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Determinants of the Financing of Investment Spikes

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Abstract

This study investigates how firms meet exceptional financing needs at the time of "investment spikes" or years with unusually large investment programs, and finds that the financing of investment during an investment spike differs from that at other times, using data for publicly traded US firms from 1988 to 2013. At the time of investment spikes, external finance, particularly debt finance, is more important than internal finance. However, firms with smaller firm size, lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity finance. This study finds that large firms' financing patterns are consistent with the pecking-order theory in the short run and with the trade-off theory in the long run, but small firms' financing patterns are neither consistent with pecking-order theory in the short run nor with the trade-off theory in the long run.

JEL classification: G31, G32, G34, E22

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1 Introduction

The lumpiness of investment has been well known to economists since Doms and Dunne's (1998) influential work showing that plant-level investment is lumpy, using plant-level investment data from US Census Bureau micro data files (Caballero *et al.*, 1995; Power, 1994; Cooper *et al.*, 1999). Firm-level investment is found to be less lumpy than plant-level investment because of the aggregation effect, but there is still a large body of literature suggesting that aggregation does not substantially eliminate the lumpiness of firm-level investment (Caballero and Engel, 1999; Doyle and Whited, 2001). In addition, there are several plausible theoretical explanations for the lumpiness of investment. Scholars have attempted to explain lumpy investment patterns through the ideas of non-convex capital adjustment costs (Rothchild, 1971), irreversibility of investment (Pindyck, 1991; Dixit, 1995; Dixit and Pindyck, 1994), and external financing costs arising from financing constraints (Whited, 2006). Nevertheless, the majority of existing empirical corporate finance studies have not effectively considered the lumpiness of investment until recently[1]. A widely accepted result is that the dominant source of finance of firms across different countries and time periods is retained earnings (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this is primarily indicative of how firms finance their routine, replacement investment rather than non-routine, expansion investment.

Recently, the way in which firms meet exceptional financing needs in relation to unusually large investment opportunities has become a central subject of an emerging body of literature including DeAngelo *et al.* (2011). They built a dynamic capital structure model in which firms deliberately but temporarily deviate from permanent leverage targets by issuing transitory debt to fund "*investment spikes*." They found that their model explains firms' debt issuance/repayment decisions better than static trade-off models and can account for the leverage changes that accompany investment spikes. In their model, firms have leverage targets as in static trade-off models, but managers sometimes choose to deviate from targets and subsequently seek to rebalance to meet

[1]The fact that corporate investment is lumpy suggests that firms change regimes between routine investment regimes and non-routine investment regimes. If financing patterns are marked different across regimes, pooling data from two regimes dilutes the sample and obscures the results, without increasing the efficiency of the estimation (Mayer and Sussman, 2005). Therefore, if one focuses on data from periods with non-routine investment regimes, one can increase the efficiency of the estimation. However, until recently researchers in empirical corporate finance have not tried to do so.

targets by reducing debt with a lag determined in part by the time path of investment opportunities and earnings realizations. Their model offers plausible explanations for otherwise puzzling aspects of observed capital structure decisions, including *i)* why firms often choose to deviate from their leverage targets and *ii)* why empirical studies find such slow average speeds of adjustment to target.

In addition to DeAngelo *et al.* (2011), there are quite a few related papers in this area. Mayer and Sussman's (2002, 2005) studies are some of the earliest works which empirically examine corporate financing behaviors around the periods categorized as investment spikes. They find that financing patterns around investment spikes differs from those at other times, and argue that financing patterns during and after investment spikes are likely to be particularly informative in understanding corporate financing behavior[2]. They propose using the flow-of-funds approach combined with a filtering device designed to identify investment spikes[3]. Unlike studies using aggregate data, Mayer and Sussman (2005) find that external sources of finance, and particularly debt, are much more important in financing corporate investment in periods when the firm's investment spending is unusually high. Using data for publicly traded non-financial US firms, they confirm that in most periods, most of the investment required for replacement and trend growth is financed internally, with very small contributions from both debt and new equity. Particularly for larger firms, the share of investment financed by debt is found to be much higher than the shares of investment financed by other sources in periods characterized as investment spikes. They also find that debt finance is less important in periods immediately after investment spikes, suggesting that debt–assets ratios adjust back towards some underlying target. Based on these results, they argue that financing patterns around investment spikes are consistent with the pecking order theory in the short run and the trade-off theory in the long run. DeAngelo *et al.* (2011) also analyze the financing decisions associated with investment spikes and find that even when leverage is above average, large investment outlays are typically accompanied by substantial debt issuances that increase leverage, confirming Mayer and Sussman's (2005) major findings.

[2]Two other papers are in support of this event-based approach. Strebulaev (2007) argues that capital structure theories can be tested without contamination from frictions by focusing on refinancing points. Elsas *et al.* (2014) also note that that large investment events provide enhanced information about firms' capital structure preferences because they tend to be accompanied by significant external financing.

[3]Mayer and Sussman (2005) were the first to notice that summary statistics for financing patterns would overstate the importance of internal finance in funding firms' investment activities

Huang *et al.* (2007) also take a similar approach to examining the financing decisions of US firms by evaluating the financing response of US firms to large perturbations in cash flow requirements. Although the perturbations in cash flow are very different from those in investment, the financing patterns are very similar. Firms with larger and longer cash flow shortages tend to rely more on equity finance than debt finance. After the perturbations, firms gradually adjust their leverage back towards their previous level by repaying debt and issuing equity. They conclude that financing patterns during a perturbation are consistent with a pecking-order theory of finance, whereas the adjustment after a perturbation is consistent with a trade-off theory. Similarly, Bond *et al.* (2006), using UK data, find that debt finance is more important in years of investment spikes than in normal periods, and also that debt finance is less important in the period immediately after investment spikes. In addition, they find that differences in firm's technologies, measured through the presence of R&D programs, Tobin's Q, or total factor productivity relative to industry norms, may be less important for explaining differences in financing patterns at the time of investment spikes than in normal periods. By studying how US firms paid for 2,073 investment spikes between 1989 and 2006, Elsas *et al.* (2014) find that large investments are mostly externally financed and test major capital structure theories, finding evidence consistent with the trade-off and market timing hypotheses but inconsistent with the standard pecking order hypothesis. Recently, Im (2014), using US data, investigates the relationship between market liquidity of firms' shares and their propensity to raise debt in funding large investment requirements, and finds that firms with more liquid shares tend to rely more on net debt issuances and less on net equity issuances at the time of investment spikes.

This paper makes several contributions to this emerging body of literature. First, this paper starts with documenting how publicly traded US firms financed their investment spikes recently (i.e. from 1988 to 2013), using a filter which has several advantages over existing filtering procedures such as Cooper *et al.* (1999), Power (1998) or Mayer and Sussman (2005). The main purpose of this paper is not, however, narrowly testing a particular theory of corporate financing, but achieving a deeper understanding of how large investment activities are financed. In this sense, Mayer and Sussman (2005), Gatchev *et al.* (2009), and Elsas *et al.* (2014) are closely related to my paper. However, the methodology developed in this paper is extended to evaluate the power of the pecking order theory and trade off theory in explaining financing patterns around investment spikes. In this paper, I fully develop a linear-regression-based filtering procedure used by Bond *et al.* (2006)[4]. Unlike Mayer and Sussman (2005) who study a narrowly selected sample of 535 investment spikes, I study a much widely selected sample of 7,494 investment spikes[5]. To describe the financing patterns, I investigate the investment-weighted proportions of financing sources as shares of base-level investment[6]. I first compare the sources of finance at the time of investment spikes across different financing sources. At the time of investment spikes, internally available funds (some 1.28 times the base-level investment) do not change much, and thus needs for external financing sources increase dramatically[7]. Among external financing sources, net long-term debt issuances become much more significant than net equity issuances at the time of investment spikes. I find that the shares of investment financed through net long-term debt issuances and net equity issuances are some 3.10 and 0.32 times the base-level investment, respectively[8]. These results are consistent with the peking-order theory predicting that when internal resources are exhausted, less information-sensitive long-term debt is preferred to more information-sensitive equity (Myers and Majluf, 1984). I then compare financing patterns during investment spikes with those before and after spikes. The share of investment financed with internally generated funds during investment spikes is similar to those in off-spike periods. However, both long-term debt finance and equity finance become much more important during investment spikes so that they also have "*spikes*" at the time of investment spikes. Some net long-term debt issuances are observed before investment spikes, but some net repayments of long-term debt are observed after investment spikes. These results seem to be consistent with the predictions of the trade-off theory. These results support Mayer and Sussman (2005) who argue that financing patterns are consistent with the pecking-order the-

[4]As a robustness test, I also use a Markov-switching filter which has a few advantages over existing filtering procedures.

[5]Before data-cleaning procedures, I obtain a sample of 8,756 investment spikes, or 9.85% of the 88,927 firm-year observations for which five consecutive years of investment data are observed. I find that 5,897 firms have at least one investment spike during the sample period and the number of investment spikes per firm ranges from 1 to 6. About 89% of firms have only one or two investment spikes during the sample period. This means that most firms have lumpy investments and inferences based on investment spikes can be applied to most firms in the sample. If too narrow a sample is used as in recent literature, in-sample inferences should not be extended to firms that are cross-sectionally out of the sample.

[6]The base-level investment is defined as the average of a firm's investment amounts in surrounding four years excluding the spike year. See Section 2.2.2 for details.

[7]See Table 2 Panel A for details.

[8]See Table 2 Panel A for details.

ory in the short run, while they are consistent with the classical trade-off theory in the long run. However, this paper shows that small firms' financing patterns are not the case.

Second, I extensively explore heterogeneity of financing patterns around investment spikes by investigating whether financing patterns vary with firm size, profitability, level of future growth opportunities, tangibility of assets, R&D intensity, industry, and business cycles. I, to that end, first investigate whether there are significant differences in the financing of investment spikes depending on firm size. The most striking finding is that small firms raise equity finance quite substantially during investment spikes, whereas large firms rely largely on debt finance during investment spikes. It is also quite surprising that small firms issue shares even before and after the years categorized as investment spikes. Nevertheless, the contribution of debt finance is still larger than that of equity finance at the time of investment spikes even for small firms. In this sense, my findings are somewhat different from those of Mayer and Sussman (2005) who find that large firms tend to issue debt to fund large investments, while small firms tend to issue equity. DeAngelo *et al.*'s (2011) findings are consistent with my results for large firms, but they do not report a significant difference between large firms and small firms. To further examine the heterogeneity of financing patterns, I investigate whether the financing patterns around investment spikes vary with the firms' profitability, level of future growth opportunities, tangibility of assets, R&D intensity, industry and business cycles. Overall, firms with lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity finance when faced with large investment requirements. However, the effects of those firm characteristics are not as strong as the effect of firm size on the financing patterns around investment spikes[9]. This study also finds that there are no substantial differences in the financing of investment spikes across industries so that in most industries, debt finance is the most important source of finance during investment spikes, followed by internal finance. In addition, the financing patterns around investment spikes during expansions are not significantly different from those during contractions.

Next, I investigate whether firm's financing patterns at the time of investment spikes are con-

[9]These results are consistent with Fama and French (2005) and Gatchev *et al.* (2009) finding that small firms, high-growth firms, and less-profitable firms use more equity to cover their financing needs than large firms, low-growth firms, and more profitable firms, respectively. Gatchev *et al.* (2009) argue that this happens because firms that are less likely to be informationally transparent typically use more equity and less long-term debt than their more informationally transparent counterparts.

sistent with the pecking-order theory in the short run, separately for large firms and small firms. Specifically, I investigate whether financing patterns vary with the magnitude of investment spikes and find that the financing patterns of large firms at the time of investment spikes are consistent with the pecking-order theory proposed by Myers (1984) and Myers and Majluf (1984)[10], but the financing patterns of small firms at the time of investment spikes are consistent with the reverse pecking-order that can be predicted under the assumption of endogenous information production in the framework of Fulghieri and Lukin (2001). Large firms tend to use only debt finance when they are faced with relatively small investment spikes but tend to use more equity finance when they are faced with relatively large investment spikes. However, small firms tend to use more equity finance when they are faced with relatively small investment spikes but more debt finance when they are faced with relatively large investment spikes. Mayer and Sussman (2005) find that large investment projects are predominantly financed with debt regardless of firm size and interpret this result as suggesting that, regardless of firm size, corporate financing patterns are consistent with the pecking-order theory in the short run. However, this paper shows that small firms' financing behaviors around investment spikes are *not* consistent with the pecking-order theory[11].

Finally, I move on to investigate whether financing patterns during and after investment spikes

[10]Fama and French (2002) and Frank and Goyal (2003) provide excellent descriptions of testable implications of the pecking order theory proposed by Myers (1984) using a framework of Myers and Majluf (1984). Frank and Goyal (2003) state as follows: "*Suppose that there are three sources of funding available to firms: retained earnings, debt, and equity. Retained earnings have no adverse selection problem. Equity is subject to serious adverse selection problem while debt has only a minor adverse selection problem. From the point of view of an outside investor, equity is strictly riskier than debt. Both have an adverse selection problem, but that premium is large on equity. Therefore, an outside investor will demand a higher rate of return on equity than on debt. From the perspective of those inside the firm, retained earnings are a better source of funds than is debt, and debt is a better deal than equity financing. Accordingly, the firm will fund all projects using retained earnings if possible. If there is an inadequate amount of retained earnings, then debt financing will be used. Thus, for a firm in normal operations, equity will not be used and the financing deficit will match the debt issues.*" In the context of the current study, the pecking order theory predicts that firms with larger investment spikes will have higher equity dependence in periods categorized as investment spikes. When firms are faced with smaller investment spikes, firms will use up internal finance first, and then they will raise less information-sensitive debt finance if they need external finance, and finally they will issue more information-sensitive equity if debt capacity is reached. When firms are faced with larger investment spikes, they are more likely to have used up internal funds and are more likely to have exhausted debt capacity, so they are more likely to issue equity. The evidence for the pecking-order theory in the literature is mixed: Shyam-Sunder and Myers (1999), Gungoraydinoglu and Öztekin (2011), and Chung *et al.* (2013) find evidence for the pecking order theory, while Chirinko and Singha (2000), Frank and Goyal (2003), and Fama and French (2002) find evidence against the pecking order theory.

[11]Fulghieri and Lukin (2001) show that a setting similar to that of Myers and Majluf (1984) can generate the reverse pecking order if information production costs are sufficiently low, i.e., if information is endogenously generated. My finding that the financing patterns of small firms are not consistent with the pecking order theory is in line with Fama and French (2002) who argue that they identify "one deep wound" on the pecking order (the large equity issues of small low-leverage growth firms).

are consistent with the trade-off theory in the long run, also separately for large firms and small firms. I analyze whether financing patterns *during* investment spikes vary with the level of initial leverage. According to the classical trade-off theory of debt[12], it is expected that regardless of firm size, firms with higher initial leverage will use more equity in financing investment requirements in periods categorized as investment spikes. However, under the dynamic trade-off theory augmented with investment spikes as outlined by DeAngelo *et al.* (2011)[13], it is possible that firms with higher initial leverage do not adjust their leverage back to their target or optimal leverage when they are given unusually good investment opportunities. Thus, firms with higher initial leverage do not necessarily use more equity to finance investment spikes. My empirical results are very interesting: i) regardless of firm size, the importance of debt finance increases with initial leverage; ii) the importance of equity finance decreases with initial leverage for small firms, while the importance of equity finance increases with initial leverage for large firms. These suggest that the financing patterns of large firms are quite consistent with the classical trade-off theory, but the financing patterns of small firms are the opposite to the predictions of the classical trade-off theory.

I then analyze whether financing patterns *after* investment spikes vary according to the level of initial leverage. According to both classical the trade-off theory and DeAngelo *et al.*'s (2011) dynamic trade-off model, it is expected that firms will adjust their leverage downwards following investment spikes, through some combination of net debt repayments and equity issues. It is also expected that this adjusting pattern will be more pronounced when initial leverage is higher. My empirical findings are summarized as follows: i) large firms, especially those with higher initial leverage, gradually adjust their leverage back to optimal leverage after investment spikes by repaying some debt and reducing share repurchases; ii) small firms gradually adjust their leverage

[12]A recent version of the trade-off theory weighs the tax benefits of debt and the agency benefits of debt against the costs of financial distress and the agency costs associated with debt. The model takes into account the tradeoff between debt and equity arising from agency problems. While increasing debt mitigates shareholder-manager conflicts by mitigating "free cash flow" problems, increasing debt exacerbates shareholder-debtholder conflicts by creating "risk shifting" problems (Jensen and Meckling, 1976; Jensen, 1986; Stulz, 1990; Harris and Raviv, 1991; Frank and Goyal, 2009). Many researchers including Hovakimian (2004) find evidence consistent with the tradeoff hypothesis, but some researchers question the power of these tests (Strebulaev, 2007; Chang and Dasgupta, 2009; Iliev and Welch, 2000). Fama and French (2002) find a negative relation between leverage and profitability and recognize it as "one scar" on the trade-off model.

[13]In their model, firms have leverage targets as in classical trade-off models, but managers sometimes choose to deviate from targets and subsequently seek to rebalance to targets by gradually reducing debt. Therefore, under this framework, it is possible that firms with higher initial leverage do not adjust their leverage back to their optimal leverage when they have unusually good investment opportunities.

back to optimal leverage after investment spikes by repaying some debt and issuing new shares. These suggest that the post-spike adjustment patterns of both large firms and small firms are quite consistent with both the classical trade-off theory and DeAngelo *et al.*'s (2011) dynamic trade-off model in the long run[14]. Putting together the empirical results during and after investment spikes, I conclude that financing patterns of both large firms and small firms can not be fully explained by the classical trade-off theory, but can be fully explained by DeAngelo *et al.*'s (2011) dynamic trade-off model augmented with investment spikes.

The rest of this paper is organized as follows. Section 2 briefly discusses the data, methodology and descriptive statistics. Section 3 investigates how investment spikes are financed by analyzing the flow of funds around investment spikes. The flow of funds analysis has been implemented in the full investment spikes sample, by subgroups based on various firm characteristics such as firm size and profitability, by industries and by business cycles. Section 4 and Section 5 investigate how the financing patterns of investment spikes vary according to the magnitude of investment spike and initial leverage to examine whether the financing patterns of large firms and small firms are consistent with the pecking-order theory in the short run and the trade-off theory in the long run. Section 6 presents conclusions and outlines some important and interesting extensions for future research.

2 Data, methodology and descriptive statistics

2.1 Data

I use data from annual consolidated financial statements[15] of publicly traded US companies reported in Standard and Poor's Compustat North America Fundamental Annual Dataset from 1988 to 2013. The data start from 1988 because the investigation of the financing patterns around in-

[14]Mayer and Sussman (2005) also found that firms tend to revert back to their initial leverage by repaying debt and issuing new equity after investment spikes and interpret this result as suggesting that corporate financing patterns are consistent with the classical trade-off theory in the long run. However, they did not take initial leverage into consideration in their analyses.

[15]The majority of US companies report the consolidated financial statements, which include both parent and subsidiaries accounts.

vestment spikes requires the use of firm-level flow-of-funds data, that is, data from the cash-flow statements.[16] I exclude firms with an standard industrial classification (SIC) code between 6000 and 6999 or between 4900 and 4999, that is, I drop firms whose main activity is financial services or regulated utilities in constructing the final sample. All nominal items from the statement of cash flows, income statement, and balance sheet are deflated or inflated to year 2000 dollars using the GDP deflator obtained from the World Bank Data Bank. An interpolated GDP deflator is used if the fiscal year ends in months other than December.

I also perform a minimum level of data cleaning. First, I drop observations if the firms are observed for less than five years. Second, I drop observations if it is missing any variable that constitutes the cash-flow identity. However, I replace the missing item with zero if at least one component of each financing source is reported because "missing" does not mean "unaccounted for." For example, note that $LTDEBT$, the amount of long-term debt finance, can be calculated as "issuance of long-term debt ($dltis$)" less "reduction of long-term debt ($dltr$)." Clearly, the firm-year observation should be deleted if both $dltis$ and $dltr$ are missing. However, if only one of the two components is missing, then it is likely that only "net issuance of long-term debt" is reported. In this case, it makes more sense to replace the missing item with zero rather than remove the firm-year observation. Finally, to reduce the effects of outliers and eradicate errors in the data, all variables in ratios are winsorized at the 1st and 99th percentiles, as in Flannery and Rangan (2006). Appendix A.1 provides details of the Compustat items used to construct the variables used in this paper.

2.2 Algorithms to identify investment spikes

This paper closely follows a novel approach suggested by Mayer and Sussman (2005).[17] The question of how investment is financed can be precisely answered using the firm-level flow-of-funds data combined with a filtering device to identify investment spikes. This new approach eliminates a potential bias caused by the merging of routine and non-routine investment periods.

[16] The sample period starts from 1988 because the "cash statements by sources and uses of fund" was replaced by "statement of cash flows" in 1988 by the Financial Accounting Standards Boards #5.

[17] Bond *et al.* (2006) and Huang *et al.* (2007) used a similar approach to study financing patterns.

The bias arises if investment is lumpy (i.e., firms' regimes switch between high investment and low investment), if financing patterns are markedly different across regimes, and if the data from the two regimes are merged to make inferences on financing patterns. Mayer and Sussman have argued that pooling data from the two regimes dilutes the sample and obscures results without increasing the efficiency of the estimation.

To focus on investment spikes, one can use a filter for identifying large investment episodes from the pool of both large investment episodes and routine replacement investments of firms. This new method eliminates a potential bias caused by the merging of routine and non-routine investment periods as mentioned earlier. Nevertheless, designing a reliable filter is not as straightforward as it might seem. Two strands of research have attempted to identify investment spikes, although the literature on financing investment spikes is scarce compared with that on empirical and theoretical explanations of the lumpiness of investment. This shows that the empirical studies based on the assumption that capital adjustments are frequent and continuous have not yet been revised in spite of the abundant evidence that capital adjustments are infrequent and lumpy (Whited, 2006).

2.2.1 Simple rules

The first strand of research uses simple rules such as absolute, relative, or combined spike criteria and includes studies by Power (1994, 1998), Cooper *et al.* (1999), and Nilsen *et al.* (2009). Power (1994) provided an extensive treatment of the definitions, causes, and consequences of investment spikes. Nilsen *et al.* (2009) summarized the traditional definitions of investment spikes in the literature. The following three definitions of investment spikes are found in the literature:

(i) *Absolute spike criterion*: If the investment rate[18] exceeds the absolute threshold, the investment is defined as an investment spike. The most commonly used threshold is 20% (see Cooper *et al.* (1999)). The absolute spike criterion focuses on large but potentially frequent investments. However, this criterion is not suitable for identifying sporadic bursts of investment that are not large in an absolute sense.

[18]The most commonly used measure of investment rates are total investment-to-total assets ratio and fixed investment-to-fixed capital ratio.

(ii) *Relative spike criterion*: If the investment rate exceeds the median investment rate or the normal investment rate by a factor that is generally set between 1.5 and 3, the investment is defined as an investment spike (see Power (1998)). The relative spike criterion focuses on unusual and potentially disruptive bursts of investment activity, although they may not be particularly large in an absolute sense. However, this criterion is not suitable for identifying smooth and potentially large expansions. Whited (2006) and DeAngelo *et al.* (2011) also followed this criterion.

(iii) *Combined spike criterion*: Power (1998) classified an investment as an investment spike if either the absolute or the relative spike criterion is satisfied. However, Nilsen *et al.* (2009) classified an investment as an investment spike if both the absolute and the relative spike criteria are satisfied. For them, the relative threshold is defined slightly differently from that used in Power (1998). They adjusted the traditional investment spike definitions by considering the fact that the investment rates of small firms are more volatile than those of large firms and that small firms are more likely to generate a larger number of investment spikes. For Nilsen *et al.* (2009), the relative threshold is defined as the conditional expectation of investment rate multiplied by a fixed factor. This implementation decreases the relative threshold of large firms. The absolute threshold never allows the threshold for a spike to be lower than 20%. Elsas *et al.* (2014) also followed this criterion.

2.2.2 Filters to identify investment spikes

The second strand of research takes more proactive approaches in the sense that they design filters to capture investment spikes rather than apply a simple rule. Mayer and Sussman (2005) suggested a filter based on the goodness-of-fit of actual five-year investment patterns to the benchmark investment spike pattern (b_{it}, b_{it}, $2b_{it}$ or above, b_{it}, b_{it}), where b_{it} represents the base-level investment which is defined as the average of firm i's investment amounts in surrounding four years excluding the year t. The filter is similar to the relative spike in the sense that the investment is more likely to be categorized as an investment spike if the investment is significantly greater than the base-level investment. However, it is different from the simple relative spike criterion for the following reasons. First, the relevant range is the five-year period rather than the whole sample period. The five-year period might be more appropriate for judging whether the middle-year investment is significantly greater than that in surrounding years. Second, the final decision is based on a measure of the goodness-of-fit of each five-year investment sequence around a spike candidate to the benchmark spike pattern. The filter is very intuitive but has some shortcomings. First, the threshold is not only arbitrarily determined but is also not statistically interpretable. Second, the filter does not use any sort of detrending. If there is a linear trend in an investment sequence, the criterion over-penalizes the squared deviations from the benchmark spike pattern.

In this paper, I fully develop a linear-regression-based filtering procedure first used by Bond *et al.* (2006). The advantages of the new filter are that the threshold is statistically interpretable and that the filter works well when there is a trend in the investment sequence. Let the investment data, $I_{i,t}$, for $i = 1, 2, \cdots, N$ and $t = 1, \cdots, T_i$, be defined as investment outlays on tangible assets, intangible assets, and acquisitions (see Appendix A.1 for the formula and the Compustat items used to measure $I_{i,t}$). See below for more details on the filter.

The first step 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[19]. The regression for identifying an investment spike can be expressed compactly as:

$$y = \mathbf{X}b + \varepsilon, \text{ where } \varepsilon \sim N(0, \sigma^2), \tag{1}$$

with the matrix $\mathbf{X}$ and the vectors b and ε specified as follows:

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

[19]If $T_i = 26$, $22 (= T_i - 4)$ regressions should be implemented for firm i. Therefore, a total of $\sum_{i=1}^{N}(T_i - 4)$ regressions should be implemented. However, the following anatomy of a regression makes the algorithm simpler in the sense that the algorithm does not require the running of a large number of full regressions. In addition, the anatomy provides interesting measures, such as $\widehat{\alpha}_{it}$, $\widehat{\delta}_{it}$, and $\widehat{\gamma}_{it}$.

$b = (\alpha_{it}, \beta_{it}, \delta_{it})'$, and $\varepsilon = (\varepsilon_{i,t-2}, \varepsilon_{i,t-1}, \varepsilon_{i,t}, \varepsilon_{i,t+1}, \varepsilon_{i,t+2})'$. Note that $n = 5$ and $k = 3$, where n is the sample size and k is the number of regressors including a constant.

Using $\widehat{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'y$, it can be easily shown that:

$$\widehat{\alpha}_{it} = \frac{I_{i,t-2} + I_{i,t-1} + I_{i,t+1} + I_{i,t+2}}{4}, \tag{3}$$

$$\widehat{\beta}_{it} = \frac{-2I_{i,t-2} - I_{i,t-1} + I_{i,t+1} + 2I_{i,t+2}}{10}, \tag{4}$$

and

$$\widehat{\delta}_{it} = I_{i,t} - \widehat{\alpha}_{it}. \tag{5}$$

In addition, the standard error of $\widehat{\delta}_{it}$ can also be shown to be:

$$se(\widehat{\delta}_{it}) = \sqrt{\frac{5}{4}s^2}, \tag{6}$$

using $\widehat{V}(\widehat{b}|\mathbf{X}) = s^2(\mathbf{X}'\mathbf{X})^{-1}$, where $s^2 = \widehat{\varepsilon}'\widehat{\varepsilon}/(n-k)$ and $\widehat{\varepsilon} = (\widehat{\varepsilon}_{i,t-2}, \widehat{\varepsilon}_{i,t-1}, \widehat{\varepsilon}_{i,t}, \widehat{\varepsilon}_{i,t+1}, \widehat{\varepsilon}_{i,t+2})'$.

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

$$t_{\widehat{\delta}_{it}} = \frac{\widehat{\delta}_{it}}{se(\widehat{\delta}_{it})} \tag{7}$$

follows a Student t-distribution with $2(= n-k)$ degrees of freedom. The final decision is made based upon the result from the one-sided t-test at a conventional significance level of 5%. That is, $I_{i,t}$ is classified as an investment spike if $\widehat{\delta}_{it}$ is positive and statistically significant at the 5% significance level, regardless of the magnitude of the coefficient[20]. Alternatively, 1% or 10% significance levels can be used.

Note that $\widehat{\alpha}_{it}$ is the base-level investment as measured by the average of investment amounts in the five-year window excluding the spike year and $\widehat{\beta}_{it}$ is the slope of a linear trend in the five year window. In addition, the magnitude of the abnormal component of an investment spike as a factor

[20] In other words, firm i has an investment spike in year t if $t_{\widehat{\delta}_{it}} > t(0.95, df = 2)$.

of the base-level investment is measured as

$$\widehat{\gamma}_{it} = \frac{\widehat{\delta}_{it}}{\widehat{\alpha}_{it}}. \tag{8}$$

Repeating the procedures as many times as $\sum_{i=1}^{N}(T_i - 4)$ will identify a total of J firm-years as those with an investment spike.

Notation

The identifier $i \in \{1,2,\cdots,N\}$ represents the firm code, whereas the identifier $j \in \{1,2,\cdots,J\}$ represents the investment spike code. The time index $t \in \{1,\cdots,T\}$ represents the fiscal year reported in Compustat, whereas the time index $\tau \in \{-2,-1,0,+1,+2\}$ represents the time in relation to an investment spike. For example, $\tau = 0$ indicates the year categorized as an investment spike, whereas $\tau = -1$ indicates one year before an investment spike. The subscripts (i,t) are used when investment spikes are not treated specially (i.e. in the whole sample), whereas the subscripts (j,τ) are used when investment spikes are treated specially (i.e. in the investment spikes sample). For instance, $I_{i,t-1}$ represents the investment of a given firm i measured in year $t-1$, while $LEV_{j,\tau=-1}$ represents the leverage measured in one year before the spike (i.e. $\tau = -1$) for the $j-$th investment spike.

Using the new notation, the base-level investment and the relative magnitude of the j-th investment spike are denoted as $BASE_j$ and $SPIKESIZE_j$, for $j \in \{1,2,\cdots,J\}$, respectively. The procedures give a sample of 8,756 investment spikes, or 9.85% of the 88,927 firm-year observations for which five consecutive years of investment data are observed. I find that 5,897 firms have at least one investment spike during the sample period and the number of investment spikes per firm ranges from 1 to 6[21]. I restrict my attention to $(0,0,1,0,0)$-type investment spikes, where 0 denotes a non-spike year and 1 denotes a spike year, obtaining 8,702 investment spikes after dropping 54 investment spikes that do not conform to this pattern. The median value of $SPIKESIZE_j$ for the 8,702 investment spikes is 3.48. This suggests that the size of the median-sized investment spike is approximately $4.48(= 3.48 + 1)$ times that of base-level investment as measured by the

[21]The number of investment spikes per firm during the sample period has the following distribution: 3,862 firms (65.49%) have 1 spike; 1,387 firms (23.52%) have 2 spikes; 494 firms (8.38%) have 3 spikes; 134 firms (2.27%) have 4 spikes; 18 firms (0.31%) have 5 spikes; 2 firms (0.03%) have 6 spikes.

average of investment amounts in the four surrounding years.

[Insert Table 1 Here.]

2.3 Descriptive statistics

Table 1 shows the summary statistics of the major variables based on the investment spikes sample, the construction of which is described in Section 2.2. Panel A, Panel B, and Panel C show the summary statistics for large, medium-sized, and small firms, respectively. The total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) are used to group firms with an investment spike into "Small firms," "Medium-sized firms," and "Large firms." The thresholds used are the 33rd and 67th percentiles. The variables reported in this table are constructed as explained in Appendix A.1. The time index τ represents the time in relation to an investment spike. For example, $\tau = 0$ indicates the year categorized as an investment spike, whereas $\tau = -1$ indicates the year before an investment spike.

The means and medians of the firm characteristics variables measured in the year before investment spikes are substantially different across groups based on firm size. In general, small firms tend to have lower profitability and fewer tangible assets, but have higher future growth opportunities and higher R&D spending. Before and during investment spikes, small firms tend to have lower leverage, as measured by both the market leverage and book leverage. It is observed that firms in all three size groups tend to increase their leverage substantially in years categorized as investment spikes.

3 Empirical Results

3.1 A general description of the financing around investment spikes

This section investigates how investment spikes are financed by analyzing the flow of funds around investment spikes. First, I describe the methodology to analyze the financing patterns around investment spikes. I then describe the flow of funds around investment spikes identified by both the regression filter and Markov-switching filter[22]. I then examine whether the shares of financing during investment spikes are similar across industries. Finally, I investigate whether the the financing patterns during investment spikes are severely affected by business cycles.

3.1.1 Methodology to analyze the financing patterns around investment spikes

In this section, I describe the methodology to analyze the financing patterns around investment spikes. I first compute each component of the cash flow identity and then aggregate each component of the cash flow identity by subgroups.

Step 1. Computation of the flow of funds

After I identify the investment spikes as in Section 2.2.2, I calculate the flow of funds according to the time index around the investment spikes ($\tau \in \{-2,-1,0,+1,+2\}$). I use the basic cash-flow identity linking investment spending to internally generated funds, long-term debt finance, new equity finance, and other sources of funding[23]:

$$I_{j\tau} \equiv OPR_{j\tau} + LTDEBT_{j\tau} + EQUITY_{j\tau} + OTHER_{j\tau}, \tag{9}$$

for $j \in \{1,2,\cdots,J\}$ and $\tau \in \{-2,-1,0,+1,+2\}$. $I_{j\tau}$ measures investment outlays on tangible assets, intangible assets, and acquisitions. It is worth noting that investment outlays are recorded on a net basis. I treated sale of existing property, plant, and equipment (PPE) and sale of subsidiaries as a negative investment outlay, not as a source of finance.[24] $OPR_{j\tau}$ measures after-tax

[22]The Markov-switching filter suggested by Im (2012) has one important advantage over Mayer and Sussman's filter and the regression filter introduced in Section 2.2.2: it can capture any conceivable patterns of lumpy investment including two-year and three-year investment spikes. This filter is described in Appendix A.2.

[23]Elsas *et al.* (2014) use the same cash-flow identity but the components of the identity are calculated slightly differently. They adjust $I_{j\tau}$, $LTDEBT_{j\tau}$, and $EQUITY_{j\tau}$ using the data from Securities Data Company (SDC) so that they can directly compare the financing of capital expenditures with that of acquisitions. However, these adjustments are not necessary if the purpose of research is to investigate how cash used for investing activities was raised. Without these adjustments, investment spikes are periods with financing deficits initiated by investment shocks, so by focusing on investment spikes one can investigate which external financing sources are more helpful in covering financing deficits.

[24]It is noteworthy that the sources of finance cannot be broken down by such types of investment as net capital expenditures, acquisitions, and other investments. The statement of cash flows does not provide information about how much long-term debt was used to fund an acquisition by a certain company in a certain year, even if it can tell us about how much long-term debt was used to fund all the investing activities of the firm in the year. Therefore, $I_{j\tau}$ is

cash flow from operating activities. $LTDEBT_{j\tau}$ measures funds from issuances of long-term debt capital net of retirements. $EQUITY_{j\tau}$ measures funds from issuances of ordinary and preferred shares net of retirements. The residual source of financing, $OTHER_{j\tau}$, is measured so as to ensure that the cash-flow identity holds. This category includes funds raised by "changes in cash, inventory, and security investments", "changes in trade credit", "changes in short-term debt", and "other minor components". In the main analysis, I do not break down this category because the sample size would decrease dramatically due to differences in accounting policy and degree of aggregation. However, in Section 3.2.1, I break down other financing sources ($OTHER_{j\tau}$) into nine components and examine which components are more important sources of finance among them. A positive sign on the right-hand side of the identity denotes a source of funds, whereas a negative sign denotes a use of funds. Appendix A.1 provides more details on the Compustat items used to measure these components of the identity.

Step 2. Aggregation of the flow of funds

The next step is to aggregate the flow of funds by subgroups. This section shows how to calculate the aggregate statistics of the flow of funds by subgroups based on various firm characteristics, including firm size, industry, investment spike size, and initial leverage. To aggregate the flow of funds of firms in each subgroup, I normalize the flow of funds using the base-level investment and then calculate the investment-weighted average of the normalized flow of funds. In the case of J large investment events in each subgroup, the aggregated sources of finance for each τ are

defined as the sum of capital expenditures, acquisitions, and other investments. However, one can study whether there are differences in funding capital expenditures and acquisitions using a dummy variable *D_AQC*, which takes a value of 1 if the proportion of acquisition is greater than zero and 0 otherwise.

calculated as

$$
\begin{aligned}
OPR_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{OPR_{j\tau}}{BASE_j} \right), && (10) \\
LTDEBT_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{LTDEBT_{j\tau}}{BASE_j} \right), && (11) \\
EQUITY_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{EQUITY_{j\tau}}{BASE_j} \right), && (12) \\
OTHER_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{OTHER_{j\tau}}{BASE_j} \right), && (13)
\end{aligned}
$$

for $\tau \in \{-2,-1,0,+1,+2\}$, where I_{j0} is the investment amount during the j-th spike[25] and $BASE_j$ is the base-level investment for the j-th spike. The aggregated measures for total assets and investment are constructed analogously as follows:

$$
\begin{aligned}
TA_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{TA_{j\tau}}{BASE_j} \right), && (14) \\
I_\tau &= \sum_{j=1}^{J} \left(\frac{I_{j0}}{\sum_{j=1}^{J} I_{j0}} \right) \left(\frac{I_{j\tau}}{BASE_j} \right). && (15)
\end{aligned}
$$

Note that investment spikes with any missing values in the cash-flow identity during the five-year event window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics. Similarly, investment spikes with missing total assets are dropped as well. Furthermore, the j-th investment spike is dropped if any $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment to minimize the effects of extreme values. Finally, investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$) are also dropped before constructing the aggregate statistics. These procedures leave 7,494 investment spikes (Sig. Level=5%) with the weighted average normalized investment (I_0) of 6.28 as shown in Table 2 Panel A.

[Insert Figure 1 Here.]

[25] Note that the weighting is based on investment amounts during investment spikes.

3.1.2 Flow of funds around investment spikes

In this section, I investigate how investment spikes are financed by analyzing the flow of funds around investment spikes. Table 2 shows the sources of finance expressed as a proportion of the base-level investment for periods around investment spikes. The aggregate statistics were constructed as described in Section 3.1.1.

A. Using the regression filter as a baseline filter

Table 2 Panel A shows the investment-weighted flows of funds around investment spikes for all firms in the investment spikes sample by the significance level in the filter. For the first instance, let us consider the case with a significance level of 5%. The column for total assets (TA) shows that total assets increase by some 52% (i.e., $25.23/((15.79+17.32)/2)-1 \approx 0.52$) during an investment spike. In this sense, investment spikes can be regarded as periods of major expansion for firms.

The financing patterns can be analyzed in two dimensions. First, I compare the sources of finance at the time of investment spikes across different financing sources. At the time of investment spikes, internally available funds do not change much so needs for external financing sources increase dramatically. Among external financing sources, net long-term debt issuances become much more significant than net equity issuances at the time of investment spikes. Note that the shares of investment financed through net long-term debt issuances and net equity issuances are some 3.10 and 0.32 times the base-level investment, respectively. These results are consistent with the peking-order theory predicting that when internal resources are exhausted, less information-sensitive long-term debt is preferred to more information-sensitive equity (Myers and Majluf, 1984). Figure 1 also clearly shows that at the time of investment spikes, investment projects are predominantly financed with debt while internal finance is not the first source of finance in terms of magnitude any more.

Second, I compare each financing source during investment spikes with that before and after investment spikes. The share of investment financed from internally generated funds during investment spikes (some 1.28 times the base-level investment) is similar to those in off-spike periods.

However, both long-term debt finance and equity finance become much more important during investment spikes. The shares of investment financed through net long-term debt issuances and net equity issuances are some 3.10 and 0.32 times the base-level investment, respectively. Some net long-term debt issuances are observed before investment spikes, but some net repayments of long-term debt are observed after investment spikes[26]. These results seem to be consistent with the predictions of the trade-off theory in the sense that the main source of finance during investment spikes appears to be debt so that leverage ratios typically exceed normal levels immediately after the spike year, but leverage ratios are subsequently adjusted downwards, through net debt repayments (for most firms) and equity issues (for some firms). Figure 1 also clearly shows that both debt finance and equity finance have spikes at the time of investment spikes while internal finance have a flat pattern.

Overall, these results are in line with Mayer and Sussman (2005) who argue that financing patterns are consistent with the pecking-order theory in the short run, while they are consistent with the trade-off theory in the long run. In Section 4 and Section 5, I show that large firm's financing behaviors around investment spikes are consistent with the pecking-order theory and the classical trade-off theory, while small firms' financing behaviors around investment spikes are *not* consistent with the pecking-order theory and the classical trade-off theory.

I then investigate whether the financing of investment spikes is different depending on the significance level used in the filter. Regardless of significance level (1%, 5%, and 10%), external finance becomes much more significant than internal finance at the time of an investment spike, and net long-term debt issuances are more important sources of finance than net equity issuances. In addition, a small proportion of net equity issuances are observed at the time of an investment spike too. Thus, all the following analyses will be based on the spikes sample in which a significance level of 5% is used.

[Insert Table 2 Here.]

B. Using the Markov-switching filter as a robustness check

One potential problem with Mayer and Sussman's filter and the regression filter used in this paper

[26] However, net equity repurchases are observed before and after investment spikes.

is that they are designed to capture only one type of lumpy investment patterns, namely (0,0,1,0,0)-type investment spikes, where 1 denotes a year categorized as an investment spike and 0 denotes a year with routine investments only. Therefore, they can identify only subsets of large investment years by their construction[27]. However, the Markov-switching filter proposed by Im (2012) can identify any conceivable patterns of lumpy investment including two-year spikes and three-year investment spikes[28]. The main idea of this filter is to apply a Markov-switching mean model to the investment rates detrended using Hodrick and Prescott's (1997) filter. The Gibbs-sampling algorithm is used to estimate unobserved state variables and model parameters, as it has several advantages over the classical maximum likelihood approach. One of the biggest advantages of the Markov-switching approach is that it provides the statistical inference on the probability of the unobserved states such as investment spikes state. See Appendix A.2 for more details.

I estimate the filter using the data over the period 1988 to 2013 for 2,627 firms whose investment rates are observed in 1988 and observed for at least 10 consecutive years, where the investment rate is defined as the sum of net capital expenditures and net acquisitions divided by total assets measured at the beginning of the year. I find that some 73.28% (81.37% among firms that survived until 2013) of firms have at least one investment spike in the sample period using the filter with the 5% level of significance. I also categorize about 6.93% of firm-years in the sample as having investment spikes.

I then investigate whether major findings on the financing of investment spikes are robust to the use of the Markov-switching filter. The upper part of Table 2 Panel B reports the flow of funds around (0,0,1,0,0)-type investment spikes identified by the Markov-switching filter with the 5% level of significance. Just as in the case of the regression filter, external finance becomes very important at the time of investment spikes. More importantly, long-term debt is the most important source of finance, while the net retirement of equity is observed even during spikes. Just as in the case of the regression filter, both debt finance and equity finance have spikes at the time of invest-

[27] Some investment projects are so large that they last more than one year. Thus, a single annual accounting period would not necessarily reflect the total expenditures necessary to complete the project. Furthermore, even a year-long project need not start at the beginning of an accounting year nor reach completion by the end of accounting year (see Power (1998) for a more detailed discussion on multi-year investment spikes).

[28] Two-year and three-year investment spikes represent (0,0,1,1,0,0)-type and (0,0,1,1,1,0,0)-type investment spikes, respectively.

ment spikes while internal finance have a flat pattern. The lower part of Table 2 Panel B reports the flow of funds around (0,0,1,1,0,0)-type investment spikes identified by the Markov-switching filter. This analysis confirms that two-year investment spikes identified by the Markov-switching filter are financed quite similarly to single-year investment spikes. Again, external finance becomes very important at the time of investment spikes and debt finance is much more important than equity finance in funding two-year investment spikes.

These results support Mayer and Sussman (2005) who argue that financing patterns are consistent with the pecking-order theory in the short run, while they are consistent with the classical trade-off theory in the long run. However, in Section 4 and Section 5, this paper shows that small firms' financing behaviors around investment spikes are consistent with the reverse pecking-order, and consistent with the dynamic trade-off theory augmented with investment spikes as proposed by DeAngelo *et al.* (2011).

3.1.3 Industry and the financing of investment spikes

Table 2 Panel C shows that the shares of financing during investment spikes are almost homogeneous across industries. In most industries, debt finance is the most important source of finance during investment spikes, followed by internal finance. Some contribution of equity finance at the time of an investment spike is also observed in most industries, whereas net retirement of equity is observed in several industries. For firms in construction-related and petrol refining industries, internally generated funds are rather more important than debt finance at the time of an investment spike, although debt finance is still quite important. In the case of the leather industry, the most important source of finance is equity finance, but this result might be attributed to the small sample size (N = 26). I conclude that there are no substantial differences in the financing of investment spikes across industries except for only a few industries.

[Insert Table 3 Here.]

3.1.4 Business cycles and the incidence and financing of investment spikes

In this section, I investigate whether the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks is observed in the sample used in this paper and whether the clustering of spikes has a significant effect on the reliability of the aggregated flow of funds around investment spikes.

A. Business cycles and the incidence of investment spikes

Figure 2 shows that, when the regression filter (Sig. Level=1%, 5%, 10%) and Markov-switching filter (Sig. Level=5%) are used, the incidence of firms with investment spikes is significantly positively correlated with real GDP growth rate and lagged S&P 500 Index return. For instance, based on the regression filter with the 5% significance level, 3.68% of firms in the sample had an investment spike in 2009 (i.e. a recession year), whereas 12.15% of firms in the sample had an investment spike in 2000 (i.e. a boom year). This shows that there is some evidence for calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks. Table 3 also shows that the average number of investment spikes per year during expansions ($6,248/18 \approx 347$) is about 11% higher than that during contractions ($1,246/4 \approx 312$). Note that, based on the business cycle reference dates announced by the NBER's Business Cycle Dating Committee, years 1991-2000, 2002-2007, and 2010-2011 are categorized as expansions, while years 1990, 2001, 2008, and 2009 as contractions.

[Insert Figure 2 Here.]

B. Business cycles and the financing around investment spikes

To investigate whether the reliability of the aggregated flow of funds is affected by the calendar-time-dependent clustering, I examine if the flow of funds during expansions (i.e., years 1991-2000, 2002-2007, and 2010-2011) is significantly different from that during contractions (i.e., years 1990, 2001, 2008, and 2009). Panel A of Table 3 shows that the financing patterns around investment spikes during expansions are not very different from the financing patterns around investment spikes during contractions. In both phases, external finance is more important than internal finance at the time of an investment spike and debt finance is more important than both internal finance and equity finance at the time of an investment spike. In addition, some equity finance is used at the time of an investment spike.

However, there are some minor differences between the flow of funds around spikes during expansions and the flow of funds around spikes during contractions. First, investment spikes during expansions tend to be spikier than those during contractions and slightly more internally generated funds are available during expansions. Second, during expansions, a higher proportion of external finance, particulary equity finance, is used in comparison with during contractions. While net repayment of debt and net retirement of equity are observed in periods after spikes in the expansions sample, some additional borrowing are observed in periods after spikes in the contractions sample. Overall, I conclude that the main findings reported in this paper are robust to the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks.

C. Financial crises and external financing sources during investment spikes

I then examine whether there are significant differences in equity dependence and debt dependence between during expansions and during contractions using Student's t-tests and Wilcoxon rank-sum tests. Equity dependence ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are constructed as follows:

$$(E/I)_{j,\tau=0} = \frac{EQUITY_{j,\tau=0}}{I_{j,\tau=0}}; \tag{16}$$

$$(D/I)_{j,\tau=0} = \frac{LTDEBT_{j,\tau=0}}{I_{j,\tau=0}}, \tag{17}$$

where I measures investment outlays on tangible assets, intangible assets and acquisitions, $LTDEBT$ measures funds from issuances of long-term debt capital net of retirements, and $EQUITY$ measures funds from issuances of ordinary and preferred shares net of retirements. See Appendix A.1 for the formulas and the Compustat items used to construct them.

Panel B of Table 3 suggests that there is a significant difference in equity dependence between two phases based on both Student's t-test (p-value=0.0000) and Wilcoxon rank-sum test (p-value=0.0000). Note that mean equity dependence during expansions is 0.30, while mean equity dependence during contractions is 0.11. However, this analysis does not find any statistically significant difference in debt dependence between during expansions and during contractions at a conventional level of significance.

[Insert Figure 3 Here.]

Figure 3 also shows the relationship between business cycles and external financing sources during investment spikes. Consistent with Panel B of Table 3, in some years categorized as expansions such as 1991-1993, 1996, and 2000, equity dependence was higher than debt dependence. However, since 2006, though the 2008-2009 financial crisis, and till 2011, equity dependence dropped significantly and debt dependence was higher than equity dependence. Note also that both equity and debt dependence dropped significantly during the 2008-2009 financial crisis. In 2009, net retirements of equity were observed and the debt dependence also recorded the lowest number in the sample period under study. In that year, equity dependence and debt dependence were -3.72% and 7.15%, respectively. To sum up, equity dependence has been much more volatile than debt dependence, and debt finance played a much more important role in funding investment spikes around the 2008-2009 financial crisis.

[Insert Table 4 Here.]

3.2 Firm characteristics and the financing of investment spikes

In this section, I explore heterogeneity of financing patterns around investment spikes by investigating whether financing patterns vary with various firm characteristics including Rajan and Zingales' (1995) four leverage factors[29].

3.2.1 Firm size and the financing of investment spikes

A. Flow of funds by sub-samples based on firm size

This section examines whether the sources of finance expressed as a proportion of the base-level

[29] I consider firm size, profitability, level of future growth opportunities, tangibility of assets, and R&D intensity as firm-level characteristics. Note that Gungoraydinoglu and Öztekin (2011) who analyze the determinants of capital structure across 37 countries find that firm-level covariates drive two-thirds of the variation in capital structure across countries, while the country-level covariates explain the remaining one-third.

investment for periods around investment spikes vary with firm size. Table 4 Panel A and Figure 4 report the investment-weighted proportions of the flows of funds around investment spikes separately for the subsamples of "Large firms" and "Small firms." The total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) are used to group firms with an investment spike into "Small firms," "Medium-sized firms," and "Large firms." The thresholds used are the 33rd and 67th percentiles. The aggregate statistics were constructed as described in Section 3.1.1.

[Insert Figure 4 Here.]

Before comparing financing patterns between large and small firms, note that small firms tend to have larger investment spikes. On average, large firms increase their total assets by some 50% (i.e., $25.21/((16.05+17.55)/2)-1 \approx 0.50$) during an investment spike, while small firms increase their total assets by some 139% (i.e., $30.38/((11.34+14.12)/2)-1 \approx 1.39$) during an investment spike. Note also that the weighted average of abnormal components of investment spikes for large firms is 5.06 (i.e., 6.06-1.00=5.06) times the base-level investment and that for small firms is 10.59 (i.e., 11.59-1.00=10.59) times the base-level investment.

There are significant differences in the financing of investment spikes for these subsamples of US firms classified by firm size. The financing proportions for large firms are very similar to those of all firms with investment spikes. The most striking finding in Table 4 Panel A is that small firms raise equity finance quite substantially before, during, and after investment spikes, whereas large firms rely largely on debt finance during investment spikes. It is also observed that the contribution of equity finance in funding investment spikes is negligible when it comes to large firms. Figure 4 clearly shows that small firms rely heavily on external finance (both debt finance and equity finance) during investment spikes. It is quite surprising that small firms issue shares even before and after the years categorized as investment spikes as well.

B. Firm size and external financing sources during investment spikes

Table 5 also shows that small firms have higher equity dependence and lower debt dependence than large firms and the difference is statistically significant at the 1% level of significance based on both Student's t-test and Wilcoxon rank-sum test. Table 6 also confirms these results using Between Group (BG) regressions in which dummy variables based on other firm characteristics such as profitability, market-to-book, assets tangibility, and/or R&D intensity as well as industry and year dummies are included as explanatory variables.[30] The Between Group regressions are more appropriate to study the heterogeneity of financing patterns around investment spikes as they exploit only the cross-sectional variation in the data. However, results from Ordinary Least Squares (OLS) and Fixed Effects (FE) regressions are almost the same as results from the Between Group regressions because one firm has on average 1.46 (i.e., $7,494/5,130 \approx 1.46$) investment spikes and within-firm variation is much smaller than between-firm variation. All these findings boil down to conclude that small firms' financing behaviors at the time of investment spikes are significantly different from large firms' financing behaviors. Therefore, all subsequent analyses have been executed separately for large firms and small firms.

C. Breakdown of other financing sources by sub-samples based on firm size

Table 4 Panel A and Figure 4 also show that the contribution of other financing sources is substantial, particulary for large firms. Therefore, in Table 4 Panel B, I break down other financing sources (i.e., $OTHER$) into nine components and examine which components are more important sources of finance among them. The nine components are "Decrease in cash and cash equivalents," "Decrease in cash dividends," "Decrease in other investments," "Decrease in inventories," "Decrease in accounts receivable," "Increase in accounts payable," "Increase in debt in current liabilities," "Increase in taxes payable," and "Increase in net other current liabilities." See Appendix A.1 for the formulas and the Compustat items used to construct them. Note that missing Compustat items have been replaced with zeros whenever appropriate. Note also that the numbers of observations in Panel B are slightly less than the numbers of observations because investment spikes without complete information on those nine components have been dropped.

Table 4 Panel B shows that for both large and small firms "Increase in debt in current liabilities," "Increase in other current liabilities," "Increase in taxes payable," "Decrease in other investments," and "Decrease in cash dividends" are used to finance investment spikes. Large firms rely a bit on "Decrease in cash and cash equivalents" and small firms rely quite significantly on "Increase in

[30] Industry and year dummies are included in the regressions as Section 3.1.3 and Section 3.1.4 report that there are some differences in funding patterns across industries and depending on business cycles.

accounts payable." Surprisingly, "Decrease in inventories" and "Decrease in accounts receivable" are not observed for both large firms and small firms. At the time of investment spikes, inventories and accounts receivable increase rather than decrease. However, this analysis should be seen with some caution because those components might include substantial measurement errors and some components could be moved to the left-hand-side of the cash flow identity. For example, instead of treating "Decrease in other investments" as a source of finance, one can treat "Other investments" as a part of investment spending. Nevertheless, this analysis increases our understanding of how investment spikes are financed.

[Insert Table 5 Here.]

3.2.2 Other firm characteristics and the financing of investment spikes

This section investigates how the financing patterns of investment spikes vary according to other firm characteristics. Particularly, I investigate the effects of the profitability of firms, level of future growth opportunities, tangibility of assets, and R&D intensity.

A. Univariate tests

Table 5 reports the results for Student's t-tests and Wilcoxon rank-sum tests as well as the means and medians of equity dependence and debt dependence, by subgroups based on firm's profitability, level of future growth opportunities, tangibility of assets, and R&D intensity as well as firm size. The investment spikes are grouped into "Above median" and "Below median" based on the median of the proxies for those firm characteristics measured at the beginning of the years with an investment spike (i.e., $\tau = -1$). Appendix A.1 describes the construction of the variables representing firm characteristics. Panel A shows that firms with lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity finance when faced with large investment requirements. These differences are statistically significant at the 1% level of significance based on both Student's t-tests and Wilcoxon rank-sum tests. Similarly, Panel B shows that firms with higher profitability, less future growth opportunities, more tangible assets, and lesser R&D spending have a higher tendency to use debt finance at the time of investment spikes. These differences are statistically significant at the 1% level of significance based on both Student's t-tests and Wilcoxon rank-sum tests, except for only one t-test.

[Insert Table 6 Here.]

B. Between Group regressions

The Between Group regressions reported in Table 6 can also be used to investigate whether the effects of those additional firm characteristics on equity dependence and debt dependence remain after firm size, industry effects and year effects are controlled for. Panel A confirms that firms with lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity finance when faced with large investment requirements. Similarly, Panel B confirms that firms with more tangible assets and lesser R&D spending have a higher tendency to use debt finance at the time of investment spikes. It appears that profitability and market-to-book ratios do not have significant influences on debt dependence during investment spikes when firm size, industry effects and year effects are controlled for. Note again that small firms' financing behaviors at the time of investment spikes are significantly different from large firms' financing behaviors. In the next two sections, I further investigate how differently small firms behave from large firms when confronted with unusually large investment programs in relation to spike size and initial leverage.

[Insert Table 7 Here.]

3.2.3 Summary and discussion

Overall, smaller firms, firms with lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity finance when faced with large investment requirements. However, the effects of those firm characteristics are not as strong as the effect of firm size on the financing patterns around investment spikes. These results are consistent with Fama and French (2005) and Gatchev *et al.*'s (2009) finding that small firms, high-growth firms, and less-profitable firms use more equity to cover their financing needs than large firms, low-growth firms, and more profitable firms. This happens because firms that are less likely to be informationally transparent–such as small firms, firms with low earnings, and high growth firms–typically use more equity and less long-term debt than their more informationally transparent counterparts. One explanation consistent with the above findings is that as firms become less informationally transparent, the contracting costs of debt issuances increase relative to the adverse selection costs of equity issuances (Gatchev *et al.*, 2009). These patterns are opposite of what one would expect in the framework of Myers and Majluf (1984) in which adverse selection considerations play the dominant role in security issuance decisions.

3.3 The flow of funds around investment spikes: capital expenditures vs. acquisitions

In this section, I investigate whether investment spikes involving acquisitions are funded differently from investment spikes involving only capital expenditures. Investment spikes are classified as acquisitions if acquisitions are involved in that year ($D\_AQC = 1$), while they are classified as capital expenditures otherwise ($D\_AQC = 0$). Although the tables are not reported, I find that investment spikes involving acquisitions tend to be spikier (i.e., larger) than investment spikes involving only capital expenditures. Therefore, it is expected that more equity finance will be involved in funding investment spikes involving acquisitions, as expected by the pecking-order theory (Myers and Majluf, 1984). However, regardless of firm size, additional investment requirements at the time of acquisitions tend to be funded by additional debt finance. Particularly, small firms rely more on equity finance to finance capital expenditures, but rely more on debt finance to finance acquisitions[31]. These are consistent with Gatchev *et al.*'s (2009) finding that organic investments are financed with more equity and less long-term debt than acquisitions. They argue that information asymmetry problems are likely to be more severe in organic investment projects than in acquisitions as investors have access to publicly available data on targets in valuing acquisitions of public companies. Based on this argument, they maintain that less informationally transparent capital

[31] Elsas *et al.* (2014) also find that external funds, particularly debt, are prominent in financing major investments across all size classes. However, small firms finance their projects with less internal funds and much more new equity than large firms, especially if the project is an acquisition. They interpret this pattern as contradicting the usual pecking order hypothesis, in which small firms suffer greater adverse selection costs when issuing equity and thus rely on internal funds or debt to finance their growth.

expenditures are financed with more equity and less long-term debt than more informationally transparent acquistions. One explanation consistent with the above findings is that as investments become less informationally transparent, the contracting costs of debt issuances increase relative to the adverse selection costs of equity issuances. These patterns are opposite of what one would expect in the framework of Myers and Majluf (1984) in which adverse selection considerations play the dominant role in security issuance decisions. Rather, these financing patterns among small firms are consistent with a reverse pecking order, which can be predicted with the assumption of endogenous information production in the framework of Fulghieri and Lukin (2001), because it appears that equity finance is considered first among external finance sources.

4 Firm size and the relation between spike size and the financing of investment spikes

In this section, I investigate whether there are differences in the relation between the magnitude of investment spike and the financing of investment spikes between large firms and small firms. These analyses shed light on whether their financing patterns are consistent with the pecking order theory or a reverse pecking order, which can be predicted with the assumption of endogenous information production in the framework of Fulghieri and Lukin (2001).

4.1 Spike size and the financing patterns during investment spikes

I first investigate whether the financing patterns vary according to the magnitude of investment spikes using the flow-of-funds analysis. Table 7 shows that financing patterns are substantially different across subgroups based on $SPIKESIZE_j$ or the magnitude of abnormal components of investment spikes. According to Table 7 Panel A, large firms tend to use only debt finance when they are faced with relatively small investment spikes but tend to use more equity finance when they are faced with relatively large investment spikes. It seems that these results are consistent with the pecking-order theory (Myers and Majluf, 1984). However, Table 7 Panel B shows that small firms tend to use more equity finance when they are faced with relatively small investment spikes but more debt finance when they are faced with relatively large investment spikes. These results seem to be consistent with the reverse pecking order that can be explained with the assumption of endogenous information production in the framework of Fulghieri and Lukin (2001).

[Insert Table 8 Here.]

I then examine further how differently small firms' equity dependence ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are affected by the size of investment spikes in comparison with large firms using regression analyses. Table 8 reports the results of Between Group regressions of equity dependence and debt dependence on a measure of spike size. The natural logarithm of the abnormal component of an investment spike ($LNSPIKESIZE_{j,\tau=0}$) is included as an explanatory variable as $SPIKESIZE_{j,\tau=0}$ is skewed to the right. In addition, interaction terms between $LNSPIKESIZE_{j,\tau=0}$ and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. The variables used in the regressions are described in Appendix A.1.

The regressions in Table 8 Panel A are designed to analyze the effects of the size of investment spikes on equity dependence at the time of investment spikes. Column (1) shows that $(E/I)_{j,\tau=0}$ is a linear function of $LNSPIKESIZE_{j,\tau=0}$ with a positive intercept and a positive slope. However, Columns (2), (3), and (4) with different regression specifications show that large firms and small firms have completely different relationships between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$: large firms have a negative intercept and a positive slope but small firms have a positive intercept and a negative slope. Similarly, the regressions in Table 8 Panel B are designed to analyze the effects of the size of investment spikes on debt dependence at the time of investment spikes. Column (1) shows that $(D/I)_{j,\tau=0}$ is a linear function of $LNSPIKESIZE_{j,\tau=0}$ with a positive intercept and a positive slope just as in $(E/I)_{j,\tau=0}$. However, Columns (2), (3), and (4) with different regression specifications show that large firms and small firms have somewhat different relationships between $(D/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$: large firms and small firms have similar slopes but small firms have a lower intercept.

According to the pecking order theory, it is expected that firms with larger investment spikes will have higher equity dependence in periods categorized as investment spikes. When firms are faced with smaller investment spikes, firms will use up internal finance first, and then they will raise less information-sensitive debt finance if they need external finance, and finally they will issue more information-sensitive equity if debt capacity is reached. When firms are faced with larger investment spikes, they are more likely to have used up internal funds and are more likely to have exhausted debt capacity, so they are more likely to issue equity. Thus, under the pecking order theory, we expect to see a positive slope in the relationship between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$. Table 8 Panel A shows that large firms have a positive relation between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$, while small firms have a negative relation between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$. These results show that large firms' financing patterns at the time of investment spikes are consistent with the pecking order theory, while small firms' financing patterns are *not* consistent with the pecking order theory.

[Insert Figure 5 Here.]

4.2 Summary and discussion

Figure 5 is used to visually examine how differently small firms' equity dependence and debt dependence are influenced by the natural logarithm of the spike size measure. The nine points in each line in the figure correspond to nine deciles of $LNSPIKESIZE_{j,\tau=0}$. Note that this figure is based on OLS regressions as deciles are based on original spike size measures, not firm-average spike size measures. Given a median-sized investment spike (i.e., 1.18 in natural logarithm), equity dependence of small firms are approximately 55% higher than that of large firms (55.34% vs. 0.03%), and debt dependence of small firms are approximately 12% lower than that of large firms (19.56% vs. 31.46%). Note that small firms have a higher tendency to use equity while large firm have a higher tendency to use debt.

In addition, in line with Table 7 Panel A, large firms tend to use only debt finance when they are faced with relatively small investment spikes but tend to use more equity finance when they are faced with relatively large investment spikes. It seems that this result is consistent with the pecking-order theory (Myers and Majluf, 1984). However, in line with Table 7 Panel B, small firms tend to use more equity finance when they are faced with relatively small investment spikes but more debt finance when they are faced with relatively large investment spikes. This result seems to be consistent with the reverse pecking order that can happen under the assumption of endogenous information production in the framework of Fulghieri and Lukin (2001). Mayer and Sussman (2005) find that large investment projects are predominantly financed with debt and interpret this result as suggesting that corporate financing patterns are consistent with the pecking-order theory in the short run. This study also confirms that the financing patterns of large firms are consistent with the pecking-order theory in the short run. However, the financing patterns of small firms are *not* consistent with the pecking-order theory, but rather consistent with the reverse pecking order prediction in the short run.

To sum up, this study finds that the financing patterns of large firms at the time of investment spikes are consistent with the pecking-order theory (Myers and Majluf, 1984), while the financing patterns of small firms at the time of investment spikes are rather consistent with the reverse pecking-order prediction (Fulghieri and Lukin, 2001).

[Insert Table 9 Here.]

5 Firm size and the relation between initial leverage and the financing of investment spikes

In this section, I investigate whether there are differences in the relation between the level of initial leverage and the financing of investment spikes between large firms and small firms. These analyses shed light on whether their financing patterns are consistent with the classical trade-off theory or a modern dynamic trade-off theory augmented with investment spikes as outline in DeAngelo *et al.* (2011).

5.1 Initial leverage and financing patterns during investment spikes

I first investigate whether financing patterns vary according to the level of initial leverage using the flow-of-funds analysis. Table 9 shows the investment-weighted flows of funds around investment spikes undertaken separately by large firms and small firms by subgroups based on a measure of initial leverage ($LEV_{j,\tau=-1}$). According to the classical trade-off theory of debt, it is expected that firms with higher initial leverage will use less debt in financing investment requirements in periods categorized as investment spikes and in normal periods. However, Panel A shows that initial leverage does not make significant differences in the financing of investment spikes in the case of large firms. That is, large firms tend to use more debt finance than equity finance in funding large investment projects regardless of the level of initial leverage. Panel B shows that the relation between the level of initial leverage and the financing of investment spikes undertaken by small firms is opposite to the prediction of the classical trade-off theory of debt. The results in this table reveal that small firms with lower initial leverage tend to use more equity finance, but small firms with higher initial leverage tend to use more debt finance to meet large investment requirements. It is also noteworthy that equity finance plays an important role in funding investment spikes, regardless of the level of initial leverage. Overall, the financing of investment spikes cannot be fully explained using the classical trade-off theory of debt.

[Insert Table 10 Here.]

I then examine how differently small firms' equity dependence ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are influenced by the initial leverage in comparison with large firms. Table 10 reports the results of Between Group regressions of equity dependence and debt dependence on a measure of initial leverage. Only the results based on market leverage ratios ($LEV_{j,\tau=-1}$) are reported, because the results based on book leverage ratios ($BLEV_{j,\tau=-1}$) are very similar to those based on market leverage ratios. In addition to market leverage ratios ($LEV_{j,\tau=-1}$), interaction terms between $LEV_{j,\tau=-1}$ and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. The variables used in the regressions are described in Appendix A.1. Column (1) in Panel A shows that $(E/I)_{j,\tau=0}$ is a linearly decreasing function of $LEV_{j,\tau=-1}$ with a positive intercept, while Column (1) in Panel B shows that $(D/I)_{j,\tau=0}$ is a linearly increasing function of $LEV_{j,\tau=-1}$ with a positive intercept. This suggests that firms with very high initial leverage ratios will have a very high debt dependence and low equity dependence during investment spikes, which will increase their leverage during investment spikes. However, this table shows that large firms and small firms have completely different relationships between initial leverage and both debt dependence and equity dependence. Columns (2), (3), and (4) in Panel A show that large firms and small firms have completely different relationships between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$: large firms have a negative intercept and a positive slope but small firms have a positive intercept and a negative slope. Similarly, Columns (2), (3), and (4) in Panel B show that both large firms and small firms have positive slopes but they have somewhat different relationships between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$: small firms have a somewhat steeper slope but have a slightly lower intercept.

Figure 6 is used to visually examine how differently small firms' equity dependence and debt dependence are influenced by initial leverage ratios. The nine points in each line in the figure correspond to nine deciles of $LEV_{j,\tau=-1}$. Note that this figure is based on the coefficients in OLS regressions, so deciles are based on original initial leverage measures, not firm-average initial leverage measures. Given median initial leverage (i.e., 18.13%), equity dependence of small firms are approximately 60% higher than that of large firms (56.96% vs. -3.10%) and debt dependence of small firms are approximately 3% lower than that of large firms (21.29% vs. 24.28%). Note that given the median initial leverage, small firms tend to issue substantial amounts of equity at the time of investment spikes, while large firm tend to retire equity at the time of investment spikes.

According to the classical trade-off theory of debt, it is expected that firms with higher initial leverage will use less debt and more equity in financing investment requirements in periods categorized as investment spikes and in normal periods. Therefore, under the classical trade-off theory, we expect to see a positive slope in the relationship between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$ and a negative slope in the relationship between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$. Table 9 shows that large firms have a weakly positive relationship between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$, while they have a strongly positive relationship between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$. In addition, large firms tend to use more debt finance than equity finance in funding large investment projects regardless of the level of initial leverage. Although these results are *not* perfectly consistent with the trade-off theory of debt, these results can be compatible with the theory. However, Table 9 also shows that small firms have a strongly negative relationship between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$, while they have a strongly positive relationship between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$. These results are completely opposite to the predictions of the classical trade-off theory of debt.

However, according to the dynamic trade-off theory augmented with investment spikes as outlined by DeAngelo *et al.* (2011), it is possible that firms with higher initial leverage do not adjust their leverage back to their target or optimal leverage when they are faced with unusually good investment opportunities, and managers sometimes choose to intentionally deviate from their targets. Thus, firms with higher initial leverage do not necessarily use more equity and less debt in financing in periods categorized as investment spikes. Therefore, under this framework, it is possible that small firms with higher initial leverage do not adjust their leverage back to their target or optimal leverage when they have unusually good investment opportunities.

[Insert Figure 6 Here.]

5.2 Analyses of financing patterns after investment spikes

I then analyze whether financing patterns *after* investment spikes vary according to the level of initial leverage. According to both classical the trade-off theory and DeAngelo *et al.*'s (2011) dynamic trade-off model, it is expected that firms will adjust their leverage downwards following investment spikes, through some combination of net debt repayments and equity issues. It is also expected that this adjusting pattern will be more pronounced when initial leverage is higher. My empirical findings are summarized as follows. First, large firms, especially those with higher initial leverage, gradually adjust their leverage back to optimal leverage after investment spikes by repaying some debt and reducing share repurchases. Note that large firms with below median initial leverage tend not to repay debt or reduce share repurchases right after investment spikes, while large firms with above median initial leverage start to repay debt or reduce share repurchases right after investment spikes. Second, small firms, regardless of initial leverage, gradually adjust their leverage back to optimal leverage after investment spikes by repaying some debt and issuing new shares. Note that small firms, unlike large firms, tend to issue some shares after investment spikes. This suggests that these adjustment patterns of both large firms and small firms are quite consistent with both the classical trade-off theory and DeAngelo *et al.*'s (2011) dynamic trade-off model in the long run. Similarly, Mayer and Sussman (2005) found that firms tend to revert back to their initial leverage by repaying debt and issuing new equity after investment spikes and interpret this result as suggesting that corporate financing patterns are consistent with the classical trade-off theory in the long run. However, they did not take initial leverage into consideration in their analyses. Putting together the empirical results during and after investment spikes, I conclude that financing patterns of both large firms and small firms can not be fully explained by the classical trade-off theory, but can be better explained by DeAngelo *et al.*'s (2011) dynamic trade-off model augmented with investment spikes.

5.3 Summary and discussion

Mayer and Sussman (2005) find that firms tend to revert back to their initial leverage by repaying debt and issuing new equity after investment spikes and interpret this result as suggesting that corporate financing patterns are consistent with the classical trade-off theory in the long run. This study also confirms that the financing patterns of large firms are *not* inconsistent with the classical trade-off theory in the long run. However, this study finds that the financing patterns of small firms after investment spikes are *not* consistent with the classical trade-off theory, i.e., opposite to the predictions of the classical trade-off theory. Despite some differences in financing patterns between large firms and small firms, the relation between the level of initial leverage and the financing of investment spikes can be better explained by the dynamic trade-off theory augmented with investment spikes as outlined by DeAngelo *et al.* (2011). Following adjustment patterns after investment spikes suggests that these adjustment patterns of both large firms and small firms are quite consistent with both the classical trade-off theory and DeAngelo *et al.*'s (2011) dynamic trade-off model in the long run. Taking into consideration the empirical results during and after investment spikes altogether, I conclude that financing patterns of both large firms and small firms can not be fully explained by the classical trade-off theory, but can be better explained by DeAngelo *et al.*'s (2011) dynamic trade-off model augmented with investment spikes.

6 Conclusions

Many studies hold that the dominant source of finance for firms across different countries and time periods is retained earnings (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this argument is primarily indicative of how firms finance their routine, replacement investment rather than their non-routine, expansion investment. Particularly, how firms meet exceptional financing needs related to unusually large investment opportunities is the subject of an emerging body of literature that includes the study by DeAngelo *et al.* (2011), Mayer and Sussman (2005), Huang *et al.* (2007), Elsas *et al.* (2014), and Im (2014). In addition to the literature, this study also contributes to the security design literature represented by authors such as Boot and Thakor (1993). Note that they provide a theory which explains why a firm raising external capital would wish to simultaneously issue multiple types of financial claims such as debt and equity against its cash flows. Therefore, the methodology used in this study can be usefully applied to test various predictions arising from the security design literature.

One of the most important findings in this study is that the financing of investment during an investment spike differs from the financing of investment at other times using data for publicly traded US firms and a new filtering procedure that has some advantages over existing filters. It is confirmed that the share of investment financed by external sources is much higher than the share of investment financed from internally generated funds. More importantly, I find that the share of investment financed by long-term debt is much higher than the share of investment financed from equity finance. I also find that small firms raise equity finance quite substantially during investment spikes, whereas large firms rely largely on debt finance during investment spikes. In addition, firms with lower profitability, more future growth opportunities, fewer tangible assets, and more R&D spending tend to use more equity finance when faced with large investment requirements. However, the effects of those firm characteristics are not as strong as the effect of firm size on the financing of investment spikes. It seems that there are no substantial differences in the financing of investment spikes across industries and time periods. Furthermore, I find that investment spikes involving acquisitions tend to be funded by a higher proportion of debt finance, although they tend to be spikier than investment spikes involving only capital expenditures.

One of the most striking findings in this study is that financing patterns are substantially different across subgroups based on the magnitude of investment spikes. Large firms tend to use only debt finance when they are faced with relatively small investment spikes, but tend to use more equity finance when they are faced with relatively large investment spikes. However, small firms tend to use more equity finance when they are faced with relatively small investment spikes but tend to use more debt finance when they are faced with relatively large investment spikes. This finding suggests that the financing patterns of large firms are consistent with the pecking-order theory (Myers and Majluf, 1984), but the financing patterns of small firms are consistent with the reverse pecking order, which can be predicted with the endogenous information production assumption (Fulghieri and Lukin, 2001).

Another striking finding in this study is that financing patterns around investment spikes are *not* consistent with the classical trade-off theory of debt but quite consistent with the predictions of the dynamic trade-off theory augmented with investment spikes, as outlined in DeAngelo *et al.* (2011). According to the classical trade-off theory of debt, firms with higher initial leverage are expected to use less debt in financing their investment requirements in periods categorized as investment spikes and in normal periods. However, large firms tend to use more debt finance than equity finance in funding large investment projects regardless of the level of initial leverage. In addition, small firms with lower initial leverage tend to use more equity finance but small firms with higher initial leverage tend to use more debt finance to meet large investment requirements, which is contrary to the prediction of the classical trade-off theory.

There are many interesting ways in which this line of research could be extended. First, it has been observed that small firms issue substantial amounts of equity at the time of an investment spike and at other times quite frequently. However, it has not been systematically studied whether they issue shares because it is optimal to issue shares or because debt finance is not available to them at the time of an investment spike. In relation to this issue, it is worth investigating whether privately placed equity rather than publicly placed equity is largely used at the time of an investment spike. A large use of private equity at the time of an investment spike may mean a change of ownership through the interventions of activists. Second, one aspect of my results which I have not fully explored is heterogeneity in the type of investment spikes. My current results suggest that debt finance is more important when the spike is associated with an acquisition, rather than capital expenditures. This could be studied further, allowing for heterogeneity within the set of acquisitions (e.g. within sector or across sectors; within the U.S. or international). These lines of investigation will uncover answers to some issues that have not been understood by previous research in empirical corporate finance.

A Appendix

A.1 Construction of Variables

The section shows the definitions of the variables used in the study. Table A1 describes variables for cash-flow identity, Table A2 describes components of other financing sources, Table A3 describes variables used in regressions, and Table A4 describes the other variables used in this paper. Unless otherwise stated, all the Compustat variables are measured at the end of year t. Note also that $\tau \in \{-2,-1,0,+1,+2\}$ denotes the time index in relation to an investment spike. The variables in ratios are winsorized at the 1st and 99th percentiles. The italicized codes in the brackets ([ ]) represent the item codes in Compustat North America.

Table A1. Variables in cash-flow identity

Abbreviation	Description	Formula
I	Total investment spending	Capital expenditures [*capx*] - Sale of property, plant, and equipment [*sppe*] + Acquisitions [*aqc*]
OPR	Internally generated funds	Income before extraordinary items [*ibc*] + Depreciation and amortization [*dpc*] - Cash dividends [*dv*]
$LTDEBT$	Long-term debt finance	Issuance of long-term debt [*dltis*] - Retirement of long-term debt [*dltr*]
$EQUITY$	Equity finance	Sale of common and preferred stock [*sstk*] - Purchase of common and preferred stocks [*prstkc*]
$OTHER$	Other types of finance	$I - OPR - LTDEBT - EQUITY$

Table A2. Components of other financing sources ($OTHER$)

Abbreviation	Description	Formula
Dec. in $CASH$	Dec. in cash and cash equivalents	Decrease in Cash and cash equivalents [*che*]
Dec. in DIV	Dec. in cash dividends	Decrease in Cash dividends [*dv*]
Dec. in OI	Dec. in other investments	Decrease in Other investments [*ivch-siv-ivstch-ivaco*]
Dec. in $INVT$	Dec. in inventories	Decrease in Inventories [*invt*]
Dec. in AR	Dec. in accounts receivable	Decrease in Accounts receivable [*rectr*]
Inc. in AP	Inc. in accounts payable	Increase in Accounts payable [*ap*]
Inc. in DLC	Inc. in debt in current liabilities	Increase in Debt in current liabilities [*dlc*]
Inc. in TXP	Inc. in income taxes payable	Increase in Income taxes payable [*txp*]
Inc. in $NOCL$	Inc. in net other current liabilities	Increase in Other current liabilities [*lco*] net of Other current assets [*aco*]

Table A3. Variables used in regressions

Abbreviation	Description	Formula
$(E/I)_{j,\tau=0}$	Equity finance dependence	$EQUITY_{j,\tau=0}/I_{j,\tau=0}$
$(D/I)_{j,\tau=0}$	Debt finance dependence	$LTDEBT_{j,\tau=0}/I_{j,\tau=0}$
$D\_SMALL_{j,\tau=-1}$	Dummy variable for small firms	1 if $LnTA_{j,\tau=-1}$ is smaller than its sample median, and 0 otherwise.
$D\_HPRF_{j,\tau=-1}$	Dummy variable for high profitability firms	1 if $EBIT\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HMB_{j,\tau=-1}$	Dummy variable for high market-to-book firms	1 if $MV\_BV_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HTAN_{j,\tau=-1}$	Dummy variable for high asset tangibility firms	1 if $FA\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.
$D\_HRD_{j,\tau=-1}$	Dummy variable for high R&D intensity firms	1 if $RD\_TA_{j,\tau=-1}$ is greater than its sample median, and 0 otherwise.

Table A4. Other variables used in this paper

Abbreviation	Description	Formula
LnTA	Firm size	Natural logarithm of Total assets [*at*]
EBIT_TA	Profitability	(Income before extraordinary items [*ib*] + Total interest and related expenses [*xint*] + Total income taxes [*txt*]) / Total assets [*at*] at the beginning of the year
MV_BV	Market-to-Book	(Total long-term debt [*dltt*] + Total debt in current liabilities [*dlc*] + Liquidation value of preferred stock [*pstkl*] + Close price at the end of calendar year [*prcc_c*] × Number of common shares outstanding [*csho*]) / Total assets [*at*]
FA_TA	Tangibility of assets	Total property, plant and equipment [*ppent*] / Total assets [*at*]
RD_TA	R&D intensity	R&D expenses [*xrd*] / Total assets [*at*] at the beginning of the year
D_AQC	Dummy variable for acquisitions	1 if a firm reports positive acquisitions [*aqc*], and 0 otherwise.
LEV	Market leverage	(Total long-term debt [*dltt*] + Total short-term debt [*dlc*]) / (Total long-term debt [*dltt*] + Total short-term debt [*dlc*] + Close price at the end of calendar year [*prcc_c*]× Number of common shares outstanding [*csho*])
BLEV	Book leverage	(Total long-term debt [*dltt*] + Total short-term debt [*dlc*]) / Total assets [*at*]

A.2 Markov-switching filter

The appendix describes the Markov-switching filter suggested by Im (2012). The basic idea of this filter is to apply a Markov-switching mean model[32] to the investment rates detrended using Hodrick and Prescott's (1997) filter. See Im (2012) for more details.

A.2.1 Input series and detrending

The data used in this approach is "Total Investment to Total Assets Ratio (I_{it}/A_{it})." Once the data is ready, the investment rates are detrended using the Hodrick-Prescott filter suggested by Hodrick and Prescott (1997). The detrending procedures are implemented separately for the time series of each individual firm $i = 1, 2, \cdots, N$ and therefore the subscript i is omitted for brevity.

Suppose that the original time series y_t consists of a trend component (τ_t) and a cyclical component (c_t). That is,

$$y_t = \tau_t + c_t, \quad t = 1, 2, \cdots, T \tag{18}$$

The Hodrick–Prescott filter starts from the following two ideas. First, the trend must follow the observed data closely. Second, the trend must be a smooth time series. Based on these two ideas, Hodrick and Prescott suggest a way to isolate c_t from y_t by the following minimization problem:

$$\min_{\{\tau_t\}_{t=1}^{T}} \quad \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \tag{19}$$

where λ is the smoothing parameter[33]. The first term in the loss function penalizes the variance of c_t, while the second term penalizes the lack of smoothness in τ_t. Having solved this minimization problem to arrive at an estimate of the trend, the cyclical component (c_t) is defined as $y_t - \tau_t$.

A.2.2 Model specification

The model used here is a simplified version of the Markov-switching mean model used in Albert and Chib (1993) and explained in Kim and Nelson (1999). It is assumed that the investment rates

[32]One may consider a Markov-switching mean and variance model but I use a simpler model because this change will increase the number of parameters.

[33]The Hodrick–Prescott filter was implemented using a MATLAB function *hpfilter* in MATLAB Econometrics Toolbox. I set the smoothing parameter as 100 as is recommended for annual data.

detrended using the Hodrick–Prescott filter are drawn from two normal distributions with different means and homoskedastic disturbances. An $AR(0)$ structure is used to model the detrended investment rates. Therefore, this model is essentially a simplified version of Hamilton's (1989) Markov-switching $AR(p)$ model.

The separate models for each firm $i = 1, 2, \cdots, N$ are used here to identify investment spikes. For brevity, the subscript i is omitted for the description of the model.

$$c_t = \mu_{S_t} + e_t \tag{20}$$

$$e_t \sim N(0, \sigma^2) \tag{21}$$

$$\mu_{S_t} = \mu_0 + \delta S_t \tag{22}$$

where $\mu_1 = \mu_0 + \delta$ and $\delta > 0$. The unobserved Markov-switching variable S_t evolves according to a two-state, first-order Markov-switching process with the following transition probabilities:

$$Pr[S_t = 0 | S_{t-1} = 0] = q \tag{23}$$

$$Pr[S_t = 1 | S_{t-1} = 1] = p \tag{24}$$

It is assumed that there are two regimes or two states: "State 0" and "State 1"."State 0" represents the regime of low investment and "State 1" represents the regime of high investment or investment spike.

A.2.3 Estimation procedures

There are two well-known procedures for estimating a Markov-switching model: the maximum likelihood approach and the Bayesian approach. Although some trials to improve the maximum likelihood approach, including Hamilton's (1990) EM algorithm and Kim's (1994) smoothing algorithm, have been made, it is known that the classical maximum likelihood approach has some shortcomings compared with the Bayesian Gibbs-sampling approach. First, it involves approximation, although the error from approximation is known to be small (see Kim (1994)). Second, in the maximum likelihood approach, the estimation of the state variables is conditional on maximum likelihood estimates of the parameters. In contrast, the Bayesian Gibbs-sampling approach treats unobserved state variables and parameters as jointly distributed random variables and in this approach they are sampled from appropriate conditional distributions. It is also known that the estimates are less sensitive to arbitrary starting values as estimation steps are repeated until convergence occurs (see Kim and Nelson (1999)). Therefore, I use the Bayesian Gibbs-sampling approach to estimate unobserved state variables along with parameters.

A.2.4 Picking investment spikes

Once Gibbs-sampling procedures are completed, the years with investment spikes can be identified. First, I check whether the Markov-switching model for a given firm satisfies the model selection criterion (*MSC*). The model selection criterion is based on the marginal posterior distributions for μ_0 and μ_1; *MSC* has a value of 1 if the $(1-\alpha)$ posterior band for μ_0, where α is the significance level, does not overlap with that for μ_1 and 0 otherwise. That is, the model satisfies the criteria only if the lower bound of μ_1 is greater than the upper bound of μ_0 since $\mu_1 = \mu_0 + \delta$ and $\delta > 0$. This is equivalent to testing the null hypothesis $H_0 : \delta = 0$ against the alternative hypothesis $H_1 : \delta > 0$. The null hypothesis means that there are no investment spikes for the firm. The next step is to find years with investment spikes based on the posterior probabilities of the investment-spike state ($Pr[S_t = 1|\widetilde{c}_T]$). I select the year as a year with an investment spike if $Pr[S_t = 1|\widetilde{c}_T] > (1-\alpha)$ where α is the level of significance. Hence, at the 5% significance level, all the years where the probability of investment spikes is greater than 0.95 are identified as years with an investment spike.

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References

[1] Albert, J.H. and Chib, S., 1993, "Bayes inference via Gibbs sampling of autoregressive time series subject to Markov mean and variance shifts," *Journal of Business and Economic Statistics* 11, 1-15.

[2] Bond, S.R., Klemm, A., and Marinescu, I., 2006, "Technology and the financing of investment spikes," *Unpublished Working Paper*, Institute for Fiscal Studies, London.

[3] Boot, A.W.A. and Thakor, A.V. 1993, "Security Design," *Journal of Finance* 48, 1349-1378.

[4] Caballero, R.J., Engel, E.M.R.A, and Haltiwanger, J.C., 1995, "Plant-level adjustment and aggregate investment dynamics," *Brookings Papers on Economic Activity* 26, 1-54.

[5] Caballero, R.J. and Engel, E.M.R.A, 1999, "Explaining investment dynamics in U.S. manufacturing: A generalized (S,s) approach," *Econometrica* 67, 783-826.

[6] Chang, X. and Dasgupta, S., 2009, "Target behavior and financing: How conclusive is the evidence?," *Journal of Finance* 64, 1767-1796.

[7] Chirinko, R.S. and Singha, A.R., 2000, "Testing static tradeoff against pecking order models of capital structure: a critical comment," *Journal of Financial Economics* 58, 417-425.

[8] Chung, Y.P., Na, H.S. and Smith, R., 2013, "How important is capital structure policy to firm survival?," *Journal of Corporate Finance* 22, 83-103.

[9] Cooper, R., Haltiwanger, J., and Power, L., 1999, "Machine replacement and the business cycle: Lumps and bumps," *American Economic Review* 89, 921-946.

[10] Corbett, J.M. and Jenkinson, T., 1997, "How is investment financed? A study of Germany, Japan, the United Kingdom and the United States," *The Manchester School Supplement* 1997, 69-93.

[11] DeAngelo, H., DeAngelo, L., and Whited, T.M., 2011, "Capital structure dynamics and transitory debt," *Journal of Financial Economics* 99, 235-261.

[12] Dixit, A., 1995, "Irreversible investment with uncertainty and scale economies," *Journal of Economic Dynamics and Control* 19, 327-350.

[13] Dixit, A. and Pindyck, R.S., 1994, *Investment under Uncertainty*, Princeton University Press, Princeton.

[14] Doms, M. and Dunne, T., 1998, "Capital adjustment patterns in manufacturing plants," *Review of Economic Dynamics* 1, 409-429.

[15] Doyle, J.M. and Whited, T.M., 2001, "Fixed costs of adjustment, coordination, and industry investment," *Review of Economics and Statistics* 83, 628-637.

[16] Elsas, R., Flannery, M.J. and Garfinkel, J.A., 2014, "Financing major investments: information about capital structure decisions," *Review of Finance* 18, 1341-1386.

[17] Fama, E. and French, K., 2002, "Testing trade-off and pecking order predictions about dividends and debt," *Review of Financial Studies* 15, 1-34.

[18] Fama, E. and French, K., 2005, "Financing decisions: who issues stock?," *Journal of Financial Economics* 76, 549-582.

[19] Flannery, M.J. and Rangan, K.P., 2006, "Partial adjustment toward target capital structures," *Journal of Financial Economics* 79, 469-506.

[20] Frank, M. and Goyal, V., 2003, "Testing the pecking order theory of capital structure," *Journal of Financial Economics* 67, 217-248.

[21] Frank, M. and Goyal, V., 2009, "Capital structure decisions: which factors are reliably important?," *Financial Management* 38, 1-37.

[22] Fulghieri, P. and Lukin, D., 2001, "Information production, dilution costs, and optimal security design," *Journal of Financial Economics* 30, 1-40.

[23] Gatchev, V.A., Spindt, P.A. and Tarhan, V., 2009, "How do firms finance their investments? The relative importance of equity issuance and debt contracting costs," *Journal of Corporate Finance* 15, 179-195.

[24] Gungoraydinoglu, A. and Öztekin, Ö., 2011, "Firm- and country-level determinants of corporate leverage: Some new international evidence," *Journal of Corporate Finance* 17, 1457-1474.

[25] Hamilton, J.D., 1989, "A new approach to the economic analysis of nonstationary time series and the business cycle," *Econometrica* 57, 357-384.

[26] Hamilton, J.D., 1990, "Analysis of time series subject to changes in regime," *Journal of Econometrics* 45, 39-70.

[27] Harris, M. and A. Raviv, 1991, "Theory of capital structure," *Journal of Finance* 46, 297-355.

[28] Hodrick, R.J. and Prescott, E.C., 1997, "Postwar U.S. business cycles: An empirical investigation," *Journal of Money, Credit and Banking* 29, 1-16.

[29] Huang, Z., Mayer, C., and Sussman, O., 2007, "How do firms finance large cash flow requirements?," *Unpublished Working Paper*, University of Oxford.

[30] Iliev, P. and Welch, I., 2010, "Reconciling estimates of the speed of adjustment of leverage ratios," *Unpublished Working Paper*, Pennsylvania State University.

[31] Im, H.J., 2012, "Lumpy investment and filtering techniques," *Unpublished Working Paper*, University of Oxford.

[32] Im, H.J., 2014, "Does share liquidity increase the propensity to raise debt finance?," *Unpublished Working Paper*, Peking University.

[33] Jensen, M.C., 1986, "Agency costs of free cash flow, corporate finance, and takeovers," *American Economic Review* 76, 323-329.

[34] Jensen, M.C. and W.H. Meckling, 1976, "Theory of the firm: managerial behavior, agency costs and ownership structure," *Journal of Financial Economics* 3, 305-360.

[35] Kim, C.J., 1994, "Dynamic linear models with Markov-switching," *Journal of Econometrics* 60, 1-22.

[36] Kim, C.J. and Nelson, C.R., 1999, *State-space Models with Regime Switching: Classical and Gibbs-sampling Approaches with Applications*, The MIT Press, Cambridge.

[37] Mayer, C., 1988, "New issues in corporate finance," *European Economic Review* 32, 1167-1183.

[38] Mayer, C. and Sussman, O., 2002, "Projects are largely external and mostly debt financed: a new approach to testing capital structure," *Unpublished Working Paper*, University of Oxford.

[39] Mayer, C. and Sussman, O., 2005, "Financing investment: a new test of capital structure," *Unpublished Working Paper*, University of Oxford.

[40] Myers, S.C., 1984, "The capital structure puzzle," *Journal of Finance* 39, 575-592.

[41] Myers, S.C. and Majluf, N.S., 1984, "Corporate financing and investment decisions when firms have information investors do not have," *Journal of Financial Economics* 13, 187-221.

[42] Nilsen, O.A., Raknerud, A., Rybalka, M., and Skjerpen, T., 2009, "Lumpy investments, factor adjustments, and labour productivity," *Oxford Economic Papers* 61, 104-127.

[43] Pindyck, R.S., 1991, "Irreversibility, uncertainty, and investment," *Journal of Economic Literature* 29, 1110-1148.

[44] Power, L., 1994, "Causes and consequences of investment spikes," *Doctoral Dissertation*, University of Maryland.

[45] Power, L., 1998, "The missing link: Technology, investment, and productivity," *Review of Economics and Statistics* 80, 300-313.

[46] Rajan, R. and Zingales, L., 1995, "What do we know about capital structure?: Some evidence from international data," *Journal of Finance* 50, 1421-1460.

[47] Rothschild, M., 1971, “On the cost of adjustment,” *Quarterly Journal of Economics* 85, 605-622.

[48] Strebulaev, I.A., 2007, “Do tests of capital structure theory mean what they say?,” *Journal of Finance* 62, 1747-1787.

[49] Stulz, R.M., 1990, “Managerial discretion and optimal financing policies,” *Journal of Financial Economics* 26, 3-27.

[50] Shyam-Sunder, L. and Myers, S.C., 1999, “Testing static tradeoff against pecking order models of capital structure,” *Journal of Financial Economics* 51, 219-244.

[51] Whited, T.M., 2006, “External finance constraints and the intertemporal pattern of intermittent investment,” *Journal of Financial Economics* 81, 467-502.

Table 1: Summary statistics: investment spikes sample

This table reports the summary statistics for the investment spikes sample. Section 2.2 describes how the investment spikes sample is constructed. Panel A, Panel B, and Panel C show the summary statistics for large firms, medium-sized firms, and small firms, respectively. The total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) are used to group firms with an investment spike into "Small firms," "Medium-sized firms," and "Large firms." The thresholds used are the 33rd and 67th percentiles. The variables reported below are constructed as explained in Appendix A.1. The time index τ represents the time in relation to an investment spike. For example, $\tau = 0$ indicates the year categorized as an investment spike, whereas $\tau = -1$ indicates one year before an investment spike.

Panel A. Large firms

Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ($\tau = 0$)	2343	0.297	0.220	0.123	0.259	0.426
Market leverage ($\tau = -1$)	2314	0.217	0.187	0.075	0.176	0.323
Book leverage ($\tau = 0$)	2473	0.315	0.211	0.175	0.295	0.426
Book leverage ($\tau = -1$)	2473	0.268	0.212	0.124	0.242	0.362
Total assets ($\tau = -1$)	2473	8691	31404	984	1985	5452
Log total assets ($\tau = -1$)	2473	7.901	1.270	6.892	7.594	8.604
Profitability ($\tau = -1$)	2381	0.121	0.105	0.068	0.111	0.168
Market-to-Book ($\tau = -1$)	2300	1.703	1.455	0.945	1.328	1.962
Assets tangibility ($\tau = -1$)	2470	0.317	0.220	0.143	0.266	0.454
R&D intensity ($\tau = -1$)	2473	0.024	0.049	0.000	0.000	0.026

Panel B. Medium-sized firms

Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ($\tau = 0$)	2444	0.232	0.240	0.013	0.165	0.372
Market leverage ($\tau = -1$)	2386	0.150	0.198	0.001	0.061	0.231
Book leverage ($\tau = 0$)	2548	0.249	0.243	0.028	0.214	0.388
Book leverage ($\tau = -1$)	2548	0.192	0.240	0.004	0.113	0.299
Total assets ($\tau = -1$)	2548	235	133	120	199	326
Log total assets ($\tau = -1$)	2548	5.298	0.577	4.792	5.294	5.786
Profitability ($\tau = -1$)	2335	0.098	0.399	0.058	0.119	0.194
Market-to-Book ($\tau = -1$)	2384	2.197	3.078	0.971	1.466	2.432
Assets tangibility ($\tau = -1$)	2547	0.254	0.212	0.086	0.194	0.360
R&D intensity ($\tau = -1$)	2548	0.055	0.125	0.000	0.000	0.061

Panel C. Small firms

Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ($\tau = 0$)	2402	0.190	0.220	0.008	0.100	0.308
Market leverage ($\tau = -1$)	2283	0.122	0.182	0.000	0.034	0.171
Book leverage ($\tau = 0$)	2473	0.209	0.250	0.016	0.148	0.331
Book leverage ($\tau = -1$)	2471	0.170	0.303	0.002	0.073	0.242
Total assets ($\tau = -1$)	2473	28	21	10	23	43
Log total assets ($\tau = -1$)	2471	2.912	1.073	2.275	3.116	3.765
Profitability ($\tau = -1$)	2284	-0.085	0.792	-0.074	0.080	0.177
Market-to-Book ($\tau = -1$)	2281	2.656	3.774	0.933	1.562	2.883
Assets tangibility ($\tau = -1$)	2471	0.216	0.207	0.067	0.144	0.292
R&D intensity ($\tau = -1$)	2471	0.096	0.194	0.000	0.010	0.111

Table 2: The flow of funds around investment spikes

This table shows the aggregate statistics for the flow of funds around investment spikes. Panel A summarizes the flow of funds around investment spikes identified by the regression filters with the 1%, 5% and 10% significance levels, Panel B summarizes the flow of funds around investment spikes identified by the Markov-switching filter with the 5% significance level, and Panel C summarizes the sources of finance during investment spikes identified by the regression filters with the 5% significance level by 30 industry groups as suggested by Mayer and Sussman (2005). The reported summary statistics are components of cash flow identity and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the corresponding spikes sample. I drop the j-th investment spike if any of $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. Investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics.

Panel A. By significance level in the regression filter

Sig. Level	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	3,167	16.99	0.9001	1.3284	0.0711	-0.2743	-0.2250
	-1	3,167	18.54	0.9709	1.5181	0.0254	-0.2534	-0.3191
1%	**0**	**3,167**	**30.74**	**9.6635**	**1.3374**	**5.0480**	**0.5534**	**2.7248**
	+1	3,167	29.73	1.0783	1.2736	-0.1232	-0.1016	0.0296
	+2	3,167	29.63	1.0506	1.4869	-0.2503	-0.2616	0.0757
	-2	7,494	15.79	0.8891	1.1576	0.1150	-0.1891	-0.1945
	-1	7,494	17.32	0.9822	1.3267	0.1107	-0.1734	-0.2817
5%	**0**	**7,494**	**25.23**	**6.2764**	**1.2831**	**3.0978**	**0.3215**	**1.5919**
	+1	7,494	24.70	1.0775	1.2120	-0.0377	-0.1081	0.0113
	+2	7,494	24.88	1.0512	1.4043	-0.1288	-0.2449	0.0205
	-2	10,744	15.05	0.8826	1.1022	0.1134	-0.1516	-0.1814
	-1	10,744	16.55	0.9980	1.2851	0.1090	-0.1503	-0.2458
10%	**0**	**10,744**	**23.05**	**5.2538**	**1.2442**	**2.5036**	**0.2186**	**1.2873**
	+1	10,744	22.65	1.0733	1.1362	0.0105	-0.1210	0.0477
	+2	10,744	22.95	1.0461	1.3585	-0.0714	-0.2242	-0.0168

Panel B. Using Markov-switching filter

Investment pattern	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	1,760	12.52	0.8588	1.0969	0.0703	-0.3578	0.0494
	-1	1,760	13.43	1.0361	1.2659	0.0535	-0.3044	0.0212
(0,0,1,0,0)-type	**0**	**1,760**	**19.33**	**3.8334**	**1.4139**	**1.5253**	**-0.1583**	**1.0525**
	+1	1,760	19.48	1.0842	1.3507	0.1453	-0.1457	-0.2661
	+2	1,760	20.05	1.0209	1.4996	0.0001	-0.3670	-0.1118
	-2	338	9.39	0.7420	0.9250	-0.0083	-0.0985	-0.0763
	-1	338	10.17	0.9193	1.2360	-0.1183	-0.2405	0.0421
(0,0,1,1,0,0)-type	**0**§	**338**	**14.86**	**2.6615**	**1.1904**	**1.1530**	**-0.1579**	**0.4761**
	+1	338	15.76	1.2095	1.2861	-0.0526	0.0400	-0.0640
	+2	338	16.43	1.1292	1.3391	0.0120	-0.2281	0.0062

§ In the case of two-year investment spikes, two-year averages of total assets (TA) and each component of the cash-flow identity (I, OPR, $LTDEBT$, $EQUITY$ and $OTHER$) are used to construct the aggregate statistics reported in this row. Base-level investment is defined as the average of investment expenditures measured in the first two years and the last two years of the five-year window.

Table 2 (Continued): The flow of funds around investment spikes

Panel C. Industry and the financing of investment spikes

Code	Industry	Obs.	I	Sources of Finance			
				OPR	$LTDEBT$	$EQUITY$	$OTHER$
1	Agriculture	32	7.9385	2.0755	4.6806	0.3408	0.8416
2	Mining	81	4.4847	1.4974	3.3357	0.7462	-1.0947
3	Oil and gas extraction	271	3.6631	0.8791	1.8863	0.4599	0.4379
4	Construction related	93	6.3917	2.1121	1.6029	0.3037	2.3730
5	Food	254	6.3977	1.5345	3.3676	-0.2628	1.7584
6	Tobacco	17	11.7531	1.4251	4.0992	-0.4653	6.6941
7	Textile	66	7.0629	1.6005	5.4536	0.1415	-0.1326
8	Apparel	87	8.8829	1.8654	5.3046	0.9986	0.7143
9	Lumber and wood	38	7.8082	1.5998	5.4852	0.2681	0.4551
10	Furniture and fixture	50	3.7587	1.3458	2.1394	-0.0898	0.3633
11	Paper	105	4.5022	1.2738	2.1875	0.0889	0.9520
12	Printer and publishing	124	7.7891	1.4316	4.2031	-0.2617	2.4160
13	Chemicals	581	9.1222	1.3795	3.9586	-0.0783	3.8624
14	Petrol refining	59	1.7000	1.3132	0.2968	0.0916	-0.0016
15	Rubber and plastic	107	5.0860	1.4104	3.2705	0.0536	0.3515
16	Leather	26	5.0580	2.3131	1.6984	4.1999	-3.1533
17	Stone and concrete	62	4.6994	1.6068	2.0694	0.4921	0.5311
18	Primary metal	151	5.7176	1.4248	3.3288	0.5399	0.4241
19	Other metal	131	4.9895	1.2716	2.9293	0.3145	0.4741
20	Machinery	495	5.5646	1.9671	2.0701	-0.2241	1.7515
21	Electrical products	776	7.3671	1.1747	3.0090	-0.0066	3.1900
22	Transportation equipment	207	4.8795	1.3664	2.5618	0.4016	0.5497
23	Other: Watches, photos	560	14.6702	0.6174	7.3235	0.3075	6.4218
24	Miscellaneous products	95	11.0760	1.4290	6.6327	2.1593	0.8551
25	Transportation services	193	2.6225	0.8099	1.2256	0.1276	0.4594
26	Communication	341	3.6821	0.9776	1.7268	0.4759	0.5018
27	Wholesale	323	6.9128	1.5562	3.8014	0.9012	0.6541
28	Retail	495	7.0961	1.3519	3.5016	0.9560	1.2866
29	Other services	1,604	10.2487	1.4353	6.3922	1.0699	1.3513
30	Other	70	2.5480	1.5924	0.7915	0.3339	-0.1697
	Total	7,494	6.2764	1.2831	3.0798	0.3215	1.5919

Table 3: Business cycles and the financing of investment spikes

This table is designed to analyze whether the financing of investment spikes is different in expansions and contractions phases of business cycles. Based on the business cycle reference dates announced by the NBER's Business Cycle Dating Committee, years 1991-2000, 2002-2007, and 2010-2011 are categorized as expansions, while years 1990, 2001, 2008, and 2009 as contractions. Panel A shows the investment-weighted flow of funds around investment spikes by the two phases in business cycles. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all the investment spikes each sample. I drop the j-th investment spike if any of $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics. Panel B reports the results for Student's t-tests and Wilcoxon rank-sum tests designed to test whether there are significant differences in equity dependence and debt dependence. See Appendix A.1 for the formulas and the Compustat items used to construct equity dependence and debt dependence. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) significance level.

Panel A. Business cycles and the flow of funds around investment spikes

Time period	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
Expansions	-2	6,248	15.1581	0.8542	1.1047	0.0689	-0.0907	-0.2287
	-1	6,248	16.4825	0.9453	1.2515	0.0344	-0.0924	-0.2481
	0	**6,248**	**24.5241**	**6.3667**	**1.2970**	**3.1792**	**0.4017**	**1.4888**
	+1	6,248	23.9939	1.1186	1.2390	-0.0734	-0.1195	0.0725
	+2	6,248	24.0293	1.0820	1.2852	-0.0901	-0.2145	0.1014
Contractions	-2	1,246	18.2100	1.0230	1.3603	0.2917	-0.5657	-0.0632
	-1	1,246	20.5150	1.1237	1.6149	0.4029	-0.4836	-0.4105
	0	**1,246**	**27.9239**	**5.9303**	**1.2300**	**2.6991**	**0.0143**	**1.9869**
	+1	1,246	27.3898	0.9200	1.1085	0.0990	-0.0643	-0.2232
	+2	1,246	28.1612	0.9333	1.8607	-0.2768	-0.3612	-0.2895

Panel B. Business cycles and equity and debt dependence during investment spikes

Sample Period	Obs.	Equity Dependence		Debt Dependence	
		Mean	Median	Mean	Median
Whole sample	7494	0.2691	0.0071	0.2734	0.1339
Expansions	6248	0.3009	0.0092	0.2780	0.1385
Contractions	1246	0.1095	0.0013	0.2508	0.1048
T-statistic/Z-statistic		5.21	6.52	1.31	1.09
P-value		0.0000***	0.0000***	0.1893	0.2748

Table 4: Firm size and the flow of funds around investment spikes

This table summarizes the flow of funds around investment spikes by firm size. Panel A reports the investment-weighted flow of funds around investment spikes undertaken by large firms and small firms. The total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) are used to group firms with an investment spike into "Small firms", "Medium-sized firms" and "Large firms". The thresholds used are the 33rd and 67th percentiles. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the sample. I drop the j-th investment spike if any of $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics. In Panel B, I break down other financing sources (i.e., $OTHER$) into nine components and examine which components are more important sources of finance among them. The nine components are "Decrease in cash and cash equivalents," "Decrease in cash dividends," "Decrease in other investments," "Decrease in inventories," "Decrease in accounts receivable," "Increase in accounts payable," "Increase in debt in current liabilities," "Increase in taxes payable," and "Increase in net other current liabilities." See Appendix A.1 for the formulas and the Compustat items used to construct them. Note that missing Compustat items have been replaced with zeros whenever appropriate and investment spikes without complete information on those nine components have been dropped.

Panel A. The flow of funds by sub-samples based on firm size

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
Large firms	-2	2,473	16.05	0.8980	1.1878	0.1187	-0.2280	-0.1806
	-1	2,473	17.55	0.9860	1.3482	0.1215	-0.2382	-0.2455
	0	**2,473**	**25.21**	**6.0591**	**1.3073**	**2.9089**	**0.2131**	**1.6299**
	+1	2,473	24.66	1.0714	1.2401	-0.0221	-0.1385	-0.0081
	+2	2,473	24.86	1.0447	1.4395	-0.1257	-0.2717	0.0026
Small firms	-2	2,473	11.34	0.6343	0.3469	-0.1538	1.0237	-0.5826
	-1	2,473	14.12	0.8508	0.3428	-0.0352	2.0557	-1.5125
	0	**2,473**	**30.38**	**11.5876**	**-0.0656**	**6.3181**	**4.7707**	**0.5643**
	+1	2,473	29.55	1.3451	-0.4152	-0.1959	1.0594	0.8968
	+2	2,473	29.44	1.1699	-0.1162	-0.2993	0.9875	0.5978

Panel B. Breakdown of other financing sources by firm size

Subsample	τ	Obs.	$OTHER$	Components of $OTHER$								
				Dec. in CASH	*Dec. in DIV*	*Dec. in OI*	*Dec. in INVT*	*Dec. in AR*	*Inc. in AP*	*Inc. in DLC*	*Inc. in TXP*	*Inc. in NOCL*
Large firms	-2	2,365	-0.18	-0.20	-0.00	0.01	-0.05	-0.12	0.09	-0.01	-0.02	0.10
	-1	2,365	-0.23	-0.34	-0.06	0.02	-0.09	-0.15	0.14	0.06	0.02	0.06
	0	**2,365**	**1.58**	**0.21**	**0.02**	**0.52**	**-0.38**	**-0.43**	**0.09**	**0.58**	**0.08**	**0.31**
	+1	2,365	0.01	-0.19	-0.06	0.15	0.04	0.16	0.07	-0.32	-0.05	0.17
	+2	2,365	0.01	-0.29	-0.01	0.09	-0.02	-0.03	0.03	-0.12	0.01	0.09
Small firms	-2	2,031	-0.62	-0.50	0.08	0.15	-0.09	-0.23	0.06	-0.25	0.03	0.06
	-1	2,031	-1.05	-0.60	0.00	-0.20	-0.17	-0.38	0.14	-0.11	0.00	0.12
	0	**2,031**	**0.69**	**-0.15**	**0.02**	**0.25**	**-1.28**	**-1.91**	**1.10**	**1.07**	**0.08**	**1.15**
	+1	2,031	0.47	0.02	-0.01	0.20	-0.06	-0.08	-0.03	0.48	-0.04	-0.10
	+2	2,031	0.48	-0.14	-0.02	-0.21	-0.01	-0.04	-0.01	0.13	0.01	0.19

Table 5: Firm characteristics and the financing of investment spikes

This table reports reports the results for Student's t-tests and Wilcoxon rank-sum tests as well as the means and medians of equity dependence and debt dependence, by subgroups based on firm's profitability, level of future growth opportunities, tangibility of assets, and R&D intensity as well as firm size. The investment spikes are grouped into "Above median" and "Below median" based on the median of the proxies for those firm characteristics measured at the beginning of the years with an investment spike (i.e., $\tau = -1$). Appendix A.1 describes the construction of the variables representing firm characteristics. Equity dependence ($[E/I]_{j,\tau=0}$) and debt dependence ($[D/I])_{j,\tau=0}$) are constructed as follows:

$$[E/I]_{j,\tau=0} = \frac{EQUITY_{j,\tau=0}}{I_{j,\tau=0}}; \qquad [D/I]_{j,\tau=0} = \frac{LTDEBT_{j,\tau=0}}{I_{j,\tau=0}},$$

where $I_{j,\tau=0}$ measures investment outlays on tangible assets, intangible assets and acquisitions, $EQUITY_{j,\tau=0}$ measures funds from issuances of ordinary and preferred shares net of retirements, and $LTDEBT_{j,\tau=0}$ measures funds from issuances of long-term debt capital net of retirements. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) significance level.

Panel A. Firm characteristics and equity dependence ($[E/I]_{j,\tau=0}$)

Category	Statistics	All spikes	Above median	Below median	T-stat / Z-stat	P-value
Firm Size	Mean	0.2691	0.0018	0.5364	-20.02	0.0000***
	Median	0.0071	0.0005	0.0218	-21.03	0.0000***
Profitability	Mean	0.2691	0.0950	0.4355	-12.30	0.0000***
	Median	0.0071	0.0037	0.0102	-10.49	0.0000***
Market-to-book	Mean	0.2691	0.3485	0.0569	11.77	0.0000***
	Median	0.0071	0.0257	0.0006	14.97	0.0000***
Tangibility	Mean	0.2691	0.1736	0.3640	-6.97	0.0000***
	Median	0.0071	0.0016	0.0205	-9.61	0.0000***
R&D intensity	Mean	0.2691	0.3886	0.1515	8.69	0.0000***
	Median	0.0071	0.0167	0.0024	7.28	0.0000***

Panel B. Firm characteristics and debt dependence ($[D/I]_{j,\tau=0}$)

Category	Statistics	All spikes	Above median	Below median	T-stat / Z-stat	P-value
Firm Size	Mean	0.2734	0.3169	0.2300	5.64	0.0000***
	Median	0.1339	0.2948	0.0000	10.11	0.0000***
Profitability	Mean	0.2734	0.3023	0.2607	2.57	0.0102**
	Median	0.1339	0.2131	0.1481	3.44	0.0006***
Market-to-book	Mean	0.2734	0.2764	0.2828	-0.41	0.6811
	Median	0.1339	0.0000	0.2628	-4.62	0.0000***
Tangibility	Mean	0.2734	0.3228	0.2239	6.42	0.0000***
	Median	0.1339	0.3329	0.0000	12.42	0.0000***
R&D intensity	Mean	0.2734	0.2206	0.3256	-6.83	0.0000***
	Median	0.1339	0.0000	0.3023	-11.20	0.0000***

Table 6: Equity and debt dependence during investment spikes—Between Group regressions

This table reports the results of the Between Group regressions designed to investigate whether the effects of various firm characteristics on equity dependence and debt dependence during investment spikes remain after firm size, industry effects and year effects are controlled for. Dependent variables are constructed as follows:

$$[E/I]_{j,\tau=0} = \frac{EQUITY_{j,\tau=0}}{I_{j,\tau=0}}; \qquad [D/I]_{j,\tau=0} = \frac{LTDEBT_{j,\tau=0}}{I_{j,\tau=0}},$$

where $I_{j,\tau=0}$ measures investment outlays on tangible assets, intangible assets and acquisitions, $EQUITY_{j,\tau=0}$ measures funds from issuances of ordinary and preferred shares net of retirements, and $LTDEBT_{j,\tau=0}$ measures funds from issuances of long-term debt capital net of retirements. Appendix A.1 describes the construction of the variables included in the regressions. Both year dummies and industry dummies are included in all the regressions. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Equity dependence during investment spikes

VARIABLES	(1) $[E/I]_{j,\tau=0}$	(2) $[E/I]_{j,\tau=0}$	(3) $[E/I]_{j,\tau=0}$	(4) $[E/I]_{j,\tau=0}$	(5) $[E/I]_{j,\tau=0}$	(6) $[E/I]_{j,\tau=0}$
$D\_SMALL_{j,\tau=-1}$	0.558***	0.521***	0.432***	0.540***	0.565***	0.358***
	(0.041)	(0.031)	(0.033)	(0.030)	(0.035)	(0.025)
$D\_HPRF_{j,\tau=-1}$		-0.371***				-0.447***
		(0.036)				(0.042)
$D\_HMB_{j,\tau=-1}$			0.293***			0.401***
			(0.029)			(0.039)
$D\_HTAN_{j,\tau=-1}$				-0.118***		-0.064**
				(0.039)		(0.032)
$D\_HRD_{j,\tau=-1}$					0.300***	0.115***
					(0.043)	(0.044)
$INTERCEPT$	-0.228	-0.096	-0.346	-0.144	-0.318	-0.201
	(0.231)	(0.208)	(0.232)	(0.228)	(0.194)	(0.242)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,494	7,000	6,965	7,488	7,492	6,481
Number of firm	5,130	4,849	4,744	5,125	5,128	4,466
Adjusted R-squared	0.091	0.108	0.097	0.093	0.100	0.133

Table 6 (Continued): Equity and debt dependence during investment spikes—Between Group regressions

Panel B. Debt dependence during investment spikes

VARIABLES	(1) $[D/I]_{j,\tau=0}$	(2) $[D/I]_{j,\tau=0}$	(3) $[D/I]_{j,\tau=0}$	(4) $[D/I]_{j,\tau=0}$	(5) $[D/I]_{j,\tau=0}$	(6) $[D/I]_{j,\tau=0}$
$D\_SMALL_{j,\tau=-1}$	-0.099***	-0.095***	-0.094***	-0.090***	-0.101***	-0.085***
	(0.020)	(0.020)	(0.018)	(0.022)	(0.020)	(0.018)
$D\_HPRF_{j,\tau=-1}$		0.023				0.011
		(0.019)				(0.018)
$D\_HMB_{j,\tau=-1}$			-0.000			0.009
			(0.019)			(0.019)
$D\_HTAN_{j,\tau=-1}$				0.054**		0.049*
				(0.024)		(0.025)
$D\_HRD_{j,\tau=-1}$					-0.112***	-0.114***
					(0.026)	(0.025)
$INTERCEPT$	0.311	0.311*	0.321	0.273	0.344*	0.330
	(0.213)	(0.188)	(0.198)	(0.201)	(0.197)	(0.252)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,494	7,000	6,965	7,488	7,492	6,481
Number of firm	5,130	4,849	4,744	5,125	5,128	4,466
Adjusted R-squared	0.018	0.018	0.018	0.020	0.023	0.024

Table 7: Spike size and the flow of funds around investment spikes

This table is designed to examine whether financing patterns are substantially different across subgroups based on the magnitude of investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes that large firms undertake according to the magnitude of investment spikes, while Panel B shows the investment-weighted flows of funds around investment spikes that small firms undertake according to the magnitude of investment spikes. The magnitudes of investment spikes are measured by $SPIKESIZE_j$ as defined in Section 2.2. $Q1$, $Q2$, and $Q3$ represent the 1st, 2nd and 3rd quartiles of $SPIKESIZE_j$, respectively. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the j-th investment spike if any $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. Investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics.

Panel A. Large firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	871	13.00	0.8856	0.9886	0.1023	-0.1054	-0.0999
	-1	871	14.23	0.9635	1.1173	0.1715	-0.1063	-0.2189
$SPIKESIZE_j < Q1$	**0**	**871**	**15.87**	**1.5498**	**1.2515**	**0.2404**	**-0.0565**	**0.1143**
	+1	871	16.03	1.0644	1.1881	0.1462	-0.1115	-0.1584
	+2	871	16.59	1.0865	1.3164	0.0562	-0.1859	-0.1001
	-2	606	16.85	0.8586	1.0140	0.1678	-0.0784	-0.2448
	-1	606	18.00	0.9301	1.2160	0.0679	-0.1616	-0.1923
$Q1 \leq SPIKESIZE_j < Q2$	**0**	**606**	**22.48**	**2.5793**	**1.2901**	**0.9376**	**-0.0201**	**0.3717**
	+1	606	22.78	1.1029	1.3660	-0.0157	-0.1917	-0.0557
	+2	606	22.96	1.1084	1.3490	-0.1006	-0.2294	0.0894
	-2	503	15.07	0.8911	1.1784	0.0714	-0.2707	-0.0879
	-1	503	17.15	0.9786	1.3392	0.1915	-0.3414	-0.2107
$Q2 \leq SPIKESIZE_j < Q3$	**0**	**503**	**21.99**	**4.1718**	**1.2622**	**1.8575**	**-0.1065**	**1.1586**
	+1	503	21.98	1.0984	1.2702	0.0021	-0.1902	0.0164
	+2	503	23.11	1.0319	1.5632	0.0362	-0.3196	-0.2479
	-2	493	19.29	0.9404	1.5172	0.1293	-0.4327	-0.2734
	-1	493	20.99	1.0503	1.6835	0.0662	-0.3723	-0.3271
$SPIKESIZE_j \geq Q3$	**0**	**493**	**38.58**	**14.1132**	**1.4016**	**7.5823**	**0.8219**	**4.3074**
	+1	493	36.43	1.0437	1.1966	-0.2171	-0.1044	0.1686
	+2	493	35.77	0.9656	1.5626	-0.4211	-0.3645	0.1886

Table 7 (Continued): Spike size and the flow of funds around investment spikes

Panel B. Small firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	420	9.73	0.7277	0.5091	-0.0806	0.5401	-0.2409
	-1	420	11.46	0.8728	0.7607	-0.0909	1.1777	-0.9748
$SPIKESIZE_j < Q1$	**0**	**420**	**13.92**	**1.7307**	**0.6686**	**0.1558**	**1.2338**	**-0.3276**
	+1	420	15.53	1.1525	0.6525	0.1890	0.6070	-0.2961
	+2	420	16.91	1.2471	0.8739	-0.0700	0.6505	-0.2074
	-2	609	11.18	0.6843	0.3755	-0.0452	0.7853	-0.4313
	-1	609	13.46	0.8560	0.5799	-0.2494	1.7498	-1.2243
$Q1 \leq SPIKESIZE_j < Q2$	**0**	**609**	**17.93**	**2.7145**	**0.4059**	**0.8405**	**1.5466**	**-0.0784**
	+1	609	18.54	1.1919	0.2683	0.1721	0.7255	0.0259
	+2	609	20.03	1.2679	0.7255	0.1928	0.8068	-0.4571
	-2	703	10.72	0.6252	0.3063	-0.0934	0.9244	-0.5120
	-1	703	13.22	0.8950	0.2823	-0.1541	1.9667	-1.1998
$Q2 \leq SPIKESIZE_j < Q3$	**0**	**703**	**20.87**	**4.2944**	**0.0264**	**1.7805**	**2.6141**	**-0.1266**
	+1	703	22.14	1.2663	-0.2276	0.3822	1.0341	0.0776
	+2	703	22.84	1.2135	-0.0902	0.1381	1.0241	0.1414
	-2	741	11.84	0.6142	0.3362	-0.2136	1.1820	-0.6905
	-1	741	14.98	0.8288	0.2579	0.0716	2.2756	-1.7763
$SPIKESIZE_j \geq Q3$	**0**	**741**	**39.31**	**17.9211**	**-0.3085**	**10.2520**	**6.8660**	**1.1115**
	+1	741	36.97	1.4381	-0.7898	-0.5676	1.2068	1.5887
	+2	741	35.95	1.1189	-0.4534	-0.6241	1.0584	1.1379

Table 8: Effects of spike size on equity dependence and debt dependence

This table reports the results of the Between Group regressions designed to examine how differently small firms' equity dependence ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are affected by the size of investment spikes in comparison with large firms. Dependent variables are constructed as follows:

$$[E/I]_{j,\tau=0} = \frac{EQUITY_{j,\tau=0}}{I_{j,\tau=0}}; \qquad [D/I]_{j,\tau=0} = \frac{LTDEBT_{j,\tau=0}}{I_{j,\tau=0}},$$

where $I_{j,\tau=0}$ measures investment outlays on tangible assets, intangible assets and acquisitions, $EQUITY_{j,\tau=0}$ measures funds from issuances of ordinary and preferred shares net of retirements, and $LTDEBT_{j,\tau=0}$ measures funds from issuances of long-term debt capital net of retirements. The natural logarithm of the abnormal component of an investment spike ($LNSPIKESIZE_{j,\tau=0}$) and interaction terms between $LNSPIKESIZE_{j,\tau=0}$ and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. The variables used in the regressions are described in Appendix A.1. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Size of investment spikes and equity dependence

VARIABLES	(1) $[E/I]_{j,\tau=0}$	(2) $[E/I]_{j,\tau=0}$	(3) $[E/I]_{j,\tau=0}$	(4) $[E/I]_{j,\tau=0}$
$INTERCEPT$	0.254***	-0.058***	-0.306	-0.257
	(0.034)	(0.020)	(0.205)	(0.186)
$D\_SMALL_{j,\tau=-1}$		0.779***	0.770***	0.590***
		(0.080)	(0.076)	(0.068)
$D\_HPRF_{j,\tau=-1}$				-0.582***
				(0.072)
$D\_HMB_{j,\tau=-1}$				0.467***
				(0.072)
$D\_HTAN_{j,\tau=-1}$				-0.149*
				(0.081)
$D\_HRD_{j,\tau=-1}$				0.182**
				(0.073)
$LNSPIKESIZE_{j,\tau=0}$	0.068***	0.070***	0.050***	0.032
	(0.022)	(0.013)	(0.015)	(0.051)
$LNSPIKESIZE_{j,\tau=0} \times D\_SMALL_{j,\tau=-1}$		-0.146***	-0.158***	-0.179***
		(0.037)	(0.039)	(0.032)
$LNSPIKESIZE_{j,\tau=0} \times D\_HPRF_{j,\tau=-1}$				0.098**
				(0.042)
$LNSPIKESIZE_{j,\tau=0} \times D\_HMB_{j,\tau=-1}$				-0.041
				(0.038)
$LNSPIKESIZE_{j,\tau=0} \times D\_HTAN_{j,\tau=-1}$				0.062
				(0.044)
$LNSPIKESIZE_{j,\tau=0} \times D\_HRD_{j,\tau=-1}$				-0.052
				(0.038)
Industry dummies	No	No	Yes	Yes
Year dummies	No	No	Yes	Yes
Observations	7,494	7,494	7,494	6,481
Number of firms	5,130	5,130	5,130	4,466
Adjusted R-squared	0.001	0.055	0.093	0.138

Table 8 (Continued): Effects of spike size on equity dependence and debt dependence

Panel B. Size of investment spikes and debt dependence

VARIABLES	(1) $[D/I]_{j,\tau=0}$	(2) $[D/I]_{j,\tau=0}$	(3) $[D/I]_{j,\tau=0}$	(4) $[D/I]_{j,\tau=0}$
$INTERCEPT$	0.115***	0.144***	0.135	0.210
	(0.021)	(0.025)	(0.173)	(0.233)
$D\_SMALL_{j,\tau=-1}$		-0.093**	-0.085*	-0.115***
		(0.038)	(0.044)	(0.029)
$D\_HPRF_{j,\tau=-1}$				-0.018
				(0.049)
$D\_HMB_{j,\tau=-1}$				0.043
				(0.034)
$D\_HTAN_{j,\tau=-1}$				-0.079
				(0.048)
$D\_HRD_{j,\tau=-1}$				-0.101**
				(0.045)
$LNSPIKESIZE_{j,\tau=0}$	0.127***	0.163***	0.175***	0.110***
	(0.013)	(0.015)	(0.015)	(0.040)
$LNSPIKESIZE_{j,\tau=0} \times D\_SMALL_{j,\tau=-1}$		-0.033	-0.041*	-0.002
		(0.023)	(0.025)	(0.022)
$LNSPIKESIZE_{j,\tau=0} \times D\_HPRF_{j,\tau=-1}$				0.031
				(0.028)
$LNSPIKESIZE_{j,\tau=0} \times D\_HMB_{j,\tau=-1}$				-0.037*
				(0.021)
$LNSPIKESIZE_{j,\tau=0} \times D\_HTAN_{j,\tau=-1}$				0.133***
				(0.027)
$LNSPIKESIZE_{j,\tau=0} \times D\_HRD_{j,\tau=-1}$				0.013
				(0.023)
Industry dummies	No	No	Yes	Yes
Year dummies	No	No	Yes	Yes
Observations	7,494	7,494	7,494	6,481
Number of firms	5,130	5,130	5,130	4,466
Adjusted R-squared	0.018	0.029	0.044	0.058

Table 9: Initial leverage and the flow of funds around investment spikes

This table is designed to examine whether financing patterns are substantially different across subgroups based on initial leverage. Panel A shows the investment-weighted flows of funds around investment spikes that large firms undertake according to initial leverage, while Panel B shows the investment-weighted flows of funds around investment spikes that small firms undertake according to initial leverage. The initial leverage is measured as market leverage at the beginning of an investment spike ($LEV_{j,\tau=-1}$). $Q1$, $Q2$ and $Q3$ represent the 1st, 2nd and 3rd quartiles of $LEV_{j,\tau=-1}$, respectively. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the j-th investment spike if any $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. Investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$) are not used to construct the aggregate statistics.

Panel A. Large firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	226	16.42	0.7791	1.7132	-0.1028	-0.8174	-0.0139
	-1	226	18.02	0.8841	2.3013	-0.0615	-1.0068	-0.3489
$LEV_{j,\tau=-1} < Q1$	**0**	**226**	**27.24**	**6.7724**	**2.2523**	**2.3695**	**-0.4953**	**2.6458**
	+1	226	27.86	1.1213	2.0207	0.5046	-1.0864	-0.3176
	+2	226	29.18	1.2156	2.3657	0.1864	-1.2356	-0.1010
	-2	468	12.43	0.8192	1.4720	0.0276	-0.3386	-0.3418
	-1	468	14.43	0.9084	1.7400	0.0067	-0.3843	-0.4540
$Q1 \leq LEV_{j,\tau=-1} < Q2$	**0**	**468**	**25.23**	**7.0871**	**1.5074**	**3.3942**	**-0.0003**	**2.1858**
	+1	468	25.39	1.1533	1.4672	0.1441	-0.2182	-0.2398
	+2	468	26.57	1.1191	1.9164	-0.0128	-0.2964	-0.4881
	-2	828	15.59	0.9332	1.1347	0.1428	-0.2635	-0.0809
	-1	828	16.95	1.0115	1.3072	0.1024	-0.2764	-0.1216
$Q2 \leq LEV_{j,\tau=-1} < Q3$	**0**	**828**	**24.44**	**6.3107**	**1.3327**	**3.1837**	**0.1990**	**1.5954**
	+1	828	23.38	1.0384	1.1302	-0.1213	-0.1243	0.1538
	+2	828	23.16	1.0169	1.2250	-0.2112	-0.3261	0.3292
	-2	795	19.89	0.9391	1.0056	0.1943	-0.0509	-0.2099
	-1	795	21.51	1.0189	1.1829	0.2612	-0.0183	-0.4070
$LEV_{j,\tau=-1} \geq Q3$	**0**	**795**	**26.95**	**4.7732**	**1.0619**	**2.2678**	**0.4194**	**1.0242**
	+1	795	26.41	1.0458	1.0966	-0.1531	-0.0087	0.1110
	+2	795	26.32	0.9963	1.2911	-0.2207	-0.0887	0.0146

Table 9 (Continued): Initial leverage and the flow of funds around investment spikes

Panel B. Small firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
$LEV_{j,\tau=-1} < Q1$	-2	773	12.98	0.5729	0.3935	-0.1837	1.5876	-1.2245
	-1	773	17.32	0.8495	0.7419	-0.2675	3.5382	-3.1631
	0	**773**	**30.04**	**8.7852**	**0.0753**	**3.0922**	**4.0359**	**1.5817**
	+1	773	30.41	1.3589	0.0011	-0.5743	1.5036	0.4285
	+2	773	30.37	1.2187	-0.2194	0.0337	0.7881	0.6163
$Q1 \leq LEV_{j,\tau=-1} < Q2$	-2	691	10.81	0.6374	0.3520	-0.0637	1.2807	-0.9316
	-1	691	13.83	0.8738	0.2530	-0.2069	2.4703	-1.6426
	0	**691**	**28.75**	**11.82**	**-0.6573**	**6.8978**	**4.3184**	**1.2580**
	+1	691	28.07	1.3357	-0.4342	-0.1448	1.2885	0.6262
	+2	691	28.14	1.1531	-.06867	-0.3683	1.3493	0.2408
$Q2 \leq LEV_{j,\tau=-1} < Q3$	-2	403	12.18	0.8276	0.6613	-0.0712	0.5256	-0.2882
	-1	403	14.02	0.9616	0.7740	-0.1237	0.8552	-0.5438
	0	**403**	**27.76**	**9.8442**	**0.4290**	**7.0327**	**1.5421**	**0.8404**
	+1	403	27.95	1.1571	0.5861	-0.3590	0.6186	0.3113
	+2	403	28.55	1.0537	1.3092	-0.3664	0.3702	-0.2593
$LEV_{j,\tau=-1} \geq Q3$	-2	409	12.13	0.6800	0.2306	-0.0159	0.3658	0.0994
	-1	409	13.42	0.8600	0.1681	0.5298	0.3854	-0.2232
	0	**409**	**33.66**	**16.0371**	**1.6153**	**11.1726**	**2.9310**	**0.3182**
	+1	409	30.81	1.3154	0.3481	-0.4652	0.4186	1.0139
	+2	409	30.27	1.1446	0.7369	-1.0281	0.3382	1.0977

Table 10: Effects of initial leverage on equity dependence and debt dependence

This table reports the results of the Between Group regressions designed to examine how differently small firms' equity dependence ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are affected by initial leverage in comparison with large firms. Dependent variables are constructed as follows:

$$[E/I]_{j,\tau=0} = \frac{EQUITY_{j,\tau=0}}{I_{j,\tau=0}}; \qquad [D/I]_{j,\tau=0} = \frac{LTDEBT_{j,\tau=0}}{I_{j,\tau=0}},$$

where $I_{j,\tau=0}$ measures investment outlays on tangible assets, intangible assets and acquisitions, $EQUITY_{j,\tau=0}$ measures funds from issuances of ordinary and preferred shares net of retirements, and $LTDEBT_{j,\tau=0}$ measures funds from issuances of long-term debt capital net of retirements. The market leverage at the beginning of an investment spike ($LEV_{j,\tau=-1}$) and interaction terms between $LEV_{j,\tau=-1}$ and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. The variables used in the regressions are described in Appendix A.1. The robust standard errors are reported in parentheses. The star signs such as *** (**) (*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Initial leverage and equity dependence

VARIABLES	(1) $[E/I]_{j,\tau=0}$	(2) $[E/I]_{j,\tau=0}$	(3) $[E/I]_{j,\tau=0}$	(4) $[E/I]_{j,\tau=0}$
$INTERCEPT$	0.574***	-0.063***	-0.375*	-0.397**
	(0.032)	(0.021)	(0.192)	(0.190)
$D\_SMALL_{j,\tau=-1}$		0.992***	0.946***	0.624***
		(0.060)	(0.058)	(0.045)
$D\_HPRF_{j,\tau=-1}$				-0.790***
				(0.068)
$D\_HMB_{j,\tau=-1}$				0.608***
				(0.061)
$D\_HTAN_{j,\tau=-1}$				0.014
				(0.052)
$D\_HRD_{j,\tau=-1}$				0.133*
				(0.071)
$LEV_{j,\tau=-1}$	-0.923***	0.264***	0.305***	0.270
	(0.076)	(0.052)	(0.054)	(0.170)
$LEV_{j,\tau=-1} \times D\_SMALL_{j,\tau=-1}$		-1.766***	-1.702***	-1.195***
		(0.125)	(0.139)	(0.099)
$LEV_{j,\tau=-1} \times D\_HPRF_{j,\tau=-1}$				1.398***
				(0.147)
$LEV_{j,\tau=-1} \times D\_HMB_{j,\tau=-1}$				-1.072***
				(0.152)
$LEV_{j,\tau=-1} \times D\_HTAN_{j,\tau=-1}$				-0.093
				(0.126)
$LEV_{j,\tau=-1} \times D\_HRD_{j,\tau=-1}$				-0.316**
				(0.140)
Industry dummies	No	No	Yes	Yes
Year dummies	No	No	Yes	Yes
Observations	7,189	7,189	7,189	6,461
Number of firms	4,904	4,904	4,904	4,453
Adjusted R-squared	0.028	0.094	0.126	0.181

Table 10 (Continued): Effects of initial leverage on equity dependence and debt dependence

Panel B. Initial leverage and debt dependence

VARIABLES	(1) $[D/I]_{j,\tau=0}$	(2) $[D/I]_{j,\tau=0}$	(3) $[D/I]_{j,\tau=0}$	(4) $[D/I]_{j,\tau=0}$
$INTERCEPT$	0.091***	0.144***	0.129	0.108
	(0.011)	(0.016)	(0.163)	(0.216)
$D\_SMALL_{j,\tau=-1}$		-0.083***	-0.094***	-0.060**
		(0.024)	(0.022)	(0.029)
$D\_HPRF_{j,\tau=-1}$				-0.000
				(0.029)
$D\_HMB_{j,\tau=-1}$				0.073***
				(0.026)
$D\_HTAN_{j,\tau=-1}$				0.015
				(0.024)
$D\_HRD_{j,\tau=-1}$				-0.056*
				(0.032)
$LEV_{j,\tau=-1}$	0.766***	0.635***	0.644***	0.679***
	(0.046)	(0.049)	(0.067)	(0.133)
$LEV_{j,\tau=-1} \times D\_SMALL_{j,\tau=-1}$		0.220***	0.221**	0.112
		(0.081)	(0.086)	(0.092)
$LEV_{j,\tau=-1} \times D\_HPRF_{j,\tau=-1}$				0.231**
				(0.091)
$LEV_{j,\tau=-1} \times D\_HMB_{j,\tau=-1}$				0.340***
				(0.091)
$LEV_{j,\tau=-1} \times D\_HTAN_{j,\tau=-1}$				-0.145
				(0.106)
$LEV_{j,\tau=-1} \times D\_HRD_{j,\tau=-1}$				0.135
				(0.125)
Industry dummies	No	No	Yes	Yes
Year dummies	No	No	Yes	Yes
Observations	7,189	7,189	7,189	6,461
Number of firms	4,904	4,904	4,904	4,453
Adjusted R-squared	0.080	0.082	0.087	0.112

Figure 1: Financing patterns around investment spikes

This figure shows the aggregate statistics for the flow of funds around investment spike identified by the regression filter with the 5% significance level. The time index τ represents the time in relation to an investment spike. The aggregate statistics are components of cash flow identity, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the spikes sample.

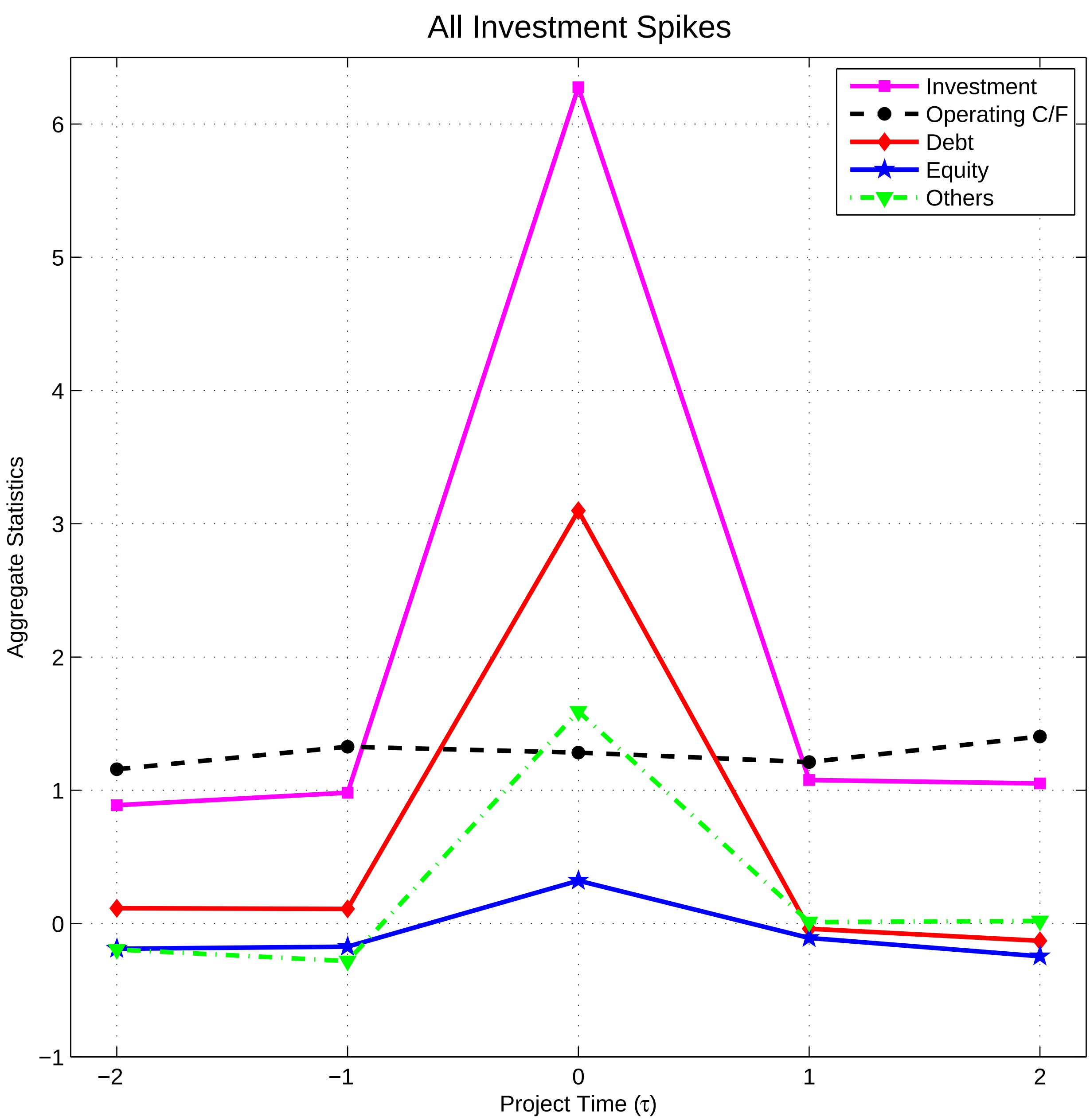
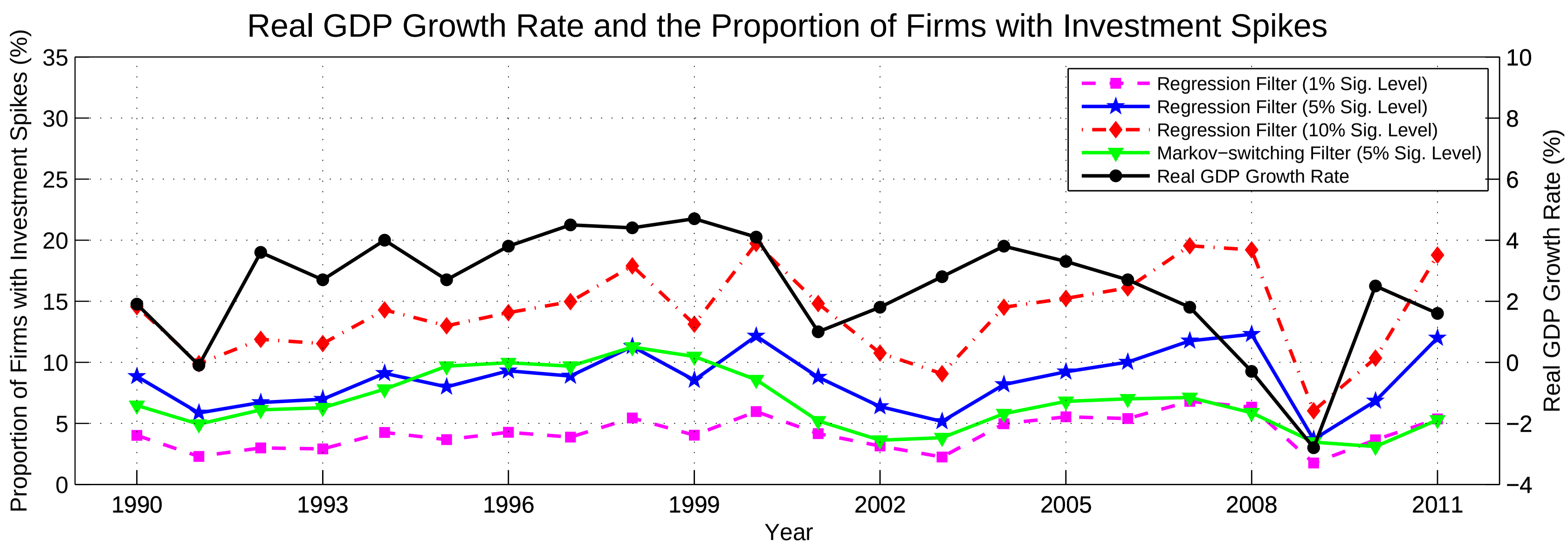


Figure 2: Business cycle and the proportion of firms with investment spikes

This figure shows the relationship between real GDP growth rate or S&P 500 Index return and the proportion of firms with investment spikes, respectively.



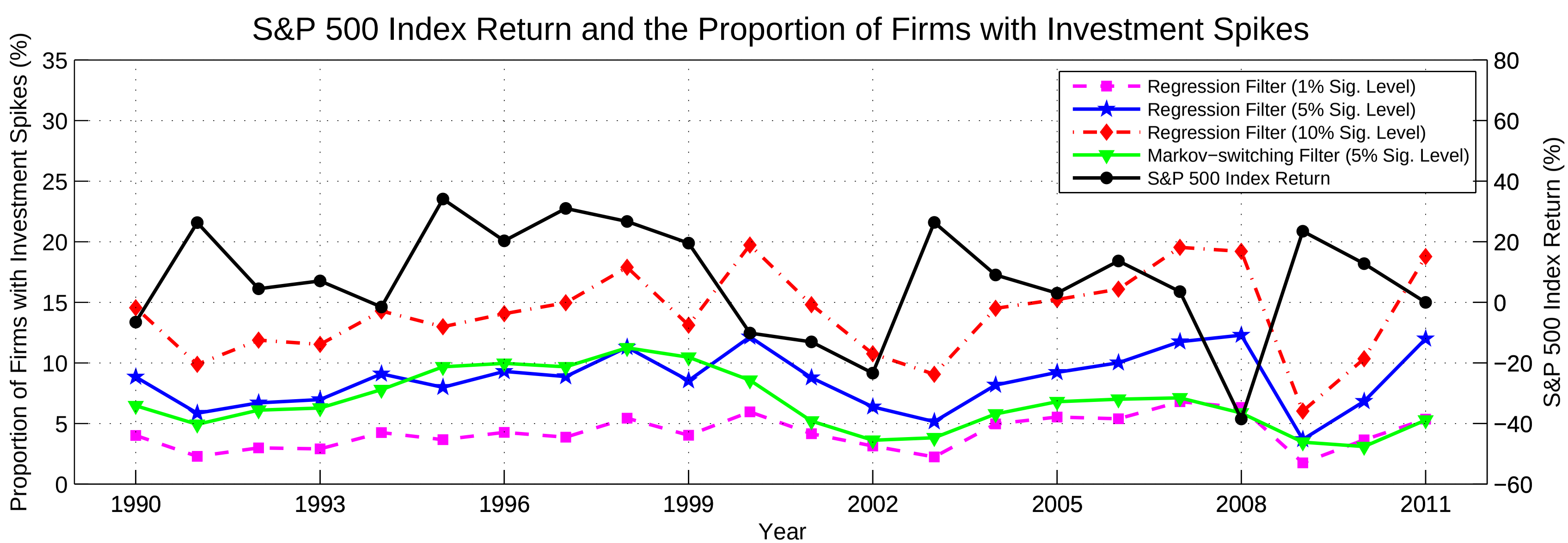
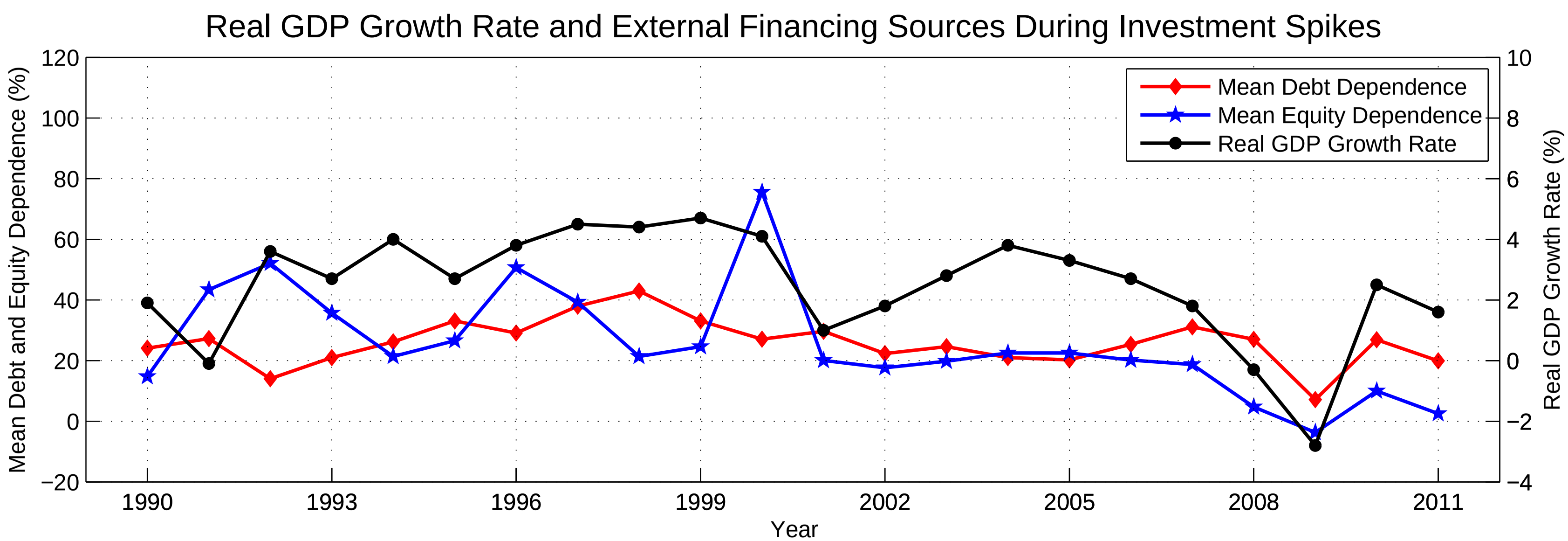


Figure 3: Business cycle and external financing sources during investment spikes

This figure shows the relationship between real GDP growth rate or S&P 500 Index return and the debt and equity dependencies during investment spikes identified by the regression filter with the 5% significance level, respectively.



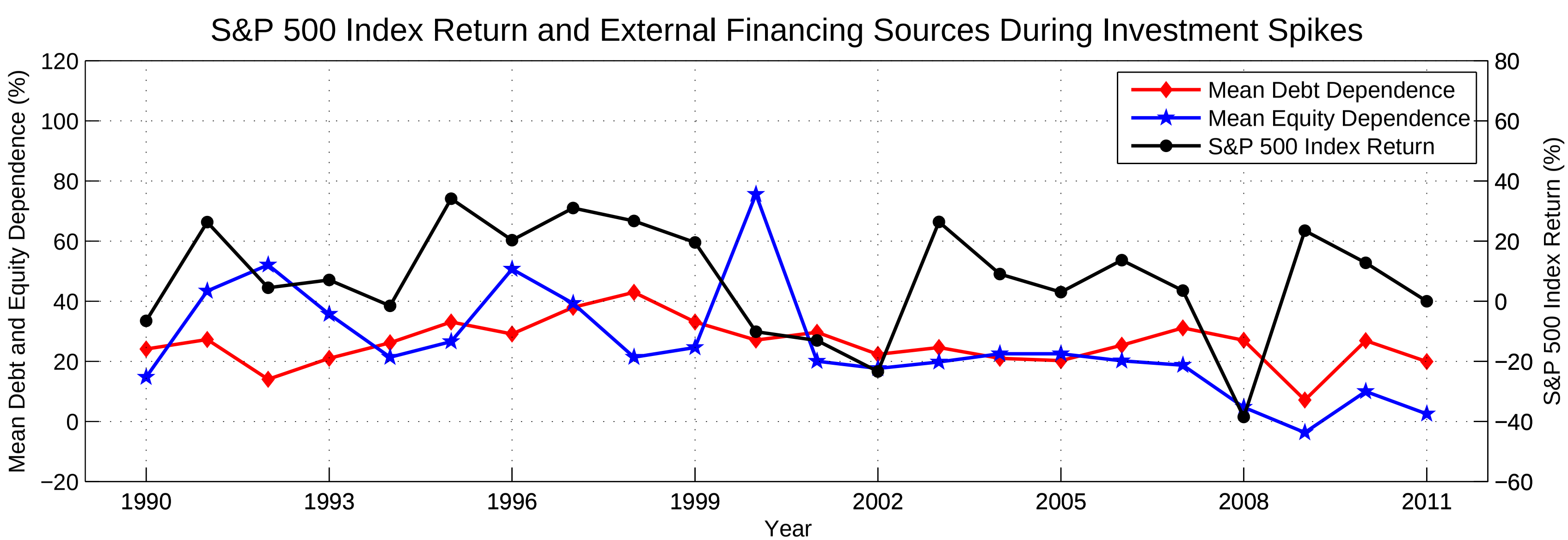
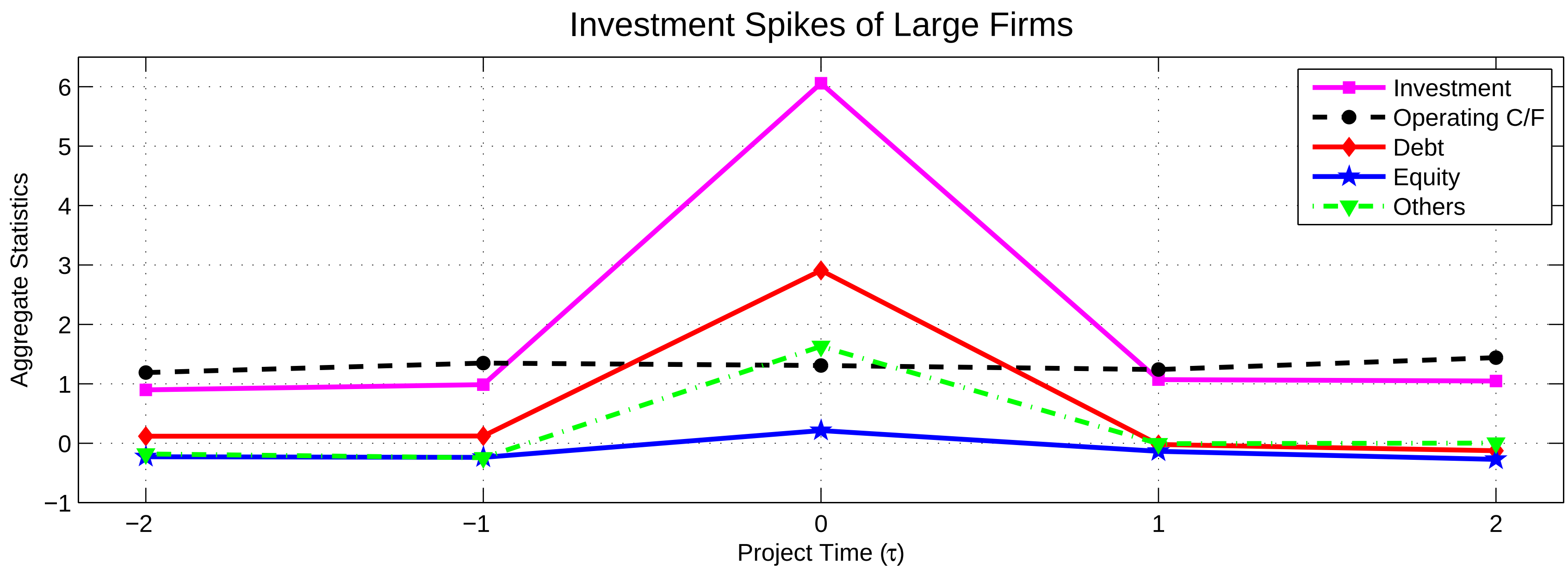


Figure 4: Financing patterns around investment spikes: by firm size

This figure shows the aggregate statistics for the flow of funds around investment spike identified by the regression filter with the 5% significance level, separately for large and small firms. The time index τ represents the time in relation to an investment spike. The aggregate statistics are components of cash flow identity, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the corresponding spikes sample.



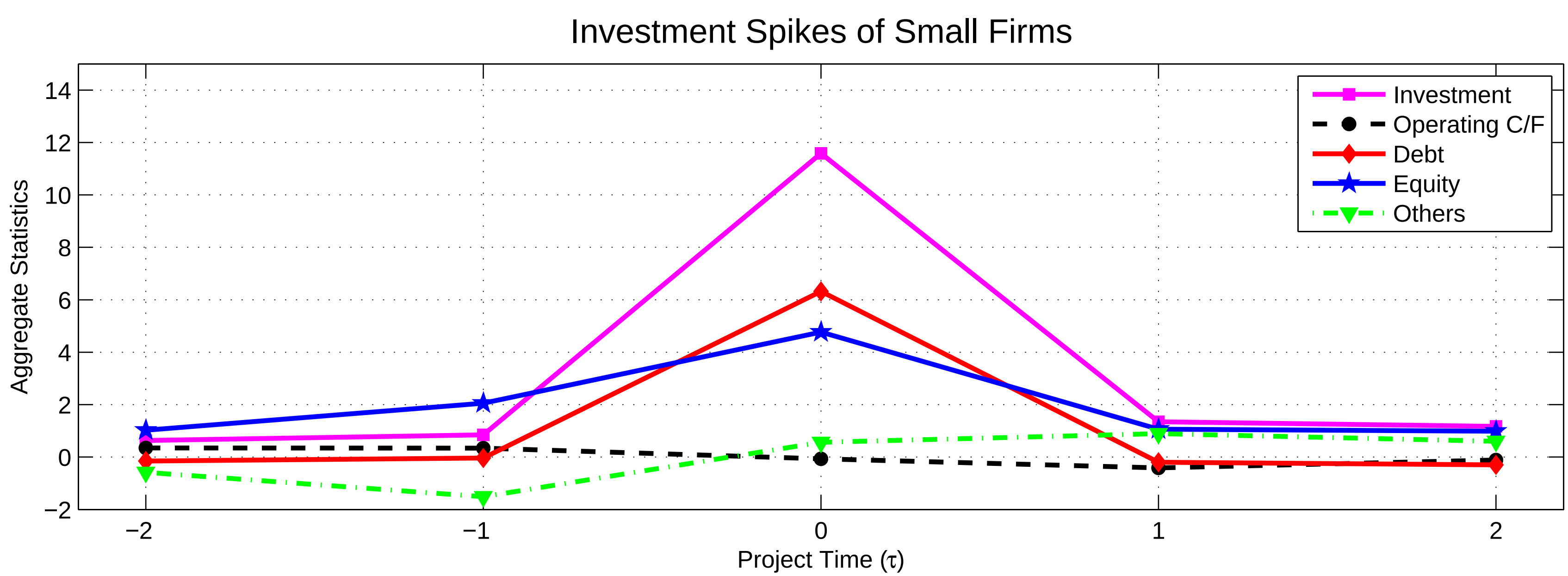
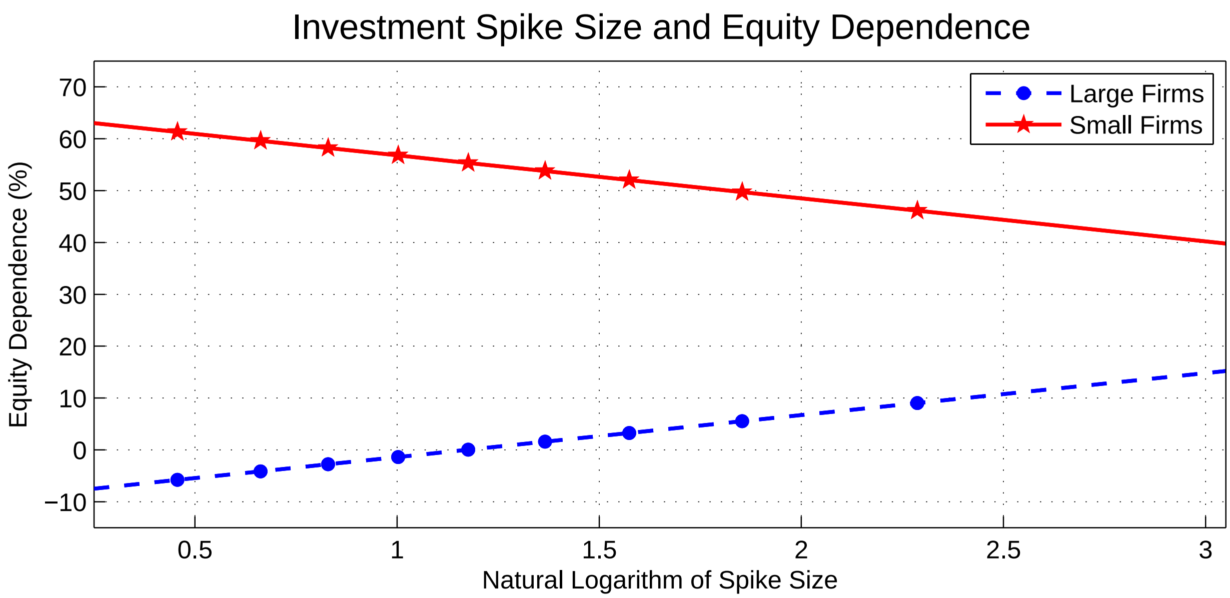


Figure 5: Investment spike size and external financing sources during investment spikes

This figure examines if the relationships between the natural logarithm of the spike size measure and debt and equity dependencies vary with firm size. The nine points in each line in the figure correspond to nine deciles of $LNSPIKESIZE_{j,\tau=0}$. Note that this figure is based on OLS regressions as deciles are based on original spike size measures.



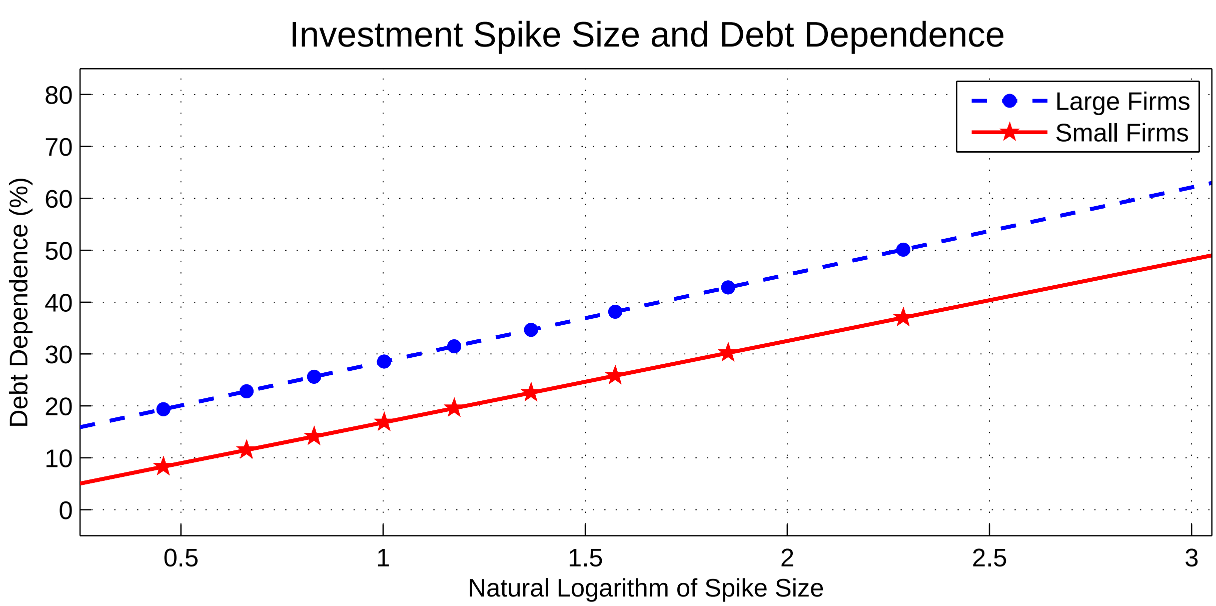


Figure 6: Initial market leverage ratio and external financing sources during investment spikes

This figure examines if the relationships between initial leverage ratios and debt and equity dependencies vary with firm size. The nine points in each line in the figure correspond to nine deciles of $LEV_{j,\tau=-1}$. Note that this figure is based on OLS regressions as deciles are based on original spike size measures.