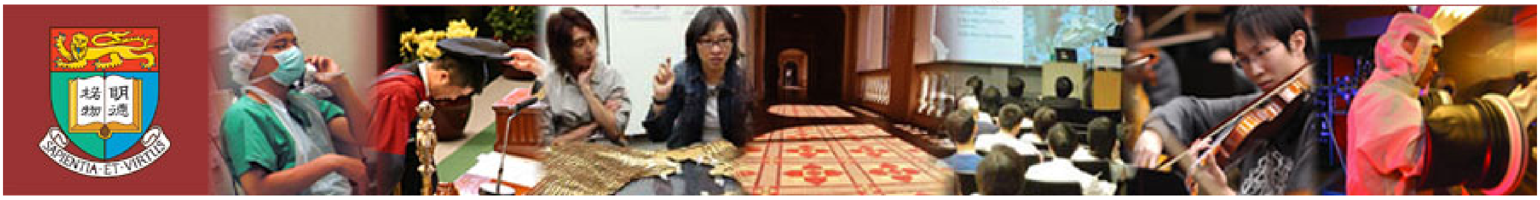

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Looking for Risk in Words: A Narrative Approach to Measuring the Pricing Implications of Financial Constraints

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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

Financial constraints arise from frictions such as information asymmetries that make external funds more costly than internal funds, sometime prohibitively so. Although financial constraints are easy to understand on this conceptual level, 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. The classic example is the sensitivity of investment to cash flow from Fazzari et al. (1988). By its nature, accounting data only provides an *indirect* way of gauging financial constraints because current accounting standards offer no means for a direct quantification of financial constraints. We circumvent this problem by looking for relevant information where it is directly available.

Financial constraints are not unidimensional and it is thus 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 on the effects of financial constraints on stock returns by constructing *several* measures of financial constraints that capture different 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 fewer 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 (Kaplan and Zingales, 1997). After our measures pass these initial "sanity checks," we continue to investigate their relation to stock returns.

To this end, we build portfolios by sorting on our 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. Thus, 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 by replacing the book-to-market ratio with our financial constraints measure in the construction of the standard HML factor. We then "average out" the size quantiles to ensure that we are picking up variation in financial constraints and not size (Fama and French, 1993; 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.

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 specific about the source of the constraints. In contrast, the second and third measures capture sources for financing frictions. In particular, extending Hoberg and Maksimovic (2014), we construct constraints measures that capture financial frictions from issuing equity, debt, or both.

Of all three measures, the constraints measure for debt appears to be most important for financial constraints risk. 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 result means that stock returns react least to equity-issuance constraints risk and most to debt-issuance constraints risk. In other words, the stock market is not overly concerned about firms' capacities to raise money through the stock market and instead prices their ability to raise money in debt markets. This result makes intuitive sense inasmuch as equity issuances are largely rare events (DeAngelo et al., 2010).

This paper is most closely related to Lamont et al. (2001), Whited and Wu (2006), and Gomes et al. (2006), who also explore the impact of financial constraints on stock returns. The key difference between this earlier work and our study is our use of a constraints measure that is based on textual analysis of SEC filings.

A related but distinct literature is the one on financial distress and stock returns (Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Campbell et al., 2008; Chava and

Purnanandam, 2010; Garlappi and Yan, 2011). The difference between this literature and our work is that financial *constraints* typically occur in fast-growing and often young companies that have *good* investment projects, but yet struggle to find sufficient funding. In contrast, *distressed* companies are near or in bankruptcy and struggle because they typically *lack* good investment projects.

In a larger context, this paper is embedded in the literature on financial constraints. These constraints are important because they are related to capital structure (Korajczyk and Levy, 2003), cash (Denis and Sibilkov, 2010), corporate goodness (Hong et al., 2012), cost of capital (Campbell et al., 2012), entrepreneurship (Kerr and Nanda, 2009), financial development and growth (Love, 2003; Desai et al., 2008), innovation (Brown et al., 2009; Li, 2011; Gorodnichenko and Schnitzer, 2013), investment (Whited, 1992; Erickson and Whited, 2000; Marquez and Yavuz, 2013), mergers and acquisitions (Liao, 2014; Erel et al., 2014), and taxes (Law and Mills, 2014).

Because being financially constrained is not a black and white issue, as noted above, measuring and quantifying financial constraints is empirically challenging. Further, as described in Farre-Mensa and Ljungqvist (2014), no consensus has yet to emerge in the literature. Prior studies have considered investment-cash flow sensitivities (Fazzari et al., 1988; Kaplan and Zingales, 1997) and extensions thereof (Gatchev et al., 2010), firm size and age (Hadlock and Pierce, 2010), structural estimation (Whited and Wu, 2006; Lin et al., 2011; Karaivanov and Townsend, 2014), and textual information (Bodnaruk et al., 2013; Hoberg and Maksimovic, 2014).

In relation to these last papers, our paper builds upon and extends the literature on textual analysis of companies' official corporate disclosures. Textual analysis of these disclosures faces several empirical challenges because traditional word lists from psychological dictionaries have limited power capturing the content of these disclosures

(Loughran and McDonald, 2011) and it is difficult to extract value-relevant information because of low readability (Loughran and McDonald, 2014). Such difficulties notwithstanding, corporate disclosures contain valuation-relevant information during IPOs (Jegadeesh and Wu, 2013; Loughran and McDonald, 2013), information about financial constraints (Bodnaruk et al., 2013; Hoberg and Maksimovic, 2014), and they dominate earnings surprises (Price et al., 2012).

Our paper is most closely related to Hoberg and Maksimovic (2014) in that we both use textual analysis to obtain measures of financial constraints. However, that paper uses measures of financial constraints to study investment and security issuance. We use a closely related measure to understand stock returns.

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, run robustness checks in Section 4, and conclude in Section 5.

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 (Feinerer et al., 2008; 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.

To this end, 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, 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. Of course it is possible that less frequent words have a greater impact, so we are careful to set the threshold high enough to remove only the *very* infrequent words, while keeping the rest. The purpose of this step is to remove words that appear so infrequently that their meaning cannot easily be picked up by our 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 in order to calculate the financial constraints score for the *whole* sample. 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 (2014) to find firms years that are financially constrained or unconstrained. In particular, Hoberg and Maksimovic (2014) 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. An important difference is that Hoberg and Maksimovic (2014) 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. This 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. We discuss the specific construction of the training samples next.

Using the lists from Hoberg and Maksimovic (2014), we combine keywords from the two "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 words from the "Delay Lists" are within twelve 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 (2014). 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.

Figure 1 shows histogram plots of the textual financial constraints measures corresponding to the various training samples. The resulting bimodal (double-peaked) distribution shows that all textual constraints measures are concentrated around zero and one, with only few observations in between. This should, by definition, *not* be interpreted as little variation, since both distributional peaks are at the opposite ends of the distribution, i.e. at zero and one. Instead, it simply means that the textual model in equation (1), whose left-hand side we plot, is most of the time relatively certain whether a given firm is financially constrained (FC index close to *one*) or unconstrained (FC index close to *zero*). In other words, the model seems to be doing a good job at capturing our *binary* variable of interest (constrained/unconstrained) by having an almost *binary* distribution.

Just having an almost binary distribution does of course not necessarily imply that the textual measures really capture financial constraints. Whether this is indeed the case is investigated in the following section where we slice various firm characteristics according to the quantiles of the textual constraints measures. However, because of the almost binary distribution, it is difficult to split up the measures into more than three quantiles, and as a consequence, we split up the textual measures into three only.

3. Results

Table 1 shows summary statistics relating financial constraint measures to firm characteristics. Its purpose is to show that our proposed measures are indeed consistent with characteristics of constrained firms, and, furthermore, to compare our measures to one of the most widely-used measures of financial constraints, the KZ index (Kaplan and Zingales, 1997). To this end, 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 has a hump-shaped pattern. 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 pattern, with larger firms being more constrained than small firms. There is agreement between the textual measures and the KZ index for dividends and Tobin's q. Consistent with all four measures, q is higher for the constrained firms and dividends are lower. Consistent with financially constrained firms being smaller growth firms, i.e. firms that have *good* investment projects but struggle to raise sufficient outside financing, constrained firms have lower debt levels according to our textual measures, consistent with the findings in Whited and Wu (2006). On the other hand, constrained firms according to the KZ index have higher debt levels, which is more consistent with firms being financially distressed instead of constrained.

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* long-only portfolios have positive alphas, independent of whether they belong to the portfolio that is long the low, middle, or high financial constraints quantile. It is important to note that we do *not* impose an adding-up constraint that the average alpha equals zero for the long-only portfolios. 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 long-only 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 long-only 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.

The all-positive alphas can be explained by the size effect, which is well-known to have reversed in our sample period, meaning that larger firms earn higher returns. Because it is easier to calculate the financial constraints index for *larger* firms that make it easier to parse 10-K textual content (e.g. because of better disclosure or corporate governance), and because we have to discard all firms where we cannot calculate the textual index, we end up with larger firms in our sample. Specifically, the firms in our sample are 39% larger than firms in the sample including *all* stocks from CRSP. If larger firms earn higher returns, it is therefore not surprising that our sample has a positive alpha to begin with.

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 long-only 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 2.0% per month while it is 1.3% for big unconstrained firms. This is an increase of 0.7 percentage points per month. In contrast, the average excess return of a small constrained firm is 0.8% while a small unconstrained firm has 0.8%. 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 0.7 percentage points 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. 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.

It should be noted that Table 5 contains long-short portfolios, and no long-only portfolio as in Table 3. As such, there is no adding-up constraint that the average alpha has to equal zero. Even if a *long-only* portfolio consisting of *all* stocks would have a zero alpha, there is no conceptual impediment to the *long-short* portfolios in Table 5 having all-positive alphas, e.g. for the Factiva and debt training samples.

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 on page 16, 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 (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 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.[1] 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 2 shows time series plots of the FC portfolio for all three training samples. When interpreting these plots, it is important to recognize that, consistent with our main research question, these are *return* plots showing how financial constraints are *prized* by the stock market. For example, a decrease in these plots may be due to a decrease in financial constraints, but it may also be due to other reasons such as changes in risk preferences. Specifically, if the plots decrease after the burst of the dot-com bubble, it should *not* necessarily be interpreted as evidence that financial constraints eased.

The plots show that all portfolios respond more strongly to financial constraints before the recession in 2001 than immediately afterwards. After the recession in 2001,

[1]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 FC portfolio from the equity training sample does not increase a lot, which explains its low excess return in Table 6. Consistent with capturing equity-related financing frictions, the only time when the equity FC measure captures returns is exactly during the growth and collapse of the dot-com bubble, when investors focused largely on equity financing. On the other hand, the FC portfolios 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 returns of the FC portfolio. A trading strategy using the textual financial constraints measure would thus have largely been unaffected by the turmoil during the financial crisis and in fact might even have profited from it, as can be seen from the increased slope of the portfolio from the debt training sample during that time.

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:

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

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. Robustness Checks

It is well known that firms with low investment, low stock issuance, or low debt issuance have higher returns.[2] 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 measures capture textual content about delays in investment and the issuance of equity and debt, as described in Section 2.2.3. 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.

To this end, we run Fama-MacBeth regressions of stock returns on our measures of financial constraints and controls (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 three quarters. Because we

[2]See for example Lyandres et al. (2008), Liu et al. (2009) and Hou et al. (2014) for investment, Ritter (1991), Ikenberry et al. (1995), Loughran and Ritter (1995), Daniel and Titman (2006), Fama and French (2008), Pontiff and Woodgate (2008), McLean et al. (2009), 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.

average forward the *dependent* variable, the resulting regression is still predictive and there is no look-ahead bias. If markets are efficient and information about financial constraints is quickly incorporated in 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 (Brown et al., 2009). If our results are only driven by investment and equity/debt issuance alone, and not by financial constraints, then the addition of capex, stk, and dbt should make the financial constraints coefficient insignificant. Table 11 shows that the *opposite* is the case. 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. Specifically, the inclusion of these additional variables does not make the financial constraint measures insignificant. In case of the Factiva and debt training samples, the constraints coefficient and test statistic even increase. We therefore infer that our textual financial constraints measures contain novel information that is not captured by investment, stock issuance, or bond issuance.

5. 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. Specifically, 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 without negative market impact. 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 of firm characteristics sorted on textual financial constraints measures and the KZ index. Details of the construction of the training samples are explained in Section 2.2.3.

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

	Unconstrained		Constrained
Cash Flow/Total Assets	0.018	0.016	-0.027
Total Assets	3269	2707	833
Debt/Total Assets	0.25	0.24	0.18
Dividends/Total Assets	0.003	0.003	0.001
Cash/Total Assets	0.13	0.14	0.31
Tobin's q	1.70	1.76	2.79
Text-Based FC Index	0.00	0.08	1.00
KZ Index	0.96	0.95	0.93

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

	Unconstrained		Constrained
Cash Flow/Total Assets	0.009	0.010	-0.012
Total Assets	2635	2480	1693
Debt/Total Assets	0.24	0.24	0.20
Dividends/Total Assets	0.002	0.003	0.002
Cash/Total Assets	0.15	0.15	0.28
Tobin's q	1.92	1.89	2.44
Text-Based FC Index	0.00	0.00	0.62
KZ Index	0.98	0.97	0.89

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

	Unconstrained		Constrained
Cash Flow/Total Assets	0.015	0.001	-0.008
Total Assets	3938	1898	973
Debt/Total Assets	0.27	0.22	0.18
Dividends/Total Assets	0.003	0.002	0.001
Cash/Total Assets	0.12	0.20	0.27
Tobin's q	1.71	2.11	2.43
Text-Based FC Index	0.00	0.57	1.00
KZ Index	1.02	0.95	0.87

Panel D: Sorted by KZ Index

	Unconstrained		Constrained
Cash Flow/Total Assets	0.005	0.014	-0.012
Total Assets	1216	3570	2023
Debt/Total Assets	0.03	0.18	0.45
Dividends/Total Assets	0.004	0.002	0.001
Cash/Total Assets	0.34	0.13	0.11
Tobin's q	1.77	1.89	2.59
Text-Based FC Index	0.62	0.46	0.48
KZ Index	-0.00	0.86	1.98

Table 2: Portfolio Characteristics

This table shows value-weighted portfolio characteristics when sorting on the textual financial constraints measure. Each panel shows the average values of the financial constraints measure, monthly excess returns (long-only), size (i.e. market equity), book-to-market, and the average number of stocks in the portfolio. 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	$r - r_f$	Size	B/M	# Stocks
FC.Low	0.001	1.41	76726	0.95	810
FC.Mid	0.047	1.35	69497	0.94	404
FC.High	0.752	1.85	49444	0.69	809

Panel B: Equity Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
FC.Low	0.001	1.52	74103	0.93	810
FC.Mid	0.001	1.52	74022	0.92	404
FC.High	0.412	1.45	58823	0.81	809

Panel C: Debt Training Sample

	FC	$r - r_f$	Size	B/M	# Stocks
FC.Low	0.006	1.28	77411	0.98	810
FC.Mid	0.448	1.62	55676	0.84	404
FC.High	0.963	1.98	54612	0.67	809

Table 3: Portfolios Sorted on Textual Financial Constraints Measure

This table shows regressions of value-weighted portfolios sorted on the textual financial constraints measure. The different panels correspond to the training samples, which are explained in Section 2.2.3. Columns one to three are long-only portfolios for different financial constraints quantiles. Column four shows a portfolio that is long the constrained and short the unconstrained quantile. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. 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
# Stocks	810	404	809	1619

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
# Stocks	810	404	809	1619

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
# Stocks	810	404	809	1619

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

This table shows monthly excess returns of value-weighted long-only 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	0.816	0.679	0.875
Medium	1.253	1.431	1.956
Big	1.416	1.362	1.875

Panel B: Equity Training Sample

	FC.Low	FC.Mid	FC.High
Small	0.966	0.817	0.694
Medium	1.526	1.346	1.846
Big	1.526	1.489	1.455

Panel C: Debt Training Sample

	FC.Low	FC.Mid	FC.High
Small	0.831	0.904	0.804
Medium	1.319	1.640	1.902
Big	1.282	1.651	2.007

Table 5: Double Sorts on Financial Constraints and Size

This table shows regressions of value-weighted portfolios that are double sorted on the textual financial constraints measure and size (i.e. market equity). Each column shows a portfolio that is long the constrained and short the unconstrained quantile, and different columns correspond to different size subgroups. The different panels correspond to the training samples, which are explained in Section 2.2.3. "# Stocks" shows the average number of stocks in the portfolio serving as the dependent variable. 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
# Stocks	661	326	631

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
# Stocks	655	329	639

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
# Stocks	638	321	661

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			

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)	

Table 11: Investment, New Stock Issues, and New Bond Issues Do Not Subsume the Financial Constraints Measure

This table shows 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) that are described in Section 2.2.3. The dependent variable is, for each firm-month, the average monthly excess return over the following three quarters. Independent variables are the financial constraints measure (FC, described in Section 2.2), the book-to-market ratio (log(b/e)), size (log(me)), past 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)). Because of poorer data quality from SEC's EDGAR database, we discard observations on or before December 1997. Independent variables are trimmed at the 1% and 99% levels. Slope coefficients are multiplied by 100 for better readability. Numbers in brackets show t-statistics. Stars indicate significance at 10%, 5%, and 1%.

	Factiva TS	Factiva TS	Equity TS	Equity TS	Debt TS	Debt TS
FC	0.22**	0.22**	0.32***	0.27***	0.14*	0.19***
	(2.02)	(2.18)	(3.10)	(2.93)	(1.91)	(2.69)
log(b/m)	0.02	−0.03	0.00	−0.05	0.00	−0.04
	(0.32)	(−0.56)	(0.02)	(−0.86)	(0.07)	(−0.67)
log(me)	−0.18***	−0.18***	−0.19***	−0.19***	−0.19***	−0.18***
	(−5.78)	(−6.02)	(−5.47)	(−5.70)	(−5.43)	(−5.58)
$r_{1,0}$	−0.44*	−0.52**	−0.44*	−0.50**	−0.43*	−0.50**
	(−1.85)	(−2.26)	(−1.77)	(−2.08)	(−1.72)	(−2.07)
$r_{12,2}$	−0.23*	−0.18	−0.22*	−0.16	−0.22*	−0.16
	(−1.84)	(−1.45)	(−1.65)	(−1.26)	(−1.65)	(−1.23)
capex		−7.32***		−7.58***		−8.14***
		(−5.03)		(−4.95)		(−4.75)
stk		−1.91**		−1.87**		−1.67*
		(−2.12)		(−1.96)		(−1.74)
dbt		−4.09***		−3.93***		−4.07***
		(−8.03)		(−7.72)		(−7.76)
Num. obs.	256444	192680	256428	192537	256466	192443

Figure 1: Histograms of Textual Financial Constraints Measures

This figure shows histogram plots of textual financial constraints measures corresponding to various training samples. The training samples are explained in detail in Section 2.2.3. Values closer to one (zero) mean that the firm is more (less) financially constrained.

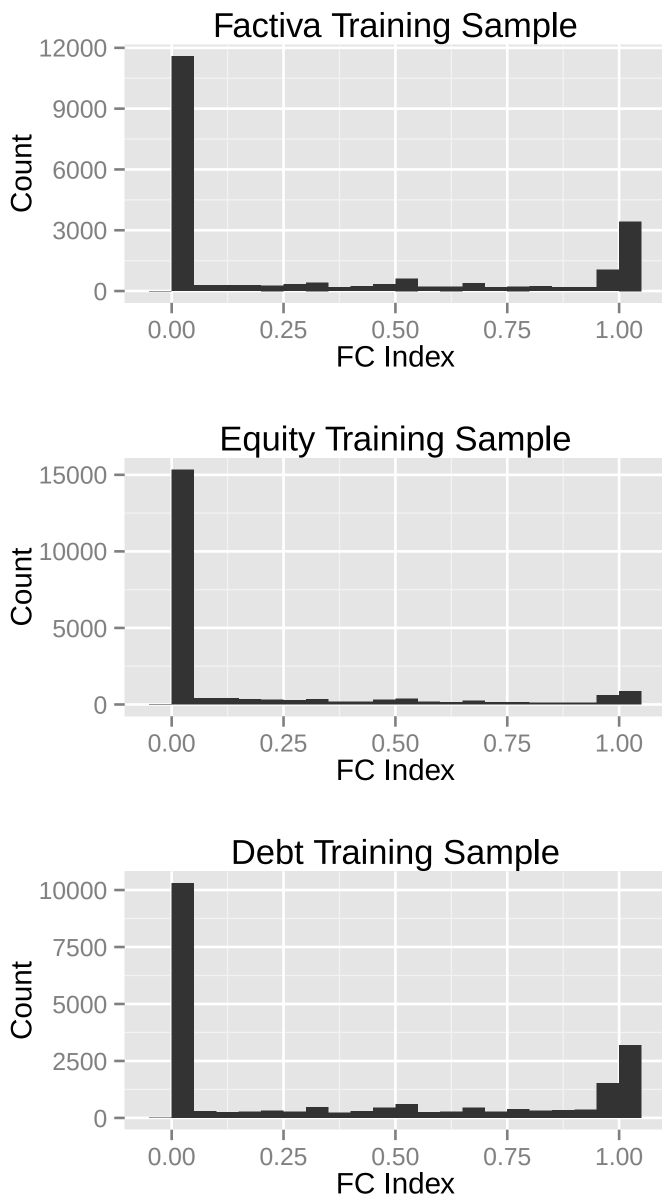
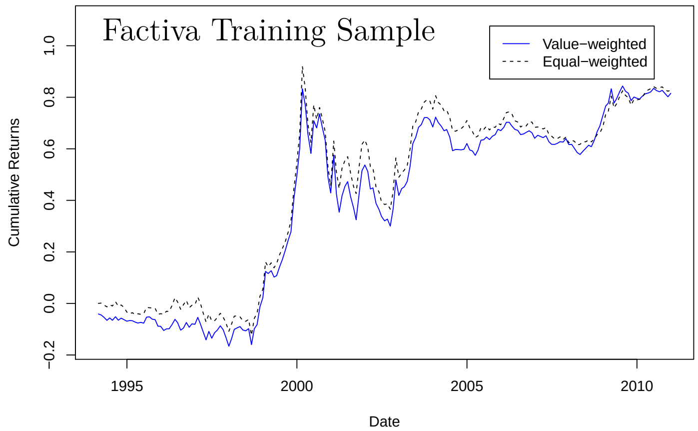
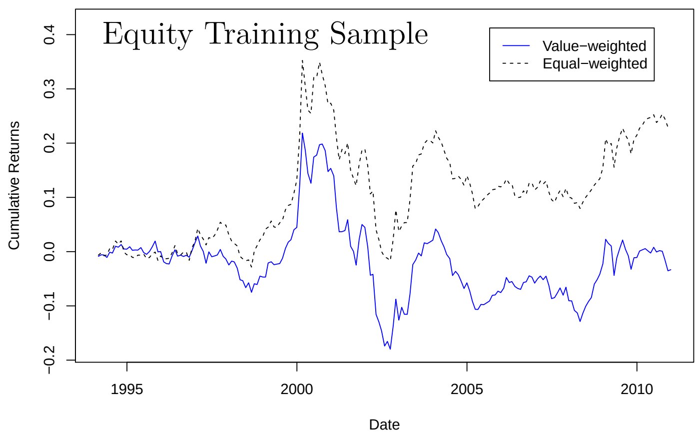
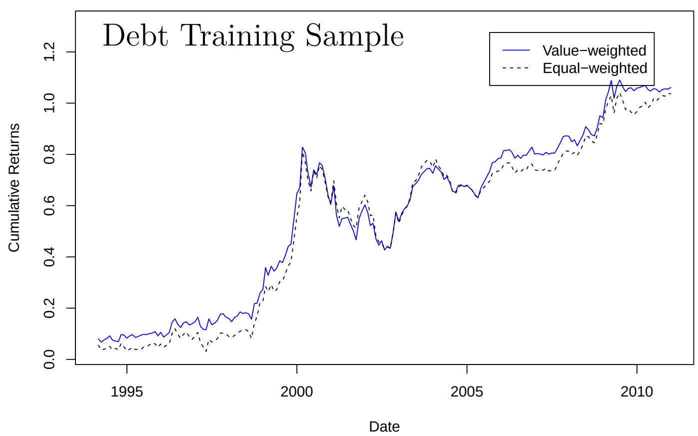


Figure 2: Monthly Cross-Sorted Financial Constraints Factor
Different figures correspond to different training samples. Section 2.2.3 explains the training samples in detail.







References

Baker, Malcolm, and Jeffrey Wurgler, 2000, The equity share in new issues and aggregate stock returns, *The Journal of Finance* 55, 2219–2257.

Bodnaruk, Andriy, Tim Loughran, and Bill McDonald, 2013, Using 10-k text to gauge financial constraints, SSRN Scholarly Paper ID 2331544, Social Science Research Network, Rochester, NY.

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen, 2009, Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom, *The Journal of Finance* 64, 151–185.

Campbell, John L., Dan S. Dhaliwal, and William C. Schwartz, 2012, Financing constraints and the cost of capital: Evidence from the funding of corporate pension plans, *Review of Financial Studies* 25, 868–912.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899–2939.

Chava, Sudheer, and Amiyatosh Purnanandam, 2010, Is default risk negatively related to stock returns?, *Review of Financial Studies* 23, 2523–2559.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *The Journal of Finance* 61, 1605–1643.

DeAngelo, Harry, Linda DeAngelo, and René M. Stulz, 2010, Seasoned equity offerings, market timing, and the corporate lifecycle, *Journal of Financial Economics* 95, 275–295.

Denis, David J., and Valeriy Sibilkov, 2010, Financial constraints, investment, and the value of cash holdings, *Review of Financial Studies* 23, 247–269.

Desai, Mihir A., C. Fritz Foley, and Kristin J. Forbes, 2008, Financial constraints and growth: Multinational and local firm responses to currency depreciations, *Review of Financial Studies* 21, 2857–2888.

Erel, Isil, Yeejin Jang, and Michael S. Weisbach, 2014, Do acquisitions relieve target firms' financial constraints?, *The Journal of Finance* .

Erickson, Timothy, and Toni M. Whited, 2000, Measurement error and the relationship between investment and q, *Journal of Political Economy* 108, 1027–1057.

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

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *The Journal of Finance* 63, 1653–1678.

Farre-Mensa, Joan, and Alexander Ljungqvist, 2014, Do measures of financial constraints measure financial constraints?, SSRN Scholarly Paper ID 2338575, Social Science Research Network, Rochester, NY.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen, 1988, Financing constraints and corporate investment, *Brookings Papers on Economic Activity* 1988, 141–206.

Feinerer, Ingo, Kurt Hornik, and David Meyer, 2008, Text mining infrastructure in r, *Journal of Statistical Software* 25, 1–54.

Garlappi, Lorenzo, and Hong Yan, 2011, Financial distress and the cross-section of equity returns, *The Journal of Finance* 66, 789–822.

Gatchev, Vladimir A., Todd Pulvino, and Vefa Tarhan, 2010, The interdependent and intertemporal nature of financial decisions: An application to cash flow sensitivities, *The Journal of Finance* 65, 725–763.

Gomes, João F., Amir Yaron, and Lu Zhang, 2006, Asset pricing implications of firms' financing constraints, *Review of Financial Studies* 19, 1321–1356.

Gorodnichenko, Yuriy, and Monika Schnitzer, 2013, Financial constraints and innovation: Why poor countries don't catch up, *Journal of the European Economic Association* 11, 1115–1152.

Greenwood, Robin, and Samuel G. Hanson, 2012, Share issuance and factor timing, *The Journal of Finance* 67, 761–798.

Griffin, John M., and Michael L. Lemmon, 2002, Book–to–market equity, distress risk, and stock returns, *The Journal of Finance* 57, 2317–2336.

Hadlock, Charles J., and Joshua R. Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ index, *Review of Financial Studies* 23, 1909–1940.

Hoberg, Gerard, and Vojislav Maksimovic, 2014, Redefining financial constraints: A text-based analysis, SSRN Scholarly Paper ID 1923467, Social Science Research Network, Rochester, NY.

Hong, Harrison G., Jeffrey D. Kubik, and Jose A. Scheinkman, 2012, Financial constraints on corporate goodness, SSRN Scholarly Paper ID 1734164, Social Science Research Network, Rochester, NY.

Hou, Kewei, Chen Xue, and Lu Zhang, 2014, Digesting anomalies: An investment approach, *Review of Financial Studies* .

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Jegadeesh, Narasimhan, and Di Wu, 2013, Word power: A new approach for content analysis, *Journal of Financial Economics* 110, 712–729.

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

Karaivanov, Alexander, and Robert M. Townsend, 2014, Dynamic financial constraints: Distinguishing mechanism design from exogenously incomplete regimes, *Econometrica* 82, 887–959.

Kerr, William R., and Ramana Nanda, 2009, Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship, *Journal of Financial Economics* 94, 124–149.

Korajczyk, Robert A, and Amnon Levy, 2003, Capital structure choice: macroeconomic conditions and financial constraints, *Journal of Financial Economics* 68, 75–109.

Lamont, O., C. Polk, and J. Saá-Requejo, 2001, Financial constraints and stock returns, *Review of Financial Studies* 14, 529–554.

Law, Kelvin, and Lillian F. Mills, 2014, Taxes and financial constraints: Evidence from linguistic cues, SSRN Scholarly Paper ID 2459912, Social Science Research Network, Rochester, NY.

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

Li, Dongmei, 2011, Financial constraints, r&d investment, and stock returns, *Review of Financial Studies* 24, 2974–3007.

Li, Feng, 2010, The information content of forward-looking statements in corporate filings—a naïve bayesian machine learning approach, *Journal of Accounting Research* 48, 1049–1102.

Liao, Rose C., 2014, What drives corporate minority acquisitions around the world? the case for financial constraints, *Journal of Corporate Finance* 26, 78–95.

Lin, Chen, Yue Ma, and Yuhai Xuan, 2011, Ownership structure and financial constraints: Evidence from a structural estimation, *Journal of Financial Economics* 102, 416–431.

Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang, 2009, Investment-based expected stock returns, *Journal of Political Economy* 117, 1105–1139.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? textual analysis, dictionaries, and 10-ks, *The Journal of Finance* 66, 35–65.

Loughran, Tim, and Bill McDonald, 2013, IPO first-day returns, offer price revisions, volatility, and form s-1 language, *Journal of Financial Economics* 109, 307–326.

Loughran, Tim, and Bill McDonald, 2014, Measuring readability in financial disclosures, *The Journal of Finance* n/a–n/a.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *The Journal of Finance* 50, 23–51.

Love, Inessa, 2003, Financial development and financing constraints: International evidence from the structural investment model, *Review of Financial Studies* 16, 765–791.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2008, The new issues puzzle: Testing the investment-based explanation, *Review of Financial Studies* 21, 2825–2855.

Marquez, Robert, and M. Deniz Yavuz, 2013, Specialization, productivity, and financing constraints, *Review of Financial Studies* 26, 2961–2984.

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

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

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *The Journal of Finance* 63, 921–945.

Price, S. McKay, James S. Doran, David R. Peterson, and Barbara A. Bliss, 2012, Earnings conference calls and stock returns: The incremental informativeness of textual tone, *Journal of Banking & Finance* 36, 992–1011.

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

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

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *The Journal of Finance* 59, 831–868.

Whited, Toni M., 1992, Debt, liquidity constraints, and corporate investment: Evidence from panel data, *The Journal of Finance* 47, 1425–1460.

Whited, Toni M., and Guojun Wu, 2006, Financial constraints risk, *Review of Financial Studies* 19, 531–559.