Inferring Financial Flexibility: Do Actions Speak Louder than Words?

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Abstract

Firms invest intermittently, and a significant part of capital formation occurs during "investment spikes". Industry-level "spike waves", during which growth opportunities in an entire industry surge and a large fraction of firms in the industry generate investment spikes, also occur quite regularly. We define *financial flexibility* as the capacity to accommodate large shortfalls between a firm's investment needs and cash flows, as is the case when it has an investment spike. We develop an index for financial flexibility (FF) based on which firm-specific variables differentiate firms that generate investment spikes and those that do not during industry spike waves. In out-of-sample tests, our FF Index outperforms five popular financial constrained (FC) indices in predicting investment spikes, as well as regular investment and R&D investment. We use ChatGPT to evaluate the financial constraint status of a large sample of firms based on management statements in 10-Ks and generate new financial constraint measures; however, FF also outperforms these measures. The superior performance of our FF measure suggests that firms' actions are more revealing of their financial status and its determinants than what is disclosed in annual reports. We validate our empirical approach using data simulated in a model adapted from Gao, Whited, and Zhang (2021). As an application, we show that the FF Index predicts the capacity of firms to sustain investment during economic downturns, and again outperforms the FC Indices.

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1 Introduction

In his 2022 Presidential Address to the American Finance Association, John Graham (Graham, 2022) notes that a recent survey of chief financial officers indicates that preserving *financial flexibility* is the most popular factor affecting capital structure decisions—even more so than reported in a well-known survey conducted two decades earlier (Graham and Harvey, 2001). The survey also shows that current profits (which are distinct from expected future profits), cash holdings, and access to borrowing are, respectively, the most, the third-most, and the fifth-most important factor (out of thirteen) cited in explaining why actual investment might differ from planned investment, further highlighting the importance of liquidity considerations for corporate investment.[1]

In this paper, following Denis (2011), we define financial flexibility as the capacity to accommodate large gaps between investment needs and cash flows. One of our main objectives in this paper is to construct an index of financial flexibility, which we label the FF Index. We examine how well the FF Index performs in comparison to some of the available indices for financial constraints (FC) in predicting investment. As discussed below, the FF Index is based on firms' actions, and not what managers disclose in the 10-K filings, which is the basis for several of the FC indices. Apart from running "horse races" between FF and the available indices, we additionally use ChatGPT to read the "Liquidity and Capital Resources" section of the 10-Ks for a large sample of firms. We classify the financial constraint status of firms in the spirit of Kaplan and Zingales (1997) and run horse races between FF and various ChatGPT-based measures. [2]

To create our FF index, we examine the cross-sectional relationship between firm-specific variables, which include balance-sheet variables as well as variables likely to proxy for financ-

[1] Notably, most of the data in the 2022 survey was collected in 2019, and the COVID-19 crisis played a relatively minor role in the survey.

[2] Arguably, our FF Index is another FC Index. However, we label it as a financial flexibility Index because some of the other FC indices focus on only one aspect of financial flexibility, namely, the frictions firms face in raising external financing, e.g., due to information asymmetry or other deadweight costs of issuance, and do not explicitly consider internal liquidity. For example, indicators such as whether a firm ever had a bond rating or a commercial paper rating, or whether it is in the top or bottom three deciles of firm size (Almeida, Campello, and Weisbach, 2004) are more closely related to external financing frictions. The Whited-Wu Index aims at estimating the shadow cost of external finance. Recent text-based indices such as the Hoberg and Maksimovic (2015) or the Bodnaruk, Loughran, and McDonald (2015) Index also reflect the extent of tightness firms face in raising external financing. Liquidity considerations play an important role in the Kaplan-Zingales Index. These issues are discussed in more detail in section 3.

ing frictions,[3] and firms' capacity to accommodate larger investments, termed *investment spikes*. The literature has documented that firms invest intermittently, and their investment behavior is characterized by investment spikes that occur infrequently (in our sample, on average once every six years) and account for a significant portion of their capital accumulation (Elsas, Flannery, and Garfinkel, 2014; Im, Mayer, and Sussman, 2020; Mayer and Sussman, 2004; Whited, 2006).[4] We focus on years of industry-spike "waves", when investment opportunities for most firms in a given industry are particularly good, and the firms are likely to experience cash-flow shortfalls when financing these large investments.[5]

To identify investment spikes, we follow the method used in Im et al. (2020), who classify a firm-year as a spike year if total investment in that year is significantly higher than "base-level" investment, defined as average investment during the two preceding years and the two subsequent years. We then define an industry-year as an *industry-spike* year if: (a) the proportion of firms that generate investment spikes in the industry in that year exceeds two times the average of the previous three years, and (b) the fraction of firms in the industry that generate investment spikes is at least 15 percent. Our results are robust to alternative criteria for identifying spikes.

For our regressions to generate the Index, we estimate logit models with year and industry fixed effects, where the outcome variable is an indicator variable that takes the value of one if a firm has an investment spike and zero otherwise. The independent variables include variables that potentially reflect corporate liquidity and financing frictions, as well as variables that proxy for investment opportunities.

These "in-sample" regressions are based only on industry-spike years. We focus on these years for several reasons. First, a major concern is that we may not be able to distinguish between firms that do not generate investment spikes because they do not have financial flexibility and those that simply do not have good enough investment opportunities (even when we control for the market-to-book ratio, cash flow, sales growth, etc.). In an industry-spike year, it is more likely that firms that do not invest aggressively lack financial flexibility rather

[3] Since one of our objectives is to compare FF and the FC indices, we do not use the latter as proxies for financing constraints when we construct FF.

[4] Doms and Dunne (1998), for example, show that between 25 and 40 percent of a firm's average plant-level investment occurs in a single year.

[5] As discussed below, to enhance the external validity of our Index, we examine whether the Index also captures firms' capacity to sustain investment activity when they experience cash-flow shortfalls in economic downturns.

than lacking investment opportunities.[6] Second, the predictive power of our regressions is likely to improve if there is reasonable variation within the same industry and year for the dependent variable of interest (i.e., whether there is an investment spike or not). Third, for external validation of the FF Index, we check the Index's out-of-sample performance. One of our out-of-sample tests involves observing how well our Index predicts firm-level investment spikes in non-industry-spike years.

Our initial regression (with a spike dummy as the dependent variable) includes, as explanatory variables, average cash and the average leverage ratio in the recent past, as well as differences between current levels (with a one-year lag) and past averages, which we call *change from trend*, or *change* for short. Firm size and the payout ratio (in the form of dividends as well as stock repurchases) in the previous period are two other components of the FF Index. Large firms are more transparent, enjoy more analyst coverage and investor attention, and are therefore less subject to information asymmetry. Accordingly, firm size serves as a proxy for financing frictions. Firms' willingness to pay out cash in the form of dividends or stock repurchases is also likely to reflect anticipated financing frictions: if these frictions are large, firms are less likely to pay out cash. We also include variables (with one year lag) that capture investment opportunities (market-to-book and sales growth) and cash flow (which could capture liquidity and is also a proxy for investment opportunities). The regression results show that cash holdings and the change in cash holdings have significant and positive coefficients, while the average leverage ratio and its change have significant and negative coefficients. The payout ratio has a positive and highly significant coefficient. Firm size has a significant and positive coefficient for the main sample, although this significance is present only for the latter half of our sample period.[7] Almost all investment opportunity variables have the expected positive signs, but cash flow is insignificant.

The above-reported results are in line with the expectation that both balance sheet financial variables and those that proxy for financing frictions, as well as variables capturing investment opportunities, play a role in determining the propensity of firms to engage in major investments during industry-spike years. Inasmuch as one of our main objectives is to capture financial flexibility, following Lamont, Polk, and Saaá-Requejo (2001), our FF Index

[6] We verify that, for the typical firm in a given industry, industry median market-to-book and firm-level market-to-book increase significantly in the year before the industry-spike cluster.

[7] Except for size, all other coefficient estimates are stable across the first and second halves of our sample period.

is a linear projection of the balance sheet variables and proxies for financing frictions based on the coefficient estimates derived from the logit models.[8] For uniformity of comparison with indices of financial constraints, we rank firms every year based on their projected value and divide the ranking by the number of firms to obtain a scaled ranking on the $(0, 1]$ interval.

We now discuss our main findings. In our first set of out-of-sample tests, we examine the explanatory power of the FF index with regard to predicting firm-level investment spikes in *non-industry-spike years* based on logit models with year and industry fixed effects.[9] The coefficient of the FF Index is highly significant in these regressions, in which we also include the investment opportunity (IO) variables, namely, cash flows, sales growth, and the market-to-book ratio, with a one-period lag. Then we examine whether the FF Index can predict other types of investment in non-industry-spike years. Specifically, we examine investment (which includes both capital expenditure and cash acquisitions), capital expenditure, cash acquisitions (all scaled by the lagged book value of assets), investment growth, and R&D investment (R&D spending scaled by lagged sales). The FF Index has a significant positive coefficient in all these regressions, where, apart from the IO variables, we also include firm and year fixed effects.

In our second set of out-of-sample tests, starting in 1985 and then at five-year intervals, we use all past available industry-spike years to construct the FF Index and predict the probability that an investment spike occurs in any given remaining *industry-spike years*. The advantage of focusing on industry-spike years for the out-of-sample tests is that, to the extent that industry-spike years correspond to shocks to an entire industry, failure to control investment opportunities properly is less likely to be crucial. The empirical results show that the FF Index has a positive and robustly significant coefficient, the magnitude of which is very similar across all periods. In these out-of-sample tests, we also control for the IO variables.

Our estimates of the impact of financial flexibility on the likelihood that major investments occur are economically important and robust. For example, compared with a non-spike year, the mean ranked FF Index in the year before a firm-level spike occurs has an 8.4 percent higher ranking, and the coefficient estimate of FF translates to about 0.9 percentage

[8]See Appendix A.2 for the FF Index details.

[9]We later document that, even for non-industry-spike years, conditional on having at least one spike, 10.4 percent of firms on average generate an investment spike. Even firms without investment spikes experience significant increases in market-to-book ratios as long as some other firms in the industry generate investment spikes, suggesting the presence of industry-wide investment opportunities.

point higher likelihood that an investment spike occurs. Given that the average likelihood of a spike is around 13 percent, this is an economically meaningful magnitude. Our results are also robust to alternative industry classifications, alternative firm-level and industry-level investment spike definitions, and alternative investment measures.

To demonstrate a potential mechanism that drives the variation in financial flexibility and the validity of our empirical methodology, we develop a model, adapted from Gao et al. (2021), in which firms are faced with the same external financing costs but are subject to both idiosyncratic and common productivity shocks. The shocks have some persistence and thus convey information about future investment opportunities. Firms are infinitely-lived and managers maximize firm value by choosing investment, cash holding, and debt and equity financing. In this model, because financing costs are exactly the same, it is the heterogeneity in internal liquidity generated by the heterogeneity of past idiosyncratic shocks that generates heterogeneity in financial flexibility. When a large common shock arrives, the heterogeneity in liquidity positions implies that while many firms are able to generate an investment spike, thereby creating a spike-cluster similar to an industry spike, those with insufficient financial flexibility are not. We calibrate this model, using model-generated data to develop an FF Index based on the spike-cluster periods. We show that this Index predicts investment spikes for the remaining periods.

While the FF Index relates firms' liquidity positions and potential financing frictions to their actions, the commonly used FC indices are predominantly based on reading the text in firms' 10-Ks. The Kaplan-Zingles (KZ) Index (Kaplan and Zingales, 1997; Lamont et al., 2001), the Hadlock-Pierce (HP) Index (Hadlock and Pierce, 2010), the Hoberg-Maksimovic (HM) Index (Hoberg and Maksimovic, 2015), and the Bodnaruk, Loughran and McDonald (BLM) Index (Bodnaruk et al., 2015) are examples of such indices. The only exception is the Whited-Wu (WW) Index (Whited and Wu, 2006), which is based on estimating a structural model. To examine whether firms' actions provide a clearer picture of their financial flexibility to what managers disclose in 10-Ks, we next run "horse races" between the FF Index and commonly used indices for financial constraints. To do so, we include the ranked FC indices one at a time alongside the ranked FF Index to predict investment spikes, as well as other types of investment, in our out-of-sample tests for non-industry-spike years.

The results are striking: while the coefficient of the FF Index remains highly significant with a positive coefficient in all regressions, only the KZ Index has a significant coefficient with the "right" sign. However, the magnitude of coefficient and z-statistic for the FF

Index are three times those for the KZ Index.[10] When we change the dependent variable to investment, capital expenditure, or acquisitions (all scaled by lagged assets), investment growth, and R&D over lagged sales, except for the KZ Index, the coefficients of FC indices are seldom significant with the correct sign. The KZ Index, on the other hand, is always significant and of the right sign, whether included with or without the FF Index. However, when included together, the FF Index is associated with higher t-statistics (except when the dependent variable is acquisitions, where the t-statistics are similar).

The fact that the KZ Index performs the best among all the remaining FC indices is noteworthy. Not surprisingly, we find that it has the highest correlation with the FF Index among all the FC Indices: its correlation with FF is -0.49, while those of HP and WW with FF are about -0.2, and those of BLM and HM with FF are close to zero.[11] The high correlation between FF and FC is perhaps not surprising for two reasons. First, the firm-specific variables used to construct these two indices are quite similar. Both use cash holdings, debt, and payout (although for KZ, the payout is limited to dividends). In addition, while KZ uses cash flow and market-to-book, FF uses the change in cash holdings and leverage relative to recent average levels, and the market-to-book does not directly enter among its determinants. Second, Kaplan and Zingales's reading of the relevant section of the 10-Ks seeks to assess whether a firm has "the ability to access internal and external funds to increase investment.". The firm-specific determinants of the answer to such a question, in principle, are likely to be similar to those that underlie the FF Index, which seeks to explain the capacity to undertake large investments. The key difference is that the KZ Index, like the most commonly used indices, is reliant on what managers disclose, not what their actions reveal. Besides, at least for the KZ and HP indices, the classifications are subjective. In addition, both KZ and HP were constructed for relatively short time periods (1970-1984 for the KZ sample and 1995-2004 for the HP sample) and on small samples.

It could be argued that because of these limitations, the "actions versus words" horse race is unfairly loaded against these older text-based measures, which are closer in spirit to the FF Index. Since it has thus far not proved feasible to update or replicate KZ's methodology for a large sample of firms [12], we asked ChatGPT to read the "Liquidity and Capital Resources"

[10] When the FF Index is not included, only the coefficients of the KZ and WW Indices are significant and of the right sign. Those for the other indices are insignificant.

[11] Higher values of FC (FF) represent more constrained (more flexible) firm-years.

[12] Hadlock and Pierce (2010) extend the Kaplan-Zingales sample of 49 firms to a random sample of 356 firms.

sections of the 10-Ks of a large sample of firms for the period 1993-2019 and assign a firm's financial constraint status in a particular year to one of the five categories outlined by Kaplan and Zingales (1997).[13] We directly use these classifications, and also create additional indices in the spirit of Lamont et al. (2001) based on these classifications to run horse races between FF and these indices. The latter include (i) an Index that recreates the KZ Index using the same explanatory variables (KZ_{GPT}), (ii) one that similarly recreates the HP Index (HP_{GPT}), and (iii) one that uses the variables in the construction of the FF Index on the ChatGPT classifications ($FC_{FF,GPT}$). The ChatGPT classifications always have the correct sign and are significant (with one exception) individually or alongside the FF Index; however, the FF Index always has a much higher t-static and explanatory power. While the KZ_{GPT} and $FC_{FF,GPT}$ typically have significant coefficients of the right sign when included individually, the latter consistently has coefficients that are significant but of the wrong sign when included alongside the FF index. The HP_{GPT} Index performs the worst, and its coefficient consistently has the wrong sign (typically significant)—whether included together with or without FF—in most regressions (logit as well as OLS).

These results suggest that the ChatGPT classifications contain some incremental information regarding the predictability of investment beyond what is captured by FF. In particular, it could reflect off-balance sheet information, such as the availability of credit lines, that the FF misses out on. However, as revealed by the weaker results corresponding to KZ_{GPT} and especially HP_{GPT}, the managers' disclosure may not correctly reflect the firms' status relative to their future actions. Thus, prediction models for financial constraints that transform the Kaplan-Zingales classifications to indices so that they can be applied widely may result in information loss and lower predictive power.

Finally, we provide an example of the applicability of the FF Index in empirical research, which also serves as another test of its external validity. Specifically, we examine whether higher values of the Index predict smaller reductions in investment during economic downturns when firms are likely to face cash shortfalls and find it difficult to raise exter-

[13] Since all the current large language models have length limitations, it is not possible to process the entire MD&A section of the 10-K in a single query at the date when we write this paper. Separating the MD&A section into multiple parts could introduce noise, making the responses hard to interpret. We follow the practice in Hoberg and Maksimovic (2015) and limit attention to the most relevant subsection of the MD&A section. This cost-efficient approach could avoid introducing too much irrelevant information to confuse the ChatGPT (The underlying model, Transformer, is also attention-based). We compare the responses from the LIQ&CAP section and the MD&A section for a random sample of firms' reports and find that the responses are largely consistent. Details are provided in Appendix B and Table A.I

nal financing.[14] We examine three NBER recessions for the 1980–2015 period, occurring in 1982, 1990, and 2009, respectively, and the "tech" recession of 2001, which affected mostly technology firms (Loughran and Ritter, 2004). With the change in investment from two years before the recession to the end of the recession (scaled by lagged total assets) as the dependent variable, we find that the two-year lagged FF Index has highly significant and positive coefficients for all three NBER recessions as well as a marginally significant positive coefficient for the tech recession. The result for the KZ Index is similar, except that it has a smaller coefficient and lower explanatory power for all the NBER recessions. None of the other FC indices is consistently significant or has the correct signs in all the regressions. The ChatGPT classifications, only available for the burst of the tech bubble and the 2009 recession, also successfully predict the ability of firms to sustain investment but with lower R-squares.

2 Literature Review

2.1 Financial Flexibility

The importance of "financial flexibility" as a desirable firm-level attribute has been recognized for quite some time. For example, a well-known survey of chief financial officers by Graham and Harvey (2001) reports that CFOs consider financial flexibility to be the most important determinant of their capital-structure decisions. A special issue of the *Journal of Corporate Finance* on financial flexibility edited by David Denis (see also Denis (2011) for an overview) explores many aspects of financial flexibility. Most of the emphasis in the issue is placed on corporate cash policy or the role of cash holdings in facilitating other corporate activities. Maintaining or creating debt capacity, as well as payout policies that favor share repurchases over dividend payments, are also recognized as elements of financial flexibility. There is also recognition that flexibility involves associated costs, e.g., lower tax savings from reducing and maintaining low debt or agency costs associated with holding too much cash (Dittmar and Mahrt-Smith, 2007; Harford, 1999; Harford, Mansi, and Maxwell, 2008).

[14] Several papers examine the role of financial flexibility—e.g., more cash holdings and lower leverage in the cross-section—in sustaining investment during economic downturns, e.g., Campello, Graham, and Harvey (2010), Duchin, Ozbas, and Sensoy (2010), Denis and Sibilkov (2010), Ang and Smedema (2011), Kahle and Stulz (2013), Giroud and Mueller (2017), Acharya and Steffen (2020), Albuquerque, Koskinen, Yang, and Zhang (2020), De Vito and Gómez (2020), Ding, Levine, Lin, and Xie (2020), Fahlenbrach, Rageth, and Stulz (2021), Ramelli and Wagner (2020), Barry, Campello, Graham, and Ma (2022).

The idea that financial flexibility enables firms to better sustain investment or employment or experience better stock returns has also been well documented. Most of this literature has focused on the role of financial flexibility during economic downturns.[15] Research on financial flexibility surged after the Global Financial Crisis (Ang and Smedema, 2011; Campello et al., 2010; Denis and Sibilkov, 2010; Duchin et al., 2010; Giroud and Mueller, 2017; Kahle and Stulz, 2013) and has surged again following the COVID-19 pandemic (Albuquerque et al., 2020; Barry et al., 2022; De Vito and Gómez, 2020; Ding et al., 2020; Fahlenbrach et al., 2021; Ramelli and Wagner, 2020).

Despite considerable interest in the topic of financial flexibility, there is no consensus regarding exactly how it should be measured, especially given that the literature recognizes multiple dimensions of financial flexibility. In this paper, we develop such a measure, and demonstrate that it is much more influential than the available FC measures in explaining corporate investment.

2.2 Investment spikes

The literature on interactions between investment spikes and financing considerations is relatively sparse. Mayer and Sussman (2004) were among the first to study how investment spikes are financed. They find (consistent with Pecking Order theory) that spikes are financed mainly with debt; however, they also find that, inconsistent with Pecking Order, internal funds play a limited role. Debt levels revert back to lower levels following spikes, which resembles what tradeoff theory would imply "in the long run". Im et al. (2020) introduce some modifications to the filters for identifying investment spikes and study the heterogeneity of spike financing, especially based on firm size. Elsas et al. (2014) also study investment-spike financing (where "investment" includes built investments as well as acquisitions that are unreported in cash flow statements) and find evidence consistent with tradeoff theory and market-timing theory. Whited (2006) is another early paper that studies investment spikes, in which the author develops a model with fixed capital adjustment costs and shows that costly external financing reduces the hazard associated with lumpy investments. Hazard

[15] An exception is Bargeron, Denis, and Lehn (2018), who examine the financing of investment spikes during World War I by U.S. firms. The authors find that, despite a tax advantage associated with equity provided by the contemporaneous imposition of an excess profits tax, the investment spikes were financed primarily by firms with sufficient debt capacity, and debt levels were brought down fairly rapidly thereafter. Denis and McKeon (2012) also provides evidence of the role of debt capacity as a source of financial flexibility and the use of transitory debt to finance investments.

model estimation finds support for this prediction. DeAngelo, DeAngelo, and Whited (2011) develop a dynamic model in which capital adjustment costs result in lumpy investments, and the lumpiness creates a need to preserve debt capacity (or financial flexibility).

3 Terminology

While the concepts of *financial flexibility* and *financial constraints* are closely related, the difference is not simply a matter of semantics. The literature often tends to associate the concept of financial constraints with *financing frictions* or the cost of raising external finance. For example, FC indices such as (the absence of) credit ratings or commercial paper ratings directly speak to such costs. Even firm size—to the extent that it is likely to be associated with information asymmetry—could be thought of as a proxy for the cost of external finance. Recent text-based indices such as the Hoberg and Maksimovic (2015) (HM) Index or the Bodnaruk et al. (2015) (BLM) Index analyze firms' 10-Ks to assess the extent of financing frictions faced by firms.

In contrast, discussions of financial flexibility invariably focus on items that capture liquidity, such as cash holdings, cash flows, and leverage, without trying to capture the extent of financing frictions. For example, in the context of the COVID-19 shock, Fahlenbrach et al. (2021) define financial flexibility as "the ease with which a firm can fund a cash flow shortfall and, therefore, ... be less affected by the shock. We consider firms to be more financially flexible if they have more cash, less short-term debt, and less long-term debt at the end of 2019."

There are also several examples of indices that are termed FC but emphasize the role of balance-sheet variables such as cash flows, cash holdings, or debt, without any explicit reference to external financing frictions. The KZ Index is an example of such a measure. The HP Index extends the methodology of Kaplan and Zingales (Kaplan and Zingales (1997)) to a somewhat larger sample of firms; however, this index associates financial constraints with a different set of variables, namely, firm size and firm age, which likely proxy for information asymmetry and the cost of external finance, and thus is appropriately labeled as an FC Index. In contrast, while the WW index ostensibly intends to capture the shadow cost of equity financing, it is built around firm-specific variables that are typically encountered in discussions of financial flexibility or liquidity.

Of course, the dichotomy between financing frictions and liquidity is not clear-cut for two important reasons. First, firms subject to financing frictions are likely to manage their liquidity positions and enhance financial flexibility. Second, the liquidity position of a firm can also affect the cost of external financing. e.g., by reducing the likelihood of default and the associated deadweight costs associated with default when debt is issued. We therefore prefer being agnostic about the distinction between financing frictions and liquidity, and argue that the concept of financial flexibility is one that incorporates both these elements in determining how firms accommodate unexpected cash flow shortfalls relative to investment needs.

In this paper, we follow Denis's (Denis, 2011) definition of financial flexibility, that is, it is the capacity to accommodate *large* shortfalls between investment needs and cash flows. We argue that one situation in which such shortfalls are especially likely occurs when an entire industry has exceptionally good investment opportunities, as evidenced by a large fraction of firms generating investment spikes. Heterogeneity in financial flexibility is more likely to differentiate firms that can accommodate spikes and those that cannot in such an environment—more so than heterogeneity in investment opportunities. Such financial flexibility (or lack thereof) reflects both balance sheet liquidity as well as external financing frictions. We relate the ability of firms to accommodate investment spikes to variables that capture (i) internal liquidity and (ii) information asymmetry, or more broadly, financing frictions.

While there are several indices of financial constraints based on what managers say or disclose in their 10-Ks about their firm's financial condition (e.g., KZ), the ability to pursue investment projects (e.g., HM), or obligations that suggest difficulty in raising external financing (e.g., BLM), to the best of our knowledge, previous research has not attempted to directly examine which firm-specific variables affect the capacity to accommodate large investments. In this paper, we develop such an Index of financial flexibility. Since the objective of many of the FC indices is to examine whether these are related to firms' ability to invest, we run horse races between our FF Index and individual FC indices to evaluate, in out-of-sample tests, whether the FF Index outperforms the FC indices in predicting investment spikes as well as regular investment in capital and R&D.

4 Data

In this section, we describe how we construct our sample, the characteristics of sample firms, and our method for identifying investment spikes in firms and industries. We obtain annual financial statement information for each U.S. firm from Compustat. The sample period runs from 1970 through 2019. The sample period begins in 1970 because the test sample period in Kaplan and Zingales (1997) starts in the same year and we want to compare our FF Index with the major FC indices. Financial services or regulated utility firms (with standard industrial classification (SIC) codes between 6000 and 6999 or between 4900 and 4999) are excluded. Observations with negative total assets and missing values for all investment components are also excluded. Firms are excluded if there are no periods with five consecutive years of observations in the sample period because our methodology needs at least a five-year window to identify an investment spike. Our identification of industry-spike years is based on the proportion of investment-spike firms relative to the total number of firms that operate in each industry. To enhance the validity of the filter, we exclude SIC three-digit industries that on average include fewer than ten firms operating in each year across the sample period. Applying the above filters results in a sample containing 18,595 firms and 138 SIC three-digit firms.

All nominal items from the statement of cash flows, income statements, and balance sheets are deflated or inflated to year-2000-end dollars using the GDP deflator from the World Bank Data. An interpolated GDP deflator is used if a relevant fiscal year ends in a month other than December. To reduce bias caused by outliers and eradicate errors in the data, all variables in ratios are winsorized at the 2.5^{th} and 97.5^{th} percentiles. We provide detailed definitions of the variables in this study in Appendix A.

5 Identifying Investment Spikes

5.1 Firms' investment spikes

In this paper, we define firm-level investment as total investment outlays including net capital expenditures and acquisitions minus sales of property, plant, and equipment (i.e., $I =$ Capital expenditures $[capx]-$Sale of property, plant, and equipment $[sppe]+$Acquisitions $[aqc]$, where all variables in italics are Compustat data items). We focus on firms' lumpy investments or investment spikes to measure financial flexibility since it should be a necessary component for firms to undertake large investments.

To identify firm-level investment spikes, we apply a linear regression-based filtering procedure proposed by Im et al. (2020). Compared with filters used in early research, e.g., Whited (2006), Elsas et al. (2014), this filter provides statistically interpretable measures and works well when there is a trend in the investment sequence.

The first step in this procedure is to regress each five-year investment sequence, $y = (I_{i,t-2}, I_{i,t-1}, I_{i,t}, I_{i,t+1}, I_{i,t+2})'$, for $i = 1, 2, \cdots, N$ and $t = 3, \cdots, (T_i - 2)$, on a constant, a linear trend, and a dummy variable for the middle year t, where N is the number of firms and T_i is the length of firm i 's investment series. This sequence can be expressed compactly as

$$y = \mathbf{X}b + \varepsilon, \tag{1}$$

where $\varepsilon \sim N(0, \sigma^2 \mathbf{I}_5)$ and $\mathbf{I}_5$ is a 5×5 identity matrix. The matrix $\mathbf{X}$ and vectors b and ε are specified as follows:

$$\mathbf{X} = \begin{bmatrix} \mathbf{1} & \tau & \mathbf{D}_{\tau=0} \end{bmatrix} = \begin{pmatrix} 1 & -2 & 0 \\ 1 & -1 & 0 \\ 1 & 0 & 1 \\ 1 & +1 & 0 \\ 1 & +2 & 0 \end{pmatrix},$$

$b = (\alpha_{i,t}, \beta_{i,t}, \delta_{i,t})'$, and $\varepsilon = (\varepsilon_{i,t-2}, \varepsilon_{i,t-1}, \varepsilon_{i,t}, \varepsilon_{i,t+1}, \varepsilon_{i,t+2})'$. Using $\widehat{b} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'y$, it can be shown that: $\widehat{\alpha}_{i,t} = \frac{I_{i,t-2}+I_{i,t-1}+I_{i,t+1}+I_{i,t+2}}{4}$, $\widehat{\beta}_{i,t} = \frac{-2I_{i,t-2}-I_{i,t-1}+I_{i,t+1}+2I_{i,t+2}}{10}$, and $\widehat{\delta}_{i,t} = I_{i,t} - \widehat{\alpha}_{i,t}$. Note that $\widehat{\alpha}_{i,t}$ is the base-level investment as measured by the average of all investments undertaken during the five-year window excluding the spike year and $\widehat{\beta}_{i,t}$ is average investment growth within the five-year window. In addition, the standard error of $\widehat{\delta}_{i,t}$ is $se\left(\widehat{\delta}_{i,t}\right) = \sqrt{\frac{5}{4}s^2}$, using $\widehat{V}(\widehat{b} \mid \mathbf{X}) = s^2 (\mathbf{X}'\mathbf{X})^{-1}$, where $s^2 = \widehat{\varepsilon}'\widehat{\varepsilon}/(n-k)$ and $\widehat{\varepsilon} = (\widehat{\varepsilon}_{i,t-2}, \widehat{\varepsilon}_{i,t-1}, \widehat{\varepsilon}_{i,t}, \widehat{\varepsilon}_{i,t+1}, \widehat{\varepsilon}_{i,t+2})'$.

In the second step we execute a one-sided t-test for $\delta_{i,t}$ or the coefficient for the dummy variable $\mathbf{D}_{\tau=\mathbf{0}}$. The null and alternative hypotheses are $H_0 : \delta_{i,t} = 0$ and $H_1 : \delta_{i,t} > 0$, respectively. Under the null hypothesis, the statistic

$$t_{\widehat{\delta}_{i,t}} = \frac{\widehat{\delta}_{i,t}}{se\left(\widehat{\delta}_{i,t}\right)}$$

follows a student t-distribution with 2 degrees of freedom. The final classification is made based on the results of the one-sided t-test at the conventional significance level of 10%. That is, $I_{i,t}$ is classified as an investment spike if $\widehat{\delta}_{i,t}$ is positive and statistically significant at the 10% level, irrespective of the magnitude of the coefficient. Repeating the above procedures $\sum_{i=1}^{N}(T_i - 4)$ times will identify a total of J firm-years in which firm-level investment spikes occur.

5.2 Industry-spike years

As stated in the introduction, our framework to construct FF index focuses on *industry-spike* years, in which firm-level investment spikes are clustered. This strategy allows us to mitigate concerns that the heterogeneity in investment opportunities rather than financial flexibility drives firms' investment decisions, and improve the predictive power of the FF Index.

Our filter for industry spikes relies on the trend in and the proportion of investment-spike firms operating within a given industry. For industry i in year t, if

$$Prop_{i,t} > 2 \times \frac{Prop_{i,t-1} + Prop_{i,t-2} + Prop_{i,t-3}}{3} \quad \& \quad Prop_{i,t} > 15\%, \tag{2}$$

where $Prop_{i,t} = \frac{\#\text{investment-spike firms}_{i,t}}{\#\text{total firms}_{i,t}}$, then this industry-year observation is treated as an industry-spike year. The first condition requires an increase in the proportion of investment-spike firms of at least 100% over the preceding three-year average. The second condition requires at least 15% of firms operating in a given industry to experience an investment spike in the same fiscal year.

This industry-spike filter differs from the firm-level filter in two main aspects: (i) Unlike the lumpiness of firm-level investments, the proportion of spike firms within a given industry is relatively stable across time. The linear filter for firm-level investment is too strict to generate an industry-spike sample of meaningful size. (ii) In addition to the time-trend criteria, we set a lower bound for the proportion of spike firms to avoid a scenario in which investment-spike firms are scarce earlier, then even one firm's spiky investment could lead to an industry spike. [16]

[16] Our main result remains stable when we use alternative criteria to identify industry spikes, e.g., the spike-firm proportion is 1.5 or 2.5 times above average; at least 10% or 20% of firms generate an investment spike.

6 Results

6.1 Summary Statistics

Table I provides selected summary statistics for investment spikes. The statistics reported in Panel A indicate that a firm-level investment spike occurs in about 13 percent of firm years. About 15 percent of the industry-year observations are classified as industry-spike years. The statistics reported in Panel B indicate that an investment spike is about 3.4 times higher than the base investment level, i.e., the average investment during the two preceding years and the two years after the spike year. Unsurprisingly, the investment level in a typical year that is not identified as a spike year where there were no spikes in the preceding or following two years is close to the base-level investment. The statistics reported in Panel C indicate the distribution of investment spike frequencies across sample firms and industries. The time gap between two spikes is about 6 years for a typical firm. In a typical industry, the corresponding number is 5.7 years. In industry-spike years, 28.6 percent of firms within a given industry, on average, respond to industry-level opportunities and generate investment spikes, while in non-industry-spike years, this number, while much smaller, is still high, at 10.4 percent.

[Table I about here.]

In Panel D of Table I we present summary statistics for key firm-specific variables for firms that generate investment spikes at time $\tau = 0$ (the first group) and those that do not generate any spikes at $\tau = 0$ nor from $\tau = -2$ to $\tau = 2$ (the second group). Statistics are reported both for year $\tau = 0$ and the preceding year $\tau = -1$. It can be seen immediately that spike years have a major impact on many of these firm-specific variables as investment and financing activities affect these variables. Focusing on year $\tau = -1$, i.e., the year before the investment spike occurs, we see that firms in the first group are larger, maintain higher cash holdings, lower leverage, and have slightly higher market-to-book ratios. These firms also pay out more and are more profitable. In the spike year, compared with the previous year, the first group experiences a major increase in size, lower cash holdings, higher leverage, much lower market-to-book ratios, and lower profitability. These results suggest that, in the year prior to an investment spike, spike firms have healthier balance sheets and higher profitability than those that do not generate investment spikes in the following three years or the year before. They appear to finance investment spikes by utilizing debt capacity through issuing debt and drawing down cash holdings.

6.2 Industry-Spike Years and Industry Growth Opportunities

Our in-sample regressions that generate the FF Indices are based on industry-spike years in which a significant fraction of firms in a given industry simultaneously generate investment spikes. There are two reasons to focus on industry-spike years. First, in an industry-shock year, most firms operating in the industry are likely to experience good investment opportunities, so it is less likely that a firm that does not invest lacks good investment opportunities rather than financial flexibility. Second, reverse causality might be involved if firms perfectly anticipate when significant investment opportunities materialize and therefore build up liquidity to be ready to invest. Reverse causality could bias both our in-sample and out-of-sample regressions.[17] Only by an extreme coincidence, however, would a large fraction of firms anticipate individual growth opportunities materializing in exactly the same year.

That said, industry-specific growth opportunities might also be anticipated—for example, if government policy initiatives affect individual industries and are announced or revealed in advance. We show next that industry-average market-to-book ratios peak exactly before industry-spike years, which makes such a possibility unlikely. Moreover, such a possibility would not explain why every firm would not create balance-sheet flexibility to prepare for undertaking major investments. Finally, if financial constraints differentiate between firms that can build up balance-sheet flexibility and those that cannot in anticipation of such policy changes or industry-wide growth opportunities, we would expect FC measures to explain cross-sectional variation in investment behavior in both our in-sample and out-of-sample tests (provided they are correctly reflect financing frictions faced by firms). As we later show, they typically do not.

We do not intend to suggest that major investment opportunities cannot be anticipated to some degree ahead of time. However, firms also respond to current shocks to investment opportunities, and continuously engage in investment and financing activities, while at the same time updating their beliefs about future shocks when the shocks are persistent. The

[17] Of these, the latter concern is more important since biased in-sample estimates would only weaken the out-of-sample predictive power of our index.

investment and financing activities they engage in affect their liquidity position at any given point of time. Therefore, the history of past shocks largely determines the liquidity position of a firm at a given point of time. To the extent that firms' histories are different, the cross-sectional heterogeneity in liquidity positions enables us to examine how liquidity and financing frictions affect firms' ability to respond to an industry-wide major investment opportunity that was not fully anticipated. In section 7, we outline and calibrate a model in which firms optimally choose investment and financing in response to both idiosyncratic and common shocks that are persistent but face the same costs of external financing. We validate our empirical results based on data generated by this model.

The results reported in Table II confirm that the industry median market-to-book ratio and the market-to-book ratio of a typical firm in a given industry are higher in the year immediately before an industry-spike year. For Panels A and B, the key independent variable is a dummy variable indicating that time t is an industry-spike year. The dependent variable in Panel A is the standardized median industry market-to-book ratio, and in Panel B is the standardized firm-size-weighted average market-to-book ratio. The dependent variable for each column is measured in a particular year relative to year t within the range $\tau = t{-}3 : t{+}2$. The regressions include year and industry fixed effects. The industry-spike year dummy has a significant positive coefficient only for the market-to-book ratio corresponding to the year before the industry-spike year, implying that the median growth opportunity in a given industry increases prior to that year. In Panel A, the industry-median market-to-book ratio is 12 percent of one standard deviation higher in the year before the industry-spike year than it is in other years. For Panel C, we run firm-level regressions. The dependent variable is the standardized firm-level market-to-book ratio, and we include firm and year fixed effects. Again, the coefficient of the dummy corresponding to the year before an industry spike year has a significant and positive coefficient. These results indicate that our industry-spike filter works well while also validating the premise underlying the in-sample regressions that investment opportunities improve across the board immediately prior to an industry-spike year.

[Table II about here.]

6.3 In-sample Regressions and the Financial Flexibility Index

In Table III Panel A we report our baseline logit model estimates with the industry-spike sample that form the basis of our FF Indices. All regressions include year and industry fixed effects. We report regression results for the full industry-spike-year sample in column (1) as well as for the first and second halves of our samples in the next two columns. This specification includes only average cash holdings and leverage ratios from $\tau = -2$ to $\tau = -4$, changes in cash and leverage ratios at $\tau = -1$ from these average values, firm size, and total payout ratios. Firm size is included to proxy for information asymmetry, while the payout ratio is expected to be associated with anticipated less binding future financing frictions.[18] We include variables designed to capture investment opportunities: these include the market-to-book ratio, sales growth, and cash flows, all as of $\tau = -1$. Cash flows are a source of liquidity as well as an indicator of growth opportunities, but as we show, they do not contribute significantly to the explanatory power of our FF Indices.

[Table III about here.]

The above regressions indicate that the coefficients of cash holdings (a positive coefficient), changes in cash (a positive coefficient) and the leverage ratio (a negative coefficient), the average past leverage ratio (a negative coefficient), and the payout ratio (a positive coefficient), are highly significant in all six columns. Firm size has a positive and significant coefficient for the full sample and the second half of the sample period. Among the IO variables, sales growth and the market-to-book have positive coefficients, but cash flows have an insignificant coefficient. This last result is noteworthy because it suggests that once we control for changes in cash holdings and leverage, the "growth opportunity" embedded in cash flow is not associated with the likelihood of investment spikes. Therefore, while cash flow at two-or-longer lag could be associated with average cash holdings and leverage, it is unlikely that these latter variables, even though they are correlated with lagged cash flows, capture growth opportunities.

The baseline FF Index is a linear projection of the regression estimates reported in column (1) of Table III. Therefore, it is $\texttt{FF} = 1.924 * \texttt{Chg cash holding} + 0.257 * \texttt{Avg cash holding} -$

[18] Dividend-paying firms have long been considered less tightly constrained financially (Fahlenbrach et al., 2021) in the literature. Many firms engage in "equity recycling", i.e., simultaneously issuing equity and engaging in payouts (Farre-Mensa and Ljungqvist, 2016).

$1.186*$`Chg book leverage`$-0.411*$`Avg book leverage`$+0.030*$`Size`$+2.419*$`payout`. For the regressions, we convert this measure to a scaled ranking measure by ranking all sample firms in a given year on the basis of this linear projection score and dividing the ranking by the number of firms to obtain a scaled ranking in the $(0,1]$ interval.

6.4 External Validation

We conduct two types of external validation. Our purpose is to examine whether the FF Index predicts investment spikes when industry-wide opportunities are less likely to happen. For Panel A of Table IV, we estimate a logit model (with year and industry fixed effects) for all non-industry-spike year observations. The dependent variable is an indicator variable that takes the value of one if a firm generates an investment spike in a given year and zero otherwise. The key explanatory variable is the (ranked) FF Index. We include the IO variables, year and industry fixed effects.

In Panel A of Table IV we present the results across several specifications. For columns (1)–(3) in the upper panel, we include the baseline FF Index, only the IO variables, and an "IO Index" for predicting investment spikes constructed the same way as the FF Index, but with only the IO variables included (together with year and industry fixed effects). Several observations emerge. First, the FF Index is valid externally, significantly predicting investment spikes in the non-industry-spike sample. Second, the IO variables are significant when the FF Index is omitted from column (2), but the regression pseudo-R-square is much smaller. This is also the case for the regression reported in column (3), where only the IO Index is included. Third, the coefficient of FF Index remains significant in column (4) and is similar in magnitude to that reported in column (1). The IO variables are also significant, and the coefficient magnitudes are similar to those reported in column (2). Thus, there is little evidence that the FF Index is related to investment opportunities.[19] Finally, a comparison of the pseudo-R-squares shows that the marginal contribution of the FF Index (comparing columns (4) with column (2) or column (3), the pseudo-R-square almost doubles) is much higher than that of the IO variables (comparing columns (4) or column (5) with column (1), there is a very slight increase in the pseudo-R-square when the IO variables are added). [20]

[19]Different from the in-sample estimation, cash flow is marginally significant in the out-of-sample test.

[20]In tests not reported here but available on request, we compare the performance of the FF Index with a parsimonious measure of financial flexibility introduced by Barry et al. (2022) (Table A.4). This BCGM proxy is the simple average of a firm's lagged cash over assets and one minus the lagged leverage over

Financial flexibility should enable firms not only to undertake large investments but also more modest investments, which might otherwise necessitate raising external financing and high costs. For the results reported in the lower panel of Panel A in Table IV, we change the dependent variable to (a) the ratio of investment to lagged total assets in column (1), (ii) the ratio of capital expenditure to lagged assets in column (2); the ratio of acquisition investment to lagged assets in column (3), investment in R&D over lagged sales in column (4), and investment growth, defined as investment over the average of past two-years' investment, in column (5). In these OLS regressions, among the control variables, we include the IO variables, firm fixed effects, and year fixed effects. The FF Index continues to have a positive and significant effect in all these columns.

[Table IV about here.]

For our second test of external validity, we restrict attention to industry-spike years. Starting in 1985, and then at five-year intervals, we use all past industry-spike years to construct our FF Indices using the methodology we used to obtain the results reported in Table III. We then use these constructs to predict firm-level investment spikes in subsequent industry-spike years. This approach avoids the issue of sample-period-overlap that is present in our first out-of-sample test, and also shows the robustness of the predictability of FF across subperiods. In addition, the concern that investment opportunities are not properly controlled for is likely to be less crucial when the underlying shock is an industry shock.

In the upper half of Table IV Panel B we report the results of in-sample regressions for constructing FF Indices. The coefficients and significance of each subperiod are close to those of the full-sample results (column (1) of Table III Panel A). The out-of-sample verification in the lower half of the panel shows that the ranked FF Indices have positive and highly significant coefficients in logit regressions that include year and industry fixed effects for all cutoff years. These results indicate that our methodology is valid and the index remains stable across sample periods.

In Table V we present some summary statistics for the FF Index for both the industry-spike sample (upper panel) and the non-industry-spike sample (lower panel). In the upper

assets. We find that the BCGM proxy is highly significant in explaining investment spikes. However, it is much less significant when included alongside the FF Index, which is highly significant. The incremental contribution of FF to the overall R-square is quite substantial, while that of the BCGM proxy is small.

subpanel of each, we present summary statistics for the linear projection based on column (1) in Table III Panel A. The lower subpanel of each panel presents the time-series change in the FF Index around the industry-spike year. The distribution and dynamic evolution of FF are similar in the industry-spike and non-industry-spike samples. The key takeaways are the following. First, the economic magnitude of FF is quite significant in the first external validity test. As can be seen in Table V, the mean ranked FF Index in the year before a firm-level spike is 8.4 percent higher than for non-spike firms in the non-industry-spike sample. Based on the coefficient reported in column (4) Table IV Panel A, this translates to a 0.9 percentage point higher likelihood that an investment spike occurs. Given that the average likelihood that a spike occurs in the non-industry-spike sample is 10.4 percent,[21] this is an economically significant magnitude. Second, while there is a significant increase in the magnitude of the linear projection from three years before to the year before the spike year for spike firms, the trend is much milder or even flipped for non-spike firms for the same years. For example, in the industry-spike sample, the FF score for firms that generate investment spikes is 26.0 percent [22] of one standard deviation higher from $\tau = -3$ to $\tau = -1$. For non-spike firms, the corresponding statistic is 2.6 percent. We see a similar pattern if we compare the value of the ranked FF Index.[23] Third, an investment spike will largely consume the firm's financial flexibility. Comparing $\tau = -1$ and $\tau = 0$, the investment spike reduces firms' financial flexibility by 0.15 (0.16), or 14 (15) percent of the ranked measure in the (non) industry-spike sample.

[Table V about here.]

Before leaving this section, it is important to comment on the regression R-squares for both the in-sample and out-of-sample tests. Especially for the logit models with investment spikes as the dependent variable, these pseudo-R-squares appear small. This could be in part because the dependent variable is a binary variable, and for investment in a particular year to be classified as a spike-year investment, we require investment to exceed the base-level

[21] The average spike firm proportion for a non-industry-spike industry-year is 10.42%, reported in Table I Panel C.

[22] (0.228 - 0.148)/0.308 = 26.0%

[23] Even if the difference in time series trend of FF Index from $\tau = -3$ to $\tau = -1$ is totally driven by different anticipation about investment opportunities, it can not fully explain the gap in FF at $\tau = -1$. Thus our measure is less likely to suffer the reverse causality.

investment at the threshold level of significance, and so likely miss out on investment-years where the investment still exceeds the base-level by some margin. Moreover, low R-squares are not unusual for regressions that attempt to explain "changes" in cross-sectional tests. For example, the regression R-squares in cross-sectional tests of stock returns (which reflect changes in stock value) can also be quite low. While the logit model precludes the inclusion of firm-fixed effects, when we include firm-fixed effects to explain investment growth in the OLS regression reported in column (5) of Table IV, the R-square increases to 12 percent. The regression R-square is substantial in all other OLS regressions reported in columns (1)-(4), where the dependent variable is a continuous variable.

6.5 Robustness

We now check whether our results are robust to alternative ways to identify firm-level investment spikes and alternative filters for the industry-spike sample. In Panel A of Table VI we report the results of repeating the same procedures as those associated with Table III and Table IV in alternative settings. In the upper part, we report the in-sample estimation to construct alternative FF Indices; in the lower part, we report the corresponding external validity in the non-industry-spike sample. The alternative settings are as follows:

- For column (1), we change the industry classification from the three-digit SIC industry to the Fama French 48 industry classification. All other settings remain the same.

- For column (2), we change the industry-spike-filter Equation (2) to

$$Prop_{i,t} > 2 \times \frac{Prop_{i,t-1} + ... + Prop_{i,t-5}}{5} \quad \& \quad Prop_{i,t} > 15\%,$$

  where $Prop_{i,t} = \frac{\#\text{investment spike firms}_{i,t}}{\#\text{total firms}_{i,t}}$. In other words, we extend the backward-looking period from three to five years.

- For column (3), we change the firm-level investment-spike filter from the linear filter to the filter in Whited (2006). The firm-year observation will be identified as an investment spike if

$$I_{j,t} > 2 \times \frac{I_{j,t-1} + ... + I_{j,t-3}}{3} \quad or \quad (I/\text{lagged total asset})_{j,t} > 30\%$$

- For columns (4), we change the dependent variable in Equation (1) from raw investment to the investment scaled by the total asset at the beginning of the year to redefine investment spikes. All other criteria remain the same.
- For columns (5), we change the dependent variable in Equation (1) from raw investment to raw capital expenditure to redefine investment spikes. All other criteria remain the same.

Reviewing the results reported in Panel A of Table VI, we observe that the alternative FF Indices have robust and significant coefficients in all out-of-sample tests. For the in-sample tests, among the baseline variables, recent changes in cash holdings, the average level of past leverage, and the change in leverage are robustly significant in all in-sample results. The payout ratio is significant in all but two of the estimations, while the average level of past cash holdings is insignificant in all the models. Firm size has mixed effects on investment spike. It has a positive coefficient in three of the regressions with marginal significance and a negative coefficient in explaining an investment spike when the definitions involved size scaling (smaller firms' investment patterns are more likely, ceteris paribus, to meet the criteria in columns (3) and (4)).

[Table VI about here.]

For Panel B of Table VI, we pick years from 1970 to 1999 one at a time and then use the following twenty-year industry-spike sample as the basis of our in-sample test to generate FF. Next, we use all the remaining observations (with both the industry-spike and non-industry-spike years) for the out-of-sample test. We repeat the above procedure to generate thirty sets of in-sample coefficient estimates to construct the FF Indices and the corresponding out-of-sample results. We report the distribution of those coefficients and results to examine parameter stability both across firms and over time. In the upper half of Panel B, the coefficients of each component in FF indices are relatively stable with similar significance (the average past cash holdings and size have slightly weak stability). The distribution of the out-of-sample coefficient estimates indicates robust external validity of FF indices based on training samples for multiple subperiods. This evidence mitigates the concern regarding the extrapolation of index coefficients expressed in Whited and Wu (2006).[24]

[24]As the authors note, one concern with the practice of out-of-sample extrapolation of index coefficients is

6.6 Horse Race I: FC Indices vs. FF

We next compare the out-of-sample performance of the FF Index in predicting investment spikes (as well as other types of, or ways of measuring, investment and change in investment) with those of commonly used indices of financial constraints. Initially, we limit attention to the following indices of financial constraints, to which we refer collectively as FC Indices. These indices are the Kaplan-Zingales (KZ) Index (Kaplan and Zingales, 1997; Lamont et al., 2001), the Hadlock-Pierce (HP) Index (Hadlock and Pierce, 2010), the Hoberg-Maksimovic (HM) Index (Hoberg and Maksimovic, 2015), the Bodnaruk, Loughran and McDonald (BLM) Index (Bodnaruk et al., 2015), and the Whited-Wu (WW) Index (Whited, 2006). Notably, all of the above indices, except the WW Index, are based on textual analysis of either the entire 10-K or sections of the 10-K that are considered relevant for firms' financial status and investment plans. The WW Index captures the shadow cost of external financing constraints as a function of several firm-specific variables from a structural model.

We run "horse races" between the FF Index and each FC Index by including each FC Index both separately and together with FF in the out-of-sample tests. In our empirical tests, all these FC Indices are converted to ranked indices like the FF Index. Inasmuch as these indices have been discussed extensively in the literature (see Bodnaruk et al., 2015; Farre-Mensa and Ljungqvist, 2016), we do not discuss them any further. The Appendix A provides detailed definitions. Importantly, lower values for all these indices correspond to *less* financially constrained firm-years, so the expected sign of the coefficients of the FC indices is negative.

Before discussing the regression results, we first show, in Table VII Panel A, the Spearman rank correlation between the FF Index and various FC measures, as well as the average values of the ranked FF Index and its component conditional on the quintile of each FC measures. The correlations of FF with KZ, HP, and WW are negative (-0.49, - 0.21, and -0.21, respectively). However, the correlations with HM and BLM are close to zero. We see a similar pattern when we compare the average ranked FF for the top (financial constraint) and bottom (financial unconstraint) quintile of each FC Index. The gap in the average FF rank between the two quintiles is largest for KZ (0.68 for the bottom quintile and 0.24 for the top quintile), followed by HP and WW, and it is marginal for HM and BLM.

For KZ, the negative association is likely due to the fact that cash holdings and leverage

"parameter stability both across firms and over time", Despite this warning, the practice continues.

have, respectively, positive and negative loadings in that index. The negative correlation between WW and HP may appear more surprising. Lower cash holding and higher debt are associated with *less* financial flexibility (lower values of the FF Index). However, Table 2 in Farre-Mensa and Ljungqvist (2016) shows that the firms classified as less constrained have lower cash holdings and higher debt. As seen from the last two columns of Panel A, while firms classified in the upper quintile of the WW Index indeed do have higher average cash holdings than those in the lower quintile, the difference in average leverage ratio is small, and the firms in the lowest quintile are much larger with more payout. Since size and payout have positive loadings in the FF Index, unconstrained firms also have higher financial flexibility. As for the HP Index, it is remarkable how similar the numbers are to those for the WW Index for both the top and bottom quintiles. Hence, the reasons for the negative correlation with FF, with an almost identical magnitude as for WW, are clear.

[Table VII about here.]

In Panel B of Table VII, we examine the time-series behavior of the FC indices around investment spike years. Only the KZ Index shows the same pattern as the FF Index shown in Table V, namely, the financial constraint rank decreases right before the spike year, and as the spike investment drains liquidity, the index rank increases in the spike year and the year after, before decreasing again. However, for the KZ Index, the percentile rank changes from 0.468 to 0.430, or by 3.8, from $\tau = -3$ to $\tau = -1$, compared to a change of 6.2 (upper panel) and 5.5 (lower panel) of Table V for the FF Index. Not surprisingly, the HP Index decreases monotonically over time as it is a function of firm size and age only. HM, BLM, and WW indices show little time-series variation.

In Panel C of Table VII, we next compare the out-of-sample performance of the FC indices with that of the FF Index during non-industry-spike years. First, for each of our FC indices, we estimate a logit model in which the dependent variable is the investment-spike dummy, and the control variables include one of the FC indices and industry and year fixed effects, but not the FF Index. We then add the FF Index to the specification. The results are reported in subpanel (a) of Table VII. Only the KZ and the WW indices have significant negative coefficients when the specifications do not include the FF Index. However, when the FF Index is included, the FF has a positive significant coefficient in all the regressions. The

KZ Index is still significant with a negative coefficient, although the associated coefficient and z-statistic are only a third of those for the FF Index. The HP, BLM, and WW indices have significant coefficients *with the wrong sign*.

Next, we estimate OLS models in which the dependent variables are the same as in the OLS results reported in the lower subpanel of Table IV. In these OLS regressions, we include the IO variables, firm and year fixed effects. We again find that the FF Index is always significant with a positive sign in all regressions when included together with one of the FC indices. Moreover, the t-statistics associated with the FF Index is typically much higher than for any of the FC indices. Of the FC indices, the KZ Index has consistently significant coefficients of the right sign, irrespective of whether the FF Index is included or not. The HP and WW indices consistently have significant coefficients *of the wrong sign*. BLM has significant coefficients of the right sign for investment and capital expenditures, while the same is true for HM in acquisitions.

The main innovation behind the FF Index is that it is based on firms' actions and not what managers disclose in their 10-Ks. In contrast, the KZ, HP, BLM, and HM indices are all based on textual analysis. Except for the KZ Index, the other three perform poorly, especially in explaining large investments or increases in investment. [25] Farre-Mensa and Ljungqvist (2016) also argue that many commonly used measures of financial constraints (including KZ, HP, and WW) do not properly differentiate financially more constrained and less constrained firms. However, they do not consider HM and BLM, which have been developed more recently based on machine-reading of firms' 10-Ks. [26]

The performance of the KZ Index is highly interesting because it is based on the subjective classification of the financial constraint status of a small sample of firms more than three decades ago. Yet, it is highly correlated with the FF Index and is consistently significant in all our tests, whether included with or without the FF Index. While the FF Index outperforms the KZ, to give text-based indices such as the KZ Index a fair chance, in the next section,

[25]Since the HP Index only depends on firm size and age, it may simply reflect the possibility that large firms invest differently than small firms.

[26]Farre-Mensa and Ljungqvist (2016) subject the classifications based on several indices to two types of tests. First, they show that following staggered state-level corporate tax increases, constrained firms raise new debt (to take advantage of the tax-deductibility of interest) more vigorously than unconstrained firms. Second, they show that both types of firms engage in "equity recycling", i.e., their payouts (dividends and share repurchases) increase when they issue more equity. They consider both types of evidence as inconsistent with the correct classification of firms based on their financial constraint status.

we ask ChatGPT to read a large sample of 10-Ks (for the period 1993-2019) [27] and classify firms according to their financial status. We then use these classifications directly, as well as several counterparts of the KZ Index based on these classifications, to rerun the horse race. We discuss these results in the next section.

6.7 Horse Race II: ChatGPT-based FC Indices vs. FF

We follow the practice in Hoberg and Maksimovic (2015) and focus on the most relevant subsection, "Liquidity and Capital Resources" (LIQ&CAP), in the MD&A part, to make a trade-off between information loss and limited corpus length as well as introducing noise. We extract the subsection from the 10-K fillings available for the period 1993-2019 from Bill MacDonald's website. [28] Kaplan and Zingales (1997) classify their sample firm-years into five mutually exclusive categories based on their reading of the LIQ&CAP section. These are: not financially constrained (NFC), likely not financially constrained (LNFC), potentially financially constrained (PFC), likely financially constrained (LFC), and financially constrained (FC).[29] We ask ChatGPT to summarize the description of each of these categories in Kaplan and Zingales (1997) (pages 180-182). We then instruct ChatGPT to take on the persona of a finance expert specializing in corporate finance and answer four questions for each LIQ&CAP section that it "reads". The first question (Q1) asks whether the particular excerpt contains any useful information about the firm's financing and investment policy and adequacy of resources to invest. The second question (Q2) asks ChatGPT to classify the firm into one of the five aforementioned categories. The third question (Q3) is directly aimed at evaluating whether the firm could find enough internal and external financing if it has a really good investment opportunity in the following year. Finally, the fourth question (Q4) asks whether the firm expects a significant investment opportunity the following year. We mainly use the responses to Q2 in our analysis and use the responses to the remaining questions as validations of our approach.

Appendix B provides the implementation details. As shown in Table A.I, the ChatGPT

[27] Our empirical exercise was conducted in September 2023 using the GPT-3.5-Turbo, which was trained on the dataset collected up until September 2021. Although in the prompt, we require GPT to answer the question based on information in the excerpt only, all GPT-based measures still could be subject to potential look-ahead biases.

[28] https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files

[29] Hadlock and Pierce (2010) also follow this classification scheme.

responses show a great deal of consistency across the different questions. First, in the top row of Panel A, in answer to Q1, it tells us that 95.5% of the LIQ&CAP sections contain useful information about the firm's financing and investment situations. In Panel B, we see that the answers to Q2 and Q3 are well-aligned: in firm-years classified as more (less) constrained (answer to Q2), firms are also less (more) likely to find enough resources to invest if it has a really good investment opportunity the following year. To alleviate concern that useful information in the rest of the Management Discussion and Analysis (MD&A) section is ignored by reading only the LIQ&CAP section, we randomly select each year 1% of the MD&A sections and ask ChatGPT the same set of questions as in Q2. As seen in Panel C, the responses for the MD&A and LIQ&CAP sections show a high degree of consistency, alleviating concerns about major information loss. Finally, to check whether there is significant noise in ChatGPT's responses, we randomly select a sample of 10-Ks and repeatedly ask ChatGPT to respond to Q2. In Panel D, we find that ChatGPT gives the same response 70% of the time and, for the remaining cases, picks one of the adjacent categories. Thus, the noise does not appear to be a major concern.

In Panel A of Table VIII, we show the distribution of ChatGPT's classifications, as compared to those generated by the Kaplan and Zingales (1997) sample and the Hadlock and Pierce (2010) sample. The distribution of the ChatGPT classification is much closer to the HP classification than the KZ classification. This is probably because the 49 firms in Kaplan and Zingales (1997)'s study is not a representative sample, which is the low-dividend paying firms identified by Fazzari, Hubbard, and Petersen (1988) as financially constrained according to the investment-cash flow criterion. In contrast, the sample of 356 firms studied in Hadlock and Pierce (2010) is randomly chosen to be broadly representative of the overall Compustat universe. Interestingly, Hadlock and Pierce (2010) note that their classification differs from KZ's because they leave out quantitative information from the 10-Ks amount of cash positions and dividend/repurchase behavior. The authors argue that including such information is inappropriate if the ultimate goal is to relate the classification categories to firm-specific variables such as cash holdings or payouts. Since we do not provide ChatGPT any instructions to disregard quantitative information, the close resemblance between the distribution of the ChatGPT classification and the HP's seems to indicate that in the absence of such instructions, ChatGPT focuses on qualitative information in the 10-Ks.

[Table VIII about here.]

In Panel B, we follow the practice in Lamont et al. (2001), reconstruct the KZ and the HP indices using the same set of covariates as in the original indices, but applied to the ChatGPT classifications. These are denoted KZ_{GPT} and HP_{GPT}, respectively. We also create a new index, $FC_{FF,GPT}$, for which we use the variables used to construct the FF Index. For the new KZ Index, except for dividends, all other variables have significant coefficients and are of the same sign, although the coefficient estimates differ substantially. For the new HP Index, the coefficient estimates for firm size and the square of firm size are remarkably similar to those in the original estimate, although that of firm age, while of the same sign and significance, is only a tenth of the original coefficient. As expected, the coefficients of the FF variables all have the opposite signs in generating $FC_{FF,GPT}$ to what they have in generating the FF index. The last column shows the correlations between the original indices and the new versions based on the ChatGPT classifications. Not surprisingly, the HP indices, given the almost identical coefficients on firm size for the original and new versions, are highly correlated. However, the correlation for the two versions of KZ is 0.5, while that for FF and the FC version of FF based on ChatGPT is more modest.

In Panel C, we report the out-of-sample results for the non-industry-spike years. In subpanel (a), we report the results for predicting investment spikes. In this specification, we add a dummy variable based on the answer for Q4 to further control the difference in expectations about investment opportunities. Except for HP_{GPT}, as standalone explanatory variables, the ChatGPT classification and the indices based on these classifications have significant coefficients of the right sign. However, when included alongside the FF index, only the ChatGPT classification retains significant coefficients of the correct sign, even though the associated z-statistic is much smaller than for the FF Index.

Turning to the OLS regressions reported in subpanel (b), we find that the ChatGPT classifications retain significant coefficients of the right sign except when the dependent variable is R&D over lagged sales even when included alongside the FF Index. However, the latter once again outperforms the ChatGPT classifications. The coefficient of KZ_{GPT} is also typically significant and of the right sign, although when included alongside the Ff Index and when the dependent variable is capital expenditure over assets, it becomes insignificant. The HP_{GPT} Index never has significant coefficients of the right sign. The FF_{GPT} indices sometimes has significant coefficients with the right sign when the FF Index is not included, but alongside the FF Index, it never has significant coefficients of the right sign.

The fact that the ChatGPT classifications could have incremental explanatory power in all regressions suggests that there is information in the 10-Ks regarding a firm's financial flexibility that is not captured by the balance sheet variables. This could be related to purely qualitative information or off-balance sheet information such as the availability of lines of credit. However, the incremental information, if any, is relatively small. The empirical evidence suggests that relating *quantitative* information to firms' actions, such as being able to invest more aggressively when the entire industry has highly favorable investment opportunities, is more effective in predicting when firms have the financial flexibility to invest. Actions do speak louder than words.

KZ_{GPT} does not predict investment quite as well as the GPT classifications. There may be some information loss in using the predicted values of the classification categories as compared to using them directly in predicting investment. $FC_{FF,GPT}$ is based on the exact same variables as the FF Index; however, when included together with FF, its coefficient has the wrong sign. This suggests that the use of quantitative information alone is not the reason for FF's superiority – it is relating such information to firm actions, not to managers' disclosures in the 10-ks. We have already discussed possible reasons for HP's poor performance in predicting investment. Based on our results, the classifications in Hadlock and Pierce (2010) are as good as those performed by ChatGPT. However, firm size may have implications for firm investment that go beyond financial constraints.

6.8 An Application: Financial Flexibility and Investment in Economic Downturns

We now illustrate an application of the FF Index. While the FF Index is constructed based on firms' capacity to *increase* investment, it is clear from the in-sample regression coefficients that higher FF is associated with healthier balance sheets (substantial cash holdings, low leverage, greater increases in cash holdings, greater reductions in leverage, higher payouts). We would expect, therefore, that the FF Index would reflect firms' ability to manage cash flow shortfalls in other situations as well. During economic downturns, firms face cash shortfalls and typically find it difficult to raise external financing (Ang and Smedema, 2011). Therefore, we would expect higher values of the FF Index also to imply smaller reductions in investment during economic downturns.[30] Finding such evidence would also be another

[30] Several papers show that firms with substantial cash holdings are able to sustain investment and (or) employment during such downturns (Campello et al. (2010), Duchin et al. (2010), Barry et al. (2022)).

means of external validation of the FF Index.

We examine three NBER recessions for the 1980–2015 period, which occurred in 1982, 1990, and 2009, and the burst of the "tech bubble" of 2001, which affected mostly technology firms (Loughran and Ritter, 2004). We follow the empirical strategy proposed in Hoberg and Maksimovic (2015) and focus on the ability of the FF index and FC indices to predict investment curtailment during bad times. The strategy is represented in the following equation:

$$I_{i,t} - I_{i,t-2} = \beta FF\ (FC)\ Indices_{t-2} + Controls_{t-2} + Industry\ fixed\ effects + \epsilon_i. \tag{3}$$

The dependent variable in this model is the change in investment between two years before a recession and the end of the recession (scaled by lagged total assets). The independent variables are measured two years before the onset of a recession and include either the FF Index or an FC Index. The ChatGPT classifications are available for the burst of the tech bubble and the 2009 recession. In addition to firm-level characteristics (i.e., firm size, age, the market-to-book ratio, and sales growth), we additionally control for industry fixed effects. The results are reported in Table IX. We find that the two-year lagged FF Index has highly significant (at the 1% level) and positive coefficients in all three NBER recessions, and a positive coefficient significant at the 5% level for the tech recession. The results obtained with the KZ Index are similar, except that it has lower t-statistics for all the NBER recessions. None of the other FC indices is consistently significant or has the correct sign in all the regressions: for the 2009 recession, only FF and KZ have significant coefficients with the right signs It may appear surprising that the HM Index is not significant in Panels C and D of Table VIII, given the significant results obtained in similar regressions in Hoberg and Maksimovic (2015). If we change the dependent variable to (changes in) CAPEX/SALES, as in their paper, we can replicate their result for the HM Index, while the FF Index remains significant. Except for the KZ index, FC measures are either insignificant or have the wrong signs for the tech bubble or financial crisis periods. These results are available on request. ChatGPT has a significant coefficient of the right sign for the tech recession, and has a marginally significant coefficient for the 2009 recession. These results suggest that while financial flexibility could help firms raise external financing (particularly debt), bridge cash-flow shortfalls, and invest more robustly during recessions, the text-based measures of financial constraints do not

Cash holdings, however, capture only one dimension of financial flexibility.

consistently predict which firms have access to internal or external financing during these times.

[Table IX about here.]

7 A Model

We now demonstrate that a key driver of the variation in the FF Index is the history of productivity shocks that affect firms' investment and financing decisions and hence their liquidity positions, even when there is no variation in the cost of external financing. In our model, productivity shocks (both idiosyncratic and common) have persistence, so that past shocks convey some information about future investment opportunities. The heterogeneity in idiosyncratic shocks implies that as firms respond to the shocks, their liquidity positions also become heterogeneous, even though they face the same external financing costs. When a major common shock occurs, because external financing is costly, the heterogeneity in internal liquidity implies that firms respond differently to this investment opportunity. Some firms are able to generate investment spikes; others are not. We calibrate this model and use model-simulated data to replicate our empirical exercise. Specifically, we create an FF Index based on the spike-cluster periods, and verify that the Index predicts spike investment in the remaining periods.

The model is adapted from Gao et al. (2021). The details pertaining to the model and the calibration are explained in Appendix C. In this model, a firm lives for infinite periods and the manager makes investment, cash-savings, and financing choices to maximize equity value. The manager's incentive is perfectly aligned with that of shareholders. External financing, including debt and equity, is costly, and cash stocks alleviate investment distortion caused by financial constraints. As mentioned, we do not consider heterogeneity in financing costs, as our main purpose is to show that, even for firms that face similar financing frictions, cross-sectional variation in internal liquidity affects their capacity to accommodate investment spikes.

Our model deviates from Gao et al. (2021) in some respects to more closely resemble the investment-spike events studied in this paper. First, our model economy experiences industry-wide productivity shocks in addition to the firm-specific shocks modeled in Gao et al. (2021). The persistence and volatility of these shocks are calibrated to match the volatility of key moments, which are reported in Panel B of Table X. Second, our non-convex adjustment cost of investment is a constant fixed cost, rather than being linear in capital, as in Gao et al. (2021). The magnitude of this cost is calibrated to match firm- and industry-level investment-spike frequencies, as reported in Panel C of Table X. Finally, fixed and linear costs of debt issuance are added to match the means and volatility of the debt-to-assets ratio. With the aforementioned exceptions, our model is identical to that in Gao et al. (2021) and we calibrate the model using their estimated parameters.

The calibrated model parameters are presented in Panel A of Table X, the model-implied key moments are presented in Panel B, and the statistics for investment spikes are presented in Panel C. All model moments are based on 100 simulated panels, each with 5,000 firms operating in the same industry and 100 years. Overall, all the key moments and dynamics of investment spikes are matched well, except that the average cash balance in the model is only half of that found in the data.

[Table X about here.]

We replicate our empirical approach and apply it to the model-simulated data. For each simulated panel, we identify firm-level investment spikes and industry-spike periods based on the methodology presented in Section 5. We then construct the balance-sheet variables used in our empirical analysis. Changes in industry and idiosyncratic productivity observed in the preproduction period are treated in the model as investment opportunity proxies. To account for industry heterogeneity, each simulated panel contains 138 industries and 100 years. The number of firms in each industry is identical to the number in the real data. Next, we conduct logit regressions based on the industry-spike sample to construct the FF index and then test its external validity with the non-industry-spike sample. We repeat these procedures 100 times and calculate the average coefficients and significance. The regression results are reported in Table XI.

[Table XI about here.]

Column (1) presents the in-sample logit estimates based on the simulated industry-spike samples, including the same balance-sheet variables, and industry-wide and firm-level productivity shocks as proxies for investment opportunities. The signs of the coefficients of the balance-sheet variables are identical to those in the results reported in Table III, except for firm size, and are highly significant. Since the financing cost does not depend on the size of the firm in this model, we do not expect size to play the same role in the FF Index as it is in the data. In addition, the fixed equity and debt issuance costs are modeled as linear in firm size, so that larger firms have little cost advantage in raising external funds over small firms as they do in the data. We then construct the FF Index as a linear projection based on the coefficients in columns (1) and convert the projected values to scaled rank measures. External validations of FF indices are reported in the remaining two columns. Columns (2) and (3) indicate the strong predictive ability of the FF Index for future investment spikes and the investment ratio, which are in line with the empirical evidence in Table IV. In summary, these results provide strong justification for our empirical approach.

8 Conclusion

In this paper, we examine whether the capacity of firms to respond to major investment opportunities in the industry is related to firm-specific variables that reflect their internal liquidity and external financing frictions. Our results show that this is indeed the case, which allows us to create an index of financial flexibility, which we call the FF Index. We show that the FF Index predicts major investments (investment spikes) out-of-sample, as well as other regular investment such as capital expenditure, cash acquisitions, and R&D investment. We run horse races between the FF Index, which infers financial flexibility based on firms' actions, and the FC indices, which are typically based on textual analysis of firms' 10-K filings. Since some of these textual measures were constructed based on 10-K filings from earlier periods, we use ChatGPT to construct updated versions of these measures. The FF Index outperforms all the text-based indices (both the earlier and the updated ChatGPT-based vintages), suggesting that "actions speak louder than words" when it comes to inferring financial flexibility. We show that the FF Index has desirable time-series properties around investment spikes. The FF Index also accurately predicts whether firms are able to sustain investment during economic downturns.

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Table I: **Summary Statistics**

This table presents the summary statistics for the empirical sample. In Panel A we report the aggregate numbers and frequencies of firm and industry investment spikes. The methodologies for identifying investment spikes are specified in Section 5. In Panel B we report the time-series pattern of investment around investment-spike years $\tau = 0$ and non-spike years. The number is scaled by the base-level investment. In Panel C we report the distribution of firm investment spike (industry-spike) frequencies and the time gap between consecutive spike (industry-spike). We also show the spike-firm proportion for industries conditional on the occurrence of an industry-spike. In Panel D we report summary statistics for firm-level characteristics around investment-spike years and non-spike years. $^{\#}$ (*) indicates that the change in a characteristic from $\tau = -1$ to $\tau = 0$ is significantly higher (lower) than zero at the 1% level. † indicates that changes are significantly different between the investment-spike and non-spike samples at the 1% level.

Panel A: Investment Spike Identification

	Firm-level	Industry-level
Number of firms/industries	18,595	138
Number of investment spike observations	25,486	962
Number of observations	194,061	6,192
Investment spike proportion	13.13%	15.53%

Panel B: Time series pattern of investment

		$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$
Investment spike at $\tau = 0$	Mean	0.927	1.043	3.406	1.098	0.983
	Median	0.820	0.973	2.771	1.050	0.932
No investment spike $\tau = -2 : +2$	Mean	1.052	0.953	0.924	0.974	1.075
	Median	0.854	0.841	0.820	0.917	0.976

Panel C: Investment spike frequency

		Mean	SD	P10	P25	P50	P75	P90
Firm-level	Spike year proportion	13.77%	16.37%	0.00%	0.00%	11.76%	20.00%	28.57%
	Time gap between two spikes	6.05	3.62	3.00	3.00	5.00	7.00	11.00
Industry-level	Spike year proportion	15.55%	5.84%	8.22%	13.33%	15.56%	20.00%	22.22%
	Time gap between two spikes	5.71	4.18	1.00	3.00	5.00	7.00	10.00
	Spike firm proportion – industry spike	28.57%	10.55%	18.18%	21.43%	26.67%	33.33%	40.00%
	Spike firm proportion – non-industry spike	10.42%	7.46%	0.00%	5.26%	10.34%	15.00%	20.00%

Panel D: Variables around investment spike

	Investment spike at $\tau = 0$					No investment spike at $\tau = 0$ (and $\tau = -2 : +2$)				
	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Total Asset$_{\tau=0}$	1522$^{\#\dagger}$	4203	30	142	761	1175$^{\#}$	3686	16	89	487
Total Asset$_{\tau=-1}$	1309	3822	23	110	600	1130	3548	16	83	457
Cash holding$_{\tau=0}$	0.156*†	0.201	0.023	0.071	0.205	0.180$^{\#}$	0.226	0.024	0.081	0.236
Cash holding$_{\tau=-1}$	0.209	0.233	0.034	0.113	0.308	0.178	0.225	0.024	0.080	0.236
Avg cash holding$_{\tau=-4:-2}$	0.180	0.203	0.035	0.097	0.253	0.173	0.204	0.032	0.087	0.237
Book leverage$_{\tau=0}$	0.271$^{\#\dagger}$	0.292	0.060	0.230	0.389	0.299$^{\#}$	0.394	0.040	0.216	0.400
Book leverage$_{\tau=-1}$	0.225	0.277	0.019	0.165	0.326	0.287	0.346	0.040	0.216	0.398
Avg book leverage$_{\tau=-4:-2}$	0.251	0.255	0.056	0.200	0.359	0.277	0.271	0.068	0.227	0.396
Market-to-book$_{\tau=0}$	1.682*†	2.438	0.685	1.024	1.741	1.930$^{\#}$	3.489	0.626	0.983	1.793
Market-to-book$_{\tau=-1}$	1.991	2.968	0.712	1.155	2.074	1.900	3.464	0.615	0.969	1.770
Payout$_{\tau=0}$	0.020*	0.037	0.000	0.001	0.024	0.016	0.034	0.000	0.000	0.017
Payout$_{\tau=-1}$	0.021	0.040	0.000	0.000	0.025	0.016	0.035	0.000	0.000	0.016
Tangibility$_{\tau=0}$	0.315$^{\#\dagger}$	0.247	0.112	0.250	0.463	0.317*	0.261	0.098	0.247	0.487
Tangibility$_{\tau=-1}$	0.284	0.238	0.089	0.217	0.417	0.321	0.261	0.103	0.251	0.491

Table II: **Investment Opportunities around Industry Spikes**

In this table we report estimates of OLS regressions of investment opportunity variables on an industry-investment-spike dummy variable for time t. The sample for Panels A and B is at the industry-year level, while that in Panel C is at the firm-year level. The sample period runs from 1970 through 2019. For Panels A, B, and C, the dependent variables are the industry median market-to-book ratio, the industry size-weighted market-to-book ratio, and the firm-level market-to-book ratio, respectively. All dependent variables are standardized by subtracting the means and dividing by the standard deviations. In each panel, in columns (1)–(6), we report the results based on the dependent variables in a particular year relative to year t in the range $\tau = t-3 : t+2$. We include industry (firm) and year fixed effects for the industry-year (firm-year) tests. Standard errors are double-clustered at the industry-year level for Panels A and B and at the firm-year level for Panel C. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Industry median market-to-book

	(1) $t-3$	(2) $t-2$	(3) $t-1$	(4) t	(5) $t+1$	(6) $t+2$
Industry spike dummy$_t$	-0.031	0.036	0.119***	0.026	-0.036	-0.017
	(-0.672)	(0.746)	(3.219)	(0.892)	(-1.236)	(-0.738)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	6,192	6,192	6,192	6,192	6,054	5,916
Adj R^2	0.459	0.459	0.488	0.546	0.574	0.562

Panel B: Industry size-weighted market-to-book

	(1) $t-3$	(2) $t-2$	(3) $t-1$	(4) t	(5) $t+1$	(6) $t+2$
Industry spike dummy$_t$	-0.085***	-0.007	0.062**	0.001	-0.048**	-0.020
	(-3.177)	(-0.271)	(2.032)	(0.040)	(-2.349)	(-0.953)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	6,192	6,192	6,192	6,192	6,054	5,916
Adj R^2	0.487	0.495	0.518	0.528	0.536	0.532

Panel C: Firm-level market-to-book

	(1) $t-3$	(2) $t-2$	(3) $t-1$	(4) t	(5) $t+1$	(6) $t+2$
Industry spike dummy$_t$	-0.014***	0.004	0.060**	0.005	-0.018**	-0.018**
	(-2.877)	(0.406)	(2.358)	(0.708)	(-2.046)	(-2.146)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	207,283	223,775	224,560	224,274	204,952	184,877
Adj R^2	0.536	0.528	0.537	0.553	0.565	0.569

Table III: **Explaining Firm Investment Spikes in Industry-Spike Sample**

This table reports the logit regressions estimation of in-sample tests based on the industry-spike sample. The definition of industry-spike year is in Section 5. The dependent variable equals one if a firm experiences an investment spike at $\tau = 0$ and zero otherwise. In columns (1) - (3), we report estimates of baseline specification for different sample periods, in which we include balance sheet variables and control variables that reflect investment opportunities (i.e., Market-to-book, Cash flow, and Sales growth). The sample period runs from 1970 through 2019. We add three-digit sic industry and year fixed effects for each specification. Standard errors are clustered at the industry-year level. z-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Logit regression, dependent variable: Investment spike dummy			
	(1)	(2)	(3)
Sample period:	1970-2019	1970-1995	1996-2019
Chg cash holding$_{\tau=-1}$	1.924***	2.058***	1.920***
	(9.975)	(5.781)	(8.011)
Avg cash holding$_{\tau=-4:-2}$	0.257*	0.409*	0.264
	(1.666)	(1.663)	(1.284)
Chg book leverage$_{\tau=-1}$	-1.186***	-1.618***	-0.935***
	(-8.031)	(-6.059)	(-5.758)
Avg book leverage$_{\tau=-4:-2}$	-0.411***	-0.557***	-0.291**
	(-4.286)	(-3.279)	(-2.522)
Size$_{\tau=-1}$	0.030***	0.012	0.045***
	(2.707)	(0.801)	(2.705)
Payout$_{\tau=-1}$	2.419***	3.284***	2.125***
	(5.548)	(3.331)	(4.259)
Market-to-book$_{\tau=-1}$	0.017**	0.019	0.017**
	(2.522)	(0.698)	(2.537)
Cash flow$_{\tau=-1}$	0.001	0.019	0.000
	(0.505)	(0.821)	(0.243)
Sales growth$_{\tau=-1}$	0.116***	0.080	0.123***
	(3.317)	(1.174)	(3.152)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Nobs	18,911	9,322	9,589
Pseudo R^2	0.025	0.025	0.031

Table IV: **External Validation**

In this table, we report the external validity of the Financial Flexibility (FF) index. The FF Index is the linear projected value of the first six variables in column (1) of Table III. The first set of out-of-sample tests examines the FF Index's predictability for firms' investment behaviors in non-industry-spike years. The dependent variables include the investment spike dummy, investment (or capital expenditure/ acquisitions only) scaled by the beginning of year total asset, R&D scaled by sales, and investment growth. The sample period runs from 1970 through 2019. Panel A shows that the FF works for all investment measures and has better explanatory power than investment opportunity proxies. We then demonstrate the validity of our framework in non-overlapping sample tests to mitigate the forward-looking concern for investment spike definition. We use all industry-spike period observations before the cutoff year to construct the subsample-based FF index and then show its predictability in subsequent years. Panel B presents the results across different cutoff years. The upper subpanel reports the in-sample estimation, and the lower two subpanels report the out-of-sample regression result in the remaining industry-spike and non-industry-spike samples. We include industry (firm) and year fixed effects for all tests in Panels A and B. Standard errors are clustered at the industry-year level for logit models and double clusters at the firm and year level for OLS models. $z(t)$-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Non-industry-spike sample validity

	Logit regression, dependent variable: Investment spike dummy				
	(1)	(2)	(3)	(4)	(5)
Rank(FF)$_{\tau=-1}$	1.054***			1.070***	1.060***
	(38.453)			(38.590)	(37.015)
Market-to-book$_{\tau=-1}$		0.025***		0.024***	
		(7.084)		(7.091)	
Cash flow$_{\tau=-1}$		0.002***		0.001*	
		(2.675)		(1.888)	
Sales growth$_{\tau=-1}$		0.096***		0.110***	
		(7.055)		(7.918)	
Rank(IO Index)$_{\tau=-1}$			0.258***		0.056*
			(8.830)		(1.849)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Nobs	171,575	160,605	160,539	160,605	160,539
Pseudo R^2	0.023	0.012	0.012	0.025	0.023

	OLS regression				
	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Investment	CAPEX	Acquisitions	R&D	Investment growth
Rank(FF)$_{\tau=-1}$	0.051***	0.024***	0.019***	0.070***	1.234***
	(23.551)	(14.094)	(12.857)	(5.914)	(56.445)
Market-to-book$_{\tau=-1}$	0.008***	0.006***	0.001***	0.008**	0.081***
	(13.042)	(12.528)	(9.410)	(2.353)	(17.609)
Cashflow$_{\tau=-1}$	0.000***	0.000	0.000***	-0.005***	-0.001
	(3.123)	(0.965)	(4.311)	(-4.442)	(-1.208)
Sales growth$_{\tau=-1}$	0.017***	0.013***	0.003***	-0.043***	0.108***
	(8.998)	(8.696)	(6.109)	(-5.254)	(9.517)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Nobs	185,815	185,815	185,815	184,151	169,575
Adj R^2	0.251	0.400	0.140	0.686	0.121

Table IV: External Validation (Continued)

Panel B: Subperiod verification

Logit regression, dependent variable: Investment spike dummy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cutoff year:	1985	1990	1995	2000	2005	2010	2015
	Industry-spike sample before cutoff year						
Chg cash holding$_{\tau=-1}$	1.774***	2.140***	2.058***	1.829***	1.866***	1.939***	1.889***
	(3.257)	(5.055)	(5.781)	(7.529)	(8.406)	(9.461)	(9.632)
Avg cash holding$_{\tau=-4:-2}$	-0.182	0.133	0.409*	0.497***	0.392**	0.379**	0.237
	(-0.437)	(0.423)	(1.663)	(2.864)	(2.312)	(2.381)	(1.508)
Chg book leverage$_{\tau=-1}$	-1.879***	-1.656***	-1.618***	-1.298***	-1.253***	-1.266***	-1.230***
	(-4.130)	(-5.255)	(-6.059)	(-6.209)	(-6.958)	(-7.400)	(-8.079)
Avg book leverage$_{\tau=-4:-2}$	-0.646***	-0.707***	-0.557***	-0.385***	-0.417***	-0.436***	-0.425***
	(-2.743)	(-3.433)	(-3.279)	(-2.906)	(-3.589)	(-3.996)	(-4.321)
Size$_{\tau=-1}$	0.012	0.024	0.012	0.020	0.018	0.020*	0.028**
	(0.574)	(1.365)	(0.801)	(1.332)	(1.315)	(1.651)	(2.473)
Payout$_{\tau=-1}$	3.379**	2.500**	3.284***	2.952***	3.030***	2.545***	2.327***
	(2.423)	(2.162)	(3.331)	(4.869)	(5.366)	(5.206)	(5.202)
Market-to-book$_{\tau=-1}$	0.027	0.025	0.019	0.024***	0.017**	0.013	0.015*
	(0.773)	(0.792)	(0.698)	(3.375)	(2.105)	(1.474)	(1.947)
Cashflow$_{\tau=-1}$	0.106	0.057	0.019	-0.005	0.003	0.004	0.000
	(1.619)	(1.352)	(0.821)	(-0.879)	(0.486)	(0.864)	(0.128)
Sales growth$_{\tau=-1}$	0.173	0.075	0.080	0.119***	0.130***	0.115***	0.119***
	(1.576)	(0.936)	(1.174)	(3.610)	(3.771)	(3.138)	(3.506)
Nobs	5,758	7,262	9,322	12,717	14,727	16,228	18,449
Pseudo R^2	0.027	0.026	0.025	0.025	0.024	0.025	0.024
	Industry-spike sample after cutoff year						
Rank(FF$_{sub}$)$_{\tau=-1}$	1.191***	1.192***	1.188***	1.219***	1.154***	1.100***	1.487***
	(15.942)	(14.048)	(12.623)	(9.670)	(7.931)	(6.422)	(3.543)
Market-to-book$_{\tau=-1}$	0.014	0.013	0.011	-0.013	0.001	0.018	0.085*
	(1.558)	(1.493)	(1.114)	(-1.135)	(0.055)	(1.504)	(1.954)
Cashflow$_{\tau=-1}$	0.001	0.001	0.001	0.000	0.000	0.001	0.012**
	(0.497)	(0.557)	(0.638)	(0.131)	(0.108)	(0.496)	(2.086)
Sales growth$_{\tau=-1}$	0.127***	0.133***	0.128***	0.043	0.013	0.120	-0.412
	(3.000)	(3.204)	(2.914)	(0.613)	(0.163)	(1.145)	(-1.570)
Nobs	13,153	11,649	9,589	6,191	4,182	2,682	462
Pseudo R^2	0.029	0.030	0.031	0.034	0.035	0.042	0.094
	Non-industry-spike sample after cutoff year						
Rank(FF$_{sub}$)$_{\tau=-1}$	1.080***	1.128***	1.125***	1.045***	1.094***	1.096***	1.015***
	(33.834)	(32.058)	(28.361)	(23.075)	(19.672)	(14.407)	(5.746)
Market-to-book$_{\tau=-1}$	0.025***	0.024***	0.022***	0.018***	0.015***	0.010	0.004
	(7.062)	(6.915)	(6.042)	(4.577)	(2.989)	(1.577)	(0.349)
Cashflow$_{\tau=-1}$	0.001*	0.001	0.001*	0.001	0.000	0.000	0.000
	(1.657)	(1.629)	(1.785)	(1.412)	(0.405)	(0.573)	(0.325)
Sales growth$_{\tau=-1}$	0.098***	0.091***	0.076***	0.076***	0.086***	0.070*	0.096
	(6.838)	(6.061)	(4.945)	(3.991)	(3.139)	(1.792)	(1.523)
Nobs	122,338	104,471	84,764	63,129	41,318	22,468	5,910
Pseudo R^2	0.025	0.027	0.028	0.032	0.032	0.024	0.035

Table V: **Distribution and Time Series Pattern of the FF Index**

In this table, we report the distribution and time series pattern of the FF Index for industry-spike and non-industry-spike samples, respectively. The upper half of each subpanel reports the distribution of raw FF for spike and non-spike firms, or both. The lower half of each subpanel reports the time series pattern of the average FF Index or ranked one from $\tau = -3$ to $\tau = 2$, conditional on firms' investment behavior at $\tau = 0$.

Industry-spike Sample								
		Mean	SD	P10	P25	P50	P75	P90
FF	All firms	0.162	0.309	-0.174	-0.002	0.155	0.318	0.512
	Spike firms	0.228	0.308	-0.093	0.056	0.208	0.377	0.591
	Nonspike firms	0.138	0.307	-0.197	-0.023	0.136	0.297	0.483
		$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Avg FF	All firms	0.135	0.142	0.162	0.122	0.099	0.118	0.141
	Spike firms	0.148	0.173	0.228	0.078	0.072	0.125	0.166
	Nonspike firms	0.130	0.131	0.138	0.138	0.109	0.116	0.132
Avg Rank(FF)	All firms	0.523	0.529	0.537	0.507	0.494	0.508	0.527
	Spike firms	0.534	0.559	0.596	0.456	0.464	0.516	0.550
	Nonspike firms	0.519	0.518	0.518	0.526	0.505	0.506	0.518
Non-industry-spike Sample								
	Sample	Mean	SD	P10	P25	P50	P75	P90
FF	All firms	0.122	0.349	-0.260	-0.054	0.127	0.308	0.518
	Spike firms	0.211	0.351	-0.163	0.026	0.202	0.397	0.631
	Nonspike firms	0.111	0.347	-0.270	-0.063	0.118	0.296	0.500
	Sample	$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Avg FF	All	0.135	0.130	0.122	0.117	0.110	0.113	0.118
	Spike firms	0.143	0.167	0.211	0.048	0.050	0.102	0.143
	Nonspike firms	0.134	0.125	0.111	0.126	0.118	0.114	0.115
Avg Rank(FF)	All firms	0.520	0.515	0.509	0.505	0.501	0.504	0.509
	Spike firms	0.528	0.551	0.583	0.435	0.445	0.496	0.531
	Nonspike firms	0.519	0.510	0.499	0.515	0.509	0.505	0.506

Table VI: **Robustness Checks**

In this table, we demonstrate the robustness and flexibility of our methodology. In the first set of robustness checks, we apply alternative industry classifications, criteria for industry- and firm-level investment spikes, and investment measures to construct alternative FF Indices and then check the external validity. Details for those alternative settings can be found in Section 6.5. Panel A reports the in-sample and out-of-sample logit estimates for each alternative setting. The second set of robustness tests checks parameter consistency. For each twenty-consecutive-year industry-spike sample, we estimate a logit model to construct a subsample FF Index and then test its validity in all the remaining samples. Panel B reports the coefficient and z-statistics distribution of each component in subsample FF indices, as well as the corresponding out-of-sample performance. For all the tests in Panels A and B, we include investment opportunity proxies and industry and year fixed effects. Standard errors are clustered at the industry-year level. z-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Alternative specifications

Logit regression, dependent variable: Investment spike dummy					
Alternative settings to identify spike	(1) *Industry classification*	(2) *Industry spike filter*	(3) *Firm spike filter*	(4) *Investment ratio spike*	(5) *CAPEX spike*
	Industry-spike sample				
Chg cash holding$_{\tau=-1}$	1.641***	2.007***	2.468***	1.390***	0.877***
	(5.042)	(10.000)	(8.832)	(5.723)	(4.556)
Avg cash holding$_{\tau=-4:-2}$	0.109	0.240	0.245	0.071	0.189
	(0.380)	(1.272)	(1.264)	(0.419)	(0.955)
Chg book leverage$_{\tau=-1}$	-0.938***	-1.386***	-1.998***	-1.510***	-1.117***
	(-5.163)	(-8.215)	(-10.835)	(-6.934)	(-6.867)
Avg book leverage$_{\tau=-4:-2}$	-0.303**	-0.393***	-0.113	-0.504***	-0.340***
	(-2.191)	(-3.616)	(-1.131)	(-4.607)	(-2.972)
Size$_{\tau=-1}$	0.022	0.027**	-0.149***	-0.005	0.017
	(1.266)	(2.098)	(-14.272)	(-0.496)	(1.494)
Payout$_{\tau=-1}$	2.095***	2.065***	-0.736	2.294***	0.048
	(2.640)	(4.353)	(-1.121)	(4.286)	(0.093)
Nobs	7,588	15,086	14,915	16,387	17,807
Pseudo R^2	0.019	0.026	0.053	0.023	0.026
	Non-industry-spike sample				
Rank(FF)$_{\tau=-1}$	1.104***	1.094***	1.509***	1.068***	0.695***
	(41.104)	(40.102)	(50.800)	(34.881)	(21.778)
Nobs	176,141	164,364	189,870	150,172	153,285
Pseudo R^2	0.025	0.025	0.058	0.024	0.026

Panel B: Parameter consistency

		Regression coefficients					z-statistics				
	Variables	Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Subsample FF Indices	Chg cash holding	1.978	0.113	1.899	1.932	2.085	6.976	1.207	5.820	7.521	7.771
	Avg cash holding	0.393	0.142	0.242	0.429	0.491	1.935	0.925	1.057	1.824	2.627
	Chg book leverage	-1.191	0.229	-1.355	-1.084	-1.031	-5.319	0.312	-5.586	-5.365	-5.033
	Avg book leverage	-0.378	0.164	-0.518	-0.301	-0.258	-2.429	0.583	-2.907	-2.431	-2.055
	Size	0.023	0.012	0.015	0.021	0.029	1.291	0.646	0.969	1.211	1.612
	Payout	2.709	0.459	2.402	2.755	2.936	3.936	1.020	3.050	4.350	4.537
	Pseudo R^2	0.029	0.003	0.026	0.029	0.031					
OOS verification	Rank(FF)	1.077	0.027	1.055	1.076	1.103	40.422	0.478	40.048	40.480	40.761
	Pseudo R^2	0.025	0.002	0.024	0.024	0.027					

Table VII: **“Horse Races” with Financial Constraint Measures**

In this table we report the results of “horse races” between the Financial Flexibility (FF) Index and financial constraint (FC) measures. FC measures include four text-based indices (i.e., KZ, HP, HM, and BLM) and the WW index estimated from a structural model. We use the rank value of indices to ensure that all indices are comparable. Panel A reports Spearman’s rank correlations between the FF Index and FC measures, as well as conditional average rank(FF) and each FF component for financially constrained (top FC quintile) and unconstrained firms (bottom FC quintile). Panel B shows the time series pattern of average rank(FC) around investment spike. Panel C presents the predictability of investment behavior across FF and FC measures in the non-industry-spike sample. In subpanel (a), we report logit estimates for the investment spike dummy, including FC measures only and with FF together. In subpanel (b), we apply the same strategies and report OLS estimates for different investment variables. The dependent variable definitions are the same as in Table IV. We control the investment opportunity variables and add fixed effects for all specifications. Standard errors are clustered at the industry-year level for logit models and double clusters at the firm and year level for OLS models. $z(t)$ -statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: FF variables for “constrained” and “unconstrained” firms

	KZ		HP		HM		BLM		WW	
Spearman rank corr	-0.492		-0.214		-0.039		-0.003		-0.202	
	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom	Top
Rank(FF)	0.246	0.683	0.392	0.598	0.491	0.515	0.468	0.511	0.423	0.613
Chg cash holding	0.036	-0.028	0.000	-0.002	0.001	-0.001	0.003	-0.001	-0.003	-0.001
Avg cash holding	0.310	0.143	0.096	0.256	0.175	0.331	0.240	0.177	0.096	0.242
Chg book leverage	-0.022	0.076	0.005	0.020	0.006	0.014	0.014	0.014	0.004	0.021
Avg book leverage	0.168	0.459	0.262	0.320	0.234	0.284	0.277	0.309	0.276	0.290
Size	4.346	3.553	7.255	1.203	5.028	4.166	3.700	5.565	7.631	2.583
Payout	0.034	0.004	0.031	0.005	0.025	0.013	0.023	0.018	0.033	0.008

Panel B: FC measures around investment spike

	$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Rank(KZ)	0.468	0.457	0.430	0.467	0.520	0.502	0.487
Rank(HP)	0.480	0.493	0.468	0.436	0.431	0.419	0.403
Rank(HM)	0.491	0.493	0.491	0.487	0.485	0.475	0.467
Rank(BLM)	0.494	0.492	0.500	0.503	0.501	0.506	0.505
Rank(WW)	0.471	0.478	0.479	0.461	0.475	0.474	0.460

Table VI: "Horse Races" with Financial Constraints Measures (Continued)

Panel C: Does the FF Index outperform FC Measures in firms' investment prediction?

FC measures	KZ		HP		HM		BLM		WW	
	(a) Logit regression, dependent variable: Investment spike dummy									
Rank(FC)$_{\tau=-1}$	-0.850***	-0.350***	-0.033	0.228***	-0.088	-0.080	0.046	0.127***	-0.118***	0.191***
	(-27.973)	(-9.585)	(-0.988)	(6.727)	(-1.451)	(-1.350)	(0.994)	(2.703)	(-3.214)	(5.156)
Rank(FF)$_{\tau=-1}$		0.891***		1.110***		1.243***		1.186***		1.091***
		(26.715)		(40.084)		(22.410)		(25.847)		(39.314)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	155,819	155,819	160,539	160,539	44,183	44,183	58,737	58,737	160,539	160,539
Pseudo R^2	0.019	0.025	0.012	0.025	0.017	0.033	0.015	0.030	0.012	0.025
	(b) OLS regression									
	Dependent variable: Investment									
Rank(FC)$_{\tau=-1}$	-0.056***	-0.034***	0.122***	0.126***	-0.004	-0.003	-0.007***	-0.004*	0.028***	0.034***
	(-18.662)	(-11.625)	(9.126)	(9.653)	(-1.048)	(-0.934)	(-3.125)	(-1.736)	(6.530)	(7.600)
Rank(FF)$_{\tau=-1}$		0.039***		0.052***		0.059***		0.057***		0.052***
		(17.278)		(25.571)		(12.358)		(12.354)		(23.632)
	Dependent variable: CAPEX									
Rank(FC)$_{\tau=-1}$	-0.027***	-0.017***	0.085***	0.086***	0.000	0.001	-0.005***	-0.004**	0.021***	0.024***
	(-10.384)	(-7.692)	(10.318)	(10.807)	(0.250)	(0.338)	(-3.409)	(-2.667)	(6.494)	(7.311)
Rank(FF)$_{\tau=-1}$		0.017***		0.025***		0.016***		0.017***		0.025***
		(14.022)		(15.457)		(8.881)		(9.184)		(14.537)
	Dependent variable: Acquisition									
Rank(FC)$_{\tau=-1}$	-0.021***	-0.013***	0.011***	0.012***	-0.004*	-0.004*	-0.002	0.000	0.002	0.004**
	(-14.098)	(-9.514)	(2.715)	(3.033)	(-2.091)	(-2.005)	(-1.192)	(0.020)	(1.235)	(2.493)
Rank(FF)$_{\tau=-1}$		0.015***		0.020***		0.031***		0.029***		0.019***
		(9.644)		(12.871)		(12.460)		(12.771)		(12.967)
	Dependent variable: R&D									
Rank(FC)$_{\tau=-1}$	-0.067***	-0.032**	-0.053	-0.048	0.059***	0.060***	-0.003	0.004	0.010	0.017
	(-4.299)	(-2.214)	(-1.343)	(-1.234)	(2.940)	(3.007)	(-0.175)	(0.288)	(0.878)	(1.504)
Rank(FF)$_{\tau=-1}$		0.060***		0.070***		0.137***		0.123***		0.070***
		(5.314)		(5.956)		(6.710)		(6.584)		(5.972)
	Dependent variable: Investment growth									
Rank(FC)$_{\tau=-1}$	-1.112***	-0.495***	1.311***	1.404***	-0.032	-0.028	-0.088***	-0.008	0.163***	0.287***
	(-40.620)	(-14.146)	(14.329)	(17.871)	(-0.799)	(-0.762)	(-3.123)	(-0.325)	(4.580)	(7.980)
Rank(FF)$_{\tau=-1}$		1.041***		1.247***		1.443***		1.419***		1.229***
		(37.673)		(57.321)		(35.490)		(40.196)		(59.345)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	155,819	155,819	160,539	160,539	44,183	44,183	58,737	58,737	160,539	160,539

Table VIII: **Measures based on ChatGPT's Classification**

In this table, we argue the indices generated from management's statement may be less reliable to measure the firm's current status. We follow the classification strategy in Kaplan and Zingales (1997) and use Generative AI to overcome the subjective classification and sample selection issue in the existing literature. The implementation details and more information about ChatGPT's practice are in Appendix B. In panel A, we compare ChatGPT's classification with that in Kaplan and Zingales (1997) and Hadlock and Pierce (2010). Panel B reports ordered logit estimation using the ChatGPT classification, with independent variables used in KZ, HP, and FF indices, respectively. We follow the practice in Lamont et al. (2001), transfer the answers for Q2 from NFC-FC to numerical value 0-4, and add industry and year fixed effects for each regression. The Spearman's rank correlations between each ChatGPT-based FC measure and the original one are reported as well. Panel C presents the predictability of the FF index, ChatGPT classification, and ChatGPT-based FC measures for firms' investment behaviors in the non-industry-spike ChatGPT sample. The dependent variable definitions are the same as in Table IV. For all specifications in Panel C, we control the investment opportunities variables and fixed effect, as well as a dummy variable indicating whether a significant investment increase is expected in ChatGPT's analysis (equals to one if the answer for Q4 is yes and zero otherwise). Standard errors are clustered at the industry-year level for logit models and double clusters at the firm and year level for OLS models. $z(t)$ -statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Classification comparison							
	NFC	LNFC	PFC	LFC	FC	LFC+FC	Nobs
KZ	54.50%	30.90%	7.30%	4.80%	2.60%	7.40%	735
HP	10.28%	50.49%	32.36%	0.32%	6.55%	6.87%	1,848
GPT	0.53%	62.80%	31.05%	5.06%	0.57%	5.63%	65,594

Panel B: Re-estimate FC measures using ChatGPT's classification								
	Cashflow	Q	Leverage	Dividend	Cash		Pesudo-R^2	Corr KZ
KZ_{GPT}	-0.011***	0.066***	0.514***	0.019	-0.007***		0.061	0.513
	(-9.48)	(20.23)	(14.13)	(0.55)	(-7.86)			
	Size	Size^2	Age				Pesudo-R^2	Corr HP
HP_{GPT}	-0.737***	0.041***	-0.007***				0.117	0.913
	(-45.36)	(24.49)	(-7.76)					
	Chg cash	Avg Cash	Chg Lev	Avg Lev	Size	Payout	Pesudo-R^2	Corr FF
$FC_{FF,GPT}$	-0.896***	-0.262***	0.611***	0.897***	-0.330***	-4.380***	0.128	-0.395
	(-12.45)	(-4.24)	(12.91)	(24.61)	(-58.47)	(-16.27)		

Table VIII: Measures based on ChatGPT's Classification (Continued)

Panel C: Predicting Firms' Investment

FC Measures		ChatGPT classification		KZ_{GPT}		HP_{GPT}		$FC_{FF,GPT}$	
	(a) Logit regression, dependent variable: Investment spike dummy								
$Rank(FC)_{\tau=-1}$		-0.200***	-0.086***	-0.564***	-0.102	-0.082	0.134*	-0.442***	0.213***
		(-6.898)	(-2.837)	(-7.769)	(-1.335)	(-1.202)	(1.883)	(-7.304)	(2.880)
$Rank(FF)_{\tau=-1}$	1.219***		1.190***		1.194***		1.236***		1.314***
	(20.727)		(19.610)		(19.454)		(20.418)		(18.419)
Excepted	0.105	0.133*	0.101	0.136*	0.103	0.142**	0.110	0.121*	0.113
	(1.502)	(1.919)	(1.447)	(1.909)	(1.438)	(2.033)	(1.577)	(1.731)	(1.611)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	37,431	37,446	37,431	35,758	35,745	37,446	37,431	37,431	37,431
Pseudo R^2	0.036	0.022	0.036	0.022	0.036	0.020	0.036	0.022	0.036
	(b) OLS regression								
	Dependent variable: Investment								
$Rank(FC)_{\tau=-1}$		-0.009***	-0.006***	-0.054***	-0.027***	0.140***	0.136***	-0.036***	0.046***
		(-8.207)	(-5.487)	(-8.103)	(-4.514)	(7.342)	(7.415)	(-3.938)	(3.829)
$Rank(FF)_{\tau=-1}$	0.061***		0.059***		0.054***		0.060***		0.072***
	(13.491)		(13.097)		(12.011)		(14.015)		(11.620)
	Dependent variable: CAPEX								
$Rank(FC)_{\tau=-1}$		-0.005***	-0.005***	-0.007***	0.002	0.068***	0.068***	0.003	0.029***
		(-7.851)	(-7.152)	(-3.008)	(0.735)	(8.805)	(8.729)	(0.560)	(4.680)
$Rank(FF)_{\tau=-1}$	0.016***		0.015***		0.016***		0.015***		0.023***
	(9.383)		(9.114)		(8.563)		(9.569)		(9.001)
	Dependent variable: Acquisition								
$Rank(FC)_{\tau=-1}$		-0.003***	-0.001**	-0.035***	-0.022***	0.037***	0.035***	-0.034***	0.005
		(-5.014)	(-2.316)	(-8.983)	(-6.294)	(3.736)	(3.706)	(-6.720)	(0.876)
$Rank(FF)_{\tau=-1}$	0.033***		0.033***		0.027***		0.033***		0.034***
	(12.341)		(12.085)		(10.356)		(12.597)		(9.916)
	Dependent variable: R&D								
$Rank(FC)_{\tau=-1}$		0.010	0.016	-0.023	0.045	0.012	0.005	-0.193***	-0.091
		(0.960)	(1.565)	(-0.846)	(1.369)	(0.128)	(0.058)	(-3.501)	(-1.398)
$Rank(FF)_{\tau=-1}$	0.112***		0.116***		0.130***		0.112***		0.089***
	(4.934)		(5.103)		(4.653)		(4.945)		(3.225)
	Dependent variable: Investment growth								
$Rank(FC)_{\tau=-1}$		-0.143***	-0.072***	-1.091***	-0.324***	1.818***	1.750***	-0.841***	1.197***
		(-9.245)	(-4.737)	(-13.100)	(-4.642)	(13.276)	(14.349)	(-10.754)	(16.097)
$Rank(FF)_{\tau=-1}$	1.472***		1.458***		1.381***		1.464***		1.781***
	(31.399)		(30.388)		(29.986)		(32.181)		(34.393)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	43,330	43,347	43,330	41,424	41,410	43,347	43,330	43,330	40,531

Table IX: **Investment Curtailment during Recessions**

This table reports the performance of the FF Index in explaining investment curtailment during recessions. We investigate four recession periods as defined by the NBER. The dependent variables are the change in firms' investment in a two-year period before and after the recession. The beginning and end years for each recession are in parentheses. The independent variables include the FF Index, FC Indices, and firm-level characteristics (i.e., size, log age, the market-to-book ratio, and sales growth) before the recessions. To represent the burst of the technology bubble (the "dot-com bubble"), the sample comprises all firms in the technology sector (as defined by Loughran and Ritter (2004)). For other recessions, the sample includes all firms. We add industry fixed effects to capture industry heterogeneity. Standard errors are clustered at the industry level. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

OLS regression, dependent variable: $(I_t - I_{t-2})/TA_{t-2}$								
Measures	FF	KZ	HP	WW	FF	KZ	HP	WW
	The Great Inflation (1981-1983)				Early 1990s Recession (1990-1992)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rank(Measure)$_{\tau=-2}$	0.107***	-0.047***	0.029	0.037	0.081***	-0.035***	0.000	-0.031
	(10.606)	(-4.451)	(0.976)	(1.403)	(11.765)	(-6.166)	(0.015)	(-1.412)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	3,674	3,582	3,675	3,669	4,350	4,205	4,354	4,345
Adj R^2	0.125	0.098	0.089	0.089	0.069	0.035	0.031	0.032

	Tech Bubble (2000-2002)						
Measures	FF	KZ	HP	HM	BLM	WW	GPT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(Measure)$_{\tau=-2}$	0.064**	-0.056***	-0.022	-0.014	-0.017	-0.136***	-0.016***
	(3.143)	(-6.054)	(-0.981)	(-1.195)	(-1.155)	(-5.715)	(-4.746)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	1,813	1,740	1,814	1,281	1,334	1,805	734
Adj R^2	0.077	0.068	0.054	0.062	0.060	0.064	0.071

	Global Financial Crisis (2007-2009)						
Measures	FF	KZ	HP	HM	BLM	WW	GPT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(Measure)$_{\tau=-2}$	0.103***	-0.059***	0.031**	-0.011	-0.011	-0.011	-0.010*
	(9.395)	(-6.111)	(2.020)	(-1.335)	(-1.583)	(-0.643)	(-1.707)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	4,472	4,269	4,472	2,458	3,067	4,468	2,354
Adj R^2	0.124	0.085	0.066	0.072	0.075	0.065	0.064

Table X: **Model Parameters and Moments**

In this table we present the estimated model parameters in Panel A and the calibrated moments in Panels B and C. λ_0 and λ_1 capture the fixed and proportional equity financing costs. ξ_0 and ξ_1 are the corresponding parameters for debt-financing costs; α is the curvature of the production function; δ is the depreciation rate; γ_0 and γ_1 are nonconvex and convex investment adjustment costs, respectively; ξ is the liquidation discount rate; c_f is fixed operational cost; r is the risk-free rate; λ_c is the maintenance cost for holding cash; τ is the corporate income tax rate; σ_x and σ_z are the conditional volatility of industry- and firm-level productivity shocks, respectively; ρ_x and ρ_z are serial correlations of productivity shocks, respectively; and k_{ss} is a firm's equilibrium capital level. In Panel B we report the model-implied averages and standard deviations of the cash-to-assets ratio $(c/(k+c))$, book leverage $(b/(k+c))$, the investment-to-capital ratio (i/k), the profits-to-assets ratio $(\pi/(k+c))$, and the frequency of equity financing. In Panel C we report the model-implied average frequency of investment spikes and the time gaps between consecutive spikes. All moments are averaged across 100 simulations.

Panel A: Estimated parameters

λ_0	λ_1	ξ_0	ξ_1	α	δ	γ_0	γ_1	ξ
0.007	0.054	0.002	0.0028	0.795	0.079	0.015*k_{ss}	0.939	0.665
c_f	r_f	τ	λ_c	ρ_x	σ_x	ρ_z	σ_z	
0.118	0.02	0.20	0.006	0.55	0.25	0.55	0.51	

Panel B: Data and model moments

Moments	Data	Model
$\overline{c/(k+c)}$	0.127	0.054
$\sigma(c/(k+c))$	0.155	0.031
$\overline{d/(k+c)}$	0.265	0.333
$\sigma(d/(k+c))$	0.237	0.149
$\overline{i/k}$	0.102	0.076
$\sigma(i/k)$	0.128	0.052
$\overline{e/(k+c)}$	0.142	0.133
$\sigma(e/(k+c))$	0.078	0.073
Freq. of equity financing	0.078	0.100

Panel C: Data and model investment spike frequency

	Moments	Data	Model
Firm-level	Spike year proportion	13.13%	9.64%
	Time gap between two spikes	6.05	9.62
Industry-level	Spike year proportion	15.53%	16.54%
	Time gap between two spikes	5.71	6.03
	Spike firm proportion – industry spike years	28.57%	29.39%
	Spike firm proportion – non-industry spike years	10.42%	6.16%

Table XI: **Financial Flexibility in Simulated Data**

This table demonstrates the Financial Flexibility (FF) Index and its external validity with simulated data. We generate simulated panels with 138 industries and 100 years, of which the number of firms in each industry equals those in the real data. We then conduct regression analyses for the FF index and its external validity. We repeat the above procedure 100 times and report the average and statistical significance of regression results. The dependent and independent variables are calculated in the same spirit as those in empirical analysis. The investment opportunities are captured by the changes in the industry- and idiosyncratic-productivity. Column (1) shows the logit regressions result based on the industry-spike sample to construct the FF index. In columns (2) and (3), we check its predictability for firms' investment in non-industry-spike samples, analogous to our out-of-sample tests in Table IV All regressions include industry and year fixed effects. Standard errors are clustered at the industry-year level. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	In-sample	Out-of-sample	
	(1)	(2)	(3)
Dep. Var.	Spike	Spike	$i/(k+c)$
Chg cash holding$_{\tau=-1}$	14.962***		
	(26.520)		
Avg cash holding$_{\tau=-4:-2}$	11.797***		
	(14.852)		
Chg book leverage$_{\tau=-1}$	-5.684***		
	(-17.034)		
Avg book leverage$_{\tau=-4:-2}$	-1.853***		
	(-18.013)		
Size$_{\tau=-1}$	-5.959***		
	(-32.596)		
Payout$_{\tau=-1}$	9.512***		
	(10.010)		
Rank(FF)$_{\tau=-1}$		1.631***	0.005***
		(31.971)	(4.562)
Chg ind. prod.$_{\tau=-1}$	1.262***	2.095***	0.054***
	(17.346)	(36.040)	(41.750)
Chg idio. prod.$_{\tau=-1}$	1.112***	2.999***	0.070***
	(4.250)	(12.055)	(13.553)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Nobs	91,650	453,246	453,246
(Pseudo) R^2	0.068	0.078	0.118

Appendix A Variable Definitions

A.1 Firm-level Variables

Investment (I) is defined as the sum of capital expenditures (Compustat item *capx*) and acquisitions (Compustat item *aqc*), minus the sale of property, plant, and equipment (Compustat item *sppe*) in year-2000 real dollars.
CAPEX is defined as capital expenditures (Compustat item *capx*) minus the sale of property, plant, and equipment (Compustat item *sppe*).
Acquisition is defined as the Compustat item *aqc*.
R&D is defined as the Compustat item *xrd*.
Investment growth is defined as the log ratio of *investment* at t to the preceding-two-year average, $log(I_{i,t}/((I_{i,t-1} + I_{i,t-2})/2))$.
Total assets (TA) is defined as the book value of assets (Compustat item *at*) in year-2000 real dollars.
Cash holdings is defined as Compustat items *che*/*at*.
Avg cash holding$_{t_1:t_2}$ is average cash holdings from t_1 to t_2.
Chg cash holding$_t$ is defined as the difference between cash holdings at t and average cash holdings from $t-3$ to $t-1$.
Book leverage is defined as the sum of long-term debt (Compustat item *dltt*) and short-term debt (Compustat item *dlc*) over total assets.
Avg book leverage$_{t_1:t_2}$ is average book leverage from t_1 to t_2.
Chg book leverage$_t$ is defined as the difference between book leverage at t and the average book leverage from $t-3$ to $t-1$.
Market-to-book follows the definition in Frank and Goyal (2009). It is defined as (the fiscal year-end closing price $prcc_f$ × common shares used to calculate earnings per share *cshpri* + the liquidation value of preferred stock *pstkl* + long-term debt *dltt* + short-term debt *dlc* – deferred taxes and investment tax credits *txditc*) / total assets *at*, where all variables in italics are Compustat data items.
Payout equals the sum of dividends plus repurchases (Compustat items *dv* + *prstkc*) scaled by the beginning-of-year total assets.
Tangbility is defined as net property, plant, and equipment (Compustat item *ppent*), over total assets.
ROA (return on assets) is defined as operating income before depreciation (Compustat item *oibdp*) over total assets.
Size is defined as the natural logarithm of the book value of assets (Compustat item at) in year-2000 real dollars.
Cashflow is defined as the sum of income before extraordinary items and depreciation and amortization (Compustat items *ib* + *dp*), scaled by beginning-of-year net property, plant, and equipment (Compustat item *ppent*).
Sales growth is defined as the annual percentage increase in sales: $Sales_{i,t}/Sales_{i,t-1} - 1$ (using Compustat item *sale*).
Age is the number of years a firm's data have been available in the Compustat dataset.

A.2 Financial flexibility and financial constraint measures

Financial Flexibility (FF) Index is the linear projected value of balance-sheet variables based on estimates in the industry-spike sample. The balance-sheet variables include lagged *Chg cash holdings*, *Average cash holding*$_{t-4:t-2}$, lagged *Chg book leverage*, *Average cash holdings*$_{t-4:t-2}$, lagged *Size*, and lagged *Payouts*. Without specification, in this paper the FF Index is based on the estimates reported in column (1) of Table III, where $\texttt{FF} = 1.924 * \texttt{Chg cash holding} + 0.257 * \texttt{Avg cash holding} - 1.186 * \texttt{Chg book leverage} - 0.411 * \texttt{Avg book leverage} + 0.030 * \texttt{Size} + 2.419 * \texttt{payout}$.
KZ Index is constructed following Lamont et al. (2001) as $-1.002(ib + dp)/\text{lagged } ppent + 0.283[(at + prcc_f \times csho - ceq - txdb)/at] + 3.139(dltt + dlc)/(dltt + dlc + seq) - 39.368(dvc + dvp)/\text{lagged } ppent - 1.315che/\text{lagged } ppent$, where all variables in italics are Compustat data items.
HP Index is constructed following Hadlock and Pierce (2010) as -0.737size + 0.043size^2 - 0.040Age, where size and age are defined as above.
HM Index comprises financial constraint measures following the methodology in Hoberg and Maksimovic (2015), which is based on the analysis of MD&A sections in 10-K files. The HM index data are sourced from the Hoberg-Maksimovic website. The sample period runs from 1997 through 2015.
BLM Index comprises financial constraint measures following the methodology in Bodnaruk et al. (2015), which is based on the frequency at which constraining words appear in 10-K files. We thank Bill McDonald for sharing the updated BLM index data. The sample period runs from 1993 through 2019.
WW Index is constructed following Whited and Wu (2006) as -0.091 $(ib+dp)/at$ - 0.062[indicator set to one if $dvc+dvp$ is positive and zero otherwise] + 0.021 $dltt/at$ - 0.044 $\log(at)$ + 0.102[average industry sales growth, estimated separately for each three-digit SIC industry and each year] - 0.035 [sales growth], where all variables in italics are Compustat data items, and sales growth is defined as above.

Appendix B Measuring Financial Constraints using AI

B.1 Prompt for ChatGPT

Here we present the detailed instructions given to ChatGPT for classifying each firm-year into one of five financial constraint groups, based on the "Liquidity and Capital Resources" subsection in 10-K Management Discussion and Analysis (MD&A). We follow the original classification scheme in Kaplan and Zingales (1997) (Section III.A) to design the description for each group. Then we ask ChatGPT to take on the role of a finance expert and focus on the relevant texts to pick up the most suitable description. In parallel, we also ask ChatGPT other questions to justify the text's relevance, the adequacy of resources to invest, and firms' anticipation about the investment opportunities.

> You are a finance expert specializing in corporate finance. Your task is to analyze the firm's financial flexibility based on an excerpt from the Management Discussion and Analysis section in the firm's 10-K filing. Note that not all content in the excerpt is pertinent; focus your analysis on texts related to the firm's financing and investment policy and the firm's discussion on the adequacy of resources to invest. You need to understand the firm's liquidity position in relation to its plans for investment currently and in the foreseeable future. Then answer the following questions based on the information in the excerpt only. Present your findings as a single JSON object, conforming to the following structure:
> {'Question1': '(choice id)'; 'Question2': '(choice id)'; 'Question3': '(choice id)'; 'Question4': '(choice id)'}
>
> Question 1: Does this excerpt contain information about the firm's financing and investment policy and discussion on the adequacy of resources to invest?
> (a) Yes (b) No
>
> Question 2: which choice best describes the firm's status?
> (a) NFC (Not Financially Constrained): Financially strong firms with surplus cash, low debt, and the freedom to invest more, as indicated by dividends and buybacks, or explicit statements indicating that they have more money than they need for future investments.
> (b) LNFC (Likely Not Financially Constrained): Financially healthy firms with cash reserves, credit lines, and potential for more investment; however, there are no explicit statements about excess liquidity or financial flexibility.
> (c) PFC (Possibly Financially Constrained): Firms in uncertain financial positions, often facing challenges or giving mixed signals about liquidity. No strong indications of financial limitations, but also no indications that they have a lot of liquidity or financial flexibility.

(d) LFC (Likely Financially Constrained): Firms likely facing financing difficulties, possibly delaying equity offerings, with limited cash; may need to cut dividends and delay investment.
(e) FC (Financially Constrained): Companies in clear financial distress, violating debt agreements, losing credit access, renegotiating debt, or reducing investments due to liquidity issues.

Question 3: If there is a very good investment opportunity in the next year that requires a significant increase in investment, do you think the firm can get enough funds (from both internal or external sources) to capture this opportunity?
(a) very likely (b) likely (c) less likely (d) highly unlikely

Question 4: Does the firm expect a significant investment increase next year?
(a) Yes (b) No (c) No relevant information

Here is the excerpt:

****
Liquidity and Capital Expenditures Subsection
****

B.2 Extract LIQ&CAP Subsection from 10-K Filings

The procedure to extract the "Liquidity and Capital Resources"(LIQ&CAP) subsection is similar to that in Hoberg and Maksimovic (2015). This section, which is also used in KZ's classification scheme, contains firms' statements concerning financial liquidity and the discussion on the adequacy of capital resources to invest.

The cleaned 10-K Files data is downloaded from Bill McDonald's Website.[31] We first extract the Management Discussion and Analysis (MD&A) section from cleaned 10-K files. MD&A generally appears as item 7 in most 10-Ks, and it is easy to identify the start and end of this subsection by matching the title format.[32]

Next, from each MD&A section, we try to extract texts for the LIQ&CAP subsection. There is no temple for this statement. We identify the beginning of this subsection based on the title name (i.e., potential names listed in Online Appendix I of Hoberg and Maksimovic (2015)) and title format (e.g., with a line break before and after the title; capitalize the first letter or all letters). The end of this subsection is much harder to locate: the subsection could contain several parts, which are titled in the same format as the subsection title. After manual and algorithmic check part of the samples, we determine the end of the subsection

[31] https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files

[32] In earlier years, when electronic filling was not common, the structures of the 10-K filings were not uniform. We manually check files that failed in identifying MD&A sections based on the item number, e.g., some of the files show the complete MD&A in reference but a summary below item 7. We design extraction algorithms to adopt various file formats and improve the sample coverage by more than 20%.

according to the following procedure: (i) If the number of identified titles with the same format as subsection title is less than 10, we locate the next unrelated title as the end of this subsection; (ii) Otherwise we extract the first 8000 letters [33] following the subsection title as the relevant texts. If several excerpts are identified in one MD&A, we combine all of them together. We acknowledge this method is not perfect for including all the information about the firms' liquidity status, but focusing on the LIQ&CAP subsection has several benefits: (a) It could reduce the noise in the text and allow the attention mechanism to concentrate on the most pertinent information, making it easier for the model to generate accurate and coherent responses. (b) The current large language models all have length limitations for input. The average MD&A length is about 20 thousand tokens, which can't be processed in one query. Separating MD&A into multiple parts could also introduce noise in text. (c) cost considerations: Models with fewer length limitations are charged much more than the standard model.

We link each extracted LIQ&CAP subsection to the CRSP/COMPUSTAT database using the central index key (CIK), and the mapping table provided in the WRDS SEC Analytics package. For firms have multiple 10-K filings in one fiscal year, we pick the longest LIQ&CAP for the firm-year observation. Finally, we get 65,594 firm-year observations for ChatGPT analysis, from fiscal year 1993 to 2019.

B.3 ChatGPT's Answer

We submit the above prompt with extracted LIQ&CAP part to GPT-3.5-turbo for analysis. In Table A.I, we report the details for the ChatGPT's response. In Panel A, we show the distribution of answers for each question, and compare the classification results with existing literature in Table VII. Based on the answers to question 1, we can find most of the extracted excerpts do contain information regarding the financing and investment policy. Answers to question 4 show only a small fraction of firms state they expect a significant investment increase in the future. We use this answer to further control the difference in investment opportunity anticipation for tests in Table VII. In Panel B, we show the response consistency between question 2 and question 3. We find in most cases, within the response, ChatGPT is logically consistent.

To shed some light on the information loss of the LIQ&CAP subsection relative to the full MD&A section, we compare the ChatGPT's answers when feeding full MD&A sections. We apply stratified sampling techniques to draw 10-K files to ensure the sample is representative. That is, we group the files based on the MD&A length and the length proportion of LIQ&CAP part relative to the full MD&A into 5 $\times$s 5 groups. Next, in each *fiscal year* $\times$ *text length* $\times$ *LIQ&CAP proportion* group, we randomly draw 1% files and finally get 742 files. Then we use the same prompt but replace the LIQ&CAP part with the corresponding complete MD&A section to query ChatGPT again. We compare the responses based on the different texts of these sections in Panel C of Table A.I. In most cases, results are consistent or similar, indicating the information loss associated with the LIQ&CAP section may not be a major issue. Finally, we also check the consistency of the ChatGPT's responses. We

[33] This number is the 90th percentile length of the subsections identified in condition (i)

randomly select one excerpt from each *fiscal year* $\times$ *text length* group, and then for each excerpt, we query ChatGPT with the same prompt five times. In Panel D, we show more than 70% of queries get the same answers as they received in the main tests, and the remaining 30% get one of the adjacent choices.

Table A.I: ChatGPT's Response and Robustness

This table reports some additional information about ChatGPT's classification. In Panel A, we report the number of ChatGPT's answers for each question in the prompt. In Panel B, we report the number of each answer combination for questions 2 and 3, to demonstrate the logical consistency of ChatGPT's analysis. In panel C, we report the difference in classification result using LIQ&CAP subsection and full MD&A section. The result based on a representative sample indicates the information loss of LIQ&CAP subsection may be not severe. Panel D reports the answer consistency of repeated queries using the same input. In most cases, ChatGPT gives a similar response.

Panel A: ChatGPT's answer

	A	B	C	D	E
Q1	62,677	2,917			
Q2	347	41,193	20,366	3,316	372
Q3	1,888	42,050	18,994	2.662	
Q4	3,572	3,9777	22,245		

Panel B: Answers for question 2 and 3

	NFC	LNFC	PFC	LFC	FC
Very likely	20	1764	205	1	1
Likely	127	35730	9087	11	3
Less likely	224	6564	13028	1264	45
Highly unlikely	2	3	148	2541	368

Panel C: Classification based on different texts

LIQ&CAP \ MD&A	NFC	LNFC	PFC	LFC	FC
NFC	0	1	0	0	0
LNFC	13	310	120	1	3
PFC	3	90	129	7	3
LFC	0	5	25	19	1
FC	0	1	3	5	3

Panel D: Answer consistency

Original \ Repeated	NFC	LNFC	PFC	LFC	FC
NFC	75%	25%	0%	0%	0%
LNFC	1%	79%	20%	0%	0%
PFC	0%	32%	63%	5%	0%
LFC	0%	1%	19%	78%	3%
FC	0%	0%	0%	0%	100%

Appendix C The Model

To validate our empirical approach, we generate data based on a model that is almost identical to that in Gao et al. (2021). In this model, a firm can remain in operation for infinitely long periods and managers make investment, cash savings, and financing choices that maximize equity value. The manager's incentive is perfectly aligned with that of the firm's shareholders. External financing is costly, and cash stock alleviates investment distortions caused by financial constraints.

C.1 Production

The firm spends capital k_t to produce output at time t. Its operating profit is given by

$$\pi(x_t, z_t, k_t) = e^{x_t+z_t} k_t^{\alpha} - c_f \tag{4}$$

where $\alpha \in (0,1)$ captures both market power and decreasing returns to scale, $c_f > 0$ is fixed operating costs arising from fixed outside opportunity costs for scarce resources (e.g., managerial labor), x_t is an industry-wide productivity shock, and z_t is a firm-specific productivity shock.[34] The productivity shocks are realized and observed by managers before investing and cash savings are set, both following an AR(1) stochastic process,

$$x_t = (1-\rho_x)\bar{x} + \rho_x x_{t-1} + \sigma_x \varepsilon_{x,t}, \tag{5}$$

$$z_t = (1-\rho_z)\bar{z} + \rho_z z_{t-1} + \sigma_z \varepsilon_{z,t}, \tag{6}$$

where $\bar{x}$ and $\bar{z}$ are the unconditional means of x_t and z_t, $\rho_x \in (0,1)$ and $\rho_z \in (0,1)$ are persistence coefficients, $\sigma_x > 0$ and $\sigma_z > 0$ are the conditional volatilities of x_t and z_t, and ε_x and ε_z are standard Gaussian shocks. Assume that industry-wide and firm-specific shocks occur independently of each other and any industry-wide (firm-specific) shock is independent of other industry-wide (firm-specific) shocks.

The firm accumulates capital through investment, $k_{t+1} = i_t + (1-\delta)k_t$, where i_t represents an investment and $\delta \in (0,1)$ is the depreciation rate. The adjustment cost of the investment is given by

$$\Phi(i_t, k_t) = \gamma_0 \mathbb{I}_{i\neq 0} + \frac{\gamma_1}{2}\left(\frac{i_t}{k_t}\right)^2 k_t, \tag{7}$$

which includes both non-convex costs, $\gamma_0 > 0$, and convex costs, $\gamma_1 > 0$.

C.2 Cash flows and financing

The firm in our model has four financing sources: current cash flows, cash stock, risky debt issuance, and equity issuance. At the beginning of the period, the firm has a stock of cash $c_t \geqslant 0$. The cash stock earns taxable interest income at the risk-free rate, r. Holding cash also incurs costs, however, which are motivated by differential borrowing and lending rates

[34] For notational simplicity, we omit the subscript that indicates specific firms. For example, z_t is a simplified notion for z_{jt} of firm j.

(Cooley and Quadrini, 2001), agency costs (Jensen, 1986; Stulz, 1990), and/or a premium paid for precautionary cash holdings (Keynes, 1936). Following DeAngelo et al. (2011), we refer to such costs as "costs of maintaining cash balances", which is assumed to be linear, λ_c, in cash holdings.[35]

If internal resources fall short of meeting investment demand, the firm can raise funds externally through debt and equity financing. The firm can issue one-period risky debt b_{t+1} at time t, which has to be paid back or rolled over in each period as it matures. The price of debt at time t, $q_t \equiv q(x_t, z_t, k_{t+1}, b_{t+1}, c_{t+1})$, depends endogenously on the firm's current productivity shock and the cash holdings, capital, and debt it chooses for the next period. Equity issuance incurs both fixed costs, λ_0, and linear costs, λ_1. Similarly, debt issuance incurs also both fixed costs, ξ_0, and linear costs, ξ_1. Following Gao et al. (2021), the fixed issuance costs are proportional to the size of the issuing firm and are not related to the size of the issuance.

Following Gao et al. (2021), each period is divided into a preproduction stage and a postproduction stage. In the preproduction stage of period t, the firm realizes productivity shocks x_t and z_t, and decides whether or not to default on the current debt outstanding b_t. If the firm chooses to default, its assets will be liquidated, internal funds will be distributed to creditors, and the remaining unpaid debt will be discharged. If the firm chooses not to default, it pays off the debt, pays the fixed operational costs, and issues new debt. In the postproduction stage, the firm first produces its output. Upon receiving the production revenue, it makes decisions regarding cash holdings and investment. The firm can issue equity in both stages when its internal funds are not sufficient.

In the preproduction stage, the firm's cash flow is given by

$$d_{1,t} = (1 + (1-\tau)(r - \lambda_c)) * c_t + q_t b_{t+1} - b_t - c_f - \mathbb{I}_{b'>0}(\xi_0 k_t + \xi_1 b_{t+1}),$$

where r is the risk-free rate, τ is the tax rate, $\mathbb{I}_{b'>0}$ is an indicator that equals one if debt issuance at t is positive and zero otherwise. If $d_{1,t} > 0$, cash flows will be carried over to the postproduction stage. If $d_{1,t} < 0$, the firm needs to raise equity to make up the shortfall. In the postproduction stage, cash flows are given by

$$d_{2,t} = (1-\tau)\pi(x_t, z_t, k_t) + \delta\tau k_t + d_{1,t}\mathbb{I}_{d_1>0} - c_{t+1} - i_t - \Phi(i_t, k_t)\,.$$

The firm also needs to raise equity issuance if $d_2 < 0$.

The separation of the preproduction and postproduction stages in a given period serves two purposes. First, operational costs have to be paid in the preproduction stage, which creates demand for cash. This assumption is consistent with findings in the cash-in-advance money demand literature (Svensson, 1985) and the survey evidence in Lins, Servaes, and Tufano (2010), who show that corporate cash is held mainly for operational purposes. Second, without this separation, debt issuance and cash accumulation occur simultaneously in the same period and only the net debt matters for firm value. That is, cash is essentially negative debt. This separation of two stages breaks the fungibility of cash and debt.

[35] In Gao et al. (2021), holding cash earns no interest, which implies a λ_c that equals the risk-free rate.

C.3 Firm value and the price of risky debt

We can write the firm's value maximization problem as

$$V_t \equiv V(x_t, z_t, k_t, b_t, c_t) = \max\{0, \max_{\{k_{t+1}, b_{t+1}, c_{t+1}\}} d_t + \frac{1}{1+r} E_t[V_{t+1}]\}$$

where the dividend d_t is given by

$$d_t = (d_{1,t} - \lambda_0 k_t + \lambda_1 d_{1,t})\mathbb{I}_{d_1<0} + d_{2,t} - (\lambda_0 k_t - \lambda_1 d_{2,t})\mathbb{I}_{d_2<0}\,.$$

The firm defaults when its equity value falls below zero. The price of the one-period risky debt is thus given by

$$q_t \equiv q(x_t, z_t, k_{t+1}, b_{t+1}, c_{t+1}) = \frac{1}{1+(1-\tau)r}\left[\mathbb{I}_{V_t\geq 0} + \mathbb{I}_{V_t<0}\frac{\xi(1-\delta)k_{t+1} + c_{t+1}}{b_{t+1}}\right],$$

where ξ is the discovery rate. The term $1-\tau$ in the discount rate acts as a tax advantage for debt by making the firm more impatient relative to the rate used to discount payments to creditors.

C.4 Calibration

Most of our parameter values are taken from the estimated values in Gao et al. (2021), with the following exceptions. First, the model economy experiences an industry-wide productivity shock in addition to the firm-specific shock included in Gao et al. (2021). The persistence and volatility of these shocks are calibrated to match the volatility of key moments reflected in Panel B of Table X. Second, our nonconvex adjustment cost of investment is a constant fixed cost rather than linear in capital, as in Gao et al. (2021). Its magnitude is calibrated to match firm- and industry-level investment-spike frequencies, as reported in Panel C of Table X. Third, fixed and linear costs of debt issuance are added to match the mean and volatility of the debt-to-assets ratio. Lastly, the maintenance cost for holding cash, λ_c, which is calibrated at the risk-free rate in Gao et al. (2021), is adjusted to match the average cash-to-assets ratio. The calibrated parameters are presented in Panel A of Table X, the model-implied and data moments are presented in Panel B, and the investment-spike statistics are presented in Panel C.