Balance Sheet Financial Flexibility

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Abstract

Firms' investment behavior is intermittent, and a significant fraction of capital formation occurs during "investment spikes". We define *financial flexibility* as the capacity to accommodate investment spikes, as potentially determined by (i) external financing frictions, and (ii) the state of firms' balance sheets. We term the contribution of balance sheet variables to overall financial flexibility *balance sheet financial flexibility*. We construct a balance sheet financial flexibility index (FF Index) by examining which balance sheet financial variables differentiate firms that generate investment spikes and those that do not during industry-level investment spike waves, which capture periods when an entire industry experiences positive shocks to investment opportunities. We consider five popular measures of financial constraints (FC), including recent "text-based" measures, and find that these measures have very little in-sample explanatory power compared with our selected balance sheet variables. The FF Index predicts the incidence of investment spikes in out-of-sample tests and outperforms all FC Indices. 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.

Keywords: financial flexibility, financial constraints, investment spikes, liquidity management, corporate cash policy

JEL Codes: G32, G34, G35

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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 factors (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]

Denis (2011) notes that financial flexibility is meaningful only in the presence of financial frictions: "...in the presence of such frictions, it can be valuable for firms to choose financial policies that preserve the flexibility to respond to unexpected periods of insufficient resources". Yet, while several indices of financial frictions (or constraints) have been proposed and have received considerable attention, few studies have attempted to measure financial flexibility.

In this paper, following Denis (2011), we define financial flexibility as the capacity to accommodate large gaps between investment needs and cash flows. We argue that both (i) the cost of external financing, and (ii) the state of a firm's balance sheet could affect financial flexibility. We term the latter element of financial flexibility, i.e., the relationship between balance sheet variables and overall financial flexibility, *balance sheet financial flexibility*. One of our main objectives in this paper is to construct an index of balance sheet financial flexibility, which we label the FF Index. We demonstrate the external validity of this Index, and provide an example of its application in empirical research.

To create this index, we examine the cross-sectional relationship between balance-sheet variables and the capacity to accommodate large 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 (Mayer and Sussman (2004); Whited (2006); Elsas, Flannery, and Garfinkel (2014); Im,

[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.

Mayer, and Sussman (2020).[2] 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.[3]

While we point to financial constraints and the state of the balance sheet as distinct determinants of financial flexibility, we recognize that the state of the balance sheet, or balance sheet financial flexibility, could itself be related to financial constraints.[4] Firms may, for example, accumulate precautionary cash balances in anticipation of future investment opportunities or cash shortfalls if they face frictions in raising external finance. Indeed, several financial constraint indices sort firms with different balance-sheet characteristics as more or less financially constrained. For example, the Kaplan-Zingales (henceforth, KZ) Index of financial constraints sorts firms with more cash holdings and less debt into the less-constrained class, while the Whited-Wu (henceforth, WW) Index does the opposite.[5] To the extent that balance-sheet adjustments are not instantaneous and investment opportunities are not perfectly anticipated, however, cross-sectional variations in the state of a firm's balance sheet may not be strongly correlated with financial constraints.

This last possibility—that financial constraints are not strongly correlated with balance sheets—is further reinforced by the fact that most balance-sheet variables are state variables that evolve dynamically in response to past random shocks to investment opportunities. Firms that have recently experienced frequent and positive productivity shocks that increase marginal returns on investment may raise external financing—both to invest and to improve balance-sheet financial health—at the same time. For example, fixed costs of issuance may encourage such firms to raise even more external financing than is needed for immediate investment plans to accumulate larger cash balances; however, firms experiencing weaker productivity shocks may not want to incur the fixed costs of issuance and may drain liquidity to invest, waiting for better shocks to raise external financing and replenish their liquidity. DeAngelo, DeAngelo, and Whited (2011) and Bolton, Wang, and Yang (2021)

[2]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.

[3]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.

[4]It is well-recognized that that corporate investment is affected both by external financing frictions and internal liquidity. For example, in the well-known "reduced form" model of Kaplan and Zingales (1997, 2000), investment is a function of both internal funds (W) and "intrinsic characteristics" that "make it more costly to raise a given amount of external funds", (k): $I = I(W, k)$.

[5]See Whited and Wu (2006), Table 2 and the associated discussion.

propose related dynamic models. In these models, for similarly constrained firms, a different history of past shocks can generate differences in the characteristics of their balance sheets and hence their capacity to respond to major investment opportunities. In section 7, we adapt a model proposed by Gao et al. (2021) and show that, even for firms facing identical financing costs, differential past shock histories generate cross-sectional variation in balance-sheet variables that explain differences in their ability to accommodate large investments. We use this model to generate data and validate our empirical approach on it.

We now discuss some details pertaining to our methodology and results. As mentioned above, to examine whether balance-sheet variables are related to the likelihood that large investments are made, we focus on industry clusters of firm-level investment spikes. 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 "baseline" investment, defined as average capital expenditures 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 in-sample regressions, 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 several balance sheet variables discussed below. The regressions are based only on industry-spike years. We focus on these years for several reasons. First, 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). Second, 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 balance sheet 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.). The industry-spike year is unlikely to be a chance occurrence reflecting *idiosyncratic* productivity shocks that affect the majority of firms at the same time if the number of firms in the industry is fairly large. With a common industry shock, it is more likely that firms that do not invest aggressively lack financial flexibility rather than lacking investment opportunities.[6] Third, for external validation of the FF Index, we want to see 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. We also include level variables (with one year lags) that capture investment opportunities (market-to-book and sales growth) and cash flows (which could capture liquidity and is also a proxy for investment opportunities). The change in cash holdings has a significant and positive coefficient, while the average leverage ratio and changes in that measure have significant and negative coefficients. Almost all of the investment opportunity variables have the expected positive signs, but cash flow is insignificant in the regression based on the main sample. 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]

The above-reported results are in line with the expectation that both balance sheet financial flexibility and 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 balance-sheet financial flexibility, our baseline FF Index is based on a parsimonious regression of the dependent variable (spike dummy) on balance-sheet financial variables only, along with firm size and the payout ratio. In this specification, the coefficients of the retained variables keep their signs and significance; in addition, the average cash holding now has a highly significant positive coefficient. Following Lamont, Polk, and Saaá-Requejo (2001), our FF Indices are linear projections of the independent variables based on the coefficient estimates derived from the logit models. 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

[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.

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.[8] The coefficient of the FF Index is highly significant in these regressions, irrespective of whether we include the investment opportunity (IO) variables, namely, cash flows, sales growth, and the market-to-book ratio, with a one-period lag.

In our second set of out-of-sample tests, starting in 1985 and then at 5-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 this methodology is that, to the extent that industry-spike years correspond to shocks to an entire industry, failure to control for 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.

To assess the relative contributions of balance-sheet financial variables and IO variables, we first show that the regression R-squares almost double when the FF Index is added to a specification that includes only the IO variables. We also construct an IO Flexibility Index (henceforth the IO Index) based on regressing the investment spike dummy (for industry-spike years) on cash flows, the market-to-book ratio, sales growth, and firm size. While the standalone IO Index is significant in out-of-sample logit regressions, when included with the FF Index the latter is much more significant and its marginal impact on the regression R-square is much greater than that of the IO Index.

The IO Index serves another important purpose in that it helps us address the issue that our baseline results might be driven by cash flows. Cash flows are a source of liquidity and could affect the balance-sheet variables, but they could also capture growth opportunities, and this is the key issue in the sizeable literature where the so-called investment–cash flow sensitivity debate has attracted attention (Fazzari, Hubbard, and Petersen (1988), Kaplan and Zingales (1997)). Cash flows are not included in our baseline FF Index, but they are a major constituent of the IO Index. The fact that the FF Index's incremental contribution

[8] 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.

over IO is sizeable confirms that the baseline FF does not simply reflect growth opportunities.

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 a 6.4 percent higher ranking and the coefficient estimate of FF translates to a 0.8 percentage 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 ways of identifying investment spikes and the classification of industry-spike clusters, an alternative definition of large changes in investment and alternative industry classifications.

We next investigate the role that financial constraints play in determining financial flexibility. To do so we also consider, in addition to the KZ and WW indices, the absence of credit ratings as well as three recent text-based indices: the Hadlock-Pierce (HP) Index from Hadlock and Pierce (2010), the Hoberg-Maksimovic (HM) Index from Hoberg and Maksimovic (2015), and the Bodnaruk, Loughran and McDonald (BLM) Index from Bodnaruk, Loughran, and McDonald (2015). Lower values for all of these indices correspond to less financially constrained firm-years.

When included one at a time, together with the variables that enter our baseline FF Index, only the KZ Index and the HP Index have significant coefficients with the correct signs in the in-sample logit regressions for predicting the likelihood that a spike occurs. We then create new FF Indices, each of which includes one of these variables alongside the baseline balance-sheet variables and re-run the out-of-sample tests. There is virtually no change in the regression R-squares relative to the baseline case where these FC variables are not included.

We run "horse races" between the FF Index and each of these FC indices by including both the FF Index and one of the FC indices as explanatory variables in our out-of-sample tests fornon-spike years. The results are striking: while 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 z-statistic for the FF Index is three times that for the KZ Index.

Balance sheet financial flexibility as reflected in our FF Index should help to alleviate financial frictions and enable firms to invest more robustly not only when investment opportunities are particularly good but also at other times. We find that the FF Index remains highly significant in OLS regressions when we change the dependent variable to investment over lagged assets. Importantly, the IO variables now have slightly greater explanatory power than the FF Index, validating the idea that balance sheet financial flexibility is more important when major investments need to be financed. When included together with the FF Index, however, among the FC Indices only the WW and the HP indices have significant coefficients with the correct signs, and the incremental explanatory power of the FC Indices is very small.

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 external financing.[9] 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 is not significant for the tech recession and has much lower t-statistics for all the NBER recessions. None of the other FC indices is consistently significant or has the correct signs in all the regressions.

Our results show that the common FC measures (with the possible exception of the KZ Index) have a limited role to play in determining the financial flexibility needed to undertake major investments. Farre-Mensa and Ljungqvist (2016) argue that the FC measures do not properly identify financially constrained firms, and our results could reflect this possibility. Our regressions generally have low explanatory power, which could be due to the fact that cross-sectional variation in financing frictions— which should be one of the major determinants of overall financial flexibility— play little role in these regressions. Our results therefore serve as a stark reminder of the gap in our understanding of the nature and source

[9] 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 (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).)

of these frictions, and the need for more research on this important issue.

We find it particularly interesting that, among all the FC indices considered here, the KZ Index performs the best in predicting major investments and exhibits properties that are similar to those of the FF Index (but FF outperforms KZ in all our tests). In other words, the KZ Index behaves more like a balance sheet financial flexibility index than an FC index. While they are constructed very differently, both are based on the capacity of firms to undertake large investments.[10] The results associated with the KZ Index are often at odds with those derived with other FC indices. Our results may shed some light on why this is the case.

2 Literature Review

2.1 Literature

2.1.1 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 (Harford (1999), Dittmar and Mahrt-Smith (2007), Harford, Mansi, and Maxwell (2008)).

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.[11] Research on

[10] The KZ Index is derived from subjective classification of firm-years based on firms' "access to internal or external funds to *increase investment*."

[11] 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

financial flexibility surged after the Global Financial Crisis (Campello et al. (2010), Duchin et al. (2010), Denis and Sibilkov (2010), Ang and Smedema (2011), Kahle and Stulz (2013), Giroud and Mueller (2017)) and has surged again following the COVID-19 pandemic (Albuquerque et al. (2020), De Vito and Gómez (2020), Ding et al. (2020), Fahlenbrach et al. (2021), Ramelli and Wagner (2020), Barry et al. (2022)).

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. Second, while most existing research focuses on the role flexibility plays during economic downturns, relatively little attention has been given to how financial flexibility—suitably defined—enables firms to respond to especially good investment opportunities. Finally, the role played by financial constraints as a determinant of financial flexibility also remains unexplored. While some authors find that cash holdings as a source of flexibility benefit firms that face tighter financial constraints, the extent to which financial constraints alone contribute to financial flexibility remains unclear. In this paper, we address all these gaps in the literature.

2.1.2 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

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 provide evidence of the role of debt capacity as a source of financial flexibility and the use of transitory debt to finance investments.

that costly external financing reduces the hazard associated with lumpy investments. Hazard model estimation finds support for this prediction. DeAngelo et al. (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 Definitions and Concepts

Compared with the emphasis that the concept of *financial constraints* has attracted in the literature, few studies have even attempted to formally define the notion of financial flexibility. An exception is Denis (2011), who defines it as "the ability of a firm to respond in a timely and value-maximizing manner to unexpected changes in the firm's cash flows or investment opportunity set." Denis (2011) goes on to note that the concept is meaningful only in the presence of external financing frictions. 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."

Although it is not formally defined as such, a notion of financial flexibility as *debt capacity* also emerges in dynamic models of financing and investment in the presence of financial frictions (DeAngelo et al. (2011) and Bolton et al. (2021)). DeAngelo et al. (2011) show that, in the presence of costly equity financing, firms focus on preserving debt capacity. When productivity shocks persist, firms that have created debt capacity by issuing equity and paying down debt subsequently undertake large investments—if investment opportunities turn out to be particularly good—by issuing "transitory debt". Debt levels are then brought down as firms try to rebuild their debt capacity.

Consistent with the above perspectives, in this paper we argue that there are two aspects to financial flexibility. First, as noted by Denis (2011), external financing frictions determine the extent to which firms are able to bridge shortfalls between optimal investment levels and cash flows from assets in place. Second, the state of a firm's balance sheet, and in particular, cash holdings and debt capacity, is likely to play an important role as well. Our concept of *balance sheet financial flexibility* reflects the extent to which balance-sheet variables contribute to overall financial flexibility. Our main objective is to construct an index of balance sheet financial flexibility and examine its contribution to the propensity in firms to undertake major investments in relation to available FC indices. To this end, we focus on firm-level investment spikes. The capacity to accommodate such major investments in response to unexpected investment opportunities could depend both on the external financing constraints firms face as well as the state of their balance sheets.

The state of a balance sheet and external financial constraints may be related. Ease of access to external financing, for example, may cause firms to issue equity or debt at levels that exceed their current investment needs and buffer up cash holdings or pay down debt as a precaution against adverse future market conditions. Conversely, if accumulating cash holdings and maintaining lower leverage ratios are costly, firms that face relatively little financing friction may not be concerned about future access to external financing and could do the opposite.[12] If the state of the balance sheet is perfectly related to financial constraints, then in cross-sectional regressions balance sheet variables may not have any incremental explanatory power.

It is, however, extremely unlikely that balance sheet variables in the cross-section of firms at any point in time are very closely related to financial constraints, for two reasons. First, balance sheet adjustments are not instantaneous; they occur slowly over time.[13] Noting that our in-sample regressions that predict firm-level investment spikes are based on years of industry-wide "spike waves", if industry-wide investment opportunities are not fully anticipated, or if firms anticipate such investment opportunities differently from one another, the state of the balance sheet is expected to provide explanatory power in cross-sectional regressions that predict firm-level investment spikes.

Second, and relatedly, balance-sheet variables are essentially state variables that respond to exogenous shocks to investment opportunities. Similarly constrained firms with differing histories of productivity shocks are likely to differ in their balance sheet financial flexibility as well. In the model of DeAngelo et al. (2011), issuing equity is more costly than issuing debt. Firms issue equity and create debt capacity when they experience relatively modest productivity shocks but issue large amounts of debt, while they exhaust their debt capacity when they experience very good shocks. The timing of these shocks thus has clear implications for cross-sectional differences in balance sheet flexibility, even among similarly constrained firms.

[12] The former behavior is consistent with how the KZ Index sorts firms into financially less and more constrained classes, while the latter is closer to how the WW Index sorts firms.

[13] It is well documented that leverage adjustments are slow.

In section 7, we present a model that illustrates these features. The model shows that firms facing the same cost of external finance at any point of time exhibit cross-sectional variation in balance-sheet variables due to different histories of past shocks. We use the model-simulated data to construct an FF Index in the same way as for the empirical sample, and demonstrate that such an Index can predict investment spikes out of sample.

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 FFI 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 any 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 in the sample. 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 that is available from the World Bank Data Bank. 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.). To measure financial flexibility, we focus on firms' lumpy investments, or investment spikes. The reason is simple: firms need to maintain financial flexibility before undertaking 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 $\varepsilon \sim N\left(0, \sigma^2 \mathbf{I}_5\right)$ and $\mathbf{I}_5$ is a 5×5 identity matrix. The matrix $\mathbf{X}$ and vectors b and ε are specified as follows:

$$\mathbf{X} = \left[\begin{array}{ccc} \mathbf{1} & \tau & \mathbf{D}_{\tau=0} \end{array}\right] = \begin{pmatrix} 1 & -2 & 0 \\ 1 & -1 & 0 \\ 1 & 0 & 1 \\ 1 & +1 & 0 \\ 1 & +2 & 0 \end{pmatrix},$$

$b = (\alpha_{i,t}, \beta_{i,t}, \delta_{i,t})'$, and $\varepsilon = (\varepsilon_{i,t-2}, \varepsilon_{i,t-1}, \varepsilon_{i,t}, \varepsilon_{i,t+1}, \varepsilon_{i,t+2})'$. Using $\widehat{b} = \left(\mathbf{X}'\mathbf{X}\right)^{-1} \mathbf{X}'y$, 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 $\widehat{V}(\widehat{b} \mid \mathbf{X}) = s^2\left(\mathbf{X}'\mathbf{X}\right)^{-1}$, 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

In this study, we also propose a filter we use to identify years in which firm-level investment spikes cluster, which we term *industry-spike years*. Firms' investment spikes are usually driven by good industry-wide investment opportunities. We focus on the industry-spike-year sample to address a concern that we control for heterogeneity in firm-level investment opportunities incorrectly. Those industry-wide shocks are reasonably exogenous events from the individual firm perspective.

The 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. 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 respects: (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 in the sample period. In addition, to improve the filter's reliability, we exclude SIC three-digit industries in which few firms operate.[14]

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 baseline 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, conditional on there occurring at least one spike, this number, while smaller, is still quite high, at 10.4 percent.

[Table I about here.]

In Panel D of Table 1 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

[14]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.

generate any spikes at $\tau = 0$ or in the two preceding or two following years (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 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 firms also, however, issue lower payouts than in the prior year. 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 as well as, perhaps, internally generated funds they have at their disposal.

6.2 Industry-Spike Years and Industry Growth Opportunities

Our in-sample regressions that generate the FF Indices as well as one set of tests of external validity are based on industry-spike years in which a significant fraction of firms in a given industry simultaneously generate investment spikes. There are several reasons to focus on industry-spike years. First, the predictive power of our in-sample regressions is likely to improve if there is reasonable variation in the dependent variable within the same industry and same year. Second, 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. Finally, reverse causality might be involved if firms perfectly anticipate when significant investment opportunities materialize and therefore build up balance sheet flexibility to be ready to invest. Only by an extreme coincidence, however, would a large fraction of firms anticipate individual growth opportunities materilizing in exactly the same year .

That said, however, 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 spikes in both our in-sample and out-of-sample tests (provided they are correctly reflected by existing FC measures).

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 for each column in Panel A is the standardized median industry market-to-book ratio, and for each column in Panel B the dependent variable 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. In the first three columns we report regression results for the full industry-spike-year sample as well as for the first and second halves of our samples, for our baseline specification. 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 heterogeneity in investment adjustment costs, while the payout ratio is expected to be associated with balance-sheet health.[15] For the last three columns we add variables designed to capture investment opportunities to the specification: 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.[16]

[Table III about here.]

The abovementioned regressions indicate that the coefficients of 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. Cash holdings have a positive and highly significant coefficient when the IO variables are included. The IO variables all have significant and positive coefficients.

The baseline FF Index is a linear projection of the regression estimates reported in column (1) of Table III. Therefore, it is $\texttt{FF} = 1.964 * \texttt{Chg cash holding} + 0.427 * \texttt{Avg cash holding} - 0.993 * \texttt{Chg book leverage} - 0.302 * \texttt{Avg book leverage} + 0.027 * \texttt{Size} + 2.357 * \texttt{payout}$. 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.

It is possible that model misspecification associated with the baseline Index occurs, as the IO variables are not included. To address this issue, we create an alternative FF Index using the coefficients reported in column (4) of Table III and include only the same set of variables as those included for column (1), which means that the FF Index is given by

[15] 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).

[16] We separate out positive and negative cash flows.

$\texttt{FF} = 1.906 * \texttt{Chg cash holding} + 0.241 * \texttt{Avg cash holding} - 1.163 * \texttt{Chg book leverage} - 0.397 * \texttt{Avg book leverage} + 0.031 * \texttt{Size} + 2.947 * \texttt{payout}$. In results that are available from us on request, we show that our results hold irrespective of which index is used.

In Panel B of Table III we present summary statistics for the linear projection (upper panel) based on column (1) in Panel A and the time-series change in the FF Index around the industry-spike year (lower panel). The key takeaways are that (a) in the upper panel, the FF score for firms that generate investment spikes is 36.5 [17] percent of one standard deviation higher than the score for those that do not, in the year before the industry-spike year, and (b) the percentile ranking of the ranked FF Index for spike firms increases 5 percent in the year before the industry-spike year compared with that four years before the industry-spike year for firms that generate spikes, while the percentile ranking for firms that do not generate spikes increases only 0.6 percent. Comparing year t-1 and year t, the investment spike reduces firms' financial flexibility by 10 percent.

6.4 External Validation

We conduct two types of external validation. Our purpose is to examine whether the FF Indices predict out-of-sample investment spikes. 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 1 if a firm generates an investment spike in a given year and zero otherwise. The key explanatory variable is the (ranked) FF Index.

It may be asked why we should expect financial flexibility to matter for investment in a non-industry-spike year if firms do not encounter particularly good investment opportunities. As we show in section 6.8, firms that make major investments typically operate in industries that experience improving investment opportunities, and firms that generate investment spikes enjoy even better investment opportunities in these industries than those that do not. As shown in Panel C of Table I, even in non-industry-spike years, when an investment spike occurs in an industry, on average, 10.42 percent of the firms that operate in the industry generate investment spikes. Our results are driven by these industry-years. We control for the IO variables in several of these out-of-sample tests.

In Panel A of Table IV we present the results across several specifications. For columns

[17] [(-0.978) - (-1.116)]/0.378 = 36.5%

(1)–(3) in the upper panel, we include the baseline FF Index, only the IO variables, and both of these as explanatory variables, respectively. 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). Third, while the FF Index continues in column (3) to have a highly significant coefficient that is similar in magnitude to that reported in column (1), the IO variables remain 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. Third, a comparison of the pseudo-R-squares in these three columns shows that the marginal contribution of the FF Index (comparing columns (3) and (2), the pseudo-R-square almost doubles) is much higher than that of the IO variables (comparing columns (3) and (1), there is a very slight increase in the pseudo-R-square when the IO variables are added).

We use the regressions whose results are reported in columns (4)–(7) of Panel A in Table IV to achieve multiple objectives. First, there could be a particular concern related to cash flows. Perhaps, as a source of liquidity as well as an indicator of investment opportunities, it drives the balance-sheet variables in our baseline in-sample regressions. If this is the case, it would be difficult to separate balance-sheet flexibility from investment opportunities. To address this issue, we construct a (ranked) IO Index based on the same methodology that was used to construct the baseline FF Index, but we now include only IO variables, i.e., cash flows, the market-to-book ratio, sales growth, and firm size, as explanatory variables. Results reported in column (4) indicate that this IO Index has significant explanatory power for investment spikes. As the results reported in column (5) indicate, however, when they are included together with the baseline FF Index, the IO Index loses much of its significance and is much less significant than the FF Index. Comparing the pseudo-R-squares in columns (1), (4), and (5) makes it clear that the incremental contribution of financial flexibility is orders-of-magnitude higher than that of investment opportunities.

In the last two columns of Panel A of Table IV we report results that enable us to compare the performance of the FF Index with a parsimonious measure of financial flexibility introduced by Barry et al. (2022) (Table A.4). This proxy (BCGM proxy hereafter) is the simple average of a firm's lagged cash over assets and one minus the lagged leverage over assets. The results reported in column (6) indicate that the BCGM proxy is highly significant for explaining investment spikes. As seen in column (7), though, the BCGM proxy 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 balance sheet financial flexibility enables firms to undertake major investments, as noted in section 3, flexibility may be less important when investment targets are modest and firms can achieve their targets with limited balance-sheet flexibility. For the results reported in the lower panel of Panel A in Table IV, we change the dependent variable to the ratio of investment to lagged total assets. The FF Index continues to have a positive and significant effect on the investment ratio. The economic magnitude of the effect of FF is modest: an increase in FF rank from the 25^{th} to the 75^{th} percentile increases the investment ratio by about 2 percentage points. The incremental contribution of FF to the overall R-square is now smaller than that of the IO variables considered collectively, or the IO Index. Overall, these results suggest that the FF Index performs very well for the purpose for which it is designed, i.e., to explain large investments, compared with its success in explaining more modest investments.

[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. An important advantage of this methodology is that 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.

One interesting feature of these regressions is that the IO variables are mostly insignificant. With the exception of sales growth, which is significant in the first three columns

(Panel A, Table IV) at the 5% level, none of the other IO variables contributes to the predictability of investment spikes during industry-spike years. This finding is consistent with the motivation for this external validity test, namely that cross-sectional variations in investment opportunities are likely to be less important than balance-sheet flexibility during industry-spike years. [18]

The distribution and dynamic evolution of FF are similar in the industry-spike and non-industry samples. Moreover, the economic magnitude of FF in the first external validity test is quite significant. As can be seen in Panel C of Table IV, the mean Ranked-FF Index in the year before a firm-level spike has a 5.7 percent higher ranking than for non-spike years. Based on the coefficient estimate of FF reported in column (1) of Panel A, this translates to a 0.7 percentage point higher likelihood that an investment spike occurs. Given that the average likelihood that a spike occurs is around 10.4 percent, this is an economically significant magnitude. The time-series variation in the FF ranking from four years before to the year immediately before a spike for firms that experience spikes corresponds to a 4.3 percent increase, which suggests a 0.5 percentage point increase in the likelihood that an investment spike occurs.

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, these pseudo-R-squares appear small. Such a result is not unusual, however, for regressions that attempt to explain "changes". For example, the regression R-squares in cross-sectional tests of stock returns (which reflect changes in stock value) can also be quite low. Noticeably, even though the FF Index plays a less important role in explaining the *investment ratio*, the regression R-square is higher, at around 10 percent. Another reason for the low R-square is that the dependent variable is binary, and the criteria used to define the spikes are somewhat arbitrary: many firms could have increased investments but those investments might not have met the criteria used to define spikes. In section 6.6, we check the robustness of our results by creating an alternative dependent variable for changes in investment: investment at time t divided by the average investment during the preceding two years. In out-of-sample OLS regressions, the R-square improves to about 6 to 8 percent in in-sample tests and around

[18] An alternative possibility is that including the FF Indices subsumes the effect of growth opportunities. As we noted in our first test of external validity reported in Table IV Panel A, however, in non-industry-spike years the IO variables are significant even when FF is included. This suggests that the FF Index does not subsume investment opportunities, and the latter become significant when there is sufficient diversity in investment opportunities in the cross-section, unlike in industry-spike years.

6 percent in out-of-sample tests.

6.5 Robustness

We now check whether our results are robust to alternative methods of identifying firm-level spikes and industry-spike years.

In Panel A of Table V we report the results of repeating the same procedures as those associated with Table III and Table IV in alternative settings. After identifying firm-level investment spikes, we identify industry-spike years, then run the in-sample regression to generate FF (based on the baseline setting), and finally test for external validity in non-industry spike samples based on the corresponding FF-alternative. In columns (1), (3), (5), and (7) we report in-sample test results (on which the linear projected value of FF is based), while in columns (2), (4), (6), and (8) we report out-of-sample test results. The alternative settings are as follows:

- For columns (1) and (2), 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 columns (3) and (4), we change the industry-spike-filter Equation 2, to as

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

  where $Prop_{i,t} = \frac{\#\text{investment spike firms}_{i,t}}{\#\text{total firms}_{i,t}}$. In other words, for identification purposes, we change the backward-looking period from 3 to 5 years.

- For columns (5) and (6), we change the firm-level investment-spike filter from the linear filter of Im et al. (2020) to the filter in Whited (2006). The firm-year observation will be identified as an investment spike if

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

- For columns (7) and (8), we change the dependent variable in Equation I from raw investment to the investment ratio to redefine investment spikes. All other criteria remain the same.

[Table V about here.]

Reviewing the results reported in Panel A, of Table V, we observe that the alternative FF Indices have robust and significant coefficients across all alternative settings. Among the baseline variables, recent changes in cash holdings, the average level of past leverage, and changse in leverage are robustly significant in all in-sample results. The payout ratio is significant in all but one of the alternative specifications, while the average level of past cash holdings is significant in two of the alternative specifications.

For Panel B of Table V, we pick years from 1970–1999 one at a time and then use the following 20 years' 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 30 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 panel 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 addresses any concern regarding the extrapolation of index coefficients expressed in Whited and Wu (2006).[19]

6.6 An Alternative Measure of Change in Investment

By construction, an investment spike occurs when investment is significantly higher than the average investment in neighboring years. We might miss cases where firms make large investments in consecutive years or in years that are in close proximity. There is also the opposite possibility that the construction of investment spikes is subject to look-ahead bias: for example, only firms whose resources are insufficient to finance consecutive large investments would exhibit spikes, as defined. To address these issues, we repeat our main tests using an alternative variable that captures investment growth—the ratio of investment in year t to the average investment in the preceding two years. Industry-year spike clusters

[19] As the authors note, one concern with the practice of out-of-sample extrapolation of index coefficients is "parameter stability both across firms and over time", Despite this warning, the practice continues.

are identified as before, however, and our in-sample tests are based on these industry-years. The in-sample tests are OLS regressions with investment growth as the dependent variable and the explanatory variables associated with columns (1) and (4) of Table III as independent variables. As before, we now generate an alternative (ranked) FF Index, labeled Rank(FF_{IG}), via linear projections based on the estimated coefficients. We then include this Index in the out-of-sample tests.

We report the results in Table VI. In the first two columns of Panel A we report the in-sample results. Changes in cash holdings and changes in leverage continue to be highly significant in all regressions. Now, average past cash holdings is robustly significant, but average past leverage is not. The payout dummy is significant when the IO variables are not included. Firm size is highly significant with a negative coefficient estimate, suggesting that larger firms are more likely to smooth out investment.

[Table VI about here.]

The results of out-of-sample tests pertaining to non-industry-spike years for the Rank(FF_{IG}) Index (based on column (1)) are reported in columns (3)–(6). In column (3) (column (4)) we report results for the new Index when IO variables are excluded (included) in the out-of-sample tests. The results show that, irrespective of whether the IO variables are included, the Rank(FF_{IG}) Index has a significant and positive coefficient. For columns (5) and (6) we use the investment ratio as the dependent variable. The coefficient of the Rank(FF_{IG}) Index remains positive and significant.

In Panel B of Table VI we report the results of external validation for industry-spike years based on varying subperiods, as we do for the exercise associated with Panel B of Table IV. The coefficient of Rank(FF_{IG}) remains positive and significant in all subperiods except the post-2015 period.

A final observation worth mentioning before we leave this section is that the regression R-squares for both the in-sample and out-of-sample tests are between 5 and 7 percent. Although these figures are not directly comparable to the pseudo-R-squares derived from the logit model estimates with investment spikes as the dependent variable, these R-squares are in line with typical cross-sectional regressions when the dependent variable is a "change" variable.

6.7 Financial Constraints and Financial Flexibility

As discussed in section 3, the tightness of external financing frictions that firms face, as measured by an index of financial constraints, should also be an important determinant of financial flexibility. In this paper, we limit attention to the following indices of financial constraints, to which we refer collectively as FC Indices. These indices (as mentioned above) are the Kaplan-Zingales (KZ) Index, the Whited-Wu (WW) Index, three recent text-based indices (the Hadlock-Pierce (HP) Index from Hadlock and Pierce (2010), the Hoberg-Maksimovic (HM) Index from Hoberg and Maksimovic (2015), and the Bodnaruk, Loughran and McDonald (BLM) Index from Bodnaruk et al. (2015) as well as a no-credit-rating indicator variable. Importantly, lower values for all these indices correspond to *less* financially constrained firm-years. In our empirical tests, all these FC Indices except for the no-credit-rating dummy 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.

We examine the contribution of the various FC Indices in three ways. First, we augment the baseline in-sample regressions for industry-spike years by including the FC measures one at a time and test whether (a) these FC variables are significant in the industry-spike-year sample, and (b) the regression pseudo-R-squares increase substantially compared with the results obtained with the baseline specification. Second, based on these in-sample regressions, we generate new financial flexibility measures (denoted as Rank(FF_{FC})), and examine their out-of-sample performance relative to that of the baseline FF Index. Finally, 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. This last exercise is motivated in part by the fact that the construction of the KZ and the WW Indices is also involves some balance sheet variables, so to differentiate the effect of balance sheet financial flexibility from the contribution of balance sheet variables to (the relaxation of) financial constraints, it is necessary to run such horse races.

Before we discuss the regression results, we first show, in Table VII Panel A, the Spearman rank correlation coefficients between the FF Index and various FC measures. The correlations are negative, although they are close to zero for the two more recent text-based indices. For KZ, WW, and HP, the correlations are larger in magnitude and suggest that, irrespective of which of these FC indices is considered, firms classified as less tightly financially constrained enjoy greater balance sheet financial flexibility. This conclusion is re-enforced by the results reported in the last two rows of Panel A, where we find that the average FF ranking of firms classified as unconstrained for these three indices is higher than that of those classified as constrained.[20]

[Table VII about here.]

Then, in Table VII Panel B, we report a series of regression results enabling us to assess whether including FC measures could improve the predictive ability of the FF Index. The results reported in subpanel (a) reflect exactly the same test as that associated with column (1) of Table III Panel A, except that here we include the financial constraint measures one at a time. We find that only the KZ and HP Indices have significant negative coefficients,[21] while the WW Index also has a negative but marginally insignificant coefficient. None of the other indices has a significant sign, except for the no-credit-rating dummy, which is significant but has the wrong sign. Moreover, the contribution of the FC Indices to the overall in-sample R-square is very small and there is hardly any improvement in the R-square over that for the baseline FF Index.

We next compare the out-of-sample performance of the Rank(FF_{FC}) indices with that of the baseline FF Index. Subpanel (b) of Table VII Panel B presents the out-of-sample performance of the Rank(FF_{FC}) indices during non-industry-spike years. Compared with those derived from the baseline FF Index, here the regression coefficients are similar in magnitude and the improvement in pseudo-R-squares is also either very marginal (e.g., for the KZ Index) or not detectable up to three decimal places.

We also run out-of-sample tests for industry-spike years only, much like the tests we ran for Table IV Panel B. We investigate whether including FC measures improves the predictability of investment spikes in the industry-spike-year sample and report the results in Panel B subpanel (c). The first four rows provide the average estimates of in-sample

[20]It is surprising that the relationship between financial flexibility and these indices is similar in KZ and WW, because Table 2 in Whited and Wu (2006) indicates that firms sorted as financially unconstrained by the WW index have less cash and more debt than those classified as constrained, while the opposite is the case with the KZ Index. These differences are, however, considerably more substantial with KZ.

[21]The HP Index is based on firm size and firm age, so we drop firm size as a control variable for the in-sample regression when including the HP Index.

tests (on the sample before the cutoff years), the corresponding z-statistics, the in-sample pseudo-R-squares based on Rank(FF_{FC}), and those based on the baseline FF Index. In the last four columns we report the corresponding out-of-sample results. Only the KZ Index has significant estimates with the right signs. The marginal improvements in R-squares obtained by including the FC Indices over the baseline are all very small. Based on the above evidence, we can safely conclude that the FC measures fail to offer much additional information that is relevant to predicting future investment spikes.

For Table VII Panel C, we run the abovementioned "horse races". In subpanel (a) of Panel C, we find that only the standalone KZ and the WW Indices have significant coefficients with the right signs. Both the z-statistic and the R-square for the regression where the FF Index is an independent variable are higher, however, than those obtained with KZ and WW as standalone independent variables. On a standalone basis, the KZ Index comes closest to matching the performance of the FF Index.

We then include the FC Indices together with FF one at a time. Only the KZ Index is significant with the right sign. The FF remains highly significant in all regressions. The z-statistic is more than three times higher for FF than for KZ. Compared with the regression R-squares reported in the immediately above panel, it is clear that including FF substantially improves the R-squares; however, including the KZ has virtually no impact.

These results are surprising, because as argued in section 3, external financing frictions should be one of the major determinants of financial flexibility. It appears as though, as argued by Farre-Mensa and Ljungqvist (2016), none of these measures properly distinguishes between tightly financially constrained firms and less tightly constrained firms. If so, our results point to a major gap in our understanding of the nature and source of financing frictions, and call for further research.

Next, we show that the FF Index outperforms the FC measures even when the dependent variable is the ratio of investment over lagged assets (the investment ratio). We noted in section 6.4 that the explanatory power of the FF Index drops (relative to that of the IO variables) when the investment ratio is the dependent variable, possibly because it is designed to explain major investments. However, it still outperforms the FC variables, as seen in subpanel (b) of Panel C, where we report the results of tests that are similar to those reported in subpanel (a). To save space, we do not report results when the FF and the FC variables are included one at a time. There, we find that FF, KZ, WW, and HP have significant coefficients with the right signs. As we see regarding the test results reported in subpanel (b), when included together with FF, the coefficient of the KZ Index has the wrong sign. The coefficients of WW and HP remain significant and have the right signs, but their incremental contribution to the regression R-square is very small. Moreover, in all regressions, FF remains significant and has a t-statistic that is more than four times that of the WW and HP Indices.

Finally, we change the dependent variable to investment growth. The results reported in subpanel (c) of Panel C indicate that the coefficient of Rank(FF_{IG}) Index has much higher t-ratios than the FC measures. Three of these FC measures —the KZ, WW, and HP Indices—have significant coefficients with the right sign when included together with the Rank(FF_{IG}) Index.

To sum up, our results suggest that, with the possible exception of the KZ Index, the FC measures play at most a small role in determining cross-sectional variation in financial flexibility, or the capacity to undertake large investments, compared with the role that balance-sheet variables play. Two of the standard FC measures do appear to explain cross-sectional variation in the investment ratio and investment growth, although the FF Index plays a much more important role. It is especially remarkable that two of the recent text-based indices have either no explanatory power for either variable or have the wrong sign.

The superior performance of the KZ Index over that of other FC indices in explaining major investments deserves a fuller discussion. For several of our regressions, the loadings on the KZ Index Index are quite similar to those for the FF Index. Low KZ index values (corresponding to less-constrained firms) pick out firms that have significantly lower debt and significantly more cash on their balance sheets—much like high-FF firms.

The KZ Index was developed on the basis of reading management discussions of operations and liquidity and letters to shareholders for 49 low-dividend firms (originally in a sample studied by Fazzari et al. (1988)) and subjective classification of firm-years based on firms' ability to "access internal or external funds to *increase investment*". Therefore, both our FF Index and the KZ Index are focused on firms' capacity to respond to major investment opportunities.

Results based on the KZ Index are often at odds with those based on other indices. *Our results show that the KZ Index is more appropriately thought of as an index of balance sheet financial flexibility, rather than as a financial constraint index.* As we have argued above, balance sheet financial flexibility need not be related to financial constraints in the cross-section or even in time series. Financial flexibility in similarly constrained firms can vary across time depending on the nature of their historical investment and financing activity in response to exogenous shocks. The same firm may see its financial flexibility over time depending on its recent history and response to such shocks.

The use of the KZ Index as an index of financial constraints has been criticized because researchers have projected the estimation results of Kaplan and Zingales (1997)—based on a small sample and subjective classification of financial constraint status—out of sample for studies in more recent periods.[22] In this paper, we develop our own index for balance sheet flexibility on the basis of firms' *actions* rather than the subjective classification of what they *say* in annual filings. Moreover, inasmuch as our index can be constructed readily for any sample period, there is less concern about small sample bias or parameter instability. As we have shown, the FF Index outperforms KZ in out-of-sample tests of the capacity to predict major investments.

6.8 Time-Series Evidence

So far, our evidence has mostly been cross-sectional in nature, with the exception of that reported in Table III Panel (lower subpanel) and Table IV Panel C (the lower subpanel), where we show that the Ranked FF for spike firms increases from three years before the investment-spike year to the year before, and then decreases over the next three years, in contrast to what occurs in firms that do not generate any spikes over this time period. We now provide more systematic evidence on the type of financing activity, the behavior of the FF and the FC measures, as well as balance sheet and IO variables, around investment spike years, for both firms that have investment spikes as well as those that do not.

To do so, we "stack" firms in the same industry that have investment spikes at time $t = 0$ and those that do not during any year from time $t - 4$ to time $t + 3$ into cohorts and run regressions as follows,

$$\begin{aligned} y_{i,\tau} =& \beta_{1,\tau} year_\tau + \beta_{2,\tau} investment\ spike_{i,t=0} \times year_\tau + \\ & \beta_3 Controls_{i,\tau-1} + Firm \times Cohorts\ FE + \epsilon_{i,t}, \text{ where } \tau = 0, \pm1, \pm2, \pm3, \end{aligned} \tag{3}$$

where y is the variable of interest, $year_\tau$ are the indicator variables for time relative to t,

[22] A similar concern has been expressed regarding applications of the WW Index. For example, Farre-Mensa and Ljungqvist (2016) observes that, "Rather than re-estimating the structural model on their own samples, users of the WW index then extrapolate out of the sample using Whited and Wu's reported coefficient estimates".

and *investment spike*$_{i,t=0}$ is the dummy variable that indicates whether firm i generates an investment spike at $t = 0$. We further control for the one-period lagged market-to-book ratio, lagged cash flows, lagged sales growth, and $firm \times cohort$ fixed effects.[23] The base period in these regressions is year $t - 4$, i.e., the coefficients of the year dummies are interpreted relative to that year. We are not interested in causal identification, but rather in illustrating variations in patterns of variables of interest for firms that generate spikes as well as those that operate in the same industry and do not, around spike years.

In Appendix Table A.I we report three sets of results, all of which involve only non-industry-spike years. In Panel A, we report investment and financing patterns for spike firms and non-spike firms. All variables in this panel are part of a firm's cash-flow identity, in which the source of funds equals the use of funds. Detailed definitions of each part of cash identity can be found in Appendix A. [24] Dividends, which typically are a minor component of a firm's cash-flow identity, are not reported. All variables are scaled by lagged total assets.

The key takeaways are that spike firms exhibit modest increases in investment prior to spike years and invest 14 percent more of lagged assets (in the DID sense) in spike years. Investment tapers off after a spike year. *Internal financing* also exhibits an increasing trend and increases by 2.3 percent of lagged assets in the year before a spike occurs. Spike firms accumulate cash prior to a spike year, increase their cash holdings by 2.6 percent of lagged assets in the year before a spike, and draw down cash in the year of the spike. *Equity financing* picks up in the two years leading to a spike year, and firms increase equity financing as a proportion of lagged total assets by about 4.5 percent and by a further 3 percent in a spike year. *Debt financing* picks up only in the spike year, increasing substantially, by about 6.5 percent of lagged assets. *Other sources* decreases prior to a spike year for spike firms—suggesting that firms reduce short-term obligations—but increase in a spike year.[25] Except for *Other sources*, non-spike firms exhibit no pre-trends with any of the variables.

Together, these investment and financing patterns suggest that firms create financial flexibility by issuing equity and accumulating cash prior to spikes, financing spikes mostly by issuing debt, issuing smaller amounts of equity, drawing down cash holdings, and using some internal funds in spike years.

[23] When one of these variables is the dependent variable of interest, we drop the corresponding variable as a control variable.

[24] We follow equation (9) in Im et al. (2020) and use their variable definitions. Im et al. (2020) also report results similar to those we report in Panel A, but our methodology is different.

[25] *Other sources* reflects primarily short-term obligations and trade credit.

To obtain the results reported in Panel B of Appendix Table A.I, we examine the time-series behavior of variables that constitute the FF Index, including the IO variables. Cash holdings increase in the two years prior to spikes for both spike and non-spike firms, but to a greater extent for the latter. We find contrasting patterns for cash holdings following spike years—increasing for non-spike firms but decreasing in spike years for spike firms and then recovering slowly. Book leverage decreases substantially prior to spikes for spike firms, but despite the substantial increase in debt issuance in spike years, the increase in book leverage in a spike year and the following year for the spike firms is a modest 1 to 1.5 percent of the lagged book value of assets. This suggests that firms manage their debt capacity through financing choices made during and prior to investment spikes.

Of particular interest in this regard is the behavior of the IO variables prior to spike years. Considering the market-to-book ratio first, there is a substantial increasing trend for non-spike firms through spike years, as the ratio increases by 0.11 relative to year $t-4$, three years after a spike year. Insofar as non-spike firms are same-industry firms by construction and given the design of our stacked DID setting, this suggests that industries in which spikes occur feature improving growth opportunities. This point is relevant to our out-of-sample tests based on non-industry-spike years: spikes typically occur in industries where good investment opportunities are found and it is therefore less likely that firms do not generate investment spikes when they lack investment opportunities. However, firms that do generate spikes encounter substantially better investment opportunities in the two years prior to spike years. This is also relevant to our out-of-sample tests and explains why our IO control variables have explanatory power.

In contrast to the above-discussed market-to-book ratio, sales growth exhibits a somewhat different pattern. Relative to time $t-4$, non-spike firms experience lower sales growth through the year of a spike. Spike firms experience increasing sales growth, however, which peaks in the years immediately before spikes, before eventually slowing down and turning negative. Inasmuch as sales growth is likely to be mean-reverting, it is difficult to interpret these time-series patterns. It is possible that sales and sales growth peak at $t-4$ or earlier for the non-spike firms and later for the spike firms.

Overall, the patterns documented in Appendix Table A.I Panels A and B are consistent with the results reported in DeAngelo et al. (2011), who suggest that firms respond to modestly good investment opportunities by financing them with equity, creating debt capacity, and building up cash holdings. If significantly better investment opportunities subsequently materialize, they utilize debt capacity by issuing less costly debt in greater amounts. While both spike and non-spike firms operating in the same industry receive positive shocks to investment opportunities, the former group receives even more positive shocks and steps up investment modestly, engaging in substantial equity financing that results in stronger balance sheets and more financial flexibility prior to spike years.

Finally, in Appendix Table A.I Panel C, we use the same stacked DID framework to illustrate the time-series pattern for the Ranked FF Index and the FC Indices around investment spikes. Figure I provides a visual representation of the regression results, where we plot the regression coefficients separately for spike and non-spike firms (vertical axis) against event times. The main takeaway is that only the FF and the KZ Indices show patterns that are consistent with the idea that the indices should change around the spike year in a manner that enables firms to undertake large increases in investment. Specifically, while the FF Index peaks immediately before the spike year and falls in the spike year, and the KZ does the opposite, none of the other indices show this pattern.

6.9 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.[26] Finding such evidence would also be another 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 "tech bubble" of 2001, which affected mostly technology firms (Loughran and Ritter, 2004). We follow the empirical strategy proposed in Hoberg and Mak-

[26]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)). Cash holdings, however, capture only one dimension of financial flexibility.

simovic (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:

$$I_{i,t} - I_{i,t-2} = \beta FF\ (FC)\ Indices_{t-2} + Controls_{t-2} + Industry\ fixed\ effects + \epsilon_i. \quad (4)$$

The dependent variable in this model is changes 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, an FC Index, or both, 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 VIII. We find that the two-year lagged FF Index has highly significant and positive coefficients in all three NBER recessions, with a marginally significant positive coefficient for the tech recession. The results obtained with the KZ Index are similar, except that it is not significant for the tech recession and has much 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.[27] 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 standard measures of financial constraints do not consistently predict which firms have access to external financing during these times.

[Table VIII about here.]

7 A Model

To confirm the intuition behind our empirical tests, we solve a model adapted from Gao et al. (2021) and repeat our empirical tests using data simulated from this model. The

[27] 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. FC measures except for the KZ index are either not significant or have the wrong signs for the tech bubble or financial crisis periods. These results are reported in Appendix Table A.II.

details pertaining to the model and the calibration are explained in Appendix B. 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, are costly, and cash stocks alleviate investment distortion caused by financial constraints. 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 balance-sheet variables 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 IX. 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 IX. 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 IX, 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 IX 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.

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 results are reported in columns (1)–(4) of Table X. To account for industry heterogeneity, we generate another set of simulated panels, each with 138 industries and 100 years. The number of firms in each industry is identical to the number in the real data. The regression results based on the multiple-industries sample are reported in columns (5)–(8).

[Table X about here.]

In columns (1) and (5) we present the baseline logit estimates for the construction of the FF Index in various simulated samples. 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. The highly skewed distribution of size in the real data may account for this difference. The results reported in columns (2) and (6) indicate that the results remain robust when we control for the industry-wide and firm-level productivity shocks. We then create the FF Index as a linear projection based on the coefficients reported in columns (1) and (5) and convert the projected values to scaled rank measures. External validations of FF indices are reported in the remaining columns. The results reported in columns (3) and (7) indicate the predictive ability of the FF Index for future investment spikes, and the results reported in columns (4) and (8) indicate the same predictive ability for the future investment ratio. These results are quite similar to what we report in Table IV, in both magnitude and significance. In summary, these results provide strong justification for our empirical approach.

Finally, we also show time-series evidence, as in section 6.8, in the simulated data. The stacked-DID results are reported in Appendix Table A.III. We focus on the times-series patterns of investment and external financing in the FF Index around spike years. Consistent with results reported in Table A.I, we find that firms improve balance sheet financial flexibility, reduce debt, and accumulate cash holdings gradually before an investment spike. After the investment spike, financial flexibility and cash reserves drop dramatically.

8 Conclusion

In this paper, we examine whether and how balance-sheet health is related to firms' capacity to undertake major investments (investment spikes). We find that both liquidity and debt capacity are important determinants of major investments in the cross-section and are much more important than investment opportunities during periods of industry-wide investment-spike clusters. We use logit regressions based on these industry-spike years to generate an index for *balance sheet financial flexibility*, which we call the FF Index. We show that this index strongly predicts firm-level investment spikes in out-of-sample tests. Financial constraint measures—especially some recent text-based measures—play a limited or no role in explaining financial flexibility. The well-known Kaplan-Zingales Index has properties similar to those of the FF Index, which suggests that the former is best interpreted as a balance sheet financial flexibility index, not as a financial constraint index. 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.

References

Acharya, V. V. and S. Steffen (2020). The risk of being a fallen angel and the corporate dash for cash in the midst of covid. *The Review of Corporate Finance Studies 9*(3), 430–471.

Albuquerque, R., Y. Koskinen, S. Yang, and C. Zhang (2020). Resiliency of environmental and social stocks: An analysis of the exogenous covid-19 market crash. *The Review of Corporate Finance Studies 9*(3), 593–621.

Ang, J. and A. Smedema (2011). Financial flexibility: Do firms prepare for recession? *Journal of Corporate Finance 17*(3), 774–787.

Bargeron, L., D. Denis, and K. Lehn (2018). Financing investment spikes in the years surrounding world war i. *Journal of Financial Economics 130*(2), 215–236.

Barry, J. W., M. Campello, J. R. Graham, and Y. Ma (2022). Corporate flexibility in a time of crisis. *Journal of Financial Economics 144*(3), 780–806.

Bodnaruk, A., T. Loughran, and B. McDonald (2015). Using 10-k text to gauge financial constraints. *Journal of Financial and Quantitative Analysis 50*(4), 623–646.

Bolton, P., N. Wang, and J. Yang (2021). Leverage dynamics under costly equity issuance. *NBER Working Paper 26802*.

Campello, M., J. R. Graham, and C. R. Harvey (2010). The real effects of financial constraints: Evidence from a financial crisis. *Journal of Financial Economics 97*(3), 470–487.

Cooley, T. F. and V. Quadrini (2001). Financial markets and firm dynamics. *American Economic Review 91*(5), 1286–1310.

De Vito, A. and J.-P. Gómez (2020). Estimating the covid-19 cash crunch: Global evidence and policy. *Journal of Accounting and Public Policy 39*(2), 106741.

DeAngelo, H., L. DeAngelo, and T. M. Whited (2011). Capital structure dynamics and transitory debt. *Journal of Financial Economics 99*(2), 235–261.

Denis, D. J. (2011). Financial flexibility and corporate liquidity. *Journal of Corporate Finance 17*(3), 667–674.

Denis, D. J. and S. B. McKeon (2012). Debt financing and financial flexibility evidence from proactive leverage increases. *The Review of Financial Studies 25*(6), 1897–1929.

Denis, D. J. and V. Sibilkov (2010). Financial constraints, investment, and the value of cash holdings. *The Review of Financial Studies 23*(1), 247–269.

Ding, W., R. Levine, C. Lin, and W. Xie (2020). Social distancing and social capital: Why us counties respond differently to covid-19. *NBER Working Paper*.

Dittmar, A. and J. Mahrt-Smith (2007). Corporate governance and the value of cash holdings. *Journal of Financial Economics 83*(3), 599–634.

Duchin, R., O. Ozbas, and B. A. Sensoy (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics 97*(3), 418–435.

Elsas, R., M. J. Flannery, and J. A. Garfinkel (2014). Financing major investments: Information about capital structure decisions. *Review of Finance 18*(4), 1341–1386.

Fahlenbrach, R., K. Rageth, and R. M. Stulz (2021). How valuable is financial flexibility when revenue stops? evidence from the covid-19 crisis. *The Review of Financial Studies 34*(11), 5474–5521.

Farre-Mensa, J. and A. Ljungqvist (2016). Do measures of financial constraints measure financial constraints? *The Review of Financial Studies 29*(2), 271–308.

Fazzari, S., R. G. Hubbard, and B. Petersen (1988). Investment, financing decisions, and tax policy. *American Economic Review 78*(2), 200–205.

Frank, M. Z. and V. K. Goyal (2009). Capital structure decisions: which factors are reliably important? *Financial Management 38*(1), 1–37.

Gao, X., T. M. Whited, and N. Zhang (2021). Corporate money demand. *he Review of Financial Studies 34*(2), 1834–1866.

Giroud, X. and H. M. Mueller (2017). Firm leverage, consumer demand, and employment losses during the great recession. *Quarterly Journal of Economics 132*(1), 271–316.

Graham, J. R. (2022). Presidential address: Corporate finance and reality. *The Journal of Finance*.

Graham, J. R. and C. R. Harvey (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics 60*(2-3), 187–243.

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies 23*(5), 1909–1940.

Harford, J. (1999). Corporate cash reserves and acquisitions. *Journal of Finance 54*(6), 1969–1997.

Harford, J., S. A. Mansi, and W. F. Maxwell (2008). Corporate governance and firm cash holdings in the us. *Journal of Financial Economics 87*(3), 535–555.

Hoberg, G. and V. Maksimovic (2015). Redefining financial constraints: A text-based analysis. *The Review of Financial Studies 28*(5), 1312–1352.

Im, H. J., C. Mayer, and O. Sussman (2020). Heterogeneity in investment spike financing. *SSRN Working Paper*.

Jensen, M. C. (1986). The agency costs of free cash flow: Corporate finance and takeovers. *American Economic Review 76*(2), 323–329.

Kahle, K. M. and R. M. Stulz (2013). Access to capital, investment, and the financial crisis. *Journal of Financial economics 110*(2), 280–299.

Kaplan, S. N. and L. Zingales (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics 112*(1), 169–215.

Kaplan, S. N. and L. Zingales (2000). Investment-cash flow sensitivities are not valid measures of financing constraints. *Quarterly Journal of Economics 115*(2), 707–712.

Keynes, J. M. (1936). *The General Theory of Employment, Interest and Money.* London: Harcourt Brace.

Lamont, O., C. Polk, and J. Saaá-Requejo (2001). Financial constraints and stock returns. *The Review of Financial Studies 14*(2), 529–554.

Lins, K. V., H. Servaes, and P. Tufano (2010). What drives corporate liquidity? an international survey of cash holdings and lines of credit. *Journal of Financial Economics 98*(5), 160–176.

Loughran, T. and J. Ritter (2004). Why has ipo underpricing changed over time? *Financial Management*, 5–37.

Mayer, C. and O. Sussman (2004). A new test of capital structure. *SSRN Working Paper*.

Ramelli, S. and A. F. Wagner (2020). Feverish stock price reactions to covid-19. *The Review of Corporate Finance Studies 9*(3), 622–655.

Stulz, R. M. (1990). Managerial discretion and optimal financing policies. *Journal of Financial Economics 26*(1), 3–27.

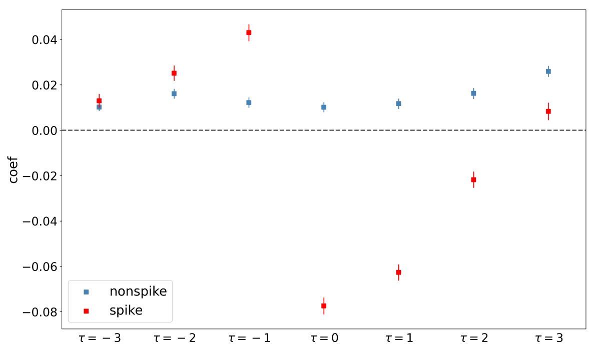
Svensson, L. E. O. (1985). Money and asset prices in a cash-in-advance economy. *Journal of Political Economics 93*(5), 919–944.

Whited, T. M. (2006). External finance constraints and the intertemporal pattern of intermittent investment. *Journal of Financial Economics 81*(3), 467–502.

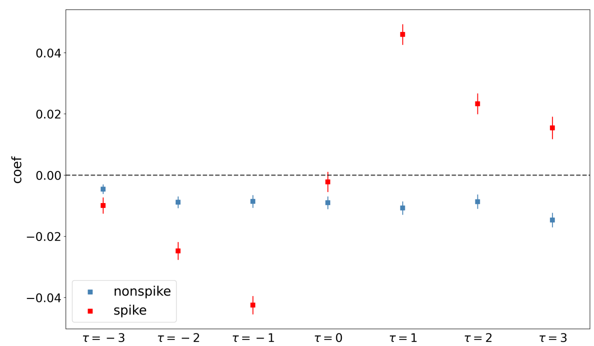
Whited, T. M. and G. Wu (2006). Financial constraints risk. *he Review of Financial Studies 19*(2), 531–559.

Figure I: **Time Series Pattern of FF/FC Measures around Investment Spike**

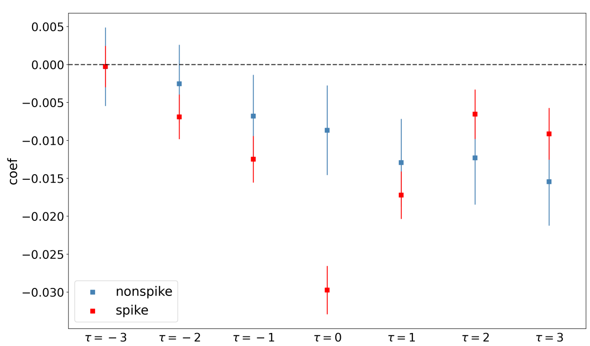
This figure is based on the Stacked DID test associated with Panel B of Table A.I, presenting the time-series pattern of the financial flexibility measure (FF) and various financial constraint measures (FC) around investment spikes. For each subplot, the benchmark is the average measure across non-spike firms at $\tau = -4$. Red squares are based on the estimation of interaction terms, showing the average measures across investment-spike firms from $\tau = -3$ to $\tau = 3$ relative to the benchmark. Blue squares are based on the estimation of time dummy variables, showing the corresponding values of comparable non-spike firms. The bars represent 95% confidence intervals for each estimation.



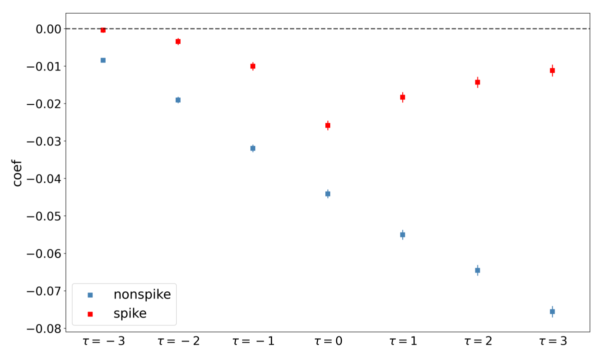
(a) Rank(FF)



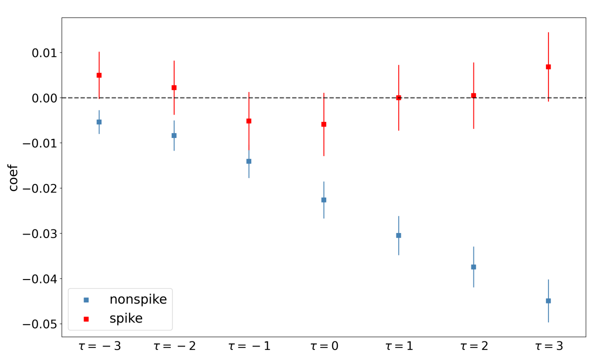
(b) Rank(KZ)



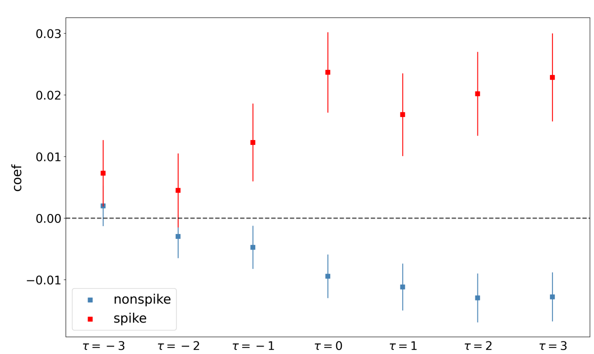
(c) Rank(WW)



(d) Rank(HP)



(e) Rank(HM)



(f) Rank(BLM)

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 baseline investment. In Panel C we report the distribution of spike years (industry-spike years) frequencies and the time gap between consecutive spike years (industry-spike years). We also show the spike-firm proportion for industries conditional on the occurrence of a spike, for industry-spike years and non-industry-spike years. 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 years	28.57%	10.55%	18.18%	21.43%	26.67%	33.33%	40.00%
	Spike firm proportion – non-industry spike years	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 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-level Investment Spikes During Industry-Spike Periods**

In this table we report the results of in-sample tests based on the industry-spike-year sample. Panel A presents the estimates of Logit regressions of the firm-investment-spike dummy variable on past firm-level characteristics. 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 based on the baseline specification for different sample periods, in which we include lagged change in cash holdings, average past cash holdings, lagged change in book leverage, average past book leverage, lagged firm size, and lagged payout ratio. In columns (4)–(6) we report estimates for different sample periods when including the lagged market-to-book ratio, lagged cash flows, and lagged sales growth to control for investment opportunities. We include 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. In Panel B we report the in-sample distribution of the Financial Flexibility (FF) Index and its time-series patterns for investment-spike and non-spike firms. The FF Index is the linear projected value of balance sheet variables associated with Panel A column (1). To obtain values for Rank(FF) we rank firms every year based on FF and divide the ranking by the total number of firms.

Panel A: Explaining investment spikes

Logit regression, dependent variable: Investment spike dummy						
Specification	Baseline			Include investment opportunities		
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period:	1970-2019	1970-1995	1996-2019	1970-2019	1970-1995	1996-2019
Chg cash holding$_{\tau=-1}$	1.964***	2.033***	1.980***	1.906***	1.927***	1.913***
	(10.589)	(6.077)	(8.639)	(9.639)	(5.294)	(7.762)
Avg cash holding$_{\tau=-4:-2}$	0.427**	0.383*	0.479**	0.241	0.253	0.260
	(2.550)	(1.686)	(2.250)	(1.487)	(1.019)	(1.217)
Chg book leverage$_{\tau=-1}$	-0.993***	-1.619***	-0.695***	-1.163***	-1.546***	-0.926***
	(-6.813)	(-6.160)	(-4.415)	(-7.967)	(-5.719)	(-5.733)
Avg book leverage$_{\tau=-4:-2}$	-0.302***	-0.565***	-0.154	-0.397***	-0.525***	-0.286**
	(-3.358)	(-3.410)	(-1.524)	(-4.165)	(-3.108)	(-2.470)
Size$_{\tau=-1}$	0.027***	0.011	0.041***	0.031***	0.018	0.045***
	(2.598)	(0.745)	(2.785)	(2.732)	(1.185)	(2.691)
Payout$_{\tau=-1}$	2.357***	3.450***	2.025***	2.325***	2.947***	2.091***
	(5.576)	(3.608)	(4.198)	(5.258)	(2.976)	(4.111)
Market-to-book$_{\tau=-1}$				0.016**	0.008	0.017**
				(2.114)	(0.296)	(2.221)
Cashflow(+)$_{\tau=-1}$				0.028	0.143***	0.010
				(1.284)	(3.251)	(0.433)
Cashflow(−)$_{\tau=-1}$				0.000	-0.028	0.000
				(0.112)	(-1.163)	(0.095)
Sales growth$_{\tau=-1}$				0.112***	0.032	0.123***
				(2.980)	(0.468)	(3.034)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	19,921	9,568	10,353	18,911	9,322	9,589
Pseudo R^2	0.023	0.026	0.028	0.025	0.026	0.031

Panel B: Summary statistic of the Financial Flexibility Index during industry-spike periods

	Firm-year	N	Mean	SD	P10	P25	P50	P75	P90
FF	All	19,921	-1.080	0.378	-1.517	-1.319	-1.094	-0.853	-0.618
	Spike	5,173	-0.978	0.381	-1.427	-1.216	-0.991	-0.752	-0.504
	Nonspike	14,748	-1.116	0.370	-1.546	-1.346	-1.125	-0.891	-0.663
	Firm-year	N	$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Avg (Rank(FF) - Rank(FF)$_{\tau=-4}$)	All	14,398	0.001	0.010	0.018	0.001	-0.007	0.003	0.012
	Spike	3,626	0.001	0.024	0.051	-0.047	-0.039	0.000	0.022
	Nonspike	10,772	0.001	0.006	0.006	0.017	0.003	0.004	0.009

Table IV: **External Validation**

In this table we report the results of tests of the external validity of the Financial Flexibility (FF) index. The FF Index is the linear projected value of the variables associated with column (1) in Table III. The sample period runs from 1970 through 2019. The first set of out-of-sample tests present the FF Index's predictive ability for future investment in the non-industry-spike-year sample. For the upper half of Panel A, the dependent variable is an investment-spike dummy; in the lower half, we change the dependent variable to the investment ratio. We also report the predictive power of investment opportunity variables, the IO Index (constructed based on investment opportunity variables and size only), and the BCGM proxy (Barry et al., 2022) for comparison. We then demonstrate the validity of the FF index in industry-spike years, using all observations before the cutoff year to construct the index, then validating it for the subsequent industry-spike years. Panel B presents the in- and out-of-sample estimates. The dependent variable is the dummy variable for investment spikes at $\tau = 0$. Columns (1)–(6) show the results with varying sample cutoffs. For all tests associated with Panels A and B, we include industry and year fixed effects. Standard errors are clustered at the industry-year level. z (t)-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. In Panel C we report the distribution of the FF Index and its time-series patterns with the non-industry-spike sample. To obtain Rank(FF) we rank firms in every year based on the index and divide the ranking by the total number of firms.

Panel A: Non-industry-spike period validity

	Logit regression, dependent variable: Investment spike dummy						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(FF)$_{\tau=-1}$	1.190***		1.144***		1.140***		1.036***
	(37.105)		(34.578)		(33.195)		(24.560)
Rank(IO Index)$_{\tau=-1}$				0.821***	0.441***		
				(16.973)	(8.609)		
Rank(BCGM Proxy)$_{\tau=-1}$						0.745***	0.158***
						(22.832)	(3.741)
Market-to-book$_{\tau=-1}$		0.021***	0.021***			0.021***	0.021***
		(6.119)	(5.710)			(6.037)	(5.670)
Cashflow(+)$_{\tau=-1}$		0.108***	0.068***			0.080***	0.066***
		(16.567)	(10.556)			(12.530)	(10.193)
Cashflow(−)$_{\tau=-1}$		0.000	0.000			0.000	0.000
		(0.098)	(0.139)			(0.639)	(0.274)
Sales growth$_{\tau=-1}$		0.068***	0.084***			0.054***	0.080***
		(4.935)	(5.993)			(3.991)	(5.702)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	171,575	160,539	160,539	160,539	160,539	160,539	160,539
Pseudo R^2	0.022	0.014	0.024	0.013	0.023	0.019	0.024
	OLS regression, dependent variable: I/lagged TA						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(FF)$_{\tau=-1}$	0.033***		0.035***		0.019***		0.037***
	(5.447)		(5.847)		(4.111)		(8.354)
Rank(IO Index)$_{\tau=-1}$				0.103***	0.096***		
				(8.036)	(7.697)		
Rank(BCGM Proxy)$_{\tau=-1}$						0.0178 ***	-0.003
						(3.194)	(-0.562)
Market-to-book$_{\tau=-1}$		0.004***	0.004***			0.004***	0.004***
		(4.793)	(4.970)			(4.954)	(4.947)
Cashflow(+)$_{\tau=-1}$		0.003***	0.002*			0.003**	0.002*
		(3.961)	(1.866)			(2.571)	(1.868)
Cashflow(−)$_{\tau=-1}$		0.000***	0.000***			0.000***	0.000***
		(3.549)	(3.773)			(3.625)	(3.743)
Sales growth$_{\tau=-1}$		0.027***	0.027***			0.026***	0.027***
		(4.397)	(4.353)			(4.342)	(4.402)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	200,631	186,392	186,392	186,392	186,392	186,392	186,392
Adj R^2	0.099	0.119	0.124	0.107	0.108	0.121	0.124

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
	In-sample regressions						
Chg cash holding$_{\tau=-1}$	1.853***	2.150***	2.033***	1.917***	1.876***	1.927***	1.923***
	(3.499)	(5.321)	(6.077)	(7.555)	(8.306)	(9.328)	(9.835)
Avg cash holding$_{\tau=-4:-2}$	-0.050	0.188	0.383*	0.713***	0.576***	0.538***	0.412**
	(-0.121)	(0.611)	(1.686)	(3.401)	(2.833)	(3.000)	(2.322)
Chg book leverage$_{\tau=-1}$	-2.018***	-1.736***	-1.619***	-1.294***	-1.157***	-1.159***	-1.092***
	(-4.549)	(-5.560)	(-6.160)	(-6.789)	(-6.646)	(-7.071)	(-7.578)
Avg book leverage$_{\tau=-4:-2}$	-0.728***	-0.747***	-0.565***	-0.306**	-0.298**	-0.368***	-0.336***
	(-3.134)	(-3.748)	(-3.410)	(-2.224)	(-2.550)	(-3.347)	(-3.466)
Size$_{\tau=-1}$	0.006	0.021	0.011	0.018	0.015	0.020*	0.027**
	(0.285)	(1.258)	(0.745)	(1.292)	(1.216)	(1.718)	(2.482)
Payout$_{\tau=-1}$	3.624***	2.616**	3.450***	2.858***	3.057***	2.499***	2.231***
	(2.606)	(2.315)	(3.608)	(4.784)	(5.518)	(5.267)	(5.149)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	5,825	7,410	9,568	13,101	15,273	16,945	19,283
Pseudo R^2	0.026	0.026	0.025	0.023	0.022	0.024	0.023
	Out-of-sample verification						
Rank(FF)$_{\tau=-1}$	1.425***	1.385***	1.347***	1.277***	1.270***	1.310***	1.719***
	(13.715)	(12.212)	(11.423)	(8.027)	(7.189)	(5.846)	(3.047)
Market-to-book$_{\tau=-1}$	0.014	0.014	0.011	-0.015	-0.000	0.019	0.081*
	(1.521)	(1.540)	(1.151)	(-1.272)	(-0.014)	(1.501)	(1.946)
Cashflow(+)$_{\tau=-1}$	0.025	0.016	0.004	0.027	0.001	-0.002	0.057
	(1.146)	(0.740)	(0.192)	(1.151)	(0.040)	(-0.051)	(0.476)
Cashflow(−)$_{\tau=-1}$	0.000	0.000	0.001	-0.000	0.000	0.001	0.011*
	(0.100)	(0.321)	(0.552)	(-0.050)	(0.057)	(0.427)	(1.939)
Sales growth$_{\tau=-1}$	0.113**	0.125***	0.125***	0.033	0.006	0.118	-0.467**
	(2.554)	(2.947)	(2.863)	(0.460)	(0.076)	(1.121)	(-1.984)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	13,153	11,649	9,589	6,191	4,182	2,682	462
Pseudo R^2	0.027	0.029	0.030	0.032	0.033	0.042	0.091

Panel C: Summary statistic of the Financial Flexibility Index during non-industry-spike periods

	Firm-year	N	Mean	SD	P10	P25	P50	P75	P90
FF	All	174,140	-1.168	0.419	-1.678	-1.426	-1.170	-0.909	-0.650
	Spike	20,313	-1.075	0.420	-1.584	-1.336	-1.083	-0.814	-0.551
	Nonspike	153,827	-1.181	0.417	-1.689	-1.437	-1.182	-0.922	-0.666
	Firm-year	N	$\tau=-3$	$\tau=-2$	$\tau=-1$	$\tau=0$	$\tau=1$	$\tau=2$	$\tau=3$
Avg (Rank(FF) - Rank(FF)$_{\tau=-4}$)	All	130,180	-0.005	-0.009	-0.010	-0.005	-0.002	-0.001	0.000
	Spike	14,806	-0.002	0.017	0.043	-0.064	-0.049	-0.007	0.013
	Nonspike	115,374	-0.003	-0.010	-0.014	0.004	0.004	0.000	-0.002

Table V: **Robustness Checks**

In this table we report the results of robustness checks of our methodology, in which we construct the Financial Flexibility (FF) index in alternative ways, and demonstrate its external validity. The first set of robustness checks demonstrates that our methodology is robust to various industry classifications and filters for industry- and firm-level investment spikes. Details can be found in Section 6.5. In Panel A we report the in-sample and out-of-sample Logit estimates in alternative settings. The dependent variable is the dummy variable for investment spikes at $\tau = 0$. In columns (1), (3), (5), and (7) we report the in-sample regression results for alternative settings in the industry-spike-year sample. In columns (2), (4), (6), and (8) we report results that demonstrate the out-of-sample validity of corresponding FF indices. The sample period runs from 1970 throughu 2019. The second set of robustness checks tests parameter stability. For each twenty-continuous-year industry-spike sample, we estimate a Logit model to construct the FF Index, and we then test the validity of this index on the remaining sample. In Panel B we report the distribution of coefficients and z-statistics for each balance sheet variable based on those in-sample tests, and we also demonstrate the out-of-sample predictive ability of the FF Index. For all the tests whose results are reported in Panels A and B, we control for 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

Alternative settings:	Industry classification		Industry spike filter		Firm spike filter		Investment ratio spike	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chg cash holding$_{\tau=-1}$	1.558***		2.018***		2.315***		1.634***	
	(5.994)		(9.658)		(9.213)		(6.469)	
Avg cash holding$_{\tau=-4:-2}$	-0.006		0.448**		0.350**		0.014	
	(-0.021)		(2.146)		(1.985)		(0.095)	
Chg book leverage$_{\tau=-1}$	-0.962***		-1.239***		-1.653***		-1.132***	
	(-5.556)		(-7.825)		(-10.430)		(-5.049)	
Avg book leverage$_{\tau=-4:-2}$	-0.296**		-0.315***		-0.009		-0.391***	
	(-2.104)		(-2.904)		(-0.112)		(-4.061)	
Size$_{\tau=-1}$	0.023		0.028**		-0.131***		-0.014	
	(1.428)		(2.291)		(-13.877)		(-1.346)	
Payout$_{\tau=-1}$	2.025***		2.050***		-0.432		2.700***	
	(2.735)		(4.440)		(-0.704)		(5.221)	
Rank(FF$_{alternative}$)$_{\tau=-1}$		1.222***		1.220***		1.558***		1.136***
		(38.797)		(38.784)		(50.581)		(26.799)
IO variables		Yes		Yes		Yes		Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	8,101	187,561	15,767	175,729	15,457	204,000	17,062	159,513
Pseudo R^2	0.018	0.023	0.024	0.023	0.039	0.049	0.021	0.018

Panel B: Parameter stability

		Regression coefficients					z-statistics				
		Mean	SD	P25	P50	P75	Mean	SD	P25	P50	P75
Industry spike period regressions	Chg cash holding$_{\tau=-1}$	1.989	0.125	1.892	1.967	2.055	7.079	1.086	6.120	7.492	7.721
	Avg cash holding$_{\tau=-4:-2}$	0.515	0.185	0.360	0.519	0.637	2.342	0.977	1.660	2.284	3.071
	Chg book leverage$_{\tau=-1}$	-1.121	0.320	-1.376	-0.991	-0.930	-5.159	0.384	-5.375	-5.248	-5.045
	Avg book leverage$_{\tau=-4:-2}$	-0.312	0.222	-0.516	-0.187	-0.151	-1.972	0.995	-3.010	-1.583	-1.206
	Size$_{\tau=-1}$	0.023	0.013	0.015	0.021	0.032	1.403	0.791	0.977	1.278	1.733
	Payout$_{\tau=-1}$	2.678	0.478	2.293	2.732	3.000	3.967	0.963	3.250	4.275	4.580
	Pseudo R^2	0.027	0.002	0.026	0.027	0.028					
Non-industry-spike period verification	Rank(FF)$_{\tau=-1}$	1.275	0.063	1.224	1.263	1.294	37.882	0.465	37.510	37.956	38.295
	Pseudo R^2	0.023	0.002	0.021	0.022	0.024					

Table VI: **Predicting Investment Growth: Alternative FF Index**

This table presents an alternative financial flexibility index (FF Index) based on the prediction of investment growth, and demonstrates its external validity, based on linear estimation. The dependent variable, *investment growth*, is defined as the ratio of investment at t over the past two-year average. In Panel A column (1) we report the OLS estimates with the industry-spike-year sample. The alternative index, FF_{IG}, represents the linear projected value of balance-sheet variables. The results reported in column (2), for which we include investment opportunity (IO) variables (i.e. the lagged market-to-book ratio, cash flows, and sales growth), are similar. In columns (3)–(6) we report results demonstrating the external validity of the alternative index FF_{IG} with the non-industry-spike-year sample. The settings are identical to those for columns (1) and (3) in Table IV Panel A. The coefficients of the IO variables are omitted for simplicity. In Panel B, we report results demonstrating the validity of the alternative FF Index in industry-spike years. We rerun the test associated with Table IV Panel B but replace the dependent variable with investment growth. For all specifications we 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.

Panel A: Explaining Investment Growth

OLS regression	Industry-spike sample		Non-industry-spike period			
Dependent variables:	Investment growth		Investment growth		I/lagged TA	
	(1)	(2)	(3)	(4)	(5)	(6)
Chg cash holding$_{\tau=-1}$	4.678***	4.352***				
	(15.351)	(15.002)				
Avg cash holding$_{\tau=-4:-2}$	1.456***	0.836***				
	(3.832)	(3.260)				
Chg book leverage$_{\tau=-1}$	-1.900***	-1.766***				
	(-11.951)	(-10.087)				
Avg book leverage$_{\tau=-4:-2}$	0.109	0.057				
	(1.090)	(0.535)				
Size$_{\tau=-1}$	-0.122***	-0.104***				
	(-8.634)	(-7.790)				
Payout$_{\tau=-1}$	1.789***	1.044**				
	(3.599)	(2.036)				
Rank(FF$_{IG}$)$_{\tau=-1}$			1.597***	1.433***	0.015***	0.012***
			(23.752)	(23.651)	(3.244)	(2.863)
IO variables		Yes		Yes		Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	20,513	20,513	173,497	173,497	175,610	175,610
Adj R^2	0.067	0.077	0.057	0.071	0.111	0.138

Table VI: Predicting Investment Growth: Alternative FF Index (Continued)

Panel B: Subperiod verification

OLS regression, dependent variable: Investment growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cutoff year:	1985	1990	1995	2000	2005	2010	2015
	In-sample regressions						
Chg cash holding$_{\tau=-1}$	4.338***	4.538***	4.762***	4.646***	4.651***	4.531***	4.649***
	(11.014)	(8.752)	(10.950)	(13.861)	(15.320)	(13.941)	(14.926)
Avg cash holding$_{\tau=-4:-2}$	1.423**	1.639***	1.774***	2.054***	1.792***	1.671***	1.490***
	(3.025)	(3.843)	(3.914)	(4.375)	(4.059)	(3.950)	(3.859)
Chg book leverage$_{\tau=-1}$	-2.433***	-1.703***	-1.845***	-1.830***	-1.852***	-1.944***	-1.946***
	(-7.307)	(-4.239)	(-5.630)	(-8.069)	(-9.905)	(-11.217)	(-11.829)
Avg book leverage$_{\tau=-4:-2}$	-0.245	0.138	0.016	0.136	0.056	0.043	0.100
	(-1.371)	(0.554)	(0.093)	(0.938)	(0.432)	(0.378)	(0.950)
Size$_{\tau=-1}$	-0.099***	-0.091***	-0.106***	-0.121***	-0.129***	-0.125***	-0.129***
	(-7.999)	(-6.426)	(-4.958)	(-7.722)	(-8.373)	(-8.418)	(-9.872)
Payout$_{\tau=-1}$	1.357	2.125	2.584*	2.412**	2.154***	2.165***	1.749***
	(0.998)	(1.584)	(2.054)	(2.653)	(2.889)	(3.921)	(3.411)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	6,064	7,654	9,843	13,680	15,853	17,517	19,976
Adj R^2	0.065	0.058	0.075	0.083	0.075	0.072	0.069
	Out-of-sample verification						
Rank(FF$_{IG}$)$_{\tau=-1}$	2.155***	2.259***	2.227***	2.145***	2.148***	2.018***	1.208
	(17.287)	(18.560)	(16.493)	(13.284)	(11.507)	(10.896)	(3.053)
Market-to-book$_{\tau=-1}$	0.059***	0.055***	0.052***	0.012	0.007	0.041	0.121
	(3.792)	(3.437)	(3.152)	(0.455)	(0.164)	(0.861)	(6.043)
Cashflow(+)$_{\tau=-1}$	0.190***	0.178***	0.172***	0.183***	0.098	0.115	0.232
	(4.859)	(4.427)	(3.790)	(3.144)	(1.578)	(1.307)	(1.250)
Cashflow(−)$_{\tau=-1}$	-0.020*	-0.018	-0.017	-0.011	-0.008	-0.009	0.006
	(-1.827)	(-1.698)	(-1.653)	(-1.220)	(-0.902)	(-0.896)	(0.218)
Sales growth$_{\tau=-1}$	0.289***	0.318***	0.344***	0.112	-0.105**	-0.091	-0.129
	(2.770)	(3.116)	(3.431)	(1.632)	(-2.719)	(-1.805)	(-0.474)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	14,449	12,859	10,670	6,833	4,660	2,995	537
Adj R^2	0.066	0.069	0.066	0.053	0.048	0.042	0.031

Table VII: **"Horse Races" with Financial Constraint Measures**

In this table we report the results of "horse races" between the Financial Flexibility Index (FF Index) and financial constraint (FC) measures. FC measures include three widely used indices (i.e. KZ, WW, and HP), two recent text-based indices (i.e. HM and BLM), and a dummy variable for the absence of a credit rating. We use the rank value of indices to ensure that all indices are comparable. In Panel A we report Spearman's rank correlations between the FF Index and FC measures as well as conditional average rankings (FF) for financially constrained and unconstrained firms. The results reported in Panel B indicate the marginal contribution of an additional FC measure to the predictive ability of the corresponding FF Index. We add the FC measure as an explanatory variable and rerun the tests associated with Table III and IV. In subpanel (a) we report the in-sample Logit estimates, and then in subpanel (b) we report results demonstrating the external validity of the corresponding FF_{FC} index (the linear projected value of balance-sheet variables and the additional FC measure based on the estimates reported in subpanel (a)). In subpanel (c), we report the subperiod verifications for all FC measures. The method is similar to that associated with Table IV Panel B, and we report the in-sample and out-of-sample average estimates across cutoff years. In each subpanel, we also report the Pseudo R^2 based on the baseline FF for comparison. The results reported in Panel C enable us to compare how the FC measures perform in predicting future firm-level investment in the non-industry-spike period with the performance of the FF Index. In each specification, we control for the investment opportunity variables. For all tests whose results are reported in Panels B and C, we include industry and year fixed effects. Standard errors are clustered at the industry-year level.

FC Measures	KZ	WW	HP	HM	BLM	No Credit Rating
Panel A: Correlation between FF and FC measures						
Spearman's rank correlation	-0.370	-0.370	-0.208	-0.030	-0.036	/
Avg rank(FF) for constrained firms	0.347	0.425	0.421	0.493	0.493	0.483
Avg rank(FF) for unconstrained firms	0.647	0.574	0.570	0.505	0.502	0.537
Panel B: Could including FC measures improve the predictive ability of the FF Index?						
	(1)	(2)	(3)	(4)	(5)	(6)
	(a) Industry-spike sample regressions					
$FC_{\tau=-1}$	-0.409***	-0.234	-0.165**	0.095	0.018	0.152**
	(-4.943)	(-1.618)	(-1.984)	(0.577)	(0.185)	(2.294)
Baseline variables	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.024	0.024	0.023	0.040	0.037	0.023
Baseline pseudo R^2	0.024	0.024	0.023	0.040	0.037	0.023
	(b) Non-industry-spike periods validity					
$\text{Rank}(FF_{FC})_{\tau=-1}$	1.220***	1.124***	1.158***	1.314***	1.281***	1.112***
	(36.528)	(34.505)	(34.632)	(19.378)	(22.500)	(34.321)
Pseudo R^2	0.025	0.024	0.024	0.032	0.029	0.024
$\text{Rank}(FF_{baseline})_{\tau=-1}$	1.152***	1.132***	1.144***	1.329***	1.279***	1.144***
	(34.055)	(34.674)	(34.578)	(19.669)	(22.465)	(34.578)
Baseline pseudo R^2	0.024	0.024	0.024	0.033	0.029	0.024
	(c) Subperiods verification					
	In-sample					
$FC_{\tau=-1}$	-0.413	-0.330	-0.086	0.039	0.006	0.150
z-stats	-3.628	-1.754	0.243	0.043	2.091	2.294
pseudo R^2	0.025	0.025	0.024	0.040	0.037	0.023
Baseline pseudo R^2	0.024	0.024	0.024	0.042	0.040	0.023
	Out-of-sample					
$\text{Rank}(FF_{FC})_{\tau=-1}$	1.459	1.296	1.362	1.437	1.718	1.349
z-stats	9.438	8.536	9.237	3.593	4.842	6.055
pseudo R^2	0.040	0.037	0.038	0.065	0.059	0.048
Baseline pseudo R^2	0.040	0.038	0.038	0.065	0.059	0.049

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

Panel C: Does the FF Index outperform FC Measures during non-industry-spike periods?

(a) Logit regression, dependent variable: Investment spike dummy

FC Measures		KZ	WW	HP	HM	BLM	No Credit Rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Rank(FF)}_{\tau=-1}$	1.177***						
	(34.987)						
$\text{FC}_{\tau=-1}$		-0.782***	-0.096***	-0.038	-0.066	0.077*	-0.004
		(-24.011)	(-2.653)	(-1.130)	(-1.097)	(1.655)	(-0.151)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	160,539	155,819	160,539	160,539	44,183	58,737	160,539
Pseudo R^2	0.025	0.019	0.015	0.014	0.020	0.018	0.014
		(7)	(8)	(9)	(10)	(11)	(12)
$\text{Rank(FF)}_{\tau=-1}$		1.014***	1.154***	1.177***	1.240***	1.226***	1.177***
		(26.041)	(34.659)	(34.968)	(19.454)	(22.837)	(34.992)
$\text{FC}_{\tau=-1}$		-0.328***	-0.029	-0.016	-0.080	0.151***	0.007
		(-8.781)	(-0.792)	(-0.476)	(-1.351)	(3.222)	(0.247)
IO variables		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Nobs		155,819	160,539	160,539	44,183	58,737	160,539
Pseudo R^2		0.025	0.025	0.025	0.033	0.030	0.025

(b) OLS regression, dependent variable: I/lagged TA

FC Measures		KZ	WW	HP	HM	BLM	No Credit Rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Rank(FF)}_{\tau=-1}$	0.035***	0.039***	0.032***	0.033***	0.033***	0.032***	0.036***
	(5.847)	(6.291)	(5.005)	(5.253)	(5.017)	(4.923)	(5.857)
$\text{FC}_{\tau=-1}$		0.006**	-0.012**	-0.009*	-0.004	0.018***	0.012***
		(2.085)	(-2.331)	(-1.897)	(-0.675)	(3.978)	(4.594)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	186,392	180,847	186,392	186,392	52,657	70,136	186,392
Adj R^2	0.124	0.125	0.128	0.124	0.137	0.122	0.124

(c) OLS regression, dependent variable: Investment growth

FC Measures		KZ	WW	HP	HM	BLM	No Credit Rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Rank}(\text{FF}_{IG})_{\tau=-1}$	1.433***	1.381***	1.465***	1.459***	1.538***	1.585***	1.430***
	(23.651)	(24.857)	(26.000)	(26.863)	(13.698)	(15.760)	(25.016)
$\text{FC}_{\tau=-1}$		-0.236***	-0.105***	-0.069	-0.038	0.235***	0.103***
		(-8.077)	(-3.113)	(-1.539)	(-0.920)	(5.196)	(3.367)
IO variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	173,497	168,213	173,497	173,497	49,594	66,176	173,497
Adj R^2	0.071	0.071	0.071	0.071	0.072	0.069	0.071

Table VIII: **External Validity: Investment Curtailment during Recessions**

In this table we report results pertaining to the performance of the Financial Flexibility (FF) Index in predicting investment curtailment during recessions. The dependent variable is the change in each firm's investment ratio from t-2 to t, where t is the end-year of recessions. The independent variables include the FF Index or FC Indices and firm-level characteristics (i.e., size, log age, the market-to-book ratio, and sales growth) at t-2. We investigate four recession periods as defined by the NBER. In Panels A through D we report the OLS estimates for the recessions that ended in 1982, 1990, 2001, and 2009, respectively. The corresponding independent variables are measured ex ante and are constructed using data from 1980, 1988, 1999, and 2007, respectively. 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 include 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/lagged TA)$_t$ - (I/lagged TA)$_{t-2}$

FC Measures		KZ	WW	HP		KZ	WW	HP
	Panel A: 1982 The Great Inflation				**Panel B: Early 1990s Recession**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rank(FF)$_{\tau=-2}$	0.092***				0.129***			
	(9.233)				(11.084)			
FC measures$_{\tau=-2}$		-0.017*	-0.048	0.078*		-0.049***	-0.106***	0.040
		(-1.755)	(-1.352)	(1.728)		(-4.947)	(-4.223)	(1.404)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	3,457	3,340	3,440	3,457	4,053	3,890	4,017	4,053
Adj R^2	0.085	0.056	0.055	0.056	0.103	0.064	0.061	0.057

Panel C: 2001 Tech Bubble

FC Measures		KZ	WW	HP	HM	BLM	No Credit Rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(FF)$_{\tau=-2}$	0.026*						
	(1.932)						
FC measures$_{\tau=-2}$		0.008	0.058	0.133***	-0.011	-0.016	-0.034**
		(0.516)	(1.106)	(3.666)	(-0.668)	(-1.102)	(-2.254)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	1,470	1,381	1,446	1,470	1,041	1,128	1,470
Adj R^2	0.182	0.185	0.176	0.187	0.181	0.173	0.183

Panel D: 2008 Financial Crisis

FC Measures		KZ	WW	HP	HM	BLM	No Credit Rating
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rank(FF)$_{\tau=-2}$	0.130***						
	(8.830)						
FC measures$_{\tau=-2}$		-0.049***	0.016	0.110***	-0.010	-0.006	-0.016
		(-4.001)	(0.427)	(3.009)	(-0.831)	(-0.554)	(-1.613)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	4,272	4,013	4,220	4,272	2,301	2,963	4,272
Adj R^2	0.169	0.144	0.139	0.140	0.136	0.113	0.137

Table IX: **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 X: **Financial Flexibility in Simulated Data**

In this table we report results pertaining to the Financial Flexibility (FF) Index and demonstrate its external validity with simulated data. We generate simulated panels in two ways: (a) with 500 firms in one industry and 100 years, and (b) with 138 industries and 100 years, with the number of firms in each industry equaling those in the real data. We then conduct regression analyses that are similar to those whose results are reported in Table III and TableIV and repeat these regressions 100 times. The independent variables are calculated in the same way as in our empirical analysis. We use changes in industry and idiosyncratic productivity as proxies for investment opportunities. We report the average coefficients and significance across 100 regression results. In columns (1) and (2) and (5) and (6) we report estimates of Logit regressions of the firm-level investment-spike dummy variable on past firm-level characteristics based on the industry-spike-period sample. The FF Indices are the linear projected values of the independent variables reported in column (1) and column (5). In columns (3) and (4) and (7) and (8) we report results demonstrating the FF Index's predictive ability for future investment for the non-industry-spike-year sample. In columns (3) and (7) we report the Logit estimates with the firm-level investment-spike dummy as the dependent variable, and in columns (4) and (8) we report the OLS estimates with the investment ratio as the dependent variable. In simulations that assume industry heterogeneity, we include industry fixed effects. 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.

Simulation Panel	Unique industry				Multiple industries			
	In-sample		Out-of-sample		In-sample		Out-of-sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chg cash holding$_{\tau=-1}$	14.619***	15.487***			14.268***	14.656***		
	(4.731)	(4.946)			(24.788)	(25.181)		
Avg cash holding$_{\tau=-4:-2}$	12.706***	13.856 ***			11.098***	11.408***		
	(2.868)	(3.311)			(12.716)	(13.343)		
Chg book leverage$_{\tau=-1}$	-5.462***	-5.542***			-5.475***	-5.717***		
	(-3.103)	(-3.827)			(-14.979)	(-16.175)		
Avg book leverage$_{\tau=-4:-2}$	-1.902***	-2.044***			-1.729***	-1.802***		
	(-3.481)	(-3.633)			(-15.823)	(-16.583)		
Size$_{\tau=-1}$	-6.107***	-6.474***			-5.688 ***	-5.791***		
	(-4.885)	(-5.634)			(-27.370)	(-29.065)		
Payout$_{\tau=-1}$	8.449**	8.903**			8.818***	9.424***		
	(1.981)	(2.139)			(9.206)	(9.680)		
Rank(FF)$_{\tau=-1}$			1.871***	0.023***			1.651***	0.011***
			(12.128)	(15.621)			(30.269)	(5.564)
Chg ind. productivity$_{\tau=-1}$		1.700 ***	2.401 ***	0.056***		1.262***	2.126***	0.054***
		(2.388)	(6.950)	(5.029)		(13.893)	(31.484)	(44.430)
Chg idio. productivity$_{\tau=-1}$		-1.306	5.056	0.130		1.112***	3.028***	0.070***
		(-0.116)	(0.681)	(0.560)		(3.986)	(11.814)	(13.818)
Industry FE					Yes	Yes	Yes	Yes
Nobs	7,690	7,690	40,310	40,310	91,650	91,650	453,246	453,246
Pseudo R^2	0.052	0.071	0.083	0.126	0.050	0.063	0.073	0.110

Appendix A Variable Definitions

A.1 Company-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.
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 $prcc_f$ $\times$ 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*). **Cashflow**(+) is equal to *Cashflow* if it is positive and zero otherwise. **Cashflow**(−) is equal to *Cashflow* if it is negative and zero otherwise.
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.
Internal financing refers to after-tax cash flows from operating activities, which is defined as (income before extraordinary items (cashflow statement) *ibc* + depreciation and amortization (cash-flow statement) *dpc* - cash dividends *dv*) in year-2000 real dollars.
Decrease in cash refers to changes in cash and cash equivalents (-1 $\times$ Compustat item *chech*) in year-2000 real dollars.
Equity financing refers to funds from issues of ordinary and preferred shares net of retire-

ments, which is defined as the difference in year-2000 real dollars between sales of common and preferred stock (Compustat item *sstk*) and purchases of common and preferred stock (Compustat item *prstkc*).

Debt financing refers to funds from issues of long-term debt net of retirements, which is defined as the difference in year-2000 real dollars between issuances of long-term debt (Compustat item *dltis*) and purchases of long-term debt (Compustat item *dltr*).

Other source refers to the residual sources of financing that ensures that cash-flow identity holds, which is defined as (*Investment - Internal financing - Decrease in cash - Equity financing - Debt financing*).

Investment growth is defined as the ratio of *investment* at t to the preceding-two-year average, $2I_{i,t}/(I_{i,t-1} + I_{i,t-2})$.

A.2 Financial flexibility and financial constraint measures

Financial Flexibility Index (FF) 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*. $\mathrm{FF}_{benchmark}$ refers to the FF Index based on the estimates reported in column (1) of Table III Panel A. $\mathrm{FF}_{alternative}$ in Table V refers to the FF Indices constructed by alternative settings. FF_{FC} associated with Table VII refers to the FF Index with financial constraint measures as additional components. FF_{IG} in Table VI refers to the FF Index based on the linear model with *investment growth* as the dependent variable.

KZ Index is constructed following Lamont et al. (2001) as $-1.002(ib + dp)$/lagged $ppent + 0.283[(at + prcc_f \times csho - ceq - txdb)/at] + 3.139(dltt + dlc)/(dltt + dlc + seq) - 39.368(dvc + dvp)$/lagged $ppent - 1.315che$/lagged $ppent$, where all variables in italics are Compustat data items.

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.

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.

No Credit Rating is an indicator that firms have not been given credit ratings from S&P, Moody's, or Fitch, using data obtained from Compustat (variable *splticrm*) and Mergent

FISD.

Appendix B 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.

B.1 Production

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

$$\pi(x_t, z_t, k_t) = e^{x_t+z_t} k_t^{\alpha} - c_f \tag{5}$$

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.[28] The productivity shocks are realized and observed by managers before investing and cash savings are set, both following an AR(1) stochastic process,

$$x_t = (1-\rho_x)\bar{x} + \rho_x x_{t-1} + \sigma_x \varepsilon_{x,t}, \tag{6}$$
$$z_t = (1-\rho_z)\bar{z} + \rho_z z_{t-1} + \sigma_z \varepsilon_{z,t}, \tag{7}$$

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

$$\Phi(i_t, k_t) = \gamma_0 \mathbb{I}_{i\neq 0} + \frac{\gamma_1}{2}\left(\frac{i_t}{k_t}\right)^2 k_t, \tag{8}$$

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

B.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

[28] 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.[29]

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.

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

B.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.

B.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 IX. 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 IX. 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 IX, the model-implied and data moments are presented in Panel B, and the investment-spike statistics are presented in Panel C.

Appendix C Other Empirical Evidence

Table A.I: **Stacked DID – Firm-level Characteristics around Investment Spikes**

In this table we report estimates of stacked difference-in-differences (DID) designs to reveal the time-series pattern of relevant variables around investment spikes as well as the difference between spike firms and non-spike firms. In each industry-year group, all firms that generate investment spikes in that year (but generate no other spikes from t-4 to t+3) are grouped together as the treated firms; all firms that do not generate any spikes in years t-4 to t+3 are control firms. All the treated and control firms in each year t constitute a cohort. We include observations from years t-4 to t+3 for each cohort in the regression. The sample period runs from 1970 through 2019. With year t-4 as the benchmark, we conduct a series of DID tests. The regression specification is shown in Equation 3. In Panel A we report the estimates for each component if cash-flow identity based on equation (9) in Im et al. (2020). Each component is scaled by lagged total assets for comparison. In Panel B we report estimates of relevant firm-level characteristics. In Panel C we report estimates of the financial flexibility index (FF Index) and financial constraint (FC) measures. We control for lagged investment opportunity (IO) variables and firm-cohort fixed effects. Standard errors are clustered at the cohort level. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cashflow identity

	(1) Investment	(2) Internal financing	(3) Decrease in cash	(4) Equity financing	(5) Debt financing	(6) Other sources
$\tau = -3$	0.001	0.001	-0.002	-0.000	0.000	-0.000
	(1.122)	(0.296)	(-0.828)	(-0.040)	(0.632)	(-0.184)
$\tau = -2$	0.002**	-0.001	-0.002	-0.001	0.001	0.002
	(1.972)	(-0.361)	(-0.714)	(-0.268)	(1.121)	(0.795)
$\tau = -1$	0.001	-0.000	0.003	-0.017***	0.002	0.010***
	(1.049)	(-0.146)	(1.509)	(-4.784)	(1.593)	(3.984)
$\tau = 0$	-0.000	-0.005*	0.003*	-0.020***	0.002**	0.015***
	(-0.304)	(-1.785)	(1.713)	(-6.199)	(2.328)	(5.928)
$\tau = 1$	-0.001	-0.009***	0.002	-0.021***	0.002*	0.018***
	(-0.899)	(-2.815)	(1.074)	(-5.600)	(1.784)	(6.519)
$\tau = 2$	-0.003**	-0.013***	0.004*	-0.025***	0.001	0.023***
	(-2.490)	(-4.283)	(1.892)	(-6.570)	(0.934)	(8.398)
$\tau = 3$	-0.004***	-0.015***	0.000	-0.025***	0.001	0.024***
	(-3.091)	(-4.277)	(0.191)	(-6.937)	(1.141)	(8.243)
Inv. spike	-0.002**	0.007*	-0.005*	0.003	0.000	-0.004
$\times$ $\tau = -3$	(-2.310)	(1.811)	(-1.829)	(0.796)	(0.084)	(-1.220)
Inv. spike	0.006***	0.016***	-0.011***	0.013***	0.002*	-0.007*
$\times$ $\tau = -2$	(4.911)	(3.842)	(-4.330)	(3.262)	(1.664)	(-1.913)
Inv. spike	0.008***	0.023***	-0.026***	0.033***	0.005***	-0.021***
$\times$ $\tau = -1$	(6.017)	(5.233)	(-9.267)	(7.458)	(3.803)	(-5.660)
Inv. spike	0.137***	0.017***	0.018***	0.028***	0.065***	0.016***
$\times$ $\tau = 0$	(63.619)	(3.868)	(7.160)	(6.568)	(34.838)	(5.625)
Inv. spike	-0.015***	-0.011***	0.007***	-0.010***	-0.003*	0.011***
$\times$ $\tau = 1$	(-10.536)	(-2.667)	(2.994)	(-3.074)	(-1.872)	(2.806)
Inv. spike	-0.014***	-0.009**	-0.001	-0.005	-0.005***	0.011***
$\times$ $\tau = 2$	(-10.266)	(-2.260)	(-0.284)	(-1.350)	(-3.406)	(3.063)
Inv. spike	-0.007***	-0.007	-0.001	0.002	-0.002	0.006
$\times$ $\tau = 3$	(-4.469)	(-1.364)	(-0.494)	(0.597)	(-1.478)	(1.371)
Market-to-book$_{\tau=-1}$	0.010***	-0.050***	-0.022***	0.046***	0.005***	0.002
	(20.675)	(-15.986)	(-16.790)	(19.407)	(16.931)	(0.886)
Cashflow$(+)_{\tau=-1}$	0.011***		0.006***	-0.013***	0.006***	-0.013***
	(20.810)		(4.391)	(-8.118)	(12.794)	(-8.845)
Cashflow$(-)_{\tau=-1}$	-0.000***		-0.001***	-0.002***	-0.000***	-0.004***
	(-6.695)		(-3.853)	(-4.109)	(-5.161)	(-6.118)
Sales growth$_{\tau=-1}$	0.014***	0.068***	0.005***	-0.008***	0.009***	-0.029***
	(16.560)	(18.990)	(2.781)	(-2.781)	(11.300)	(-12.375)
Firm-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	287,098	283,462	287,098	284,001	287,098	278,054
$Adj R^2$	0.468	0.632	0.007	0.310	0.118	0.347

Panel B: Relevant firm characteristics

	(1) Cash holdings	(2) Book leverage	(3) Size	(4) Payout	(5) Market-to-book	(6) Sales Growth
$\tau = -3$	0.004***	-0.002*	0.019***	0.001***	0.035*	-0.007
	(4.457)	(-1.704)	(4.210)	(3.870)	(1.763)	(-1.595)
$\tau = -2$	0.006***	-0.002*	0.042***	0.001***	0.050**	-0.009*
	(5.742)	(-1.742)	(6.285)	(5.945)	(2.179)	(-1.707)
$\tau = -1$	0.004***	0.000	0.082***	0.002***	0.055**	-0.029***
	(4.193)	(0.039)	(10.601)	(8.107)	(2.340)	(-5.495)
$\tau = 0$	0.004***	0.003	0.119***	0.003***	0.061***	-0.044***
	(3.222)	(1.543)	(13.157)	(10.447)	(2.829)	(-7.845)
$\tau = 1$	0.004***	0.005***	0.157***	0.003***	0.054**	-0.059***
	(3.008)	(2.695)	(15.143)	(11.308)	(2.411)	(-10.417)
$\tau = 2$	0.004***	0.009***	0.186***	0.003***	0.063***	-0.069***
	(3.723)	(4.163)	(16.284)	(11.706)	(2.916)	(-11.984)
$\tau = 3$	0.008***	0.006***	0.238***	0.004***	0.088***	-0.067***
	(6.160)	(2.640)	(19.462)	(13.484)	(4.109)	(-11.829)
Inv. spike	0.006***	-0.008***	0.005	0.000	0.008	0.002
$\times \quad \tau = -3$	(4.310)	(-4.576)	(0.852)	(0.464)	(0.528)	(0.326)
Inv. spike	0.012***	-0.017***	0.041***	0.001***	0.064***	0.025***
$\times \quad \tau = -2$	(7.563)	(-8.314)	(5.536)	(3.229)	(3.332)	(4.414)
Inv. spike	0.022***	-0.028***	0.113***	0.002***	0.147***	0.053***
$\times \quad \tau = -1$	(12.215)	(-12.188)	(12.816)	(4.246)	(6.123)	(9.036)
Inv. spike	-0.026***	0.021***	0.286***	0.001*	-0.123***	0.108***
$\times \quad \tau = 0$	(-14.084)	(8.132)	(27.920)	(1.809)	(-6.160)	(17.190)
Inv. spike	-0.020***	0.021***	0.211***	-0.001***	-0.187***	0.022***
$\times \quad \tau = 1$	(-10.750)	(7.921)	(18.791)	(-3.668)	(-8.599)	(3.620)
Inv. spike	-0.010***	0.011***	0.177***	-0.000	-0.144***	-0.037***
$\times \quad \tau = 2$	(-5.006)	(3.986)	(14.577)	(-0.278)	(-6.911)	(-6.299)
Inv. spike	-0.006***	0.010***	0.147***	-0.000	-0.117***	-0.015**
$\times \quad \tau = 3$	(-2.607)	(3.315)	(11.173)	(-0.070)	(-5.678)	(-2.441)
Market-to-book$_{t=-1}$	0.008***	0.001*	0.008***	0.001***		0.038***
	(15.672)	(1.695)	(2.929)	(7.918)		(28.641)
Cashflow$(+)_{t=-1}$	0.011***	-0.025***	0.074***	0.004***	0.101***	-0.013***
	(11.459)	(-19.886)	(21.326)	(25.634)	(10.120)	(-5.418)
Cashflow$(-)_{t=-1}$	-0.001***	-0.001***	0.008***	-0.000	-0.027***	-0.007***
	(-9.346)	(-5.756)	(6.195)	(-1.573)	(-7.917)	(-11.352)
Sales growth$_{t=-1}$	-0.014***	0.001	0.199***	-0.001***	0.041***	
	(-14.270)	(0.966)	(28.883)	(-4.879)	(2.745)	
Firm-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	277,687	276,651	284,745	287,098	81,433	108,068
Adj R^2	0.539	0.633	0.741	0.961	0.628	0.491

Panel C: FF and FC measures

	(1) FF	(2) KZ	(3) WW	(4) HP	(5) HM	(6) BLM
$\tau = -3$	0.010***	-0.005***	-0.000	-0.008***	-0.005**	0.002
	(5.997)	(-2.942)	(-0.056)	(-14.432)	(-2.053)	(0.608)
$\tau = -2$	0.016***	-0.009***	-0.003	-0.019***	-0.008**	-0.003
	(7.422)	(-4.674)	(-0.495)	(-22.248)	(-2.499)	(-0.844)
$\tau = -1$	0.012***	-0.009***	-0.007	-0.032***	-0.014***	-0.005
	(5.328)	(-4.147)	(-1.252)	(-31.718)	(-3.803)	(-1.352)
$\tau = 0$	0.010***	-0.009***	-0.009	-0.044***	-0.023***	-0.009***
	(4.692)	(-4.360)	(-1.467)	(-37.802)	(-5.530)	(-2.659)
$\tau = 1$	0.012***	-0.011***	-0.013**	-0.055***	-0.030***	-0.011***
	(5.138)	(-4.916)	(-2.240)	(-42.159)	(-7.071)	(-2.940)
$\tau = 2$	0.016***	-0.009***	-0.012**	-0.065***	-0.037***	-0.013***
	(6.745)	(-3.724)	(-2.004)	(-45.037)	(-8.307)	(-3.259)
$\tau = 3$	0.026***	-0.015***	-0.015***	-0.076***	-0.045***	-0.013***
	(10.652)	(-6.123)	(-2.661)	(-49.946)	(-9.459)	(-3.215)
Inv. spike	0.013***	-0.010***	-0.000	-0.000	0.005	0.007
$\times \quad \tau = -3$	(4.308)	(-3.742)	(-0.099)	(-0.594)	(0.952)	(1.351)
Inv. spike	0.025***	-0.025***	-0.007**	-0.003***	0.002	0.005
$\times \quad \tau = -2$	(7.381)	(-8.525)	(-2.355)	(-3.756)	(0.372)	(0.750)
Inv. spike	0.043***	-0.042***	-0.012***	-0.010***	-0.005	0.012*
$\times \quad \tau = -1$	(11.539)	(-14.201)	(-4.079)	(-8.931)	(-0.802)	(1.949)
Inv. spike	-0.077***	-0.002	-0.030***	-0.026***	-0.006	0.024***
$\times \quad \tau = 0$	(-20.649)	(-0.672)	(-9.349)	(-19.983)	(-0.843)	(3.625)
Inv. spike	-0.063***	0.046***	-0.017***	-0.018***	-0.000	0.017**
$\times \quad \tau = 1$	(-17.664)	(13.553)	(-5.501)	(-13.080)	(-0.002)	(2.503)
Inv. spike	-0.022***	0.023***	-0.007**	-0.014***	0.000	0.020***
$\times \quad \tau = 2$	(-6.127)	(6.883)	(-2.006)	(-9.738)	(0.061)	(2.965)
Inv. spike	0.008**	0.015***	-0.009***	-0.011***	0.007	0.023***
$\times \quad \tau = 3$	(2.075)	(4.198)	(-2.679)	(-7.090)	(0.889)	(3.201)
Market-to-book$_{t=-1}$	0.005***	-0.007***	-0.004***	-0.001***	0.001	-0.006***
	(7.614)	(-10.751)	(-3.791)	(-3.891)	(1.361)	(-9.721)
Cashflow$(+)_{t=-1}$	0.017***	-0.059***	-0.012***	-0.008***	-0.004***	-0.011***
	(18.998)	(-27.655)	(-11.765)	(-19.232)	(-3.273)	(-9.791)
Cashflow$(-)_{t=-1}$	0.000	0.000	0.000***	-0.001***	-0.001***	0.000
	(0.373)	(0.508)	(2.611)	(-3.998)	(-4.984)	(1.517)
Sales growth$_{t=-1}$	-0.016***	0.004*	-0.002	-0.021***	0.007***	-0.000
	(-11.296)	(1.847)	(-1.253)	(-26.995)	(3.337)	(-0.176)
Firm-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	277,687	276,651	284,745	287,098	81,433	108,068
Adj R^2	0.539	0.633	0.741	0.961	0.628	0.491

Table A.II: **Capital Expenditure Curtailment during Recessions**

For this table we replicate the test associated with Tables V and VI in Hoberg and Maksimovic (2015) to compare the predictive ability of the FF Index with that of FC measures for changes in capital expenditures during recessions. All specifications are identical to those for Table VIII, except the dependent variable is changes in each firm's CAPEX/sales.

OLS regression, dependent variable: (CAPEX/lagged sales)$_t$ - (CAPEX/lagged sales)$_{t-2}$

FC Measures		KZ	WW	HP		KZ	WW	HP
	Panel A: 1982 The Great Inflation				**Panel B: Early 1990s Recession**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rank(FF)$_{\tau=-2}$	0.085***				0.108***			
	(6.452)				(3.933)			
FC measures$_{\tau=-2}$		-0.043**	-0.060	0.094*		-0.065***	-0.036	0.068*
		(-2.138)	(-1.455)	(1.834)		(-3.208)	(-0.609)	(1.863)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	3,350	3,245	3,343	3,350	3,589	3,455	3,574	3,589
Adj R^2	0.157	0.146	0.138	0.138	0.103	0.095	0.087	0.087

Panel C: 2001 Tech Bubble

FC Measures	(1)	KZ (2)	WW (3)	HP (4)	HM (5)	BLM (6)	Credit Rating (7)
Rank(FF)$_{\tau=-2}$	0.067**						
	(2.292)						
FC measures$_{\tau=-2}$		-0.064**	-0.141	-0.011	-0.015**	-0.008	-0.005
		(-2.113)	(-1.275)	(-0.155)	(-2.153)	(-0.289)	(-0.173)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	1,308	1,232	1,292	1,308	944	1,033	1,308
Adj R^2	0.201	0.194	0.188	0.198	0.261	0.196	0.198

Panel D: 2008 Financial Crisis

FC Measures	(1)	KZ (2)	WW (3)	HP (4)	HM (5)	BLM (6)	Credit Rating (7)
Rank(FF)$_{\tau=-2}$	0.058*						
	(1.947)						
FC measures$_{\tau=-2}$		-0.092**	0.166**	0.020	-0.052***	-0.033*	0.004
		(-2.549)	(1.999)	(0.428)	(-4.140)	(-1.720)	(0.213)
Firm characteristics$_{\tau=-2}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Nobs	3,954	3,725	3,939	3,954	2,177	2,790	3,954
Adj R^2	0.335	0.342	0.348	0.333	0.320	0.298	0.333

Table A.III: **Time- Series Patterns around Investment Spikes in Simulated Data**

For this table we replicate the stacked difference-in-differences (DID) tests associated with Appendix Table A.I based on simulated data. For each year t in the simulated data, all firms that generate investment spikes (but generate no other spikes from t-4 to t+3) are grouped together as the treated firms; all firms that do not generate any spikes in years t-4 to t+3 are control firms. All the treated and control firms in each year t constitute a cohort. We include observations from years t-4 to t+3 for each cohort in the regression. With year t-4 as the benchmark, we conduct a series of DID tests. The regression specification is shown in Equation 3. We repeat the sample-generation and regression analysis 100 times and report the average coefficients and significances. Standard errors are clustered at the cohort level. t-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Rank(FF)	(2) Investment	(3) Debt financing	(4) Decrease in cash	(5) Equity financing
$\tau = -3$	-0.002	-0.001	-0.001	0.001	0.000
	(-0.423)	(-0.364)	(-0.944)	(0.610)	(0.209)
$\tau = -2$	0.002	-0.001	-0.001	0.001	0.000
	(0.418)	(-0.374)	(-0.686)	(0.360)	(-0.096)
$\tau = -1$	0.003	0.000	-0.001	0.001	0.000
	(0.665)	(-0.088)	(-0.613)	(0.570)	(0.114)
$\tau = 0$	-0.002	-0.002	-0.002	0.001	0.000
	(-0.320)	(-0.511)	(-0.699)	(0.900)	(0.205)
$\tau = 1$	0.004	-0.006	-0.003	0.001	0.000
	(0.784)	(-1.378)	(-1.222)	(0.812)	(0.677)
$\tau = 2$	0.013***	-0.006	-0.002	0.001	0.000
	(2.620)	(-1.271)	(-1.029)	(0.979)	(0.112)
$\tau = 3$	0.029 ***	-0.007	-0.003	0.001	0.000
	(5.798)	(-1.601)	(-1.156)	(0.750)	(0.327)
Inv. spike	0.023**	-0.012***	-0.002	0.001	0.000
$\times$ $\tau = -3$	(2.193)	(-4.808)	(-1.595)	(1.013)	(0.402)
Inv. spike	0.085***	-0.018***	-0.004***	-0.001	0.000
$\times$ $\tau = -2$	(6.009)	(-5.932)	(-2.948)	(-0.786)	(0.501)
Inv. spike	0.167***	-0.016***	-0.007***	0.002	0.000
$\times$ $\tau = -1$	(12.183)	(-4.416)	(-4.671)	(-0.971)	(0.033)
Inv. spike	-0.060***	0.059***	0.008***	0.009***	-0.002**
$\times$ $\tau = 0$	(-3.940)	(20.518)	(3.720)	(3.603)	(-2.026)
Inv. spike	-0.002	0.007**	0.011***	-0.013***	-0.001 **
$\times$ $\tau = 1$	(-0.098)	(2.200)	(4.712)	(-6.621)	(-1.925)
Inv. spike	-0.016	0.000	-0.005***	0.004**	0.001*
$\times$ $\tau = 2$	(-1.076)	(0.119)	(-2.508)	(2.161)	(1.766)
Inv. spike	-0.006	-0.005 *	-0.001	-0.001	0.000
$\times$ $\tau = 3$	(-0.462)	(-1.795)	(-0.525)	(-0.759)	(-0.195)
Chg ind. productivity$_{\tau=-1}$	-0.006	0.064***	0.011***	0.010***	-0.001*
	(-1.496)	(23.547)	(8.372)	(4.935)	(-1.780)
Chg idio. productivity$_{\tau=-1}$	-0.017	0.101	0.024	-0.016	-0.001
	(-0.191)	(1.391)	(0.648)	(-0.514)	(-0.084)
Cohort FE	Yes	Yes	Yes	Yes	Yes
Nobs	116,987	116,987	116,987	116,987	116,987
$Adj R^2$	0.012	0.252	0.053	0.019	0.002