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ABSTRACT

This is one of the most comprehensive studies to date to employ filtering techniques to distinguish between routine and "investment spike" financing. It records marked differences in how US publicly traded firms finance the two types of investments. The funding of investment spikes depends particularly on external, predominantly debt, finance. Smaller, less profitable firms with greater growth opportunities, fewer tangible assets, and larger R&D expenditures use more equity finance. Results are consistently observed across industries, but vary over business cycles, by firm types, and between acquisitions and capital expenditures. The results have important implications for existing corporate finance theories.

JEL classification: G31, G32, G34, E22

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There is a growing interest in the empirical study of firm-level investment "spikes", measured against "routine" investments: e.g., Mayer and Sussman (2005), Bond *et al.* (2006), DeAngelo *et al.* (2011), and Elsas *et al.* (2014) among others. The reason is simple: finance presents a problem when cash is short. No frictions arise when investment is fully funded internally: the problem of which investment should be undertaken can be reduced to a trivial capital budgeting exercise. Now, any viable company must generate sufficient cash from operations in order to fund the replacement of depreciated capital, long-term trends in industry growth and other components of routine investments. Indeed, residual cash flows net of routine investments should be sufficient to pay debt- and equity-holders the risk-adjusted market rate of return. From time to time, however, a firm might face a lumpy, non-divisible investment "project" that cannot be smoothed over time. Such lumpy investment may be the building of a new plant, developing a new product line, or a takeover of another company. It follows that, over time, a firm is likely to experience a "regime change", where the cash constraint is switching from loose to binding. It is the latter regime that provides the best opportunity to study the patterns of finance. A sample of mixed regimes might give rise to various biases. For example, a firm may be maintaining its capital structure in normal times, borrowing heavily in a spike and paying back debt following the spike, as observed in the data. We suggest the study of these patterns by aligning segments of time series in "project time" and by tracking changes in the flow of funds accordingly.

In his famous presidential address, Myers (1984) offers a dichotomous classification, whereby trade-off and pecking-order theories are separate, conflicting, and non-reconcilable one with the other; see also Frank and Goyal (2003) and Fama and French (2005) for a theoretical discussion and an empirical test. Modern theory has developed away from the dichotomy, offering a whole continuum of predictions, with funding patterns that vary dynamically and nonlinearly over the investment cycle. Among other things, the theory allows for leverage to increase upon an investment spike and then adjust gradually to some target. Clearly, the slower the adjustment, the closer the pattern is to the pecking order, perhaps to an extent that the target is no longer identifiable in the data. In contrast, the higher the speed of adjustment, the closer the patterns is to static trade-off theory, though the literature is already quite conclusive in rejecting the second pattern; see Fama and French (2002). Once the theory is formulated in terms of the speed of adjustment, it is easy to fit in additional effects such as company size, industry, or asset tangibility.

Another development is a growing awareness to the complexity of equilibrium responses to well-defined fundamental effects. Take, for example, the basic insight of Myers and Majluf (1984): debt is less information-sensitive than equity. Their original analysis went as follows: managers who, on the basis of private information, are not optimistic about future cash flows would prefer to share losses with external providers of finance by issuing equity. Thus, the potential buyers of these shares would take the issue as a signal of bad news and price it accordingly. In equilibrium, bad projects are priced out of the market and good projects are debt financed. The result was interpreted as: debt first, and equity only as a last resort. However, Fulghieri and Lukin (2001) developed the argument in the opposite direction: exactly because of information sensitivity, optimistic managers would issue equity so as to encourage market participants to collect information about them, trade the shares, and reveal the positive information. Given this more nuanced interpretation of the theory, we make no attempt to formulate sharp tests so as to reject either the trade-off theory or the pecking-order theory. Rather, our aim is to provide a richer description of the dynamic patterns of finance around investment spikes.

We make several contributions to the existing literature. First, we offer a structured filtering technique to select the spikes in the sample, based on a combination of a Hodrick-Prescott detrending procedure and a Markov-switching model. We compare the results to simpler filters used by Mayer and Sussman (2005) and Bond *et al.* (2006). Since the new filter is more flexible, and since the results are not much different, the analysis helps to establish the validity of the earlier filters. The procedure ends with a much bigger sample: 7,494 spike episodes compared with only 535 episodes in Mayer and Sussman (2005). The vast majority of that sample comes from a period of economic expansion: not only are there far fewer spikes during contraction times, contraction spikes are slightly smaller than expansion spikes. The larger sample allows us to explore in great detail the heterogeneity of patterns, conditional on firm size, profitability, the level of future growth opportunities, asset tangibility, R&D intensity, industry, and business cycle.

Second, we find that the most significant differences in funding patterns are size-related. There are hardly any equity issues among large firms. In contrast, among small firms, about a third of the spike is funded by equity issues. Other factors that affect equity issues are profitability (negatively), growth prospects as indicated by market to book (positively), asset tangibility (negatively), and R&D operations (positively). The results survive when all these factors are included in the same ordinary-least-squares (OLS) or between-group (BG) regressions. The results are both economically and statistically significant. Surprisingly, small firms borrow more (and issue less equity) the larger their initial leverage: it seems that high initial leverage indicates a high debt capacity, which affects both the long-term "target" leverage and the deviation from that target conditional on an investment spike. Again surprisingly, when the magnitude of investment spikes is larger, small firms issue less equity (and borrow more).

Third, there is strong evidence that the patterns of finance change around spikes. Both small and large firms tend to repay debts that they have taken during the spikes in the first two years after the spike. These debt repayments are small relative to the magnitude of the spike, indicating that the adjustment back to the long-term target is slow, in the spirit of Myers' (1984) original argument. Equity dynamics differ across large and small firms: while large firms tend to buy back equity both before and after spikes, small firms tend to issue equity both before and after spikes.

Lastly, this study executes tests to identify further heterogeneity in investment spike financing. While the results are quite consistently observed across industries, there are marked variations in financing patterns across time. Investment spikes are much more prevalent during booms than recessions and were, for example, markedly lower in the wake of the 2008/09 financial crisis. Equity finance is more widely used during expansions than contractions. Investment spikes that involve acquisitions are larger than those that are solely capital expenditure driven and they are consistently more debt- than equity-financed, even in small firms which, as previously noted, use more equity finance than large firms.

The rest of this paper is organized as follows. Section I describes the data, methodology, and descriptive statistics. Section II investigates how investment spikes are financed by analyzing the flow of funds around investment spikes for subgroups based on various firm characteristics such as size and profitability, industry, and business cycle. Section III investigates how investment spikes' financing patterns vary according to the magnitude of the investment spike and initial leverage to examine whether the financing patterns of large and small firms are consistent with the pecking-order theory in the short run and the trade-off theory in the long run. Section IV presents conclusions.

I. Data, Methodology, and Descriptive Statistics

A. Data

This study uses data from the consolidated annual financial statements 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 investigating financing patterns around investment spikes requires firm-level flow-of-funds data available from cash-flow statements, which replaced the "cash statements by sources and uses of fund" in 1988 by the Financial Accounting Standards Boards #5. Firms with standard industrial classification (SIC) codes between 6000 and 6999 or between 4900 and 4999 are excluded as these firms focus on financial services or are regulated utilities.

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 available from the World Bank Data Bank. An interpolated GDP deflator is used if the fiscal year ends in months other than December. Observations are excluded if less than five years of data are available on a firm or any variables that constitute the cash-flow identity are missing. 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 provides details of the formulas and Compustat items used to construct the variables used in this study.

B. Algorithms to Identify Investment Spikes

This paper closely follows the novel approach suggested by Mayer and Sussman (2005) and used elsewhere to study financing patterns, such as in Bond *et al.* (2006). It is possible to determine exactly how investment is financed 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 merging routine and non-routine investment periods, which arises if investment is lumpy (i.e., firms' regimes switch between high and low investment), financing patterns are markedly different across regimes, and the data from the two regimes are merged to make inferences about financing patterns. Mayer and Sussman (2005) argue 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, it is possible to use a filter to identify large investment episodes from the pool of both large investments and routine replacement investments, which also helps to eliminate the potential bias from merging the investment regimes. Nevertheless, designing a reliable filter is not as straightforward as it might seem. Two strands of research have attempted to identify investment spikes, though the literature on investment spike financing is scarce compared with that on empirical and theoretical explanations of the lumpiness of investment. This shows that empirical studies that assume that capital adjustments are frequent and continuous have not yet been revised despite the abundant evidence that capital adjustments are infrequent and lumpy (Whited, 2006).

B.1. Simple Rules

The first strand of research uses simple rules such as absolute, relative, or combined spike criteria, as represented 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 found in the literature, of which there are three:

(i) *Absolute spike criterion*: If the investment rate, measured by the total investment-to-total assets and fixed investment-to-fixed capital ratios, 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, though it is not suitable for identifying sporadic bursts of investment that are not large in an absolute sense.

(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), Whited (2006), and DeAngelo *et al.* (2011)). 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.

(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. They define the relative threshold slightly differently from Power (1998) by adjusting the traditional investment spike definitions considering 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. Nilsen *et al.* (2009) define the relative threshold as the conditional expectation of the investment rate multiplied by a fixed factor, which 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 follow this criterion.

B.2. Filters to Identify Investment Spikes

The second strand of research takes more proactive approaches in 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 defined as the average of firm i's investments during the five-year period excluding year t. The filter is similar to a 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, though there are several differences. First, the five-year period is the relevant range, 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 classification of an investment spike 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 de-trending, so if there is a linear trend in an investment sequence, the criterion over-penalizes the squared deviations from the benchmark spike pattern.

This study develops a linear-regression-based filtering procedure based on that used by Bond *et al.* (2006). The new filter provides statistically interpretable measures and 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 total investment outlays including net capital expenditures and acquisitions (see Appendix A for the formula and the Compustat items used to measure $I_{i,t}$).

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, so 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 are required. However, an anatomy of the following regression makes the algorithm simpler in the sense that the algorithm does not require executing a large number of full regressions. In addition, the anatomy provides interesting statistics, such as $\widehat{\alpha}_{it}$, $\widehat{\delta}_{it}$, and $\widehat{\gamma}_{it}$. The regression for identifying an investment spike can be expressed compactly as:

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

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

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

$b = (\alpha_{it}, \beta_{it}, \delta_{it})'$, 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 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 $\widehat{\delta}_{it}$ is:

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

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 classification is made based on the results from the one-sided t-test at the 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% level, regardless of the magnitude of the coefficient. In other words, firm i has an investment spike in year t if $t_{\widehat{\delta}_{it}} > t(0.95, df = 2)$. It is also possible to use the 1% or 10% significance levels.

Note that $\widehat{\alpha}_{it}$ is the base-level investment as measured by the average of the investments during 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 of the base-level investment is:

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

Repeating the procedures $\sum_{i=1}^{N}(T_i - 4)$ times 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, and $j \in \{1, 2, \cdots, J\}$ represents the investment spike code. The time index $t \in \{1, \cdots, T\}$ represents the fiscal year reported in Compustat, and 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, and $\tau = -1$ 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 spike 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 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 filter provides 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. Of these, 5,897 firms have at least one investment spike, with 1 to 6 spikes with 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. This study considers only $(0,0,1,0,0)$-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, which suggests that the size of the median investment spike is approximately $4.48 (= 3.48 + 1)$ times that of base-level investments as measured by the average investments in the four surrounding years.

C. Descriptive Statistics

Table I reports the summary statistics for the major variables in the investment spikes sample. Panels A, B, and C report the summary statistics for large, medium, and small firms, respectively. The firms are grouped by size according to the total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) at the 33rd and 67th percentiles. Appendix A describes how the variables are constructed in detail. The means and medians of the firm characteristic variables measured in the year before investment spikes differ substantially across the 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 market and book leverage. Firms in all three groups tend to increase their leverage substantially during investment spike years.

[Insert Table I Here.]

II. Empirical Results

A. General Description of Financing around Investment Spikes

This section investigates how investment spikes are financed by analyzing the flow of funds around investment spikes identified by both the regression filter and the Markov-switching filter. It then analyzes investment spike financing by industry and whether it is severely affected by business cycles.

A.1. Method to Analyze Financing Patterns around Investment Spikes

A.1.1. Computation of Flow of Funds

We calculate the flow of funds according to the time index around the investment spikes ($\tau \in \{-2,-1,0,+1,+2\}$) using the basic cash-flow identity to link investment spending to internally generated funds, long-term debt finance, new equity finance, and other sources of funding. While Elsas *et al.* (2014) use the same cash-flow identity as we do, they calculate the components in a slightly different manner to directly compare financing for capital expenditures with that of acquisitions. However, these adjustments are not necessary if the research aims 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 it is possible to investigate which external financing sources are more helpful in covering financing deficits.

The cash-flow identity is stated as follows:

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

for $j \in \{1, 2, \cdots, J\}$ and $\tau \in \{-2, -1, 0, +1, +2\}$. $I_{j\tau}$ measures total investment outlays including net capital expenditures and acquisitions. Sales of existing property, plant, and equipment (PPE) and subsidiaries are treated as a negative investment outlay, not as a source of finance. Unfortunately, it is not possible to break the sources of finance down by investment type such as net capital expenditures and acquisitions. 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 reports the amount of long-term debt used to fund all investment activities during the year. Therefore, $I_{j\tau}$ is defined as the sum of capital expenditures and acquisitions. However, it is possible to examine 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 acquisitions is greater than zero and 0 otherwise.

$OPR_{j\tau}$ measures after-tax cash flow from operating activities. $LTDEBT_{j\tau}$ measures funds from issues of long-term debt net of retirements. $EQUITY_{j\tau}$ measures funds from issues of ordinary and preferred shares net of retirements. The residual source of financing, $OTHER_{j\tau}$, ensures that the cash-flow identity holds, and includes funds raised by "changes in cash, inventory, and security investments," "changes in trade credit," "changes in short-term debt," and "other minor components". This category is not disaggregated because to do so would reduce the sample size significantly. However, in Section II.B.1, these other financing sources ($OTHER_{j\tau}$) are broken into nine components and examined to determine the most important sources of financing among them. A positive sign on the right side of the identity denotes a source of funds, whereas a negative sign denotes a use of funds. Appendix A provides more details on the Compustat items used to measure the components of the identity.

A.1.2. Aggregation of Flow of Funds

The next step is to aggregate the flow of funds by subgroups and calculate statistics based on various firm characteristics, including firm size, industry, investment spike size, and initial leverage. We first 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 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 (where the weighting is based on investment amounts during investment spikes) and $BASE_j$ is the base-level investment for the j-th spike. The aggregated measures for total assets and investment are similarly constructed:

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

Note that the aggregate statistics do not include investment spikes with any missing values in the cash-flow identity during the five-year event window ($\tau \in \{-2,-1,0,+1,+2\}$). Similarly, investment spikes with missing total assets are also dropped. Furthermore, the j-th investment spike is dropped if either $OPR_{j,\tau}/BASE_j$ 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 II Panel A.

[Insert Table II Here.]

A.2. Flow of Funds around Investment Spikes

This section provides the analysis of how investment spikes are financed by analyzing the flow of funds around investment spikes. Table II shows the sources of finance expressed as a proportion of the base-level investment for periods around investment spikes.

A.2.1. Using the Regression Filter as a Baseline Filter

Table II Panel A shows the investment-weighted funding flows around investment spikes for all firms in the investment spike sample at the 5% significance level. The column listing total assets (TA) shows that these 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, we compare the sources of finance during investment spikes by funding source. During investment spikes, internally available funds do not change much so the need for external financing sources increases dramatically. Among the external financing sources, net long-term debt issues become much more significant than net equity issues. Note that the shares of investment financed through net long-term debt and net equity issues are some 3.10 and 0.32 times the base-level investment, respectively. These results are consistent with the pecking-order theory that predicts 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 during investment spikes, investment projects are predominantly financed with debt while internal finance is no longer the first source of finance in terms of magnitude.

[Insert Figure 1 Here.]

Second, we compare financing sources during investment spikes with those 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 that in off-spike periods. However, both long-term debt and equity finance become much more important during investment spikes. The shares of investment financed through net long-term debt and net equity issues are some 3.10 and 0.32 times the base-level investment, respectively. Some net long-term debt issues are observed before investment spikes and some net repayments of long-term debt are observed after investment spikes. However, net equity repurchases occur before and after investment spikes. These results seem consistent with predictions in trade-off theory in the sense that the main source of finance during investment spikes appears to be debt, so leverage ratios typically exceed normal levels immediately after the spike year, but 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 and equity finance increase significantly during investment spikes, while internal finance remains flat.

Overall, these results are in line with Mayer and Sussman's (2005) argument that financing patterns are consistent with pecking-order theory in the short run, and consistent with trade-off theory in the long run. The additional analysis in Section III shows that large firms' financing behaviours around investment spikes are consistent with pecking order theory and classical trade-off theory, while small firms' financing around investment spikes is *not* consistent with either.

Regardless of significance level (1%, 5%, and 10%), external finance becomes much more significant than internal finance during an investment spike, and net long-term debt issues are more important sources of finance than net equity. In addition, a small proportion of net equity issues are also observed during an investment spike. Thus, all following analyses are based on spikes in the sample with a 5% significance level.

A.2.2. Using the Markov-Switching Filter as a Robustness Check

One potential problem with Mayer and Sussman's filter and the main filter used in this study is that they are designed to capture only one type of lumpy investment pattern, namely (0,0,1,0,0)-type investment spikes, where 1 denotes an investment spike year and 0 denotes a year with only routine investments. Therefore, they can identify only subsets of large investment years. However, some investment projects are so large that they last more than one year, so 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 of multi-year investment spikes). However, our Markov-switching filter can identify any conceivable pattern of lumpy investment including two- and three-year investment spikes, representing (0,0,1,1,0,0)-type and (0,0,1,1,1,0,0)-type investment spikes, respectively. This filter applies a Markov-switching mean model to the investment rates de-trended 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. A major advantage of the Markov-switching approach is that it provides the statistical inference on the probability of the unobserved states such as investment spike state. See Appendix B for more details.

We estimate the filter using the data over the 1988 to 2013 period for 2,627 firms whose investment rates are observed in 1988 and 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. Approximately 73.28% (81.37% among firms that survived until 2013) of firms have at least one investment spike using the filter at the 5% significance level. Additionally, about 6.93% of the firm-years in the sample are classified as investment spikes.

We then investigate whether the major findings on investment spike financing are robust to the use of the Markov-switching filter. The upper part of Table II Panel B reports the flow of funds around (0,0,1,0,0)-type investment spikes identified by the Markov-switching filter at the 5% level of significance. Just as in the regression filter, external finance becomes very important during investment spikes. More importantly, long-term debt is the most important source of finance, while net retirements of equity are observed even during spikes. Additionally, just as in the regression filter, both debt and equity finance have spikes during investment spikes while internal finance remains flat. The lower part of Table II 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 the two-year investment spikes identified by the Markov-switching filter are financed similarly to single-year investment spikes. Again, external finance becomes very important during investment spikes and debt finance is much more important than equity finance in funding two-year investment spikes.

These results support Mayer and Sussman's (2005) argument that financing patterns are consistent with pecking order theory in the short run, and consistent with classical trade-off theory in the long run. However, the additional analysis in Section III shows that small firms' financing behaviours around investment spikes are consistent with reverse pecking order theory and dynamic trade-off theory augmented with investment spikes, as proposed by DeAngelo *et al.* (2011).

A.3. Industry and Investment Spike Financing

Table II 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 funding during investment spikes, followed by internal finance. There are some contributions from equity finance 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 during an investment spike, although debt finance is still quite important. In the leather industry, the most important source of finance is equity, but this result might be attributed to the small sample size (N = 26). There are no substantial differences in investment spike financing across industries save for only a few.

A.4. Business Cycles and the Incidence and Financing of Investment Spikes

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

A.4.1. Business Cycles and Incidence of Investment Spikes

Figure 2 shows that, when the regression (Sig. Level=1%, 5%, 10%) and Markov-switching filters (Sig. Level=5%) are used, the incidence of firms with investment spikes is significantly positively correlated with real GDP growth and the lagged S&P 500 Index return. For instance, based on the regression filter at 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 had an investment spike in 2000 (i.e., a boom year). This shows that there is some evidence for calendar-time-dependent investment spike clusters generated by macroeconomic shocks. Table III 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 expansions, while 1990, 2001, 2008, and 2009 are contractions.

[Insert Figure 2 Here.]

[Insert Table III Here.]

A.4.2. Business Cycles and Financing around Investment Spikes

To investigate whether calendar-time-dependent clustering affects the reliability of the aggregated flow of funds, we examine whether the flow of funds during expansions is significantly different from that during contractions. Panel A of Table III 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, and debt finance is more important than both internal and equity finance during an investment spike, though some some equity finance is used during an investment spike.

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

A.4.3. Financial Crises and External Financing Sources during Investment Spikes

This section investigates whether there are significant differences in equity dependence and debt dependence between expansions and 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 total investment outlays including net capital expenditures and acquisitions; $LTDEBT$ measures funds from issues of long-term debt capital net of retirements, and $EQUITY$ measures funds from issues of ordinary and preferred shares net of retirements. See Appendix A for the formulas and the Compustat items used to construct them.

Panel B of Table III suggests that there is a significant difference in equity dependence between the 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 expansions and contractions at a conventional level of significance.

Figure 3 also shows the relationship between business cycles and external financing sources during investment spikes. Consistent with Panel B of Table III, in some expansionary years, equity dependence was higher than debt dependence. However, since 2006, through the 2008-2009 financial crisis, and till 2011, equity dependence dropped significantly and debt dependence was higher. 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 debt dependence also recorded its lowest level in the sample period under study. In that year, equity dependence and debt dependence were -3.72% and 7.15%, respectively. Equity dependence has therefore 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 Figure 3 Here.]

B. Firm Characteristics and Investment Spike Financing

This section explores the heterogeneity of financing patterns around investment spikes by investigating whether financing patterns vary with firm characteristics, including Rajan and Zingales' (1995) four leverage factors. We 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) analyze the determinants of capital structure across 37 countries and 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.

B.1. Firm Size and Investment Spike Financing

B.1.1. 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 investment for periods around investment spikes vary with firm size. Table IV Panel A and Figure 4 report the investment-weighted proportions of the funding flows around investment spikes for large and small firms, grouped by the total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) at the 33rd and 67th percentiles.

[Insert Table IV Here.]

[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 investment spike financing for these subsamples 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 IV Panel A is that small firms raise substantial equity before, during, and after investment spikes, whereas large firms rely largely on debt finance. The contribution of equity finance in funding investment spikes is negligible for large firms. Figure 4 clearly shows that small firms rely heavily on external finance (both debt and equity) during investment spikes. Surprisingly, small firms issue shares both before and after years with investment spikes.

B.1.2. Firm Size and External Funding Sources during Investment Spikes

Table V 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 based on both Student's t-test and the Wilcoxon rank-sum test. Table VI 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, and industry and year dummies are also included. The regressions include industry and year dummies and, as Sections II.A.3 and II.A.4 report, there are some differences in funding patterns across industries and business cycles. The between-group regressions are more appropriate to study the heterogeneity of financing patterns around investment spikes as they use only the cross-sectional variation in the data. However, results from ordinary-least-squares (OLS) and within-group (WG) regressions are very similar to the results from the between-group regressions in so far as a firm has on average 1.46 (i.e., $7,494/5,130 \approx 1.46$) investment spikes, and within-firm variation is much less than between-firm variation. Thus, small firms' financing behaviours during investment spikes are significantly different from large firms'. Therefore, all subsequent analyses are conducted separately for large and small firms.

[Insert Table V Here.]

[Insert Table VI Here.]

B.1.3. Other Financing Sources by Sub-samples based on Firm Size

Table IV Panel A and Figure 4 show a substantial contribution of other financing sources, particularly for large firms. Table IV Panel B breaks the other financing sources (i.e., $OTHER$) into nine components to examine which are more important sources of finance. 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 for the formulas and the Compustat items used to construct them. Note that missing Compustat items have been replaced with zeros whenever appropriate, and that there are slightly less observations in Panel B because investment spikes without complete information on these nine components have been dropped.

Table IV Panel B shows that for both large and small firms, investment spikes are financed using “Increase in debt in current liabilities,” “Increase in other current liabilities,” “Increase in taxes payable,” “Decrease in other investments,” and “Decrease in cash dividends.” Large firms rely a little on “Decrease in cash and cash equivalents” and small firms rely quite significantly on “Increase in accounts payable.” Surprisingly, “Decrease in inventories” and “Decrease in accounts receivable” are not observed for both large and small firms. During investment spikes, inventories and accounts receivable increase rather than decrease. However, this should be analyzed cautiously because these components might include substantial measurement errors, and some components could be moved to the left 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.

B.2. Other Firm Characteristics and Investment Spike Financing

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

B.2.1. Univariate Tests

Table V reports the results for Student’s t-tests and Wilcoxon rank-sum tests as well as the means and medians of equity and debt dependence by subgroups based on profitability, level of future growth opportunities, tangibility of assets, R&D intensity, and firm size. The investment spikes are grouped into “Above Median” and “Below Median” based on the median of the proxies for the firm characteristics measured at the beginning of the years with an investment spike (i.e., $\tau = -1$). Appendix A 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 based on both Student's t-tests and Wilcoxon rank-sum tests. Similarly, Panel B shows that firms with higher profitability, fewer future growth opportunities, more tangible assets, and less R&D spending have a higher tendency to use debt finance during investment spikes. These differences are statistically significant at the 1% level based on both Student's t-tests and Wilcoxon rank-sum tests, with the exception of one t-test.

B.2.2. Between-Group Regressions

The between-group regressions reported in Table VI show whether the effects of additional firm characteristics on equity 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 less R&D spending have a higher tendency to use debt finance during investment spikes. It appears that profitability and market-to-book ratios do not have a significant influence on debt dependence during investment spikes when firm size, industry effects, and year effects are controlled for. Note again that small firms' financing behaviours vary significantly from large firms' financing behaviours during investment spikes.

B.3. Summary and Discussion

Overall, smaller firms and those with lower profitability, more future growth opportunities, fewer tangible assets, and greater R&D spending tend to use more equity to fund large investment requirements. However, company size affects financing patterns around investment spikes more than these characteristics. These results are consistent with Fama and French's (2005) and Gatchev *et al.*'s (2009) findings 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.

One explanation consistent with the above findings is as follows. 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. As firms become less informationally transparent, the contracting costs to issue debt increase relative to the adverse selection costs to issue equity. Thus, less informationally transparent firms are likely to use more equity to finance large investment requirements. These patterns run counter to Myers and Majluf's (1984) framework predicting that adverse selection considerations play a dominant role in decisions regarding security issuance. Rather, these financing patterns among small firms are consistent with the reverse pecking order, which can be predicted by assuming endogenous information production in Fulghieri and Lukin's (2001) framework because it appears that equity finance is considered first among external finance sources.

C. Funding Flows around Investment Spikes: Capital Expenditures vs. Acquisitions

In this section, we investigate whether investment spikes involving acquisitions are funded differently from investment spikes involving only capital expenditures. Investment spikes are classified as acquisitions if that year includes acquisitions ($D\_AQC = 1$), and classified as capital expenditures otherwise ($D\_AQC = 0$). Table VII shows that investment spikes involving acquisitions tend to be larger than investment spikes involving only capital expenditures. Therefore, it is expected that investment spikes involving acquisitions will use more equity finance according to the pecking-order theory (Myers and Majluf, 1984). However, regardless of firm size, additional investment requirements during acquisitions tend to be funded by additional debt. In particular, small firms rely more on equity to finance capital expenditures, but rely more on debt to finance acquisitions.

[Insert Table VII Here.]

This is 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 expenditures are financed with more equity and less long-term debt than more informationally transparent acquisitions. One explanation consistent with the this findings is that as investments become less informationally transparent, the contracting costs to issue debt increase relative to the adverse selection costs to issue equity. Again, these patterns contradict the expectations from Myers and Majluf's (1984) framework, and are rather consistent with the reverse pecking order predicted by the endogenous information production model of Fulghieri and Lukin (2001).

III. Further Analyses of the Heterogeneity in Investment Spike Financing

A. Firm Size and Relationship between Spike Size and Investment Spike Financing

This section provides an additional investigation into whether there are differences in the relationship between the magnitude of an investment spike and investment spike financing between large and small firms. These analyses shed light on whether their financing patterns are consistent with the pecking order theory or with a reverse pecking order, as predicted with the assumption of endogenous information production in Fulghieri and Lukin's (2001) framework.

We first investigate whether financing patterns vary according to the magnitude of investment spikes by analyzing the flow of funds. Table VIII shows that financing patterns differ substantially across subgroups based on $SPIKESIZE_j$ or the magnitude of abnormal components of investment spikes. Panel A in the table shows that large firms tend to use only debt finance when facing relatively small investment spikes but tend to use more equity finance for relatively large investment spikes. These results seem consistent with pecking order theory (Myers and Majluf, 1984). However, Panel B shows that small firms tend to use more equity finance for relatively small investment spikes and more debt to finance relatively large investment spikes, which seem consistent with the reverse pecking order outlined by Fulghieri and Lukin (2001).

[Insert Table VIII Here.]

Table IX reports the results of between-group regressions of equity and debt dependence on a measure of spike size to examine how small firms' equity ($(E/I)_{j,\tau=0}$) and debt ($(D/I)_{j,\tau=0}$) dependence are differently affected by spike size compared to large firms'. 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, the interaction terms between $LNSPIKESIZE_{j,\tau=0}$ and the dummy variables, such as $D\_SMALL_{j,\tau=-1}$, are included as explanatory variables. Appendix A describes the variables used in the regressions.

[Insert Table IX Here.]

The regressions in Table IX Panel A are designed to analyze the effects of the size of the investment spike on equity dependence during 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) use different regression specifications and show that large 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; small firms have a positive intercept and a negative slope. Similarly, the regressions in Table IX Panel B are designed to analyze the effects of the size of the investment spike on debt dependence during 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 for $(E/I)_{j,\tau=0}$. However, Columns (2), (3), and (4) use different regression specifications and show that large and small firms have somewhat different relationships between $(D/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$: large and small firms have similar slopes, though small firms have a lower intercept.

According to the pecking order theory, firms with larger investment spikes will depend more on higher equity during investment spikes. When firms are faced with smaller investment spikes, they will first use internal sources, and then raise less information-sensitive debt finance if they need external finance before issuing 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, the pecking order theory predicts a positive slope in the relationship between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$. Table IX Panel A shows that large firms have a positive relationship between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$, while small firms have a negative relationship between $(E/I)_{j,\tau=0}$ and $LNSPIKESIZE_{j,\tau=0}$. These results show that large firms' financing patterns during investment spikes are consistent with pecking order theory, while small firms' financing patterns are not.

Figure 5 illustrates how small firms' debt and equity dependence are differently influenced by the natural logarithm of the spike size measure compared to large firms'. The nine points in each line in the figure correspond to the nine deciles of $LNSPIKESIZE_{j,\tau=0}$. Note that this figure is based on the coefficients in OLS regressions rather than BG regressions, so the 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 the natural logarithm), small firms' equity dependence is approximately 55% higher than that of large firms (55.34% vs. 0.03%), and their debt dependence is 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.

[Insert Figure 5 Here.]

In addition, as in Table VIII Panel A, large firms tend to rely only on debt finance to fund relatively small investment spikes but tend to use more equity when they are faced with relatively large investment spikes, a result that seems consistent with the pecking-order theory (Myers and Majluf, 1984). However, in line with Table VIII Panel B, small firms tend to use more equity finance to fund relatively small investment spikes and more debt to finance relatively large investment spikes, a result that seems more consistent with the reverse pecking order outlined by Fulghieri and Lukin (2001). Mayer and Sussman (2005) find that large investment projects are predominantly financed with debt and argue that this result suggests that corporate financing patterns are consistent with the pecking-order theory in the short run. This study also confirms that large firms' financing patterns are consistent with pecking-order theory in the short run, but small firms' financing patterns are *not* consistent with the pecking-order theory, and instead are consistent with the reverse pecking order prediction in the short run.

B. Firm Size and Relationship between Initial Leverage and Investment Spike Financing

This section examines whether there are differences in the relationship between the level of initial leverage and investment spike financing between large and small firms. These analyses shed light on whether their financing patterns are consistent with the classical trade-off theory or with DeAngelo *et al.*'s (2011) modern dynamic trade-off theory augmented with investment spikes.

Table X shows the investment-weighted flows of funds around investment spikes undertaken separately by large and small firms by subgroups based on a measure of initial leverage ($LEV_{j,\tau=-1}$) to investigate whether financing patterns vary according to the level of initial leverage. According to the classical trade-off theory of debt, firms with higher initial leverage will use less debt to finance investment requirements in normal periods and during investment spikes. However, Panel A shows that initial leverage does not make a significant difference in large firms' investment spike financing, as they tend to use more debt than equity to fund large investment projects regardless of the level of initial leverage. Panel B shows that the relationship between the level of initial leverage and investment spike financing undertaken by small firms contradicts 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 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 classical trade-off theory of debt does not fully explain investment spike financing.

[Insert Table X Here.]

Table XI reports the results of between-group regressions of equity and debt dependence on a measure of initial leverage to examine how small and large firms' equity ($(E/I)_{j,\tau=0}$) and debt ($(D/I)_{j,\tau=0}$) dependence are differently influenced by 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. In addition to market leverage ratios ($LEV_{j,\tau=-1}$), the interaction terms between $LEV_{j,\tau=-1}$ and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. Appendix A describes the variables used in the regressions. 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 have a high debt dependence and low equity dependence during investment spikes, which will increase their leverage during investment spikes. However, this table shows that large and small firms have completely different relationships between initial leverage and both debt and equity dependence. Columns (2), (3), and (4) in Panel A show that large and small firms have different relationships between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$: large firms have a negative intercept and a positive slope, and small firms have a positive intercept and a negative slope. Similarly, Columns (2), (3), and (4) in Panel B show that both large and small firms have positive slopes but have somewhat different relationships between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$: small firms have a somewhat steeper slope but a slightly lower intercept.

[Insert Table XI Here.]

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

[Insert Figure 6 Here.]

According to the classical trade-off theory of debt, firms with higher initial leverage will use less debt and more equity to fund investment requirements during both normal periods and investment spikes. Therefore, the classical trade-off theory predicts 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 XI shows that large firms have a weakly positive relationship between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$, and a strongly positive relationship between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$. In addition, large firms tend to use more debt than equity to finance large investment projects regardless of the level of initial leverage. Although these results are *not* perfectly consistent with the trade-off theory of debt, they are compatible. However, Table XI also shows that small firms have a strongly negative relationship between $(E/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$, and a strongly positive relationship between $(D/I)_{j,\tau=0}$ and $LEV_{j,\tau=-1}$, which is completely inconsistent with predictions of the classical trade-off theory of debt.

However, according to DeAngelo *et al.*'s (2011) dynamic trade-off theory augmented with investment spikes, 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 intentionally deviate from their targets. Thus, firms with higher initial leverage do not necessarily use more equity and less debt to fund investment spikes. According to this, 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.

C. Analyses of Financing Patterns after Investment Spikes

According to both the classical trade-off theory and dynamic trade-off theory (Fischer *et al.*, 1989; DeAngelo *et al.*, 2011), firms will adjust their leverage downwards following investment spikes through some combination of net debt repayments and equity issues.[1] Additionally, this adjustment pattern will be more pronounced when initial leverage is higher. This study has several empirical findings. First, large firms, especially those with higher initial leverage, gradually adjust their leverage back to optimal levels 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 begin to repay debt or reduce share repurchases immediately after investment spikes. Second, small firms, regardless of initial leverage, gradually adjust their leverage back to optimal levels after investment spikes by repaying some debt and issuing new shares. Note that small firms, unlike large firms, tend to issue shares after investment spikes, suggesting that the adjustment patterns of both large 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) 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. However, they did not consider initial leverage in their analyses. The empirical results in this study indicate that

[1] In Fischer *et al.*'s (1989) model, firms adjust leverage only if the benefits of doing so exceed the costs of reducing the firm's deviation from target leverage. In DeAngelo *et al.*'s (2011) model, firms have leverage targets as in static trade-off models, but managers sometimes choose to deviate from targets. This requires a re-balancing by reducing debt with a lag determined in part by the time path of investment opportunities and operating cash flows.

the classical trade-off theory does not fully explain the financing patterns of both large and small firms, and are better explained by DeAngelo *et al.*'s (2011) dynamic trade-off model augmented with investment spikes.

IV. Conclusion

Many studies have found that retained earnings are the dominant source of funding for firms across different countries and time periods (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this argument applies primarily to how firms finance their routine, replacement investment rather than their non-routine, expansion investment. How firms meet exceptional financing needs related to unusually large investment opportunities is the subject of an emerging body of literature that includes studies by DeAngelo *et al.* (2011), Mayer and Sussman (2005), and Elsas *et al.* (2014). This study also contributes to the security design literature, as described for example in Boot and Thakor (1993), which explains why a firm raising external capital would simultaneously issue multiple types of financial claims such as debt and equity against its cash flows. Therefore, this study's methodology can also be used to test predictions arising from the security design literature.

One of this study's most important findings is that financing investments during an investment spike differs from financing investments at other times using data for publicly traded US firms and a new filtering procedure that has several advantages over existing methods. This study confirms that the share of investment financed by external sources is much higher than that financed from internally-generated funds. More importantly, the share of investment financed by long-term debt is much higher than that financed through equity.

We find that small firms raise substantial equity finance during investment spikes, whereas large firms rely largely on debt finance. Firms with lower profitability, more future growth opportunities, fewer tangible assets, and more R&D spending tend to use more equity finance to fund large investment requirements. However, the effects of these firm characteristics are not as strong as the effect of firm size on investment spike financing. There are no substantial differences in funding sources for investment spikes across industries and time periods. Furthermore, investment spikes involving acquisitions tend to be funded by a higher proportion of debt, and acquisition spikes tend to be sharper than those involving only capital expenditures.

One of the most noteworthy findings in this study is that financing patterns differ substantially across subgroups based on the magnitude of investment spikes. Large firms tend to use only debt to fund relatively small investment spikes, but tend to use more equity to finance relatively large investment spikes. However, small firms tend to use more equity finance to fund relatively small investment spikes and more debt to finance relatively large investment spikes. This finding suggests that large firms' financing patterns are consistent with pecking-order theory (Myers and Majluf (1984)), but those of small firms resemble the reverse pecking order predicted by the endogenous information production model of Fulghieri and Lukin (2001).

Additionally, this study finds that financing patterns around investment spikes are *not* consistent with the classical trade-off theory of debt but are quite consistent with 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 use less debt to finance their investment requirements during normal periods and investment spikes. However, large firms tend to use more debt than equity finance to fund large investment projects, regardless of the level of initial leverage. In addition, small firms with lower initial leverage tend to use more equity finance and small firms with higher initial leverage tend to use more debt to meet large investment requirements, which contradicts the classical trade-off theory.

Appendix

A. *Construction of Variables*

This section defines the variables used in the study. Table AI describes the variables for cash-flow identity, Table AII describes components of other financing sources, Table AIII describes the variables used in regressions, and Table AIV describes the other variables used in this paper. Unless otherwise stated, all 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 brackets ([ ]) represent the Compustat North America item codes.

Table AI. 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 AII. 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 AIII. Regression Variables

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 AIV. Other Variables

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*]

B. Markov-Switching Filter

This section describes the Markov-switching filter used as a robustness check. The basic idea of this filter is to apply a Markov-switching mean model to the investment rates de-trended using Hodrick and Prescott's (1997) filter. While it is possible to use a Markov-switching mean and variance model, this study uses a simpler model because this change will increase the number of parameters.

B.1. Input Series and De-trending

The data used in this approach is "investment-to-assets ratio (I_{it}/A_{it})." The investment rates are de-trended using the Hodrick-Prescott (1997) filter. The de-trending 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 has two starting points: first, the trend must follow the observed data closely, and second, the trend must be a smooth time series. Hodrick and Prescott suggest a way to isolate c_t from y_t from these requirements using 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[2]. 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 $y_t-\tau_t$.

B.2. Model Specification

The model used here is a simplified version of the Markov-switching mean model from Albert and Chib (1993), and explained in Kim and Nelson (1999). It is assumed that the investment rates de-trended 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 de-trended investment rates. Therefore, this model is essentially a simplified version of Hamilton's (1989) Markov-switching $AR(p)$ model.

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

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

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

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

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:

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

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

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

[2]We chose the smoothing parameter as 100 which is recommended for annual data. The Hodrick-Prescott filter was implemented using a MATLAB function *hpfilter* in MATLAB Econometrics Toolbox.

B.3. Estimation Procedures

There are two well-known procedures to estimate a Markov-switching model: the maximum likelihood approach and the Bayesian approach. Although there have been some efforts to improve the maximum likelihood approach, including Hamilton's (1990) EM algorithm and Kim's (1994) smoothing algorithm, the classical maximum likelihood approach has some shortcomings compared with the Bayesian Gibbs-sampling approach. First, it involves approximation, though the error from approximation is 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 they are sampled from appropriate conditional distributions. The estimates are also less sensitive to arbitrary starting values as estimation steps are repeated to reach convergence (see Kim and Nelson (1999)). Therefore, we use the Bayesian Gibbs-sampling approach to estimate unobserved state variables along with parameters.

B.4. Selecting Investment Spikes

It is possible to identify the years with investment spikes once the Gibbs-sampling procedures are completed. First, we check whether the Markov-switching model for a given firm satisfies the model selection criterion (*MSC*), which are 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 states 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 ($Pr[S_t = 1|\widetilde{c}_T]$). Years are classified as those 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 years where the probability of investment spikes is greater than 0.95 are identified as years with an investment spike.

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Table I

Summary Statistics—Investment Spikes Sample

This table reports the summary statistics for the investment spikes sample. Panels A, B, and C show the summary statistics for large, medium, and small firms, respectively. Firms are grouped according to the total assets at the beginning of the year with an investment spike ($TA_{j,\tau=-1}$) at the 33rd and 67th percentiles. Appendix A describes how the variables are constructed in detail. 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 II
Funding Flows around Investment Spikes

This table reports 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 at the 1%, 5%, and 10% significance levels; Panel B summarizes the flow of funds around investment spikes identified by the Markov-switching filter at the 5% significance level; and Panel C summarizes the sources of finance during investment spikes identified by the regression filters at the 5% significance level by the 30 industry groups 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 sample. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. The aggregate statistics do not include investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$).

Panel A. 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, the two-year averages of total assets (TA) and each component of 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.

Panel C. Sources of Finance by Industry Group

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 III
Business Cycles and Investment Spike Financing

This table is designed to analyze whether investment spike financing differs during expansion and contraction 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 are contractions. Panel A shows the investment-weighted flow of funds around investment spikes according to these phases. The summary statistics report 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 each sample. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ 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 included. Panel B reports the results for Student's t-tests and Wilcoxon rank-sum tests to test whether there are significant differences in equity and debt dependence between expansions and contractions. See Appendix A for the formulas and the Compustat items used to construct equity dependence and debt dependence. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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 IV
Firm Size and Funding Flows 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, medium, and large firms at the 33rd and 67th percentiles. The summary statistics report 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. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. The aggregate statistics do not include investment spikes with any missing values in the cash-flow identity during the five-year event window ($\tau \in \{-2,-1,0,+1,+2\}$). Panel B shows other financing sources (i.e., $OTHER$) broken into nine components to examine which components are more important sources of finance: "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 for the formulas and the Compustat items used to construct these. Note that missing Compustat items have been replaced with zeros whenever appropriate and investment spikes without complete information for these components have been dropped.

Panel A. Flow of Funds by Sub-samples based on Firm Size

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-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
Large firms	**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
	-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
Small firms	**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*
	-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
Large firms	**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
	-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
Small firms	**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 V
Firm Characteristics and Investment Spike Financing

This table reports the results for Student's t-tests and Wilcoxon rank-sum tests as well as the means and medians of equity and debt dependence by subgroups based on profitability, level of future growth opportunities, tangibility of assets, R&D intensity, and 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 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 total investment outlays including net capital expenditures and acquisitions; $EQUITY_{j,\tau=0}$ measures funds from issues of ordinary and preferred shares net of retirements; and $LTDEBT_{j,\tau=0}$ measures funds from issues of long-term debt capital net of retirements. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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 VI
Equity and Debt Dependence during Spikes—BG Regressions

This table reports the results of the between-group (BG) regressions to investigate whether the effects of various firm characteristics on equity and debt dependence during investment spikes remain after firm size, industry effects, and year effects are controlled for. The 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 total investment outlays including net capital expenditures and acquisitions; $EQUITY_{j,\tau=0}$ measures funds from issues of ordinary and preferred shares net of retirements; and $LTDEBT_{j,\tau=0}$ measures funds from issues of long-term debt capital net of retirements. Appendix A describes the construction of the variables included in the regressions. All regressions include both year and industry dummies. The robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for the 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)
Observations	7,494	7,000	6,965	7,488	7,492	6,481
Number of firms	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

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)
Observations	7,494	7,000	6,965	7,488	7,492	6,481
Number of firms	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 VII

Flow of funds around investment spikes—capital expenditures vs. acquisitions

This table compares the financing patterns of capital expenditures with those of acquisitions. Investment spikes are classified as acquisitions if there are positive acquisitions in that year ($D\_AQC > 0$), while otherwise they are classified as capital expenditures. 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. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ 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 A. Large firms

Sub-sample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	963	12.45	0.8515	0.9994	0.0967	-0.0408	-0.2038
	-1	963	13.84	0.9746	1.1549	0.1704	-0.0203	-0.3304
Capital expenditures	**0**	**963**	**15.91**	**1.8218**	**1.1885**	**0.3691**	**0.0259**	**0.2384**
	+1	963	15.98	1.0843	1.1508	0.1301	-0.0636	-0.1330
	+2	963	16.53	1.0896	1.2705	0.0632	-0.1328	-0.1112
	-2	1,510	17.94	0.9222	1.2863	0.1302	-0.3259	-0.1684
	-1	1,510	19.50	0.9919	1.4492	0.0959	-0.3520	-0.2012
Acquisitions	**0**	**1,510**	**30.07**	**8.2732**	**1.3694**	**4.2360**	**0.3109**	**2.3569**
	+1	1,510	29.19	1.0647	1.2868	-0.1016	-0.1776	0.0571
	+2	1,510	29.21	1.0212	1.5279	-0.2244	-0.3443	0.0621

Panel B. Small firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-2	1,532	11.89	0.6726	0.0016	-0.0961	1.2166	-0.4495
	-1	1,532	14.72	0.9544	-0.1124	-0.0825	2.4559	-1.3066
Capital expenditures	**0**	**1,532**	**23.41**	**5.8665**	**-1.1786**	**2.3036**	**4.6303**	**0.1112**
	+1	1,532	22.63	1.2686	-1.8416	0.5224	1.2579	1.3299
	+2	1,532	22.46	1.1043	-1.3337	-0.0075	1.8385	0.6070
	-2	941	11.04	0.6131	0.5373	-0.1856	0.9173	-0.6559
	-1	941	13.79	0.7937	0.5937	-0.0092	1.8351	-1.6260
Acquisitions	**0**	**941**	**34.22**	**14.7416**	**0.5480**	**8.5313**	**4.8481**	**0.8141**
	+1	941	33.37	1.3872	0.3711	-0.5919	0.9500	0.6581
	+2	941	33.28	1.2060	0.5550	-0.4601	0.5184	0.5927

Table VIII

Spike Size and Funding Flows around Investment Spikes

This table is designed to examine whether financing patterns differ substantially across subgroups based on the magnitude of investment spikes. Panel A shows the investment-weighted funding flows around investment spikes for large firms according to the magnitude of investment spikes, while Panel B shows the investment-weighted funding flows around investment spikes for small firms according to the magnitude of investment spikes. The magnitudes of investment spikes are measured by $SPIKESIZE_j$ as defined in Section I.B. $Q1$, $Q2$, and $Q3$ represent the 1st, 2nd, and 3rd quartiles of $SPIKESIZE_j$, respectively. The summary statistics report 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. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. The aggregate statistics do not include investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$).

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

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 IX

Effect of Spike Size on Equity and Debt Dependence

This table reports the results of the between-group regressions designed to examine how small firms' equity ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are affected by the size of investment spikes compared to large firms. The 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 total investment outlays including net capital expenditures and acquisitions; $EQUITY_{j,\tau=0}$ measures funds from issues of ordinary and preferred shares net of retirements; and $LTDEBT_{j,\tau=0}$ measures funds from issues of long-term debt capital net of retirements. The natural logarithm of the abnormal component of an investment spike ($LNSPIKESIZE_{j,\tau=0}$), 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. The robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for the two-tailed tests.

Panel A. Size of Investment Spike 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

Panel B. Size of Investment Spike 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 X

Initial Leverage and Funding Flows around Investment Spikes

This table examines whether financing patterns differ substantially across subgroups based on initial leverage. Panel A shows the investment-weighted flows of funds around investment spikes for large firms according to initial leverage, while Panel B shows the investment-weighted flows of funds around investment spikes for small firms according to initial leverage, 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 summary statistics report 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. We drop the j-th investment spike if either $OPR_{j,\tau}/BASE_j$ or $OTHER_{j,\tau}/BASE_j$ falls outside the [-40,40] segment. The aggregate statistics do not include investment spikes with any missing values in the cash-flow identity during the five-year window ($\tau \in \{-2,-1,0,+1,+2\}$).

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

Panel B. Small Firms

Subsample	τ	Obs.	TA	I	Sources of Finance			
					OPR	$LTDEBT$	$EQUITY$	$OTHER$
	-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
$LEV_{j,\tau=-1} < Q1$	**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
	-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
$Q1 \leq LEV_{j,\tau=-1} < Q2$	**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
	-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
$Q2 \leq LEV_{j,\tau=-1} < Q3$	**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
	-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
$LEV_{j,\tau=-1} \geq Q3$	**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 XI
Effects of Initial Leverage on Equity and Debt Dependence

This table reports the results of the between-group regressions to examine how small firms' equity ($(E/I)_{j,\tau=0}$) and debt dependence ($(D/I)_{j,\tau=0}$) are affected by initial leverage compared to large firms. The 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 total investment outlays on net capital expenditures and acquisitions; $EQUITY_{j,\tau=0}$ measures funds from issues of ordinary and preferred shares net of retirements; and $LTDEBT_{j,\tau=0}$ measures funds from issues of long-term debt capital net of retirements. The market leverage at the beginning of an investment spike ($LEV_{j,\tau=-1}$), interaction terms between $LEV_{j,\tau=-1}$, and the dummy variables such as $D\_SMALL_{j,\tau=-1}$ are included as explanatory variables. Appendix A describes the variables used in the regressions. The robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively for the 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

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 spikes identified by the regression filter at 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.

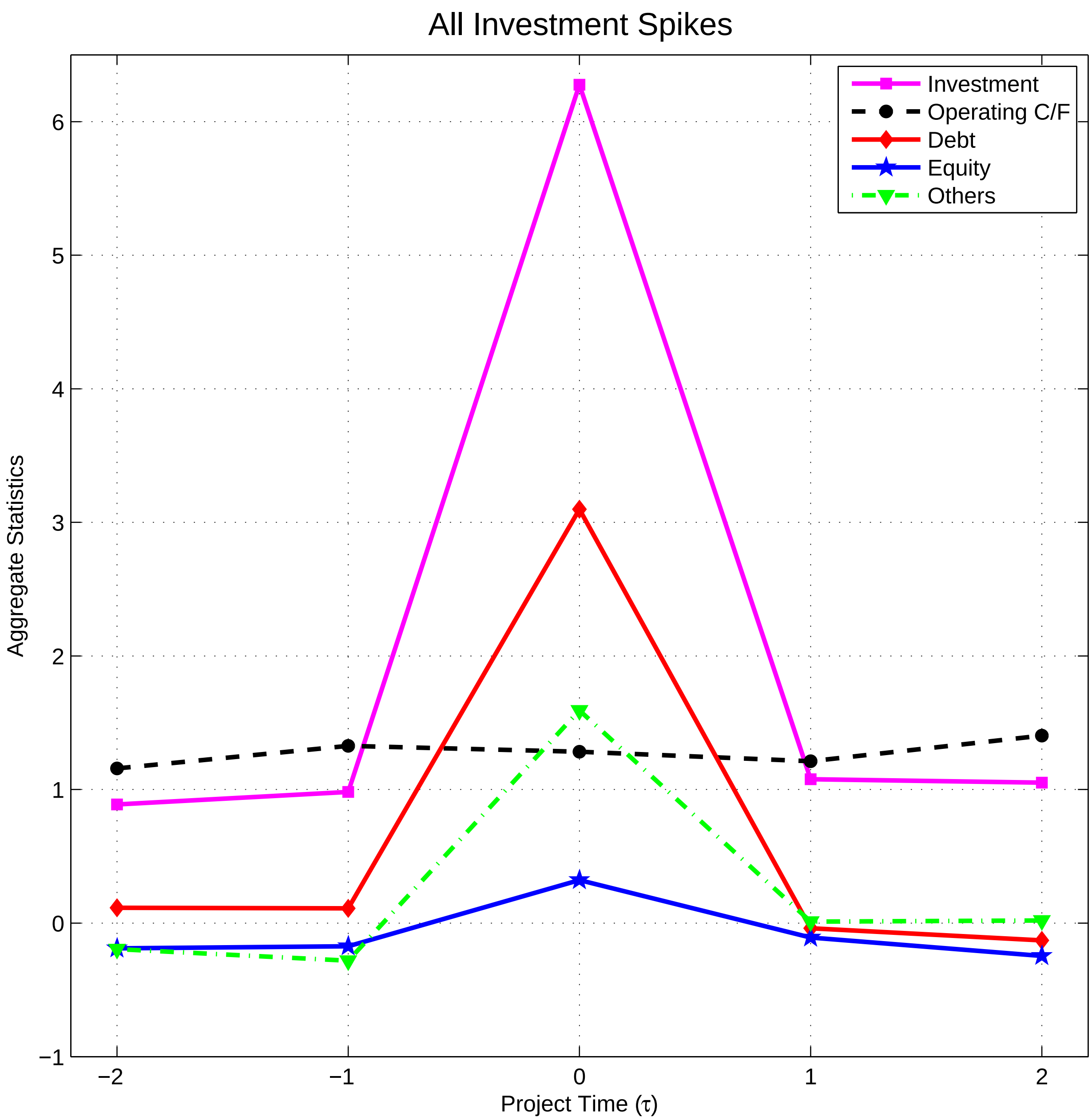
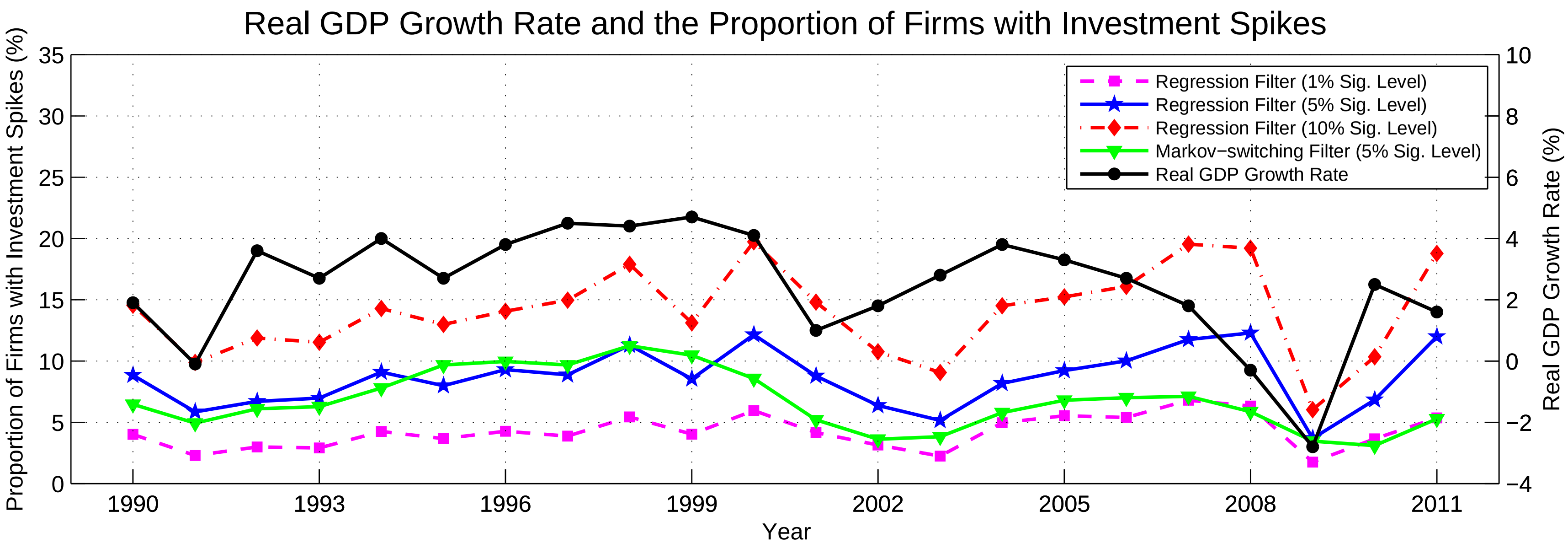


Figure 2. Business Cycles and the Proportion of Firms with Investment Spikes

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



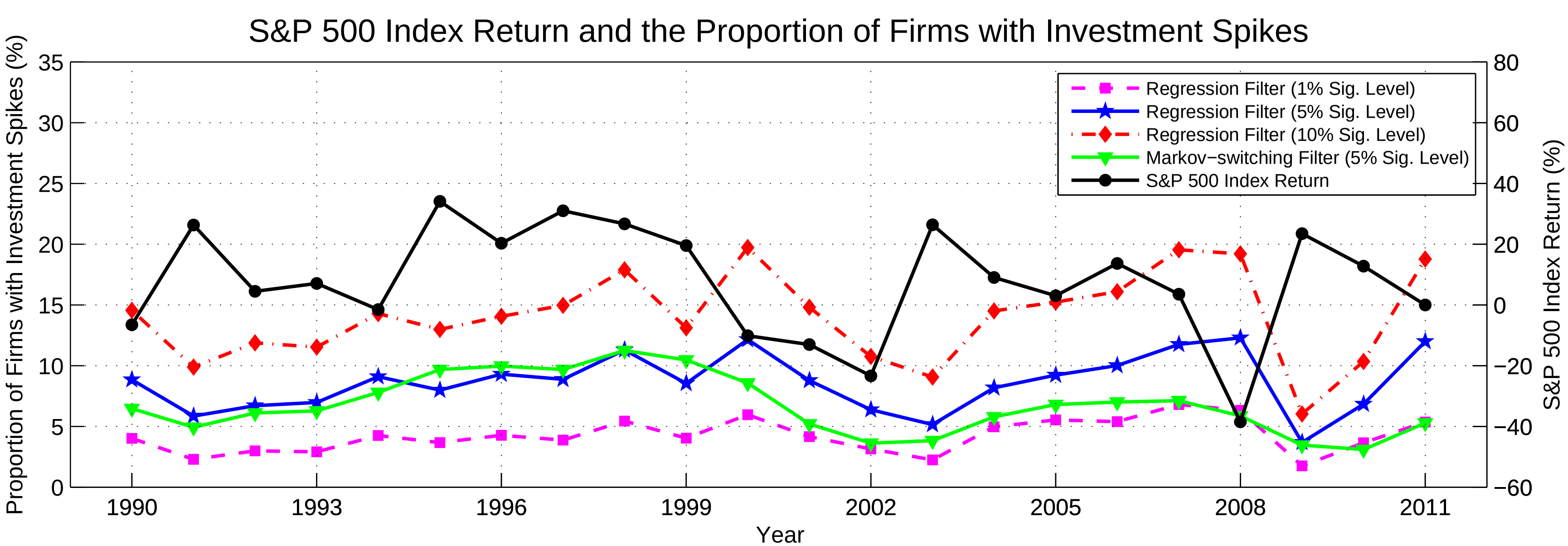
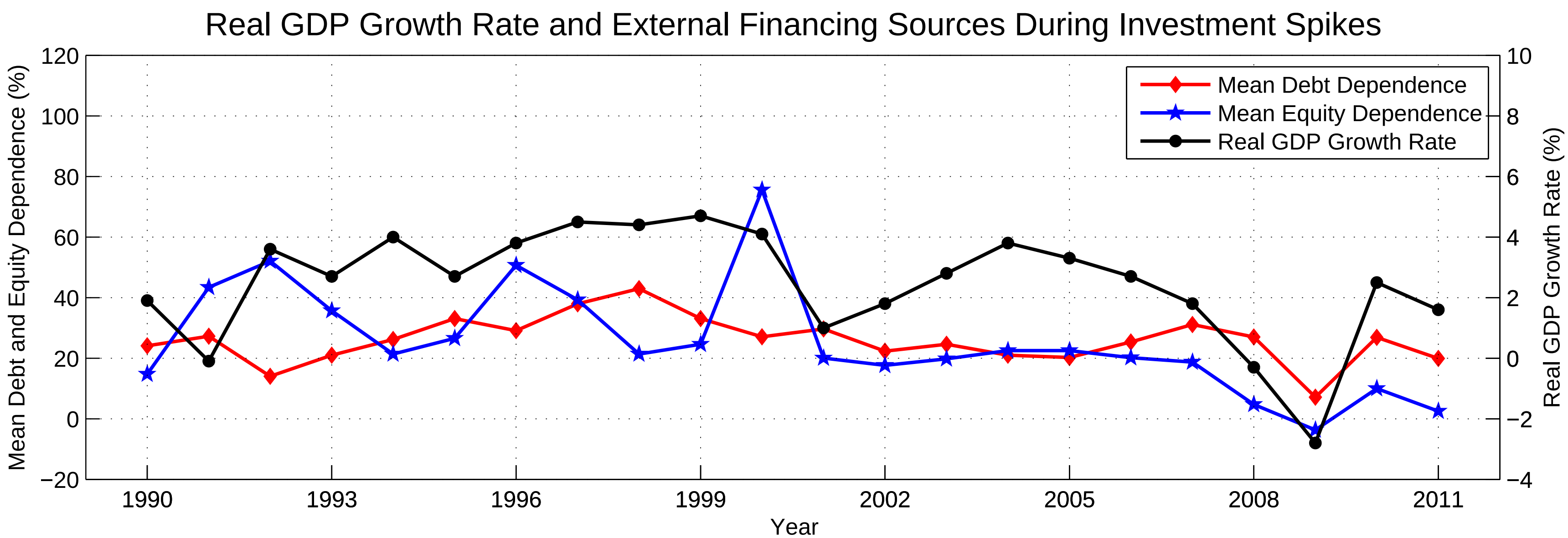


Figure 3. Business Cycles and External Financing Sources during Investment Spikes

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



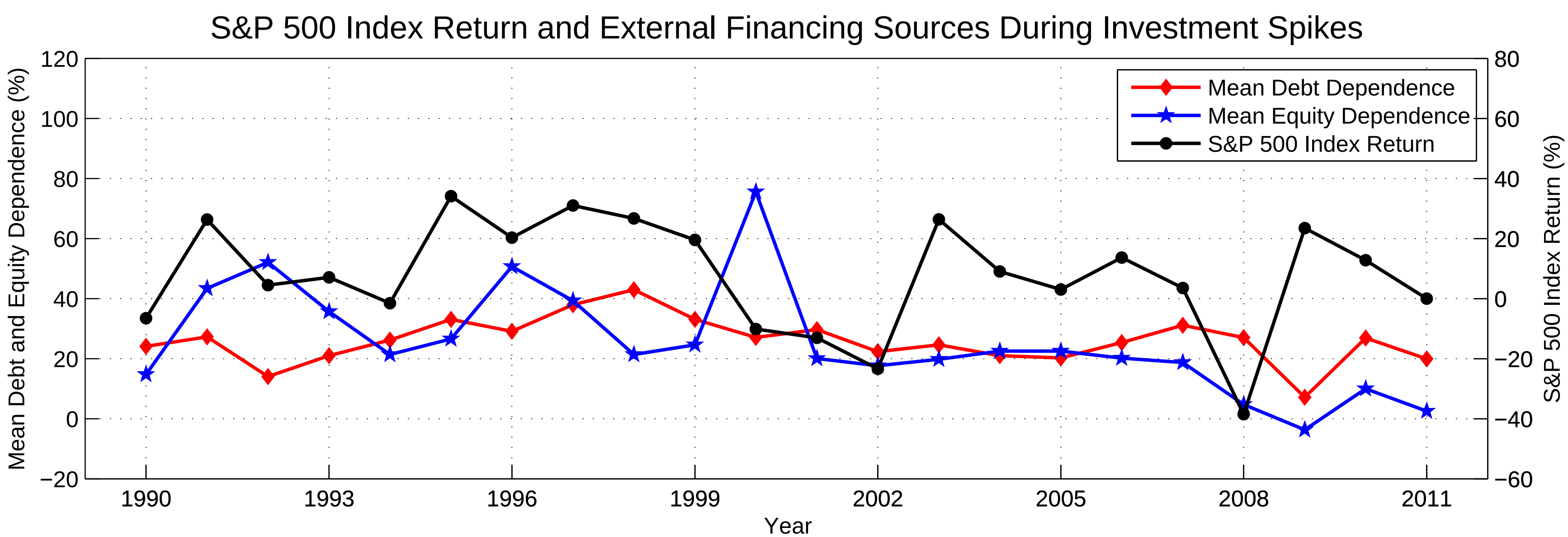
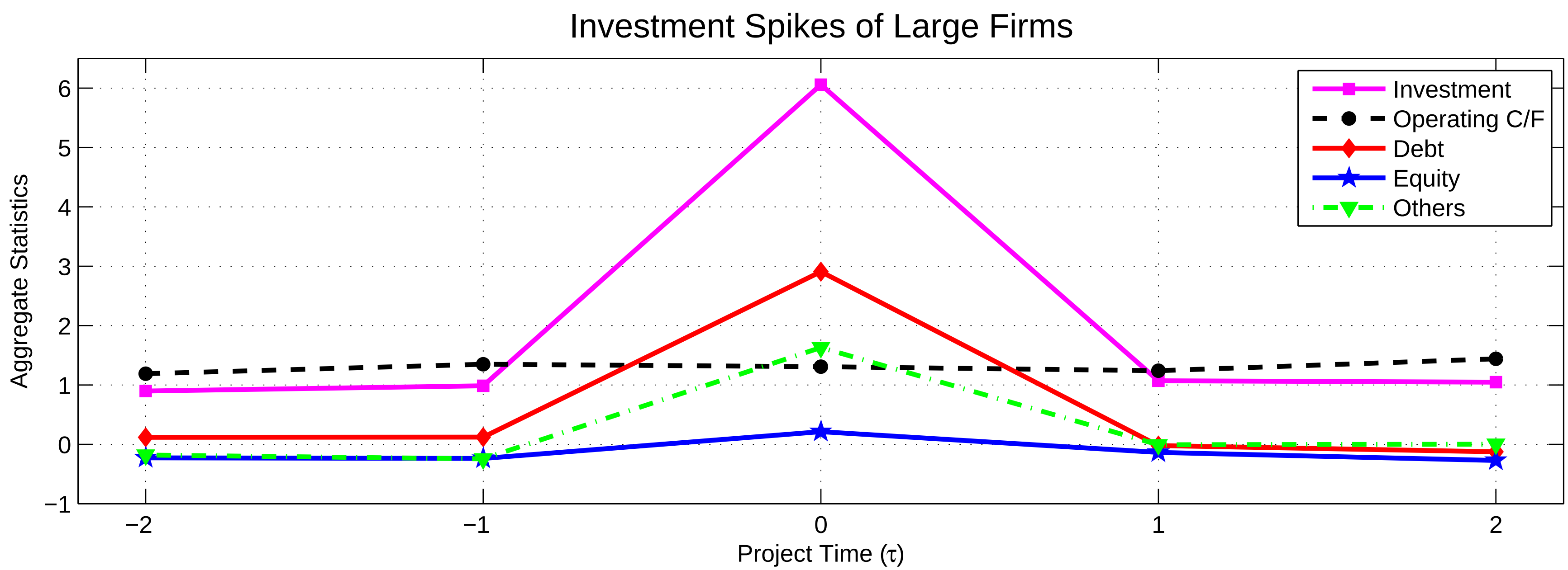


Figure 4. Financing Patterns around Investment Spikes by Firm Size

This figure shows the aggregate statistics for the flow of funds around investment spikes identified by the regression filter at the 5% significance level 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 sample.



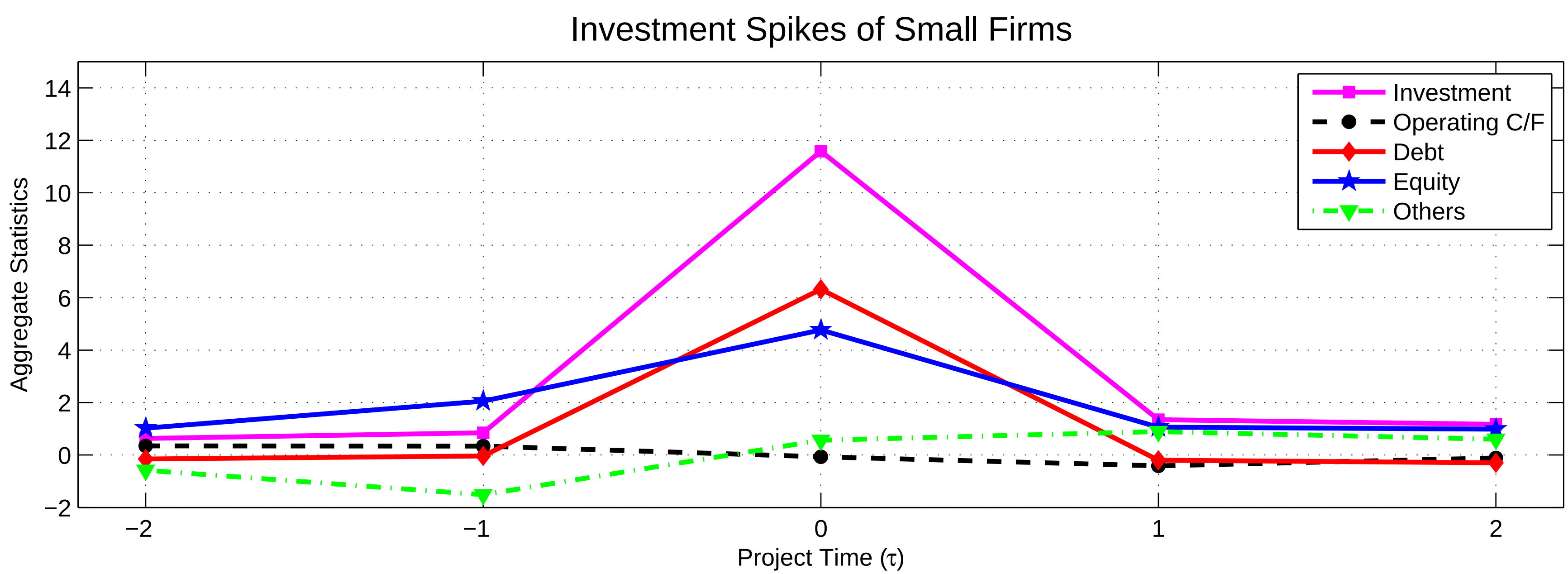
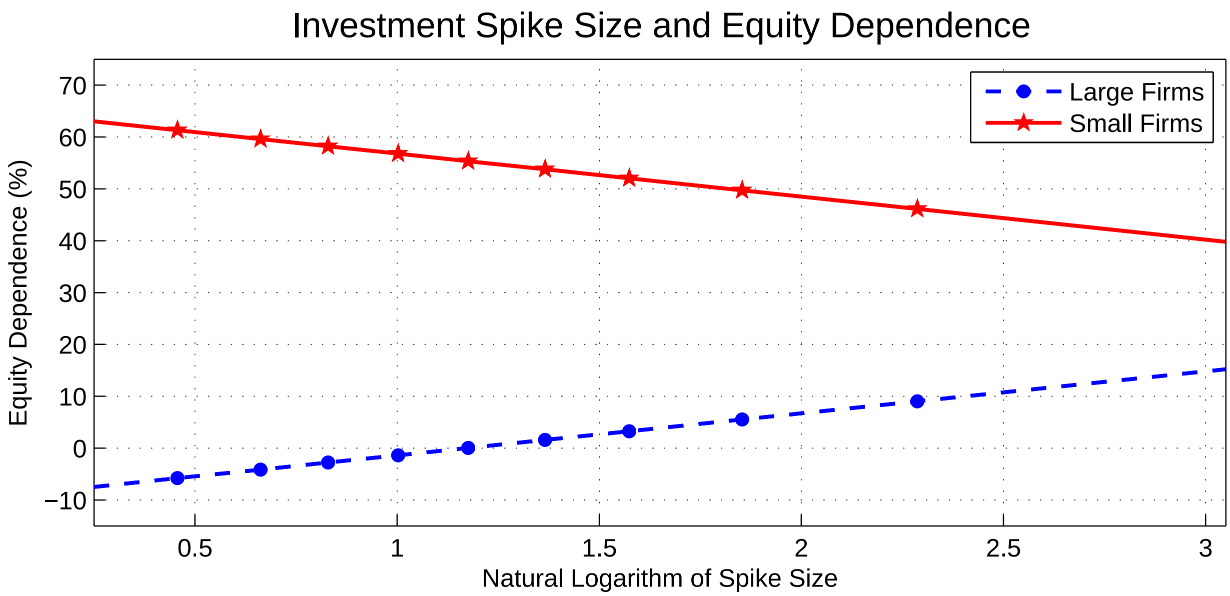


Figure 5. Investment Spike Size and External Financing Sources during Investment Spikes

This figure examines if the relationships between the natural logarithm of the spike size and debt and equity dependencies vary with firm size. The nine points in each line in the figure correspond to the nine deciles of $LNSPIKESIZE_{j,\tau=0}$. Note that this figure is based on the coefficients in OLS regressions rather than BG regressions, so the deciles are based on original spike size measures, not firm-average ones.



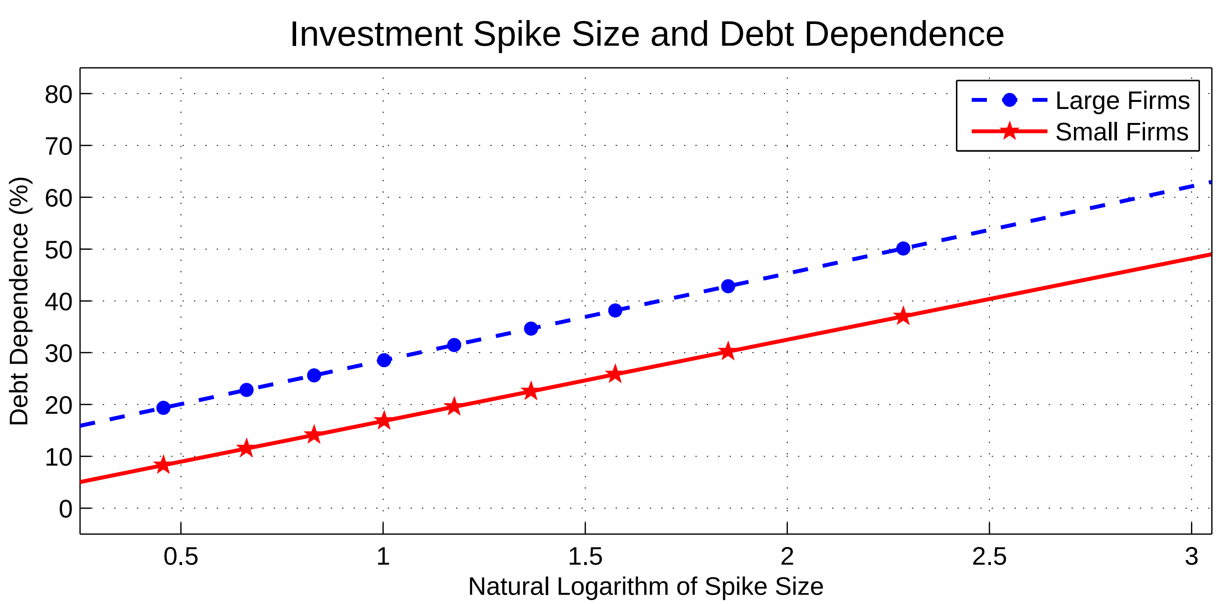


Figure 6. Initial Market Leverage Ratio and External Financing Sources during Investment Spikes

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 the nine deciles of $LEV_{j,\tau=-1}$. Note that this figure is based on the coefficients in OLS regressions rather than BG regressions, so the deciles are based on original initial market leverage ratios, not firm-average ones.