Looking for Risk in Words: A Narrative Approach to Measuring the Pricing Implications of Financial Constraints

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Abstract

We construct a novel measure of financial constraints using textual analysis and investigate its impact on stock returns. Unlike other financial constraints measures, ours is consistent with firm characteristics of constrained firms. We find that constrained firms' returns move together. The variation of a financial constraints factor cannot be explained by the Fama-French and momentum factors, earning an annualized risk-adjusted excess return of 7%. A stock trading strategy based on financial constraints is most profitable for large and liquid stocks, and when the financial constraints are measured by access to debt markets instead of equity markets.

Keywords: Financial constraints, textual analysis, market efficiency.

JEL Codes: G14, G32

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1 Introduction

The concept of a financial constraint is simple, typically arising from frictions such as information asymmetries that make external funds more costly than internal funds, sometime prohibitively so. Financial constraints are easy to understand on this conceptual level, but it remains an empirical challenge to *quantify* them. As pointed out by Farre-Mensa and Ljungqvist (2014), many of the measures based on accounting data are likely flawed. We contribute to this literature by developing a novel measure of financial constraints based on textual analysis. We then revisit the question posed by Lamont et al. (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—companies' annual reports. This method is fundamentally different from other approaches taken in the prior literature, where information about financial constraints is extracted from accounting data, e.g. investment or cash flow (see Fazzari et al., 1988). By its nature, accounting data only provides an *indirect* way of gauging financial constraints, since there is no accounting number available that directly measures financial constraints. We circumvent this problem by looking for relevant information where it is directly available. This is one way to come closer to reality, and another way is discussed next.

Reality is complex, and so are financial constraints. It is naïve to assume that financial constraints for a given company can be boiled down to a *single* number. For example, a company might face constraints raising equity but not debt, while another company might face the opposite problem. We extend the existing literature by acknowledging that financial constraints are multi-layered and that they cannot be boiled down to a single number. In particular, using textual analysis, we construct *several* measures of financial constraints that capture several financial dimensions along which companies can be constrained. For example, we distinguish between constraints that arise from issuing equity versus debt. We thus addresses long-standing conceptual problems of constraints measures used in the prior literature.

We find that our financial constraints measures do a good job capturing firm characteristics that are typically associated with financial constraints. For example, constrained firms are small, have lower cash flow to assets ratios, and pay out less dividends. This finding is in contrast to other measures used in the literature. For example, according to the KZ index, constrained firms are larger than unconstrained ones (see Kaplan and Zingales (1997)). After our measures pass these initial "sanity checks," we continue to investigate stock returns.

To this end, we build portfolios by sorting on the financial constraints measures. We find that excess returns are higher for financially constrained firms, suggesting that investors need compensation for financial constraints risk (Whited and Wu (2006)). We then regress these portfolios on well-known risk-factors and find that alphas are increasing in financial constraints, thus confirming our previous result in a more rigorous setting.

The next question we ask is 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 size, we find the largest excess returns for constrained mid-caps and constrained large-caps, but not for constrained small-caps. It means that our results are not driven by illiquid stocks. Instead, a trading strategy using financial constraints is most profitable for liquid stocks.

To further investigate financial constraints risk, we construct a zero-cost financial constraints factor. The difference to the HML factor is that we replace book-to-market with financial constraints. We then "average out" the size quantiles to ensure that we are picking up variation in financial constraints and not size (see Fama and French (1993) and Whited and Wu (2006)). Regressing this factor on the market, the Fama-French factors, and momentum yields an annualized alpha of 7.1% for one of our financial constraints measures. We discuss the differences between our financial constraints measures next.

To capture the different aspects of financial constraints, we use three different textual measures. On a conceptual level, the first measure is most closely related to the measures used in the prior literature. Its intention is to capture financial constraints in a general way, without being too specific as to where the constraints originate. In contrast, the second and third measures capture more specifically the source of the financing frictions. In particular, extending Hoberg and Maksimovic (2013), we construct a constraints measure that captures financial frictions from issuing equity. Another measure does the same thing for debt.

Of all three measures, the constraints measure for debt captures financial constraints risk most accurately. The annualized excess returns for a zero-cost factor are 6.7% for debt, 0.1% for equity, and 4.6% for the general constraints measure. This means that stock returns react most weakly to equity-issuance constraints risk and most strongly to debt-issuance constraints risk. In other words, the stock market is not overly concerned about raising money through the stock market and instead is more concerned about the ability of other markets to provide financing to corporations.

This paper is most closely related to Whited and Wu (2006) and Gomes et al. (2006), who use a structural financial constraints measure to explore the impact of financial constraints on stock returns. The key difference to this paper is that we use a different constraints measure that is based on textual analysis of annual reports of companies, while the other papers use an investment Euler equation to obtain the index as the shadow value of scarce external funds. For the construction of the textual constraints measure we borrow ideas from Hoberg and Maksimovic (2013). In particular, we use their keyword lists to find a suitable estimation sample for our statistical model of textual content. Using keyword lists pertaining to debt and equity, we are able to disentangle different financial constraints originating from debt versus equity. A key difference is that we find strong support for the relevance of debt-related constraints, while Hoberg and Maksimovic find equity-related constraints to be more important.

The remainder of this article is organized as follows. We describe the data and the textual constraints measures in Section 2, present the results in Section 3, and conclude in Section 4.

2 Data

The following Section 2.1 provides an overview about our data sources and how we screen the data. We then describe how we construct the textual financial constraints measure in Section 2.2.

2.1 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 screens. We omit firms with SIC classification between 4900 and 4999 and between 6000 and 6999 to omit regulated and financial firms. To eliminate coding errors, we delete firms that report smaller total debt than short-term debt (DLCQ $>$ DLTTQ). If a firm experiences a merger that accounts for more than 15% of the book value of its assets (AQCQ $> 0.15 *$ ATQ), we delete it. Firms with less than eight consecutive quarters get dropped. We delete firms that have more than two consecutive quarters of negative sales growth to filter out companies that are in financial distress, since we want to consider firms that face external financial constraints but are not distressed. Finally, we exclude firm-quarters for which total assets (ATQ), the gross capital stock (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 CRSP with Compustat. In particular, for each firm-month in CRSP, add the most recent Compustat observation from the past, without any look-ahead bias. This is the same principle as in Fama and French (1993), adapted for quarterly (instead of yearly) accounting data.

From EDGAR we download all filings of Form 10-K that are available from the beginning of 1994 until the end of 2010. Following Li (2010), we extract the MD&A section from each 10-K filing, since the MD&A contains the a narrative explanation of the past performance of the firm, its financial condition, and its future prospects. As such, the MD&A is the part of the 10-K filing that most likely captures the *textual* information we are looking for, i.e. textual information about potential financial constraints.

2.2 Constructing the Textual Financial Constraints Measure

The construction of the textual financial constraints measure is done in three steps: preprocessing of each MD&A, classifying each MD&A, and the selection of appropriate training samples. Each step is discussed in detail in the following sections.

2.2.1 Preprocessing

After extracting the MD&A section from each 10-K filing, we preprocess each MD&A (see Feinerer et al. (2008) and Li (2010)). The following preprocessing steps are all standard and their goal is to make the following textual analysis more precise by reducing unnecessary noise in the text. In particular, 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. Consider for example the following sentence:

> Diamond is the latest in a line of U.S. oil companies that have cut its contract, or posted, 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 hav cut it contract, or posted, price over the last two days cit weak oil markets.

Finally, we remove all words that have at least a 99% percentage of occurring zero times in a document. The purpose of this step is to remove words that appear so infrequently that their meaning cannot be easily picked up by the textual analysis.

2.2.2 Classifying

For the text classification, we use the naïve Bayes algorithm, which is one of the oldest and most well-established tools in computational linguistics. In particular, using naïve Bayes, we model the probability of being financially constraint 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 counts 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 (i.e. each firm year), we obtain a text classification score that shows the probability that this firm year is financially constrained.

Here it is important to note that we model each MD&A as a "bag-of-words" with disregard for grammar and word order. The only relevant information is how *often* a word appears while the *location* of the word within the text document is ignored. This "bag-of-words" approach follows common practice in computational linguistics.

The application of the naïve Bayes model consists of two steps. In the first step, we estimate model (1) on a relatively *small* training sample that has relatively few observations. In the second step, we use the fitted model (1) to predict the financial constraints status for the *whole* sample. That is, 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 on the MD&A from that firm year.

The reason for this two-step procedure is that for a *small* training sample, we are able to obtain reliable observations of financial constraint status (i.e. the left-hand side of (1)), but not for the *whole* sample consisting of all MD&As. The basic idea is that by estimating the model on the small training sample, we pick up the relation between financial constraints and MD&A word counts from this small training sample. Assuming that this relation is stable (which has been shown to be true many times in computational linguistics), we then extrapolate this information on the whole sample consisting of all MD&As. As can be seen from this description, obtaining a high-quality training sample is essential to reliably capture financial constraints. We discuss this aspect of textual analysis in the following section.

2.2.3 Training

The previous section documents the importance of finding a reliable training sample, and we discuss this aspect of textual analysis in more detail here. When forming training samples, it is important to keep in mind that we need reliable observations of the *left*-hand side of (1), i.e. financial constraints status. (The observations of the *right*-hand side of (1) are readily available by counting the words in the MD&As.) We create three different types of training samples and discuss each way in turn in the following paragraphs.

In the first way of obtaining a training sample, we search the Dow Jones Factiva database for news articles that document cases where a firm is financially constrained. We then find the relevant MD&A of the same firm mentioned in the news and we verify that this MD&A also mentions the financial constraint status of this firm. While this method of obtaining a training sample produces the desired observations of the left-hand side of (1), it might be viewed as subjective, since we cannot search the whole Factiva database for financially constrained cases due to the download limits imposed by Factiva. We thus consider additional ways of obtaining training samples that are more directly tied to the MD&As (instead of taking the detour through Factiva).

For the second and third way, we follow Hoberg and Maksimovic (2013) to find firms years that are financially constrained or unconstrained. In particular, Hoberg and Maksimovic (2013) contains lists of keywords that are about delaying investment as well as the issuance of various securities such as equity and debt. The basic idea is that if investment is delayed because there are problems issuing securities (i.e. financing problems), then keywords that are about delays should show up in the proximity of keywords that are about security issuance in the MD&A. All our keyword lists are taken from Hoberg and Maksimovic (2013).

We combine keywords from the "Delay Lists" with the "Equity Focused List" to find a training sample where investments are delayed due to a firm's problems in issuing equity. To ensure that the delay pertains to equity (and not to something else), we count how often a word from the "Delay Lists" is within eight words distance of a word from the "Equity Focused List." The top one hundred MD&As that score highest according to this criterion are used as "financially constrained" for the training sample, while the nine hundred MD&As that score lowest are used as "financially unconstrained" for the training sample. The reason for choosing one hundred vs. nine hundred is based on the consideration that most firms are unconstrained. The results are robust to choosing a different ratio of constrained vs. unconstrained firms for the training sample. By combining the keywords from the "Delay Lists" and the "Equity Focused List," we obtain a training sample that is about financial constraints relating to *equity* issuance (the "equity training sample"). In analogy, by combining keywords from the "Delay Lists" and the "Debt Focused List," we obtain an additional training sample that is about financial constraints relating to *debt* issuance (the "debt training sample").

In total, we have three different training samples. The training sample from Factiva ("Factiva training sample") is based on a manual screening of news articles, while the "equity training sample" and the "debt training sample" are based on the keyword lists from Hoberg and Maksimovic (2013). Using these three training samples, we obtain three measures of financial constraints, as discussed in Section 2.2.2: one that captures general financial constraints, one that captures financial constraints relating to the delay of investment due to problems issuing equity, and one that is about investment delays due to problems issuing debt.

3 Results

Table 1 shows summary statistics relating financial constraint measures to firm characteristics. The first three panels show our own textual measures of financial constraints, while the last panel shows the KZ index for comparison.

All of the textual measures of financial constraints show similar patterns, which are in sharp contrast to the KZ index. Cash flow to assets is smaller for our highly constrained firms, while for the KZ index cash flow is larger for unconstrained firms. At the same time, consistent with precautionary savings of financially constrained firms, cash to assets is larger for our highly constrained firms, while the KZ index implies the opposite results. According to the textual measures, small firms are more constrained than large firms, while the KZ index has a hump-shaped patter, with larger firms being more constrained than small firms. Constrained firms pay out less dividends according to the textual measures, while the KZ index again displays a hump-shaped patters, with most dividends paid out by firms that are neither fully constrained nor fully unconstrained. Finally, there is agreement between the textual measures and the KZ index for Tobin's q. Consistently with all four measures, q is higher for the constrained firms.

It is worth observing that our textual measures of financial constraints are concentrated approximately around zero and one. That is, although there are also observations strictly between zero and one (e.g. in the vicinity of 0.5), these observations are few. The reason for this behavior can be seen directly from equation (1), which implies that for most firm years, the textual analysis is relatively sure that the firm is constrained (close to one) or unconstrained (close to zero). The text classification method used in this paper is thus doing a good job capturing financial constraints.

Although the text classification works well in capturing financial constraints, there might be concerns that the variation of the constraints measures is too low, i.e. too close to a Bernoulli distribution taking *only* values one or zero. For this concern, it is important to keep in mind that Table 1 shows sufficient variation when using the quantiles of the financial constraints distribution. And the quantiles is precisely what interests us in this paper. The textual measures therefore capture financial constraints with sufficient variation.

We have shown in Table 1 that the textual financial constraints index is likely to be more informative about the existence of financial constraints than the KZ index. We examine next whether financial constraints affect asset returns. In particular, we ask whether there is a financial constraints factor and whether returns of constrained firms are subject to common shocks.

As an initial step towards this goal, we form portfolios by sorting the textual financial constraints measure into three terciles. We follow Whited and Wu (2006) and use top-40%, middle-20%, and bottom-40%. Table 2 shows the portfolio characteristics. We find that excess returns increase with financial constraints. This increase is particularly strong for the Factiva training sample and the debt training sample. Furthermore, similar to our earlier results, we find that constrained firms tend to be small.

Next we regress the constraints-sorted portfolios on the market factor and the Fama-French factors, as shown in Table 3. For both the Factiva training sample and the debt training sample, the alphas are higher when financial constraints are more severe. Likewise when building a "high minus low" portfolio based on the financial constraints measure, the resulting alphas are significantly positive for the Factiva and debt training samples, and insignificant for the equity training sample. The high minus low regressions load positively on SMB, confirming that financially constrained firms tend to be small. They load negatively on HML, indicating that constrained firms tend to be growth stocks.

It turns out in Table 3 that *all* portfolios have positive alphas, independent of whether they belong to the low, middle, or high financial constraints sample. It is important to note that we do *not* impose an adding-up constraint that the average alpha equals zero. Instead, the particular *sample* of stocks on which we run these regressions has a positive alpha to begin with, independent of the sorting scheme. To this end, there are two points to note. First, the distinguishing feature of our sample is that, in order to sort on financial constraints, we require a non-missing value for the financial constraints measure. In other words, if we cannot calculate the financial constraints measure for a given firm-year, e.g. because of a missing Form 10-K or because the MD&A section cannot be parsed, we exclude all stock returns matching that particular firm-year. This specific way of constructing the sample, which is necessary in order to sort on financial constraints, happens to yield a positive alpha to begin with; a portfolio consisting of all stocks in that sample, without any sorting, has a *significantly* positive alpha (untabulated). Second, this result is still consistent with prior studies. If we relax the requirement of having a matching financial constraints firm-year, and instead use the *larger* sample from the basic data screens in Section 2.1, we obtain an *insignificant* alpha for a portfolio consisting of all stocks in this particular sample (untabulated), consistent with prior studies. To summarize, we obtain *all*-positive alphas because of the specific composition of our sample, which requires a matching textual financial constraints measure. However, our main point is not so much that the alphas are positive, but that they increase in the degree of financial constraints.

In the next step we double-sort firms based on size and textual financial constraints into top-40%, middle-20%, and bottom-40%, following Whited and Wu (2006). We then classify each firm into one of the following nine groups: small size and low index (SL), small size and middle index (SM), small size and high index (SH), medium size and low index (ML), medium size and middle index (MM), medium size and high index (MH), large size and low index (BL), large size and middle index (BM), and finally large size and high index (BH). Based on this sorting scheme, we calculate monthly portfolio returns using CRSP data.

Table 4 shows the excess returns for all nine portfolios. An interesting pattern emerges in the sense that the effect of financial constraints becomes *stronger* as the companies get larger. Consider for example the debt training sample, where this effect is most pronounced. Here the average excess return of big constrained firms is 2.2% per month while it is 1.2% for big unconstrained firms. This is an increase of 1 percentage point per month. In contrast, the average excess return of a small constrained firm is 0.9% while a small unconstrained firm has 0.9%. In other words, the excess returns of small firms only react very weakly (if at all) to changes in financial constraints status. In contrast, the excess returns of big firms are more sensitive to changes in financial constraints, changing by 1 percentage point per month. The results for the remaining two training samples share the same pattern as the debt training sample, albeit on a smaller scale. The strongest pattern remains for the debt training sample.

Table 5 further investigates whether this effect is economically significant even among the largest, most liquid stocks. By double-sorting portfolios on financial constraints status as well as size, it regresses zero-cost "high minus low" financial constraints portfolios on the market and on the Fama-French factors. The alphas are insignificant for the small subsample, while they are significantly positive for the mid-cap firms and big firms.[1] This shows that the economic significance is not driven by small firms. Instead, the economic significance of financial constraints becomes stronger for the larger and more liquid stocks. This could reflect that larger firms have better disclosures in their accounting reports, allowing for a higher precision of textual information, which our financial constraints measure depends upon.

To further investigate the economic significance of financial constraints, we follow Whited and Wu (2006) to add three further portfolios. These portfolios build upon the double sorted portfolios constructed earlier, where the double sort is done on both financial constraints and size. In particular, we form the following portfolios.

$$\begin{aligned} \text{HIGHFC} &= (BH + MH + SH)/3 \\ \text{LOWFC} &= (BL + ML + SL)/3 \\ \text{FC} &= \text{HIGHFC} - \text{LOWFC} \end{aligned} \tag{2}$$

The HIGHFC portfolio is the equal-weighted average of the most constrained portfolios, LOWFC is an equal-weighted portfolio of the lowest-constrained firms, and the FC portfolio is the difference between both. In particular, the FC portfolio is constructed in the same way as the Fama-French benchmark portfolio , with book-to-market replaced by the textual financial constraints measures (see Fama and French (1993)). FC is thus a zero-cost factor-mimicking portfolio for financial constraints.

Table 6 shows portfolio characteristics and returns, and exhibits several patterns. First, it shows that size is negatively correlated with financial constraints. For small-cap firms, we have more firms that are in the upper quantile of the financial constraints index, while for large-cap firms there are more firms in the low index quantile. Likewise, more firms that are in the upper constraints quantile can be found in the small-cap category than in the large-cap category. Furthermore, the average size of firms in the HIGHFC portfolio is always smaller than in the LOWFC portfolio. These results are

[1]The reason for the all-positive alphas in the Factiva and debt training samples is identical to the one discussed previously for Table 3.

consistent for all the textual constraints measures based on all training samples. Second, constrained firms earn higher excess returns. This pattern holds for all three constraints measures, and is particularly strong with the debt training sample. Specifically, the average monthly excess return for the FC portfolio with the debt training sample is 0.56% with a t-statistic of 2.53. Financially constrained firms thus earn a positive risk premium, and this risk premium is particularly large and significant for the debt training sample. This means that financial constraints from delaying investment because of problems with debt issuance command a high risk premium and these financing frictions are reflected in stock prices.[2] Third, debt-to-assets is higher for unconstrained firms. This reflects unconstrained firms' ability to raise debt financing. The difference in debt-to-assets between constrained and unconstrained firms is largest for the debt training sample, showing that the textual analysis consistently picks up the relevant variation in financial constraints. Finally, book-to-market is larger for unconstrained firms. Value stocks thus tend to be less financially constrained, while growth stocks are more constrained. Again the difference in book-to-market is largest for the debt training sample, suggesting that financial frictions from debt issuance play an important role for value and growth stocks.

Figure 1 shows time series plots of the FC portfolio for all three training samples. All portfolios capture the increase in financial constraints before the recession in 2001 and the subsequent decrease. After the recession in 2001, the FC portfolio from the equity training sample does not increase a lot, which explains its low excess return in Table 6. On the other hand, the FC portfolio from the Factiva training sample and the debt training sample increase after the recession in 2001, and thus have much larger excess returns in Table 6. Interestingly, the financial crisis that started to unfold in 2007 did not have a major effect on the FC portfolio. A trading strategy using the textual financial constraints measure would thus have been largely unaffected by the turmoil during the financial crisis. This is consistent with the notion that quantitative easing helped alleviate the financial frictions of nonfinancial companies.

Tables 7 to 9 test whether returns of financially constrained firms move together. Controlling for other sources of common variation, we regress the returns of all nine size and constraints double sorted portfolios on three reference portfolio returns. Following Whited and Wu (2006), these reference portfolios consist of a proxy for the market factor (BIG), a proxy for the size factor (SMALL), and the FC factor. In particular, we define BIG and SMALL as follows:

$$\begin{aligned} \text{BIG} &= (BM + BL + MM + ML)/4 \\ \text{SMALL} &= (SL + SM)/2 \end{aligned} \tag{3}$$

[2]Note that the excess returns are slightly different than in Table 4 because for a given company we have omitted multiple securities outstanding that have the lowest trading volume. The results stay robust if we include all securities outstanding.

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 reported in Tables 7 to 9, we exclude the left-hand side portfolio from the construction of the right-hand side variables in order to avoid spurious regression results. Each Table 7 to 9 shows the regression results for the three financial constrains measures based on the three training samples (Factiva, equity, and debt training samples).

Tables 7 to 9 show consistently for all three financial constraints measures that returns of financially constrained firms covary with the returns of other financially constrained firms. Specifically, for each size category, the loading on FC increases when the left-hand side variable becomes more constrained. Furthermore, for the Factiva and debt training samples, the FC loading is positive and significant for medium-constrained and high-constrained portfolios, while the FC loading is negative and significant for the least-constrained portfolios. For the equity training sample, the results are qualitatively the same, with the difference that only the high-constrained portfolios are significant. These results show that financially constrained firms move together with other firms that are also constrained. This confirms the existence of a financial constraints factor, controlling for the market and size effect.

Table 10 examines whether the FC factor reflects other factors such as the market, size, market-to-book, and momentum. In particular, we regress the FC factor on these other known empirical factors. If the FC factor is correctly priced, the intercepts of these regressions should be zero and the R^2 should be high.

The FC factor is positively correlated with the market factor and negatively correlated with the book-to-market factor. Consistent with the earlier findings from Table 6, value stocks are less constrained than growth stocks. The FC factor also loads positively on the size factor, showing that smaller firms are more likely to be financially constrained.

For the Factiva training sample and debt training sample, we find that the intercepts are positive and highly significant. The four-factor model thus cannot correctly price the FC factor. For the equity training sample, however, the intercept is positive and insignificant. For all specifications, the R^2 falls between 30% and 70%, leaving a significant portion of the variation of the FC factor unexplained. We thus find that the FC factor is an anomaly that cannot be explained by the other known empirical factors.

4 Conclusion

We construct a novel measure of financial constraints and investigate whether it impacts stock returns. In contrast to other measures used in the literature, we find that our measure consistently captures firm characteristics that are associated with financial constraints. Furthermore, we are able to capture several different aspects of financial constraints. For example, depending on whether a firm has difficulties issuing debt or equity, we are able to construct different "flavors" of our measure that capture this difference.

We find that our measure is able to capture prized financial constraints risk in stock returns. In particular, financially constrained firms have higher returns. This effect is not concentrated in small and illiquid firms. Instead, it is most prevalent in large and liquid stocks, making it easier to form a trading strategy. A zero-cost factor-mimicking portfolio earns an annualized risk-adjusted excess return of 7% when trading on financial constraints. Financial constraints from equity issuance do not command a significant risk premium, while debt issuance constraints risk is significantly prized.

Table 1: Summary Statistics

This table shows summary statistics for the textual financial constraints measure and the KZ index. Details of the construction of the training samples are explained in Section 2.2.3.

	Least constrained			Most constrained
Panel A: Sorted by Textual FC Index: *Factiva* Training Sample				
Cash Flow/Assets	0.04	0.04	0.02	-0.02
Total Assets	3177.84	3086.63	1975.96	851.86
Debt Assets	841.26	826.37	512.45	186.45
Dividends	14.71	14.12	8.55	3.21
Cash/Assets	0.13	0.13	0.21	0.31
Tobin's q	1.71	1.70	2.16	2.78
Text-Based FC Index	0.00	0.00	0.44	1.00
KZ Index	0.82	0.83	0.81	0.81
Panel B: Sorted by Textual FC Index: *Equity* Training Sample				
Cash Flow/Assets	0.03	0.03	0.03	-0.01
Total Assets	2589.79	2543.01	2482.01	1477.47
Debt Assets	686.81	662.90	665.01	351.54
Dividends	11.78	11.71	10.55	6.55
Cash/Assets	0.15	0.16	0.16	0.31
Tobin's q	1.90	1.91	1.91	2.62
Text-Based FC Index	0.00	0.00	0.00	0.83
KZ Index	0.83	0.84	0.83	0.77
Panel C: Sorted by Textual FC Index: *Debt* Training Sample				
Cash Flow/Assets	0.04	0.03	0.01	0.01
Total Assets	3845.27	3138.87	1077.35	1030.80
Debt Assets	1060.45	869.52	219.31	216.46
Dividends	19.24	14.99	3.58	2.78
Cash/Assets	0.12	0.14	0.26	0.26
Tobin's q	1.72	1.78	2.41	2.45
Text-Based FC Index	0.00	0.09	1.00	1.00
KZ Index	0.89	0.85	0.76	0.78
Panel D: Sorted by KZ Index				
Cash Flow/Assets	0.01	0.03	0.04	0.00
Total Assets	1018.69	3484.23	3008.39	1580.96
Debt Assets	88.67	692.83	863.10	721.81
Dividends	10.15	17.17	10.49	2.78
Cash/Assets	0.38	0.16	0.11	0.13
Tobin's q	1.63	1.88	1.90	2.94
Text-Based FC Index	0.46	0.34	0.29	0.35
KZ Index	-0.19	0.48	0.96	2.01

Table 2: Portfolio Characteristics

This table shows portfolio characteristics when sorting on the textual financial constraints measure. Each panel shows the average values of the financial constraints measure, excess returns r^e, size (i.e. market equity), and book-to-market. The values are split up according to the percentiles of the constraints measure. The different panels correspond to the training samples, which are explained in Section 2.2.3.

Panel A: Factiva Training Sample

	FC	r^e	Size	B/M
FC.Low	0.001	0.014	76726	0.95
FC.Mid	0.047	0.014	69497	0.94
FC.High	0.752	0.018	49444	0.69

Panel B: Equity Training Sample

	FC	r^e	Size	B/M
FC.Low	0.001	0.015	74103	0.93
FC.Mid	0.001	0.015	74022	0.92
FC.High	0.412	0.015	58823	0.81

Panel C: Debt Training Sample

	FC	r^e	Size	B/M
FC.Low	0.006	0.013	77411	0.98
FC.Mid	0.448	0.016	55676	0.84
FC.High	0.963	0.020	54612	0.67

Table 3: Portfolios Sorted on Textual Financial Constraints Measure

This table shows regressions of portfolios sorted on the textual financial constraints measure. The different panels correspond to the training samples, which are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

Panel A: Factiva Training Sample

	FC.Low	FC.Mid	FC.High	High-Low
α	0.0096***	0.0092***	0.0141***	0.0045**
	(8.6779)	(7.1106)	(8.0417)	(2.2017)
$r_{mkt} - r_f$	0.9534***	0.8687***	1.0902***	0.1368***
	(39.5196)	(30.5714)	(28.4648)	(3.0534)
SMB	−0.1358***	0.0378	0.2666***	0.4023***
	(−4.1998)	(0.9917)	(5.1941)	(6.7010)
HML	0.0539	−0.0337	−0.6040***	−0.6579***
	(1.5805)	(−0.8386)	(−11.1520)	(−10.3835)
R^2	0.8902	0.8416	0.8741	0.5880
Num. obs.	203	203	203	203

Panel B: Equity Training Sample

	FC.Low	FC.Mid	FC.High	High-Low
α	0.0106***	0.0108***	0.0102***	−0.0004
	(9.6725)	(6.6801)	(8.9734)	(−0.2760)
$r_{mkt} - r_f$	0.9739***	0.9213***	0.9564***	−0.0175
	(40.3804)	(26.0747)	(38.2738)	(−0.5339)
SMB	−0.0597*	0.0333	0.0635*	0.1233***
	(−1.8488)	(0.7029)	(1.8970)	(2.8034)
HML	−0.0584*	−0.0796	−0.2216***	−0.1632***
	(−1.7127)	(−1.5928)	(−6.2722)	(−3.5175)
R^2	0.8999	0.7973	0.9025	0.1362
Num. obs.	203	203	203	203

Panel C: Debt Training Sample

	FC.Low	FC.Mid	FC.High	High-Low
α	0.0083***	0.0117***	0.0152***	0.0068***
	(8.6618)	(6.5203)	(8.3940)	(3.4430)
$r_{mkt} - r_f$	0.9203***	0.9705***	1.0840***	0.1637***
	(43.7064)	(24.5754)	(27.3652)	(3.7540)
SMB	−0.1358***	0.2965***	0.2208***	0.3566***
	(−4.8118)	(5.6040)	(4.1603)	(6.1035)
HML	0.0676**	−0.3957***	−0.4727***	−0.5403***
	(2.2711)	(−7.0868)	(−8.4390)	(−8.7638)
R^2	0.9080	0.8295	0.8526	0.5368
Num. obs.	203	203	203	203

Table 4: Excess Returns of Double Sorts on Financial Constraints and Size

This table shows excess returns of portfolios that are double sorted on the textual financial constraints measure and size (i.e. market equity). The different panels correspond to the training samples, which are explained in Section 2.2.3.

Panel A: Factiva Training Sample

	FC.Low	FC.Mid	FC.High
Small	0.984	0.924	0.905
Medium	1.594	1.666	2.167
Big	1.382	1.310	1.951

Panel B: Equity Training Sample

	FC.Low	FC.Mid	FC.High
Small	1.070	0.940	0.819
Medium	1.824	1.532	2.006
Big	1.417	1.557	1.569

Panel C: Debt Training Sample

	FC.Low	FC.Mid	FC.High
Small	0.917	1.118	0.870
Medium	1.651	1.707	2.077
Big	1.226	1.591	2.229

Table 5: Double Sorts on Financial Constraints and Size

This table shows regressions of portfolios that are double sorted on the textual financial constraints measure and size (i.e. market equity). The different panels correspond to the training samples, which are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

Panel A: Factiva Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	0.0009	0.0073***	0.0049**
	(0.3534)	(2.9780)	(2.3087)
$r_{mkt} - r_f$	0.1661***	0.2324***	0.1309***
	(3.1088)	(4.3270)	(2.8366)
SMB	0.2784***	0.3123***	0.3693***
	(3.8888)	(4.3401)	(5.9708)
HML	−0.6595***	−0.8100***	−0.6752***
	(−8.7284)	(−10.6654)	(−10.3441)
R^2	0.4638	0.5636	0.5668
Num. obs.	203	203	203

Panel B: Equity Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	−0.0026	0.0032*	−0.0004
	(−1.4481)	(1.6597)	(−0.2860)
$r_{mkt} - r_f$	0.0582	0.0587	−0.0205
	(1.4592)	(1.3867)	(−0.6029)
SMB	0.0410	0.1630***	0.1114**
	(0.7690)	(2.8761)	(2.4489)
HML	−0.2462***	−0.3664***	−0.1623***
	(−4.3767)	(−6.1293)	(−3.3801)
R^2	0.1439	0.2870	0.1180
Num. obs.	202	202	203

Panel C: Debt Training Sample

	FCHML (Small)	FCHML (Medium)	FCHML (Big)
α	0.0006	0.0075***	0.0071***
	(0.2744)	(3.7553)	(3.4602)
$r_{mkt} - r_f$	0.0469	0.0275	0.1636***
	(1.0172)	(0.6281)	(3.6150)
SMB	0.0989	0.0741	0.3250***
	(1.6001)	(1.2626)	(5.3589)
HML	−0.4911***	−0.7424***	−0.5558***
	(−7.5287)	(−11.9890)	(−8.6843)
R^2	0.3069	0.4921	0.5119
Num. obs.	203	203	203

Table 6: Portfolio Characteristics and Returns

This table provides a summary of portfolio characteristics and portfolio returns. The different panels correspond to the training samples, which are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

			Value weighted				Equal weighted			
	Category label	Number of firms	Excess returns	D/A	B/M	Size	Excess returns	D/A	B/M	Size
Panel A: Factiva Training Sample										
Small-cap firms										
Low index	SL	288	0.83	0.25	3.53	0.12	0.19	0.26	5.01	0.08
Middle index	SM	155	0.67	0.24	3.25	0.12	0.06	0.25	4.58	0.08
High index	SH	406	0.88	0.19	1.97	0.12	-0.05	0.21	3.09	0.08
Mid-cap firms										
Low index	ML	162	1.30	0.24	1.99	0.38	1.26	0.24	2.06	0.36
Middle index	MM	82	1.41	0.23	1.91	0.38	1.42	0.23	1.98	0.35
High index	MH	179	1.96	0.18	1.17	0.38	1.84	0.18	1.21	0.35
Large-cap firms										
Low index	BL	398	1.45	0.23	0.97	76.56	1.52	0.25	1.31	7.60
Middle index	BM	187	1.38	0.23	0.94	69.91	1.61	0.25	1.26	7.45
High index	BH	263	1.88	0.17	0.67	52.44	2.33	0.19	0.89	5.54
HIGHFC			1.57	0.18	1.27	17.64	1.37	0.19	1.73	1.99
LOWFC			1.19	0.24	2.16	25.69	0.99	0.25	2.79	2.68
FC			0.38	-0.06	-0.89	-8.05	0.38	-0.06	-1.06	-0.69
t-stat of FC			1.21				1.15			
Panel B: Equity Training Sample										
Small-cap firms										
Low index	SL	327	0.86	0.24	3.16	0.12	0.07	0.25	4.48	0.08
Middle index	SM	165	0.78	0.23	3.05	0.12	-0.10	0.25	4.24	0.08
High index	SH	356	0.71	0.20	2.24	0.12	-0.01	0.21	3.45	0.08
Mid-cap firms										
Low index	ML	161	1.52	0.23	1.82	0.38	1.48	0.23	1.88	0.36
Middle index	MM	80	1.29	0.23	1.84	0.38	1.25	0.23	1.90	0.36
High index	MH	182	1.83	0.19	1.38	0.37	1.76	0.19	1.43	0.35
Large-cap firms										
Low index	BL	358	1.58	0.23	0.93	73.94	1.72	0.24	1.25	7.22
Middle index	BM	179	1.48	0.23	0.92	75.62	1.67	0.24	1.23	7.30
High index	BH	310	1.46	0.21	0.82	60.46	1.95	0.22	1.03	6.41
HIGHFC			1.33	0.20	1.48	20.32	1.23	0.21	1.97	2.28
LOWFC			1.32	0.23	1.97	24.81	1.09	0.24	2.53	2.55
FC			0.01	-0.03	-0.49	-4.49	0.14	-0.03	-0.57	-0.27
t-stat of FC			0.06				0.94			
Panel C: Debt Training Sample										
Small-cap firms										
Low index	SL	273	0.64	0.27	4.18	0.12	-0.09	0.28	5.99	0.08
Middle index	SM	180	0.79	0.22	2.65	0.12	0.16	0.23	3.78	0.08
High index	SH	394	0.89	0.19	1.82	0.12	0.01	0.20	2.77	0.08
Mid-cap firms										
Low index	ML	153	1.25	0.26	2.28	0.38	1.24	0.26	2.36	0.36
Middle index	MM	87	1.70	0.21	1.57	0.38	1.63	0.21	1.64	0.36
High index	MH	184	1.87	0.17	1.11	0.37	1.78	0.17	1.14	0.35
Large-cap firms										
Low index	BL	420	1.31	0.25	0.99	76.98	1.39	0.26	1.40	8.46
Middle index	BM	157	1.63	0.20	0.84	58.77	1.92	0.22	1.09	6.20
High index	BH	269	2.12	0.15	0.63	56.56	2.40	0.18	0.82	4.91
HIGHFC			1.63	0.17	1.19	19.02	1.40	0.18	1.58	1.78
LOWFC			1.07	0.26	2.48	25.83	0.85	0.27	3.25	2.96
FC			0.56	-0.09	-1.29	-6.81	0.55	-0.08	-1.67	-1.18
t-stat of FC			2.53				2.45			

Figure 1: Monthly Cross-Sorted Financial Constraints Factor
Different figures correspond to different training samples. Section 2.2.3 explains the training samples in detail.

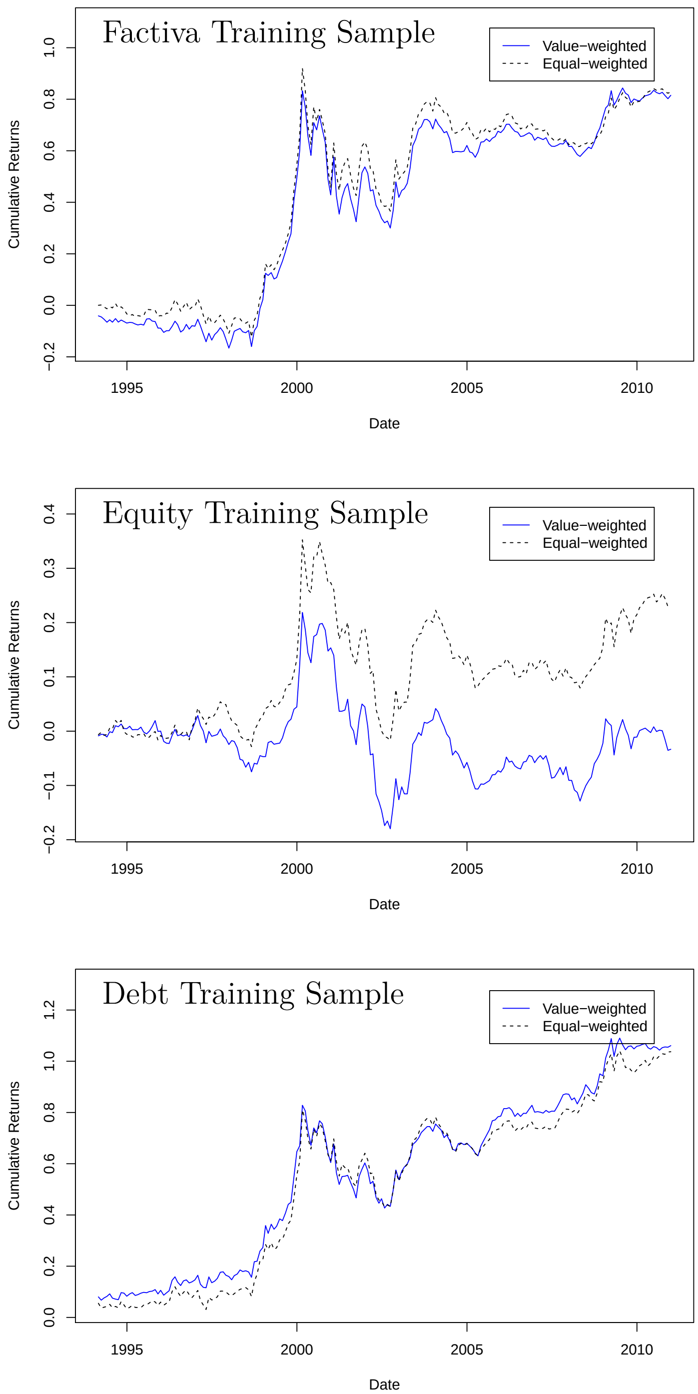

Table 7: Covariance Tests of Portfolios: *Factiva* Training Sample (Equal-Weighted)

The different training samples are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

	Regression results					Variable definitions		
	Constant	BIG	SMALL	FC	R^2	BIG	SMALL	FC
Small-cap firms								
Low index (SL)	-0.00	0.20***	0.77***	-0.07***	0.93	(BM+BL+MM+ML)/4	SM	(BH+MH-BL-ML)/2
	(-0.59)	(4.79)	(21.91)	(-2.60)				
Mid-index (SM)	-0.00**	0.11**	0.92***	0.09***	0.93	(BM+BL+MM+ML)/4	SL	(BH+MH-BL-ML)/2
	(-2.38)	(2.35)	(21.91)	(3.01)				
High index (SH)	-0.00**	-0.13*	1.19***	0.61***	0.90	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+MH-BL-ML)/2
	(-2.08)	(-1.72)	(18.11)	(13.32)				
Mid-cap firms								
Low index (ML)	0.00	0.82***	0.30***	-0.12***	0.92	(BM+BL+MM)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(0.02)	(17.99)	(7.60)	(-3.88)				
Mid-index (MM)	0.00	0.79***	0.31***	0.16***	0.90	(BM+BL+ML)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(1.10)	(14.33)	(6.56)	(4.21)				
High index (MH)	0.00	0.93***	0.16***	0.84***	0.94	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+SH-BL-SL)/2
	(1.61)	(16.57)	(3.12)	(22.20)				
Large-cap firms								
Low index (BL)	0.00*	0.91***	-0.09**	-0.14***	0.90	(BM+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.70)	(22.00)	(-2.28)	(-4.66)				
Mid-index (BM)	0.00	0.98***	-0.16***	0.15***	0.86	(BL+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.49)	(18.41)	(-3.24)	(4.04)				
High index (BH)	0.00*	1.26***	-0.30***	0.86***	0.88	(BM+BL+MM+ML)/4	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.78)	(17.83)	(-4.75)	(17.61)				

Table 8: Covariance Tests of Portfolios: *Equity* Training Sample (Equal-Weighted)

The different training samples are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

		Regression results				Variable definitions		
	Constant	BIG	SMALL	FC	R^2	BIG	SMALL	FC
Small-cap firms								
Low index (SL)	-0.00	0.17***	0.85***	0.04	0.93	(BM+BL+MM+ML)/4	SM	(BH+MH-BL-ML)/2
	(-0.09)	(3.86)	(22.80)	(0.72)				
Mid-index (SM)	-0.00***	0.13***	0.85***	0.00	0.93	(BM+BL+MM+ML)/4	SL	(BH+MH-BL-ML)/2
	(-2.86)	(2.95)	(22.80)	(0.02)				
High index (SH)	-0.00***	0.13***	0.91***	0.41***	0.94	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+MH-BL-ML)/2
	(-2.61)	(2.99)	(24.99)	(7.72)				
Mid-cap firms								
Low index (ML)	0.00	0.93***	0.20***	-0.01	0.94	(BM+BL+MM)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(0.58)	(22.26)	(5.92)	(-0.18)				
Mid-index (MM)	0.00	0.75***	0.37***	0.05	0.91	(BM+BL+ML)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(0.00)	(15.09)	(9.07)	(0.65)				
High index (MH)	0.00**	0.87***	0.23***	0.92***	0.93	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+SH-BL-SL)/2
	(2.44)	(17.81)	(5.52)	(12.03)				
Large-cap firms								
Low index (BL)	0.00**	0.96***	-0.14***	0.08	0.91	(BM+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(2.17)	(24.51)	(-4.05)	(1.54)				
Mid-index (BM)	0.00	0.98***	-0.16***	0.05	0.90	(BL+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.48)	(23.41)	(-4.38)	(0.86)				
High index (BH)	0.00*	1.10***	-0.14***	0.68***	0.90	(BM+BL+MM+ML)/4	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.73)	(22.68)	(-3.34)	(10.18)				

Table 9: Covariance Tests of Portfolios: *Debt* Training Sample (Equal-Weighted)

The different training samples are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

	Regression results					Variable definitions		
	Constant	BIG	SMALL	FC	R^2	BIG	SMALL	FC
Small-cap firms								
Low index (SL)	-0.00*	0.26***	0.68***	-0.29***	0.91	(BM+BL+MM+ML)/4	SM	(BH+MH-BL-ML)/2
	(-1.72)	(6.04)	(19.20)	(-6.80)				
Mid-index (SM)	-0.00	0.11*	0.95***	0.33***	0.90	(BM+BL+MM+ML)/4	SL	(BH+MH-BL-ML)/2
	(-1.32)	(1.89)	(19.20)	(6.44)				
High index (SH)	-0.00***	0.03	0.98***	0.32***	0.95	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+MH-BL-ML)/2
	(-2.89)	(0.81)	(28.93)	(9.04)				
Mid-cap firms								
Low index (ML)	0.00	0.79***	0.32***	-0.34***	0.92	(BM+BL+MM)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(0.73)	(18.30)	(8.80)	(-7.09)				
Mid-index (MM)	0.00	0.91***	0.24***	0.32***	0.92	(BM+BL+ML)/3	(SM+SL)/2	(BH+SH-BL-SL)/2
	(0.26)	(17.98)	(5.68)	(6.13)				
High index (MH)	0.00	0.81***	0.22***	0.57***	0.93	(BM+BL+MM+ML)/4	(SM+SL)/2	(BH+SH-BL-SL)/2
	(1.55)	(18.12)	(5.64)	(12.16)				
Large-cap firms								
Low index (BL)	0.00*	0.74***	-0.01	-0.35***	0.86	(BM+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.77)	(18.32)	(-0.19)	(-7.03)				
Mid-index (BM)	0.00	1.11***	-0.21***	0.52***	0.85	(BL+MM+ML)/3	(SM+SL)/2	(MH+SH-ML-SL)/2
	(1.20)	(18.19)	(-3.89)	(7.90)				
High index (BH)	0.00***	1.13***	-0.16***	0.71***	0.90	(BM+BL+MM+ML)/4	(SM+SL)/2	(MH+SH-ML-SL)/2
	(2.68)	(22.46)	(-3.72)	(12.39)				

Table 10: Relating the Financial Constraints Factor to the Four-Factor Model
This table shows regressions of the FC factor on the market, the Fama-French factors, and the momentum factor. The different panels correspond to the training samples, which are explained in Section 2.2.3. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

Dependent variable	Constant	Market	SMB	HML	Momentum	R^2
Panel A: Factiva Training Sample						
Value-weighted FC factor	0.0043**	0.1729***	0.3213***	-0.7138***		0.6574
	(2.4000)	(4.4100)	(6.1200)	(-12.8800)		
Value-weighted FC factor	0.0050***	0.1340***	0.3344***	-0.7445***	-0.0905***	0.6698
	(2.8000)	(3.2600)	(6.4400)	(-13.3700)	(-2.7300)	
Equal-weighted FC factor	0.0042**	0.1781***	0.3915***	-0.7370***		0.6817
	(2.3200)	(4.4600)	(7.3200)	(-13.0600)		
Equal-weighted FC factor	0.0050***	0.1335***	0.4065***	-0.7722***	-0.1037***	0.6963
	(2.7800)	(3.2000)	(7.7300)	(-13.6900)	(-3.0900)	
Panel B: Equity Training Sample						
Value-weighted FC factor	0.0001	0.0354	0.1029***	-0.2507***		0.3100
	(0.0698)	(1.3329)	(2.8868)	(-6.6657)		
Value-weighted FC factor	0.0004	0.0188	0.1085***	-0.2639***	-0.0388*	0.3200
	(0.3081)	(0.6645)	(3.0460)	(-6.9042)	(-1.7057)	
Equal-weighted FC factor	0.0013	0.0528**	0.1566***	-0.2898***		0.4271
	(1.0699)	(2.0276)	(4.4907)	(-7.8757)		
Equal-weighted FC factor	0.0014	0.0442	0.1595***	-0.2966***	-0.0200	0.4294
	(1.1837)	(1.5909)	(4.5518)	(-7.8897)	(-0.8931)	
Panel C: Debt Training Sample						
Value-weighted FC factor	0.0059***	0.0791***	0.1824***	-0.5779***		0.6225
	(4.2891)	(2.6050)	(4.4806)	(-13.4523)		
Value-weighted FC factor	0.0060***	0.0754**	0.1837***	-0.5809***	-0.0088	0.6227
	(4.2845)	(2.3210)	(4.4825)	(-13.2130)	(-0.3366)	
Equal-weighted FC factor	0.0060***	0.0530*	0.2138***	-0.6039***		0.6527
	(4.3913)	(1.7839)	(5.3711)	(-14.3752)		
Equal-weighted FC factor	0.0061***	0.0464	0.2160***	-0.6091***	-0.0153	0.6533
	(4.4247)	(1.4632)	(5.3947)	(-14.1763)	(-0.5975)	

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