.15)	−4.58 (−0.92)	−10.79 (−1.74)*
HML	−24.10 (−3.34)***	−10.04 (−1.64)	−1.72 (−0.23)
RMW	−56.65 (−6.20)***	−54.65 (−7.08)***	−11.23 (−1.17)
CMA	−0.04 (−0.00)	−28.66 (−3.38)***	−26.97 (−2.55)**
R^2	0.36	0.41	0.08
Num. obs.	176	176	176
# Stocks	765	339	194

Table A22: Covariance Tests of Portfolios (Dot-Com Bubble Removed)

This table presents regressions analogous to those in Table 6, except that the time period of the dot-com bubble has been removed from the sample. Portfolios starting with S/M/B belong to the small/medium/big percentile, while portfolios ending with L/M/H belong to the low/mid/high financial constraints index percentile. The excess returns of each portfolio are regressed on three reference portfolios: a market proxy (*BIG*), a size factor proxy (*SMALL*), and the financial constraints factor (*FC*). *BIG* is the portfolio of less-constrained medium-size and large firms, $BIG = (BM + BL + MM + ML)/4 - r_f$. *SMALL* consists of less-constrained small firms, $SMALL = (SM + SL)/2 - r_f$. *FC* is the financial constraints factor, $FC = HIGHFC - LOWFC$, where $HIGHFC = (SH + MH + BH)/3$, $LOWFC = (SL + ML + BL)/3$. In each regression, we omit the portfolio on the left-hand side from the portfolios on the right-hand side. Furthermore, for *FC*, the matching portfolio on the short side is omitted. Numbers in parentheses are *t*-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Factiva Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	0.02	−0.02	−0.03*	−0.02	0.00	−0.02	0.01	0.02	0.04*
	(1.19)	(−1.57)	(−1.94)	(−1.37)	(0.40)	(−1.58)	(0.54)	(1.37)	(1.95)
BIG	0.05	0.40***	0.17**	0.62***	0.65***	0.64***	1.10***	1.04***	1.09***
	(0.66)	(8.08)	(2.36)	(13.11)	(14.65)	(11.91)	(15.41)	(13.22)	(13.68)
SMALL	0.99***	0.64***	0.95***	0.46***	0.42***	0.45***	−0.25***	−0.25***	−0.27***
	(17.07)	(17.07)	(16.98)	(13.06)	(12.75)	(10.55)	(−4.35)	(−3.82)	(−4.25)
FC	−0.02	0.04	0.63***	−0.06	0.03	0.56***	−0.14**	0.30***	0.51***
	(−0.23)	(0.81)	(9.17)	(−1.32)	(0.70)	(11.19)	(−2.17)	(4.09)	(6.54)
R^2	0.93	0.95	0.94	0.95	0.96	0.95	0.86	0.82	0.81
Num. obs.	176	176	176	176	176	176	176	176	176

Panel B: Equity Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.02	0.02	−0.03*	−0.00	−0.01	−0.02	0.03	0.01	0.02
	(−1.50)	(1.08)	(−1.80)	(−0.13)	(−0.54)	(−1.37)	(1.42)	(0.71)	(1.26)
BIG	0.40***	0.17**	0.22***	0.57***	0.48***	0.78***	0.96***	1.12***	1.22***
	(6.73)	(2.43)	(2.71)	(11.52)	(9.51)	(14.37)	(9.75)	(13.11)	(17.22)
SMALL	0.69***	0.82***	0.90***	0.48***	0.56***	0.36***	−0.17**	−0.33***	−0.33***
	(15.07)	(15.07)	(13.92)	(12.87)	(14.95)	(8.63)	(−2.13)	(−4.69)	(−6.03)
FC	0.13	−0.11	0.63***	0.04	0.11*	0.50***	0.30***	0.03	0.50***
	(1.50)	(−1.22)	(5.95)	(0.66)	(1.72)	(8.02)	(2.76)	(0.33)	(6.21)
R^2	0.94	0.92	0.92	0.94	0.94	0.96	0.76	0.80	0.87
Num. obs.	176	176	176	176	176	176	176	176	176

Panel C: Debt Training Sample

	SL	SM	SH	ML	MM	MH	BL	BM	BH
Intercept	−0.00	−0.00	−0.04**	−0.01	0.01	−0.02	−0.00	0.03	0.04**
	(−0.08)	(−0.31)	(−2.36)	(−1.12)	(0.70)	(−1.48)	(−0.26)	(1.65)	(2.18)
BIG	0.22***	0.24***	0.17**	0.56***	0.54***	0.73***	1.08***	1.21***	1.09***
	(3.76)	(4.13)	(2.34)	(11.95)	(11.75)	(12.85)	(15.28)	(13.89)	(14.28)
SMALL	0.84***	0.78***	0.97***	0.50***	0.48***	0.43***	−0.22***	−0.40***	−0.28***
	(17.79)	(17.79)	(17.03)	(14.19)	(13.84)	(9.69)	(−3.82)	(−5.62)	(−4.63)
FC	−0.10	0.12*	0.65***	−0.06	0.07	0.66***	0.02	0.18**	0.48***
	(−1.56)	(1.96)	(8.63)	(−1.18)	(1.38)	(11.64)	(0.29)	(2.39)	(6.77)
R^2	0.94	0.94	0.94	0.95	0.95	0.95	0.87	0.81	0.84
Num. obs.	176	176	176	176	176	176	176	176	176

Table A23: Relating the Financial Constraints Factor to the Fama-French Five Factors (Dot-Com Bubble Removed)

This table presents regressions analogous to those in Table 7, except that the time period of the dot-com bubble has been removed from the sample. The table presents the results of regressions of the value-weighted (VW) and equal-weighted (EW) financial constraints factor *FC* on the Fama-French five factors. The different training samples (Factiva, equity, and debt) for constructing FC are explained in Section 1.2.3. The α's display the annualized risk-adjusted returns of the *FC* factors. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Factiva FC (VW)	Factiva FC (EW)	Equity FC (VW)	Equity FC (EW)	Debt FC (VW)	Debt FC (EW)
α	1.33	1.93	0.71	1.10	3.59^{**}	3.95^{**}
	(0.92)	(1.44)	(0.59)	(1.00)	(2.45)	(2.54)
$r_{\text{Mkt}} - r_f$	0.14	−1.47	3.01	6.46^{***}	−0.07	−0.01
	(0.05)	(−0.52)	(1.20)	(2.81)	(−0.02)	(−0.00)
SMB	−6.69	−1.52	-7.97^{**}	−2.78	−4.83	−2.06
	(−1.57)	(−0.38)	(−2.26)	(−0.86)	(−1.11)	(−0.45)
HML	-36.75^{***}	-40.87^{***}	-9.71^{**}	-13.31^{***}	-11.95^{**}	-27.59^{***}
	(−7.00)	(−8.40)	(−2.24)	(−3.34)	(−2.24)	(−4.89)
RMW	-32.95^{***}	-32.30^{***}	-34.35^{***}	-39.69^{***}	-40.84^{***}	-46.77^{***}
	(−4.97)	(−5.26)	(−6.27)	(−7.87)	(−6.06)	(−6.56)
CMA	2.36	19.11^{***}	−2.92	0.41	-18.56^{**}	−1.32
	(0.32)	(2.84)	(−0.49)	(0.07)	(−2.51)	(−0.17)
R^2	0.43	0.45	0.33	0.50	0.34	0.41
Num. obs.	176	176	176	176	176	176

A.5 HXZ Factors

Table A24: Single-Sorted Portfolios Regressed on the HXZ Factors

This table presents regressions analogous to those in Table 3, except that instead of controlling for the Fama-French factors, we control here for the Hou-Xue-Zhang factors. *ME* is the (small-minus-big) size factor, *I/A* is the (low-minus-high) investment-to-assets factor, and *ROE* is the (high-minus-low) profitability factor. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−0.69 (−0.47)	1.39 (1.23)	4.21 (3.35)***	4.90 (2.37)**
$r_{mkt} - r_f$	102.18 (33.52)***	101.32 (43.32)***	94.79 (36.32)***	−7.38 (−1.72)*
ME	1.54 (0.44)	2.00 (0.75)	−5.83 (−1.97)*	−7.37 (−1.51)
I/A	15.01 (2.71)***	4.07 (0.96)	−40.05 (−8.44)***	−55.07 (−7.06)***
ROE	9.36 (2.05)**	5.26 (1.50)	−8.28 (−2.12)**	−17.64 (−2.74)***
R^2	0.89	0.93	0.93	0.24
Num. obs.	200	200	200	200
# Stocks	551	880	879	1430

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	2.05 (1.35)	0.04 (0.03)	4.92 (3.59)***	2.87 (1.45)
$r_{mkt} - r_f$	97.35 (30.82)***	99.36 (34.52)***	95.81 (33.69)***	−1.55 (−0.38)
ME	1.03 (0.29)	−5.25 (−1.61)	−1.01 (−0.31)	−2.04 (−0.44)
I/A	−24.61 (−4.28)***	25.30 (4.83)***	−46.47 (−8.98)***	−21.87 (−2.93)***
ROE	−4.39 (−0.93)	12.70 (2.94)***	−17.22 (−4.04)***	−12.83 (−2.09)**
R^2	0.89	0.89	0.92	0.08
Num. obs.	200	200	200	200
# Stocks	700	755	855	1555

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−1.66 (−1.25)	2.20 (1.98)**	5.05 (3.56)***	6.70 (3.38)***
$r_{mkt} - r_f$	100.02 (36.42)***	99.20 (43.14)***	94.67 (32.19)***	−5.35 (−1.30)
ME	3.08 (0.99)	−5.77 (−2.21)**	−3.18 (−0.95)	−6.26 (−1.34)
I/A	23.88 (4.78)***	−10.96 (−2.62)***	−42.08 (−7.86)***	−65.95 (−8.81)***
ROE	10.96 (2.66)***	1.18 (0.34)	−12.50 (−2.84)***	−23.46 (−3.80)***
R^2	0.90	0.94	0.91	0.36
Num. obs.	200	200	200	200
# Stocks	579	932	800	1379

Table A25: Double-Sorted Portfolios Regressed on the HXZ Factors
This table presents regressions analogous to those in Table 5, except that instead of controlling for the Fama-French factors, we control here for the Hou-Xue-Zhang factors. *ME* is the (small-minus-big) size factor, *I/A* is the (low-minus-high) investment-to-assets factor, and *ROE* is the (high-minus-low) profitability factor. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	2.01 (0.82)	3.87 (1.71)*	5.72 (2.54)**
$r_{mkt} - r_f$	−1.86 (−0.36)	−8.29 (−1.77)*	−6.85 (−1.47)
ME	19.47 (3.37)***	16.82 (3.16)***	−6.86 (−1.29)
I/A	−37.30 (−4.03)***	−44.79 (−5.26)***	−55.98 (−6.59)***
ROE	−28.73 (−3.76)***	−36.05 (−5.14)***	−17.50 (−2.50)**
R^2	0.28	0.34	0.22
Num. obs.	200	200	200
# Stocks	846	371	211

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.84 (1.58)	1.08 (0.59)	2.74 (1.24)
$r_{mkt} - r_f$	−7.41 (−1.47)	2.25 (0.59)	−0.40 (−0.09)
ME	29.72 (5.18)***	14.96 (3.47)***	−5.81 (−1.12)
I/A	−31.82 (−3.46)***	−33.35 (−4.83)***	−19.84 (−2.38)**
ROE	−50.39 (−6.65)***	−22.54 (−3.96)***	−8.45 (−1.23)
R^2	0.43	0.35	0.05
Num. obs.	200	200	200
# Stocks	973	382	200

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	3.96 (1.72)*	4.94 (2.30)**	7.13 (3.34)***
$r_{mkt} - r_f$	1.42 (0.30)	1.48 (0.33)	−5.69 (−1.29)
ME	16.79 (3.09)***	16.32 (3.23)***	−8.24 (−1.64)
I/A	−35.04 (−4.03)***	−48.90 (−6.04)***	−67.80 (−8.41)***
ROE	−32.33 (−4.52)***	−31.30 (−4.69)***	−22.92 (−3.45)***
R^2	0.33	0.40	0.33
Num. obs.	200	200	200
# Stocks	807	362	208

A.6 Liquidity Factors

Table A26: Portfolios Sorted on Textual Financial Constraints Measures (Liquidity Factor Included)

This table presents regressions analogous to those in Table 3, except that we include the liquidity factor from Pástor and Stambaugh (2003). The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios after trading costs. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−1.77 (−1.27)	0.04 (0.04)	2.66 (2.13)**	4.42 (2.28)**
$r_{mkt} - r_f$	101.20 (36.08)***	103.12 (47.01)***	98.28 (39.04)***	−2.92 (−0.75)
SMB	6.11 (1.69)*	8.69 (3.08)***	−3.11 (−0.96)	−9.22 (−1.83)*
HML	14.63 (3.02)***	−0.68 (−0.18)	−25.55 (−5.87)***	−40.18 (−5.93)***
RMW	12.02 (2.21)**	17.86 (4.20)***	1.42 (0.29)	−10.60 (−1.40)
CMA	−0.78 (−0.11)	2.62 (0.49)	−6.13 (−1.00)	−5.35 (−0.56)
L	10.00 (3.85)***	4.82 (2.37)**	2.33 (1.00)	−7.68 (−2.11)**
R^2	0.91	0.94	0.93	0.37
Num. obs.	200	200	200	200
# Stocks	551	880	879	1430

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low
α	0.85 (0.55)	−1.42 (−1.11)	3.50 (2.64)***	2.65 (1.37)
$r_{mkt} - r_f$	100.12 (32.45)***	100.20 (38.90)***	99.06 (37.04)***	−1.06 (−0.27)
SMB	9.53 (2.40)**	0.35 (0.10)	−1.58 (−0.46)	−11.12 (−2.22)**
HML	−11.97 (−2.24)**	10.49 (2.35)**	−25.56 (−5.52)***	−13.58 (−2.01)**
RMW	11.85 (1.98)**	22.93 (4.60)***	−15.36 (−2.97)***	−27.21 (−3.61)***
CMA	−15.42 (−2.06)**	11.43 (1.83)*	−5.56 (−0.86)	9.85 (1.04)
L	0.63 (0.22)	7.82 (3.27)***	3.95 (1.59)	3.32 (0.92)
R^2	0.90	0.91	0.93	0.17
Num. obs.	200	200	200	200
# Stocks	700	755	855	1555

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low
α	−2.88 (−2.26)**	0.84 (0.76)	3.54 (2.39)**	6.42 (3.19)***
$r_{mkt} - r_f$	101.32 (39.47)***	102.28 (45.85)***	96.64 (32.28)***	−4.68 (−1.15)
SMB	7.82 (2.37)**	−2.01 (−0.70)	0.47 (0.12)	−7.35 (−1.41)
HML	4.16 (0.94)	−15.94 (−4.13)***	−11.32 (−2.18)**	−15.48 (−2.20)**
RMW	21.97 (4.42)***	13.62 (3.15)***	−9.20 (−1.59)	−31.17 (−3.96)***
CMA	15.94 (2.56)**	7.10 (1.31)	−19.79 (−2.73)***	−35.73 (−3.63)***
L	5.73 (2.41)**	1.42 (0.68)	6.43 (2.32)**	0.70 (0.19)
R^2	0.91	0.94	0.91	0.38
Num. obs.	200	200	200	200
# Stocks	579	932	800	1379

Table A27: Double Sorts on Size and Textual Financial Constraints (Liquidity Factor Included)

This table presents regressions analogous to those in Table 5, except that we include the liquidity factor from Pástor and Stambaugh (2003). The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios after trading costs. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	2.07 (0.99)	3.97 (2.34)**	5.17 (2.37)**
$r_{mkt} - r_f$	3.38 (0.80)	−4.03 (−1.18)	−2.26 (−0.51)
SMB	8.22 (1.52)	2.98 (0.68)	−7.37 (−1.30)
HML	−49.29 (−6.77)***	−47.80 (−8.09)***	−37.94 (−4.98)***
RMW	−32.68 (−4.01)***	−48.12 (−7.28)***	−8.59 (−1.01)
CMA	30.94 (3.03)***	26.97 (3.26)***	−9.65 (−0.90)
L	−7.36 (−1.89)*	−4.41 (−1.39)	−7.52 (−1.84)*
R^2	0.51	0.65	0.31
Num. obs.	200	200	200
# Stocks	846	371	211

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	4.83 (2.42)**	2.31 (1.45)	2.31 (1.04)
$r_{mkt} - r_f$	−2.57 (−0.64)	1.38 (0.43)	−0.13 (−0.03)
SMB	13.70 (2.65)***	2.62 (0.63)	−12.63 (−2.19)**
HML	−31.51 (−4.52)***	−17.55 (−3.15)***	−10.50 (−1.35)
RMW	−68.55 (−8.79)***	−44.40 (−7.12)***	−19.95 (−2.30)**
CMA	26.50 (2.72)***	0.63 (0.08)	6.26 (0.58)
L	−8.28 (−2.22)**	−2.35 (−0.79)	4.25 (1.02)
R^2	0.64	0.53	0.09
Num. obs.	200	200	200
# Stocks	973	382	200

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	4.66 (2.32)**	5.57 (3.18)***	6.68 (3.02)***
$r_{mkt} - r_f$	3.58 (0.88)	−0.84 (−0.24)	−4.74 (−1.06)
SMB	5.16 (0.99)	1.47 (0.32)	−7.01 (−1.22)
HML	−28.45 (−4.06)***	−19.14 (−3.13)***	−12.97 (−1.68)*
RMW	−49.44 (−6.30)***	−61.97 (−9.05)***	−27.13 (−3.14)***
CMA	15.27 (1.55)	−6.79 (−0.79)	−42.14 (−3.89)***
L	−4.78 (−1.27)	7.25 (2.21)**	0.60 (0.15)
R^2	0.52	0.63	0.32
Num. obs.	200	200	200
# Stocks	807	362	208

A.7 Controlling for the WW Index

Table A28: Excess Returns of Double Sorts on the Whited-Wu index and Textual Financial Constraints

This table presents results analogous to those in Table 4, except that we substitute the WW index for size. The different panels correspond to the training samples, which are described in Section 1.2.3.

Panel A: Factiva Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Low WW	7.21	7.16	6.98	-0.23	-0.09
Mid WW	4.68	6.87	10.47	5.79	1.73
High WW	7.33	13.26	7.64	0.31	0.07

Panel B: Equity Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Low WW	6.82	6.71	7.20	0.39	0.16
Mid WW	7.67	7.33	8.90	1.23	0.38
High WW	8.84	10.29	8.67	-0.17	-0.06

Panel C: Debt Training Sample

	Low FC	Mid FC	High FC	High-Low	t-statistic
Low WW	5.85	6.63	8.13	2.29	0.92
Mid WW	6.22	8.15	9.50	3.28	0.91
High WW	10.67	9.62	7.98	-2.69	-0.71

Table A29: Double Sorts on the Whited-Wu index and Textual Financial Constraints
This table presents results analogous to those in Table 5, except that we substitute the WW index for size. The different panels correspond to the training samples, which are described in Section 1.2.3. The α's display the annualized risk-adjusted returns of the constraints-sorted portfolios. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Factiva Training Sample

	FCHML (Low WW)	FCHML (Mid WW)	FCHML (High WW)
α	2.86 (1.16)	8.28 (2.77)***	4.47 (1.30)
$r_{mkt} - r_f$	−4.45 (−0.90)	2.64 (0.44)	−3.43 (−0.50)
SMB	−12.64 (−1.98)**	−4.58 (−0.59)	2.20 (0.25)
HML	−35.61 (−4.15)***	−50.44 (−4.84)***	−62.07 (−5.19)***
RMW	−13.31 (−1.39)	−23.88 (−2.05)**	−69.97 (−5.23)***
CMA	−9.79 (−0.82)	10.36 (0.71)	34.15 (2.05)**
R^2	0.27	0.32	0.49
Num. obs.	188	188	188
# Stocks	163	274	837

Panel B: Equity Training Sample

	FCHML (Low WW)	FCHML (Mid WW)	FCHML (High WW)
α	1.46 (0.55)	6.44 (2.09)**	2.23 (1.00)
$r_{mkt} - r_f$	−1.23 (−0.23)	−2.30 (−0.37)	0.88 (0.20)
SMB	−12.37 (−1.80)*	−27.47 (−3.44)***	4.44 (0.77)
HML	−13.21 (−1.43)	−3.33 (−0.31)	−23.72 (−3.04)***
RMW	−6.23 (−0.60)	−63.19 (−5.25)***	−45.71 (−5.24)***
CMA	5.58 (0.43)	−18.90 (−1.26)	9.13 (0.84)
R^2	0.04	0.25	0.43
Num. obs.	188	188	188
# Stocks	153	288	978

Panel C: Debt Training Sample

	FCHML (Low WW)	FCHML (Mid WW)	FCHML (High WW)
α	5.77 (2.38)**	9.56 (3.55)***	0.79 (0.27)
$r_{mkt} - r_f$	−7.05 (−1.45)	0.48 (0.09)	1.59 (0.27)
SMB	−5.30 (−0.84)	−24.26 (−3.48)***	7.78 (1.03)
HML	−6.44 (−0.76)	−38.79 (−4.13)***	−28.31 (−2.78)***
RMW	−17.67 (−1.87)*	−63.14 (−6.01)***	−73.82 (−6.48)***
CMA	−40.09 (−3.40)***	−21.52 (−1.64)	15.13 (1.06)
R^2	0.19	0.53	0.49
Num. obs.	188	188	188
# Stocks	164	269	797

A.8 Additional Fama/MacBeth Regressions

Table A30: Debt Covenants and Independent Oversight

This table shows the results for Fama-MacBeth regressions of monthly stock returns on individual firm characteristics. The columns are grouped by the training samples ("TS" in the column headers below) used for the construction of the financial constraints (FC) measure. The training samples are described in Section 1.2.3. The dependent variable is, for each firm-month, the average monthly excess return over the following two quarters. Independent variables are the financial constraints measure (FC, described in Section 1.2), the book-to-market ratio (log(b/m)), size (log(me)), past stock return performance measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$), capital expenditures ($capex$=$CAPXQ$/lag(ATQ)), net cash raised from stock issues (stk=($SSTKQ-PRSTKCQ$)/lag(ATQ)), net new long-term debt (dbt=($DLTISQ-DLTRQ$)/lag(ATQ)), distance to default for current ratio (*DD (CR)*) and net worth (*DD (NW)*) covenants following Chava and Roberts (2008), firm-level leverage (($DLCQ+DLTTQ$)/ATQ), the number of analysts covering the firm (from I/B/E/S), and the fraction of outside directors on the company's board (from ISS/IRRC). The last two variables capture the degree of independent oversight. In Panel B, all variables involving interaction terms are standardized with mean zero and a standard deviation of one. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

Panel A: Debt Covenants and Independent Oversight

	Factiva TS	Factiva TS	Equity TS	Equity TS	Debt TS	Debt TS
FC	0.35**	0.27**	0.54**	0.35*	0.44***	0.33***
	(2.04)	(2.42)	(2.01)	(1.80)	(2.98)	(3.65)
log(b/m)	0.18**	0.15***	0.24***	0.18***	0.19**	0.17***
	(2.06)	(2.76)	(3.24)	(3.78)	(2.08)	(2.87)
log(me)	−0.22***	−0.21***	−0.22***	−0.20***	−0.23***	−0.21***
	(−3.94)	(−4.28)	(−4.08)	(−4.41)	(−4.00)	(−4.23)
$r_{1,0}$	0.24	0.13	0.14	0.04	0.17	0.10
	(0.75)	(0.53)	(0.45)	(0.15)	(0.54)	(0.40)
$r_{12,2}$	0.52***	0.46***	0.54***	0.44***	0.50***	0.44***
	(3.95)	(3.78)	(4.51)	(3.75)	(3.90)	(3.69)
capex	−1.07	−4.63**	−0.75	−4.81***	−1.80	−5.45***
	(−0.50)	(−2.56)	(−0.37)	(−2.77)	(−0.80)	(−2.87)
stk	−8.21***	−6.81***	−8.28***	−6.70***	−8.29***	−7.14***
	(−4.05)	(−4.52)	(−4.49)	(−4.54)	(−4.17)	(−4.85)
dbt	−6.35***	−5.03***	−6.10***	−4.86***	−6.16***	−4.99***
	(−9.62)	(−8.58)	(−9.44)	(−8.51)	(−9.06)	(−8.33)
Leverage	−1.44***	−0.85***	−1.23***	−0.75***	−1.49***	−0.89***
	(−4.95)	(−3.95)	(−4.98)	(−3.88)	(−4.85)	(−3.99)
DD (CR)	0.02		0.02		0.03	
	(0.80)		(1.04)		(1.16)	
DD (NW)	0.00***		0.00***		0.00***	
	(5.78)		(5.96)		(5.91)	
# Analysts		0.24***		0.23***		0.23***
		(4.21)		(4.30)		(3.99)
Out. Dir.		−0.00		−0.00		−0.00
		(−0.20)		(−0.34)		(−0.35)
Num. obs.	184173	283143	184025	283242	184004	283147

Table A30: Debt Covenants and Independent Oversight (cont.)
Panel B: Interaction Terms With Covenants

	Factiva TS	Factiva TS	Equity TS	Equity TS	Debt TS	Debt TS
FC	0.10**	0.07**	0.15*	0.08	0.14***	0.11***
	(2.04)	(2.14)	(1.84)	(1.54)	(2.91)	(3.75)
FC * DD (CR)	0.05		0.06		0.07***	
	(1.31)		(0.84)		(3.52)	
DD (CR)	0.05**		0.05**		0.06***	
	(2.38)		(2.01)		(3.35)	
FC * DD (NW)		−0.04***		−0.06		−0.01
		(−3.27)		(−1.23)		(−0.78)
DD (NW)		0.11***		0.10***		0.12***
		(4.16)		(3.60)		(4.43)
log(b/m)	0.22***	0.13**	0.28***	0.15***	0.23***	0.14**
	(2.63)	(2.18)	(3.98)	(3.00)	(2.62)	(2.24)
log(me)	−0.31***	−0.26***	−0.29***	−0.24***	−0.30***	−0.26***
	(−4.57)	(−4.55)	(−4.78)	(−4.72)	(−4.52)	(−4.55)
$r_{1,0}$	0.29	0.17	0.19	0.08	0.21	0.14
	(0.94)	(0.70)	(0.65)	(0.31)	(0.70)	(0.58)
$r_{12,2}$	0.59***	0.48***	0.61***	0.46***	0.57***	0.46***
	(4.71)	(3.98)	(5.28)	(3.98)	(4.61)	(3.91)
capex	−2.95	−4.33**	−2.48	−4.53***	−3.37	−5.17***
	(−1.26)	(−2.42)	(−1.14)	(−2.63)	(−1.39)	(−2.77)
stk	−8.77***	−6.92***	−8.50***	−6.78***	−8.61***	−7.16***
	(−4.55)	(−4.67)	(−4.75)	(−4.64)	(−4.50)	(−4.90)
dbt	−6.35***	−5.04***	−6.10***	−4.87***	−6.18***	−5.05***
	(−9.60)	(−8.70)	(−9.32)	(−8.66)	(−9.03)	(−8.51)
Leverage	−1.35***	−0.93***	−1.15***	−0.84***	−1.40***	−0.97***
	(−4.77)	(−4.26)	(−4.79)	(−4.25)	(−4.69)	(−4.29)
# Analysts	0.32***	0.25***	0.29***	0.24***	0.30***	0.24***
	(4.24)	(4.31)	(4.24)	(4.41)	(4.08)	(4.09)
Out. Dir.	0.00***	−0.00	0.00***	−0.00	0.00***	−0.00
	(2.91)	(−0.49)	(3.24)	(−0.66)	(2.89)	(−0.76)
Num. obs.	184157	283143	184011	283242	183988	283147

Table A31: Information Disclosure

This table shows the results for Fama-MacBeth regressions of monthly stock returns on individual firm characteristics. The columns are grouped by the training samples ("TS" in the column headers below) used for the construction of the financial constraints (FC) measure. The training samples are described in Section 1.2.3. The dependent variable is, for each firm-month, the average monthly excess return over the following two quarters. Independent variables are the financial constraints measure (FC, described in Section 1.2), the book-to-market ratio (log(b/m)), size (log(me)), past stock return performance measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$), capital expenditures ($capex$=$CAPXQ$/lag(ATQ)), net cash raised from stock issues (stk=($SSTKQ-PRSTKCQ$)/lag(ATQ)), net new long-term debt (dbt=($DLTISQ-DLTRQ$)/lag(ATQ)), the word count of the most recent 10-K (WC), earnings persistence (EP), and sales growth estimated over a three-year rolling window (SG). All variables used for interaction terms are centered with mean zero. Numbers in parentheses are t-statistics. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficients are multiplied by 100 for readability.

	Factiva TS	Factiva TS	Equity TS	Equity TS	Debt TS	Debt TS
FC	0.25^{**}	0.29^{**}	-1.00	-1.24^{*}	0.22^{**}	0.24^{***}
	(2.15)	(2.56)	(-1.57)	(-1.70)	(2.42)	(2.65)
log(b/m)	0.14^{**}	0.11^{**}	0.17^{***}	0.14^{***}	0.15^{***}	0.12^{**}
	(2.54)	(2.03)	(3.69)	(3.04)	(2.61)	(2.16)
log(me)	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}
	(-2.88)	(-3.04)	(-3.04)	(-3.17)	(-2.86)	(-2.99)
$r_{1,0}$	-0.09	-0.08	-0.19	-0.19	-0.11	-0.10
	(-0.35)	(-0.30)	(-0.74)	(-0.71)	(-0.41)	(-0.38)
$r_{12,2}$	0.40^{***}	0.40^{***}	0.39^{***}	0.40^{***}	0.38^{***}	0.38^{***}
	(3.10)	(3.15)	(3.18)	(3.26)	(3.01)	(3.07)
capex	-2.87^{*}	-2.50	-2.99^{*}	-2.48	-3.65^{**}	-3.32^{**}
	(-1.75)	(-1.54)	(-1.82)	(-1.53)	(-2.16)	(-1.97)
stk	-6.08^{***}	-5.74^{***}	-6.10^{***}	-5.69^{***}	-5.99^{***}	-5.75^{***}
	(-3.57)	(-3.40)	(-3.57)	(-3.34)	(-3.54)	(-3.43)
dbt	-4.48^{***}	-4.45^{***}	-4.16^{***}	-4.12^{***}	-4.53^{***}	-4.50^{***}
	(-8.23)	(-8.06)	(-7.66)	(-7.46)	(-8.07)	(-7.91)
log(1+WC)	0.10^{***}	0.09^{***}	0.11^{***}	0.10^{***}	0.09^{***}	0.07^{**}
	(3.65)	(2.76)	(3.85)	(3.05)	(3.20)	(2.36)
EP	-0.03	-0.02	-0.03	-0.01	-0.02	-0.01
	(-1.03)	(-0.51)	(-0.96)	(-0.44)	(-0.86)	(-0.38)
SG		-1.11^{***}		-1.30^{***}		-1.19^{***}
		(-3.33)		(-3.74)		(-3.56)
log(1+WC) * SG		-0.42		-0.47		-0.26
		(-1.02)		(-1.17)		(-0.61)
EP * SG		-0.38		-0.57		-0.44
		(-0.69)		(-0.98)		(-0.80)
Num. obs.	233065	231504	233095	231566	232604	230984

B. Annual Report Excerpts

This section contains excerpts from the annual reports of 10 randomly chosen large firms classified as constrained according to our debt constraints measure.

Year	Firm	Relevant 10-K Text
1998	Advanced Micro Devices	To the extent that FASL is unable to secure the necessary funds for FASL II, the Company may be required to contribute cash or guarantee third-party loans ... In the event the Company is unable to obtain the external financing necessary to meet its covenants under the Credit Agreement, it will also be unable to fund its capital investments planned ... There can be no assurance that the Company will be able to obtain the funds necessary to fulfill these obligations and any such failure would have a material adverse effect on the Company.
1998	IBP	Net interest expense rose significantly in 1997 versus 1996 due mainly to the Foodbrands and Bruss acquisitions ... The company's effective average interest rate increased also, due primarily to the addition of Foodbrands' $112 million of 10.75% Senior Subordinated Notes. Management expects that net interest expense in the foreseeable future will continue to be significantly higher than in 1996.
2001	Micrel	Additionally, the cost of any investment we may have to make to expand our manufacturing capacity is expected to be funded through ... additional debt ... We may not be able to obtain the additional financing necessary to fund the construction and completion of any new manufacturing facility.
2001	McKesson HBOC	The Company discovered improper accounting practices at HBOC. ... 85 lawsuits have been filed against the Company ... The Company renewed its 364-day revolving credit agreement ... except that a 364-day term out option was reinstated ... The Company's ratings are on negative credit outlook.
2003	Affiliated Computer Services	In order to pursue such opportunities, which could require significant commitments of capital, we may be required to incur debt or to issue additional potentially dilutive securities in the future. No assurance can be given as to our future acquisition and expansion opportunities and how such opportunities will be financed.

2003	PanAmSat	The indenture governing the Senior Notes and the agreement governing the Senior Secured Credit Facility contain various covenants which impose significant restrictions on our business. These covenants limit our ability to, among other things: incur or guarantee additional indebtedness; make restricted payments, including dividends; create or permit to exist certain liens ... In addition, if we were to consummate any strategic transactions or undertake any other projects requiring significant capital expenditures, we may be required to seek additional financing. There can be no assurance that additional funds will be available at all or that, if available, will be obtained at terms favorable to us. ... The failure to obtain such financing could have a material adverse effect on our financial condition and results of operations. ... We may not be able to raise adequate capital to complete some or all of our business strategies ... If we are unable to meet our debt obligations, we could be forced to restructure or refinance our indebtedness, seek additional equity capital or sell assets. We may be unable to obtain financing or sell assets on satisfactory terms, or at all ... We expect that we would require additional financing from third parties to fund any such purchases, and we cannot assure you that we would be able to obtain financing on satisfactory terms or at all.
2006	Consol Energy	CONSOL Energy was no longer able to participate as a seller of commercial paper due to Standard and Poor's lowering its rating of our short-term debt. ... There can be no assurance that additional capital resources, including debt financing, will be available to CONSOL Energy on terms which CONSOL Energy finds acceptable, or at all. ... We may choose to defer certain capital projects in light of operating results and the availability of financing.
2006	Echostar Communications	Our working capital and capital expenditure requirements could increase materially ... These factors could require that we raise additional capital in the future. There can be no assurance that we could raise all required capital or that required capital would be available on acceptable terms. ... We may, however, decide to raise additional capital ... There can be no assurance that additional financing will be available on acceptable terms, or at all, if needed in the future. ... Future material investments or acquisitions may require that we obtain additional capital. ... There can be no assurance that we could raise all required capital or that required capital would be available on acceptable terms.

2009	Newell Rubbermaid	... reduced the dividend payable ... The new dividend policy better positions the Company to protect its investment grade credit rating and maintain continuing access to credit markets ... The Company plans to address these obligations through the capital markets or other arrangements; however, access to the capital markets or successful negotiation of other arrangements cannot be assured. ... However, the Company's current short-term debt credit ratings, coupled with turmoil in the credit markets, may preclude it from accessing the commercial paper market. ... Access to the commercial paper market cannot be assured with the Company's current short-term debt credit ratings ... The Company plans to address these obligations through the capital markets or other arrangements; however, access to the capital markets cannot be assured, particularly in light of the recent turmoil and uncertainty in the global credit markets, the February 2009 downgrade by Moody's and Standard & Poor's of the Company's credit ratings to the lowest rating considered "investment grade," and alternative financing arrangements may result in higher borrowing costs for the Company.
2009	Denbury Resources	Use of these operating leases is dependent upon being able to secure acceptable financing and as of February 27, 2009, we had not yet secured most of this financing. ... Although we remain interested in acquiring mature oil fields that we believe have potential as future tertiary flood candidates, with the general lack of liquidity in the capital markets, our ability to fund any significant acquisitions will be limited ... Based on capital market conditions in early October, and a desire to refrain from increasing our leverage in that environment, we cancelled the contract to purchase the Conroe Field.

C. Miscellaneous Unreported Results

This section contains two tables. The first reports the pairwise correlations between our measures of financial constraints, as well as the KZ index and the WW index.

Table A33: Pairwise Correlations between Financial Constraints Measures

This table reports the pairwise Spearman correlations between our Factiva-based measure of financial constraints, our debt-based measure, our equity-based measure, the KZ index, and the WW index. The second is a recomputation of Table 3 with a portfolio based on the WW index.

	Factiva	Debt	Equity	KZ	WW
Factiva	1.00	0.64	0.24	-0.07	0.13
Debt		1.00	0.32	-0.01	0.10
Equity			1.00	-0.07	0.06
KZ				1.00	-0.13
WW					1.00

Table A34: Portfolios Sorted on the WW Index

This table is structured exactly as Table 3, except that we have used the WW index to form portfolios.

	Low FC	Mid FC	High FC	High-Low
α	0.74 (0.69)	0.28 (0.14)	4.00 (2.66)***	3.26 (1.64)
$r_{mkt} - r_f$	96.69 (45.09)***	116.92 (30.27)***	106.39 (35.17)***	9.70 (2.43)**
SMB	−13.72 (−4.96)***	29.05 (5.83)***	81.33 (20.85)***	95.05 (18.50)***
HML	−3.62 (−0.97)	−11.34 (−1.69)*	−31.45 (−5.99)***	−27.82 (−4.02)***
RMW	20.52 (4.93)***	−5.33 (−0.71)	−38.79 (−6.61)***	−59.31 (−7.67)***
CMA	2.71 (0.52)	−26.64 (−2.85)***	−0.90 (−0.12)	−3.61 (−0.37)
R^2	0.94	0.91	0.96	0.87
Num. obs.	188	188	188	188
# Stocks	238	428	1317	1555