

# **ESSAYS IN CORPORATE FINANCE**

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# Declaration

**I declare that this thesis represents my own work, and that it has not been previously included in a thesis, dissertation or report submitted to this University or to any other institution for a degree, diploma or other qualifications.**

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**NAME: HYUN JOONG IM**

**DATE: 2 JULY 2012**

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# ABSTRACT

This thesis contributes to the empirical literature on how firms meet exceptional financing needs in relation to “investment spikes” or years with unusually large investment activities. In the earlier part of the thesis, I show that the financing of investment during an investment spike is very different from that at other times. I have done this using data for publicly traded US firms over the period 1988 to 2007 and a filtering procedure suggested by Bond *et al.* (2006). Specifically, external finance, in particular debt finance, is very important in financing investment in years categorized as investment spikes, confirming the findings of Mayer and Sussman (2005). In addition, it has been found that firms with smaller size, lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance in relation to large investment requirements. I also propose the use of the Markov-switching filter to identify investment spikes. In implementing the Markov-switching filter, I apply a first-order two-state Markov-switching mean model to the investment rates de-trended using Hodrick and Prescott’s (1997) filter. A Gibbs-sampling procedure is used to produce the marginal posterior distributions of unobserved state variables and model parameters. Among other advantages, this filter allows us to identify multi-year investment spikes. I show that two-year investment spikes identified by the Markov-switching filter are financed quite similarly to single-year investment spikes and that main findings are robust to calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks. In the later part of the thesis, I find there is a positive effect of share liquidity on the propensity to raise debt finance. Using a sample of firm-year observations identified as investment spikes, I find that firms with more liquid shares tend to rely more heavily on debt to finance investment spikes. This result is robust to a control for the effects of firm size and other firm characteristics, the use of various leverage measures, and the use of a whole sample with investment spike characteristics. Another important finding is that firms with more liquid shares tend to have higher target leverage ratios. One interpretation of these results is that information spillovers from the presence of more informative share prices allow firms with more liquid shares to borrow on more favourable terms in normal times, as well as to obtain additional debt finance at lower costs when taking advantage of unusually large investment opportunities.

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# **Part I**

## **OVERVIEW AND BACKGROUND**

# Chapter 1

## Introduction

The lumpiness of investment has been well known to economists since Doms and Dunne's (1998) influential work suggesting that plant-level investment is lumpy, which used plant-level investment data from US Census Bureau micro data files (Caballero *et al.*, 1995; Power, 1994; Cooper *et al.*, 1999). Firm-level investment is found to be less lumpy than plant-level investment because of the aggregation effect, but there is still a large body of literature suggesting that aggregation does not substantially eliminate the lumpiness of firm-level investment (Caballero and Engel, 1999; Doyle and Whited, 2001). In addition, there are several promising theoretical explanations for the lumpiness of investment. Scholars have attempted to explain lumpy investment patterns through the ideas of non-convex capital adjustment costs (Rothchild, 1971), irreversibility of investment (Pindyck, 1991; Dixit, 1995; Dixit and Pindyck, 1994), and external financing costs arising from the presence of financing constraints (Whited, 2006). Nevertheless, the majority of existing empirical corporate finance

studies have not properly taken the lumpiness of investment into account. A widely accepted result is that by far and away the dominant source of finance of firms across different countries and time periods is retained earnings (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this is primarily indicative of how firms finance their routine, replacement investment rather than non-routine, expansion investment.

Mayer and Sussman (2002, 2005) were the first to properly take the lumpiness of investment into account when studying corporate financing behaviour. They found that the financing of investment around investment spikes is very different to the financing of investment at other times and that financing patterns during and after investment spikes are likely to be particularly informative in understanding corporate financial behaviour. They proposed using the flow-of-funds approach combined with a filtering device designed to identify “*investment spikes*” or years with unusually large investment activities. Unlike studies using aggregate data, Mayer and Sussman (2005) established the importance of external sources such as debt and new equity in funding investment spikes. For most firms, the main source appears to be debt, so that leverage ratios typically exceed normal or target level immediately after the investment spike. Following financing patterns after the spike year suggests that leverage ratios are subsequently adjusted downwards, through some combination of net debt repayments and equity issues. Using a structural estimation method, DeAngelo *et al.* (2011) analyse the financing decisions associated with investment spikes and find that, even when leverage is above average, large investment outlays are typically accompanied by substantial debt issuances that increase leverage, confirming Mayer and Sussman’s (2005) major findings.

In Chapter 3, I propose the use of the Markov-switching filter to identify investment spikes. In using Markov-switching filter, I apply a first-order two-state Markov-switching mean model to the investment rates de-trended using Hodrick and Prescott's (1997) filter. A Gibbs-sampling procedure is used to produce the marginal posterior distributions of unobserved state variables and model parameters. Among other advantages, this filter allows us to identify multi-year investment spikes. Some investment projects are so large that they last more than one year. Thus, a single annual accounting period would not necessarily reflect the total expenditure 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 an accounting year. I estimate the filter using Compustat data over the period 1988 to 2007 for 504 firms without any missing values in the period. I find that some 86% of firms have lumpy investment using the filter with the 5% level of significance. I also categorize about 12% of firm-years in the sample as having investment spikes.

In Chapter 4, I examine the financing patterns around investment spikes using data for publicly traded US firms over the period 1988 to 2007 and a new filtering procedure suggested by Bond *et al.* (2006). I investigate the investment-weighted proportions of financing sources as shares of base-level investment for periods around 5,528 investment spikes for which source-of-funds data are available for five-year event windows, confirming the finding of Mayer and Sussman (2005) that the financing of investment during an investment spike is very different to the financing of investment at other times. The share of investment financed by external sources is much higher than the share of investment financed from internally generated funds.

More importantly, I find that the share of investment financed by long-term debt is much higher than the share of investment financed from equity finance. I also show that these findings are robust to the use of different thresholds, the use of the Markov-switching filter suggested in Chapter 3, and the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks. I also find that small firms raise equity finance quite substantially during investment spikes, whereas large firms chiefly rely on debt finance during investment spikes.

In addition, firms with lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance when confronted with large investment requirements. I also find that investment spikes involving acquisitions tend to be funded by a higher proportion of debt finance, although they tend to be spikier than investment spikes involving only capital expenditures. A further investigation of the relationship between the magnitude of investment spikes and financing patterns suggests that the financing patterns of large firms are consistent with the pecking-order theory (Myers and Majluf, 1984), whereas the financing patterns of small firms are consistent with the reverse pecking order which can be predicted with endogenous information production (Fulghieri and Lukin, 2001). An analysis of the relationship between initial leverage and the financing of investment spikes reveals that financing patterns around investment spikes are not consistent with the classical trade-off theory of debt, but are quite consistent with the predictions of a dynamic trade-off theory augmented with investment spikes as outlined in DeAngelo *et al.* (2011).

Chapter 5 extends this line of research to examine whether the financing of investment

spikes varies with share liquidity using the same data and methodology used in Chapter 4. Specifically, I investigate whether there are significant differences in the financing of investment spikes for these sub-samples of US firms classified by share liquidity measured in the year before investment spikes. The most important finding is that low-liquidity firms tend to raise substantial amounts of new equity finance during investment spikes, whereas high-liquidity firms tend not to rely on new equity issuances. Even in the periods before and after investment spikes, low-liquidity firms tend to issue some new equity, but high-liquidity firms tend to buy back existing shares. Another finding is that shares of small firms tend to be less liquid and shares of large firms tend to be more liquid, although the share liquidity of medium-sized firms is symmetrically distributed. This partly explains why the financing patterns of high-liquidity (low-liquidity) firms are similar to those of large (small) firms. This analysis motivated me to investigate the effect of share liquidity on the propensity to raise debt finance more thoroughly, which appears as Chapter 6.

In Chapter 6, I aim to examine whether share liquidity increases the propensity to raise debt finance after controlling for the size of investment spikes and various firm characteristics, and through which channels this works. My main finding is that firms with more liquid shares tend to rely more heavily on debt to finance investment spikes. While it is the case that larger firms also tend to have more liquid shares, this pattern does not simply reflect differences in firm size. Using a sample of firm-year observations identified as spike years, I estimate a dynamic regression specification relating the change in leverage in that year to initial leverage, a set of standard controls for influences on target leverage ratios, and measures of the size of the

investment spike. Positive coefficients on the spike size measures reflect the tendency of firms to increase borrowing in order to finance these investment spikes. More importantly, I find that firms with more liquid shares tend to increase borrowing more than firms with less liquid shares, when financing a spike of a given size. In my specification, this is reflected in a positive coefficient on an interaction term between spike size and an indicator for above-median share liquidity, based on two alternative share liquidity measures. Controlling for share liquidity, I find little additional information in firm size, suggesting that patterns previously attributed to firm size may in fact reflect differences in share liquidity. Another finding of this study is that firms with more liquid shares also tend to have higher normal or target leverage ratios. This is found using the whole sample of data for publicly traded US firms over the period 1988–2007 and is also found to be robust to controlling for firm size and other firm characteristics. Thus, I conclude that high-liquidity firms have a higher propensity to raise debt finance.

I then examine the underlying mechanisms through which this works. This study finds the strongest support for the information spillover and credit rating explanations as to why high-liquidity firms have a higher propensity to raise debt finance. Firms with more liquid shares are less likely to have problems arising from asymmetric information between informed investors including firm managers and uninformed investors. Therefore, firms with more liquid shares are likely to have more informative share prices. In addition, it is likely that there is more publicly available information on high-liquidity firms because those firms are followed by a relatively large number of financial analysts and the shares of those firms are owned by a relatively large number of financial institutions. Therefore, banks can monitor those firms

more efficiently by supplementing their own information with publicly available information such as share prices. Due to the lower monitoring costs, banks would thus propose lower borrowing costs to firms with more liquid shares. Moreover, firms with more liquid shares tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, those firms have lower costs of raising debt finance in subsequent periods and are likely to raise relatively more debt finance to finance large investment requirements.

My thesis is organized as follows. Part I, which consists of Chapter 1 and Chapter 2, provides the overview and background of the thesis. The literature related to lumpy investment and its implications, algorithms to identify investment spikes, empirical literature on financing patterns, and estimation of speed of leverage adjustment are discussed in Chapter 2. Part II, which includes Chapter 3 and Chapter 4, is concerned with a filtering technique and the financing of investment spikes. In Chapter 3, I propose the Markov-switching filter to identify investment spikes and investigate the statistical properties of this filter. In Chapter 4, I investigate the financing patterns around investment spikes according to sub-groups based on a number of criteria, such as firm size, other firm characteristics, spike size, and initial leverage. In addition, I explore the sensitivity of the results to the choice of significance level in the Regression filter and the use of the Markov-switching filter. Part III, which consists of Chapter 5 and Chapter 6, extends this line of research, focusing on differences in financing behaviours between firms whose shares are more or less liquid. I investigate the effect of share liquidity on the flow of funds around investment spikes in Chapter 5, while I investigate the effect of share liquidity on the change in leverage during an investment spike in Chapter 6. Finally, Part

IV, consisting of Chapter 7, concludes and outlines some important and interesting extensions for future research.

# Chapter 2

## Related Literature

*“Investment by manufacturing plants is characterized by periods of intense investment activity interspersed with periods of much lower investment activity.”*

Doms and Dunne (1998)

*“By focusing on large investment events, we do not throw away information; On the contrary, we prevent firms in ‘repayment regimes’ from contaminating inferences about firms in ‘investment regimes’, thereby enhancing the power of the tests.”*

Mayer and Sussman (2005)

This chapter summarizes the existing literature related to this thesis. First of all, I review the literature related to lumpy investment and its implications for how to study financing patterns. Using a hypothetical example which motivates the development of the filtering technique, I explain why large investment events or investment spikes are highly informative. Second, I discuss the filters to identify investment spikes from the pool of large investment episodes

and routine replacement investment periods. Third, I briefly summarize the empirical findings based on aggregate data and those based on flow-of-funds data combined with a filtering technique. Finally, I summarize the empirical literature on the speed of leverage adjustment and deal with econometric issues regarding the estimation of the speed of leverage adjustment.

## **2.1 Lumpy investment and its implications**

There is established empirical evidence that investment is lumpy. Several empirical studies such as Caballero *et al.* (1999), Power (1994), Cooper *et al.* (1999), and Doms and Dunne (1998) have found a great deal of lumpy adjustment using the plant-level investment data from US Census Bureau micro data files. One of their major findings is that investment by manufacturing plants is characterized by periods of intense investment activity interspersed with periods of much lower investment activity. According to Doms and Dunne (1998), more than half of the plants in their sample experience a one-year capital adjustment of at least 37%. They also report that, in a given year, 80% of the plants change their net capital stock less than 10% and these relatively small changes account for 52% of the total sample investment. Doms and Dunne (1998) provide the evidence for within-plant lumpy investment patterns by comparing the mean capital growth rates by rank from the sample with those for the values from a simulation with  $(S, s)$  behaviour. In the simulation model, the larger the trigger levels, the lumpier investment is. The simulation model which best fits the observed data has a trigger level substantially different from zero and this suggests that the observed investment data is very lumpy. They also find that there is substantial heterogeneity in investment patterns.

The firm-level investment may be less volatile than plant-level investment because of the aggregation effect but there is a large body of literature suggesting that firm-level investment is still lumpy. Bloom *et al.* (2007) find that a smaller proportion of observations with zero investment are found in the firm-level data compared with more disaggregated data such as the single plant or establishment level. However, Bertola and Caballero (1994), Caballero and Engel (1999), Abel and Eberly (2002), and Doyle and Whited (2001) show that aggregation does not eliminate the impact of lumpy micro-investment decisions for more aggregated investment dynamics. Whited (2006) also finds that the lumpiness of investment is due not only to the costs of adjusting capital stock but also to external financing costs. In both the simulated data from the theoretical model and the data from the sample used in her paper, the investment spike hazard is upward sloping for both financially constrained and financially unconstrained firms<sup>1</sup>. However, the slope of the spike hazard of constrained firms is less steep. These results provide evidence of lumpy adjustment at the firm-level investment, although this interpretation may be blurred in large firms due to aggregation effects<sup>2</sup>.

Moreover, there are several promising theoretical explanations. Standard neoclassical investment models based on assumptions such as convex adjustment costs and reversibility predict that firms continuously and smoothly adjust their capital stock over time. These models generally fail to adequately explain investment fluctuations and this has entailed the re-examination of potentially unrealistic assumptions of convex adjustment costs and reversibil-

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<sup>1</sup>Whited (2006) grouped firms into a priori constrained firms and a priori unconstrained firms based on size (small firms vs. large firms), belonging to a conglomerate (small single-segment firms vs. same-size segments of conglomerates), and distribution policy (firms with a consistent history of no cash distributions vs. other firms).

<sup>2</sup>It should be noted that the firm-level data, rather than plant-level data, should be used to investigate the firms' choices to fund investment activities, given that financing decision is made by the Chief Financial Officer of the whole company and that financial statements do not provide any breakdown of financing sources by plants.

ity. From early on, Rothchild (1971) argued that adjustment costs faced by plants and firms possess non-convexities for such reasons as increasing returns, costs of the equipment, costs associated with disruption, and cost of installation. More recently, investment models with irreversibility have received a great deal of attention (see Pindyck (1991), Dixit (1995), and Dixit and Pindyck (1994)). Models with non-convex adjustment costs and irreversibility predict that firms occasionally adjust their capital stock in discrete bursts when the capital stock falls below a trigger level. Whited (2006) also find that the lumpiness of investment is due not only to the costs of adjusting capital stock or irreversibility of investment but also external financing costs. By estimating the investment spike hazard using both the simulated data from the theoretical model and the data from the sample used in her paper, she found evidence of lumpy investment.

Does knowing that firm-level investment is lumpy affect the way of answering the question? This can be answered by analysing the following hypothetical example. Table 2.1 is a slightly modified version of Mayer and Sussman's (2005) hypothetical example. Consider two firms A and B that finance a project costing 300. Both firms undertake lumpy investment projects which are too large to be financed from internal sources in a single year. However, the financing patterns of the two firms are quite different. Firm A is internally financed; it accumulates liquid assets to pay for capital expenditure and executes the project once it has sufficient cash. Firm B is largely externally financed; two-thirds of the amounts needed (i.e. 200 out of 300) is funded by external sources. Considering A and B altogether, 200 out of 600 (one-third) is funded by external sources. Hence, a correct summary statistic should indicate that one-third

of investment amounts is externally financed<sup>3</sup>.

[Insert Table 2.1 Here.]

Panel A describes the hypothetical situation explained above. It should also be noted that the data set in Panel A is actually a panel data set composed of investment and flow-of-funds data with  $N=2$  and  $T=3$ , where  $N$  is the number of firms and  $T$  is the length of time periods. Hence, there are six firm-year observations. Panel A also describes the effects of aggregating observations in time-dimension. Time aggregation implies that external flow of fund to both firms is zero<sup>4</sup>. Panel B shows the effects of aggregating all firm-year observations in the sample in both time- and cross-sectional dimensions. Using the aggregate flow-of-funds data is equivalent to aggregating in this way. This aggregated data also shows that their investment is only internally funded when in fact Firm B is externally financed. Hence, the weighted average of financing proportions for all firm-year observations in the panel data set may be misleading in the direction of exaggerating the importance of internal financing. Panel C shows the effects of filtering. The main idea of filtering is to filter out only investment spikes from the pool of lumps and bumps of investment. It is clear that only two firm-year observations, (A,3) and (B,1), are investment spikes in this hypothetical example. The summary statistics such as the sum and weighted average work correctly in the sample of lumpy investments only; one-third (200 out of 600) of lumpy investments are externally financed. To summarize, flow-

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<sup>3</sup>In this example, it may be regarded somewhat strange to calculate average financing proportions because we are considering only two heterogeneous firms. However, if we consider the real world, we can assume that there are a lot of Type A and Type B firms. In this case, the summary statistics will actually tell us what proportion of firms are Type A and Type B, if we assume that there are only two type of firms.

<sup>4</sup>Aggregating across time is problematic but this is not very interesting because these aggregated data are not commonly used.

of-funds data aggregated in both the time- and cross-sectional dimensions cannot answer what proportion of total investment spending is externally financed. To answer this question, we need to identify large investment years. By focusing on large investment years, we prevent the observations of the firms in “savings regimes<sup>5</sup>” or “repayment regimes<sup>6</sup>” from contaminating inferences about the observations of the firms in “investment regimes” such as (A,3) and (B,1).

Large investment years or “investment spikes” are highly informative for the following reasons. First, investment spikes have attractive statistical properties. For example, one can analyse whether internal funds are accumulated prior to the spikes or whether external funds are raised during the spikes. In addition, when external financing is required, the type of financing (debt financing or equity financing) and the post-spike flows of finance can be used to test hypotheses about capital structure. More importantly, Mayer and Sussman (2005) argue that we can enhance the power of tests by focusing on investment spikes:

*“By focusing on large investment events, we do not throw away information; On the contrary, we prevent firms in ‘repayment regimes’ from contaminating inferences about firms in ‘investment regimes’, thereby enhancing the power of the tests.”*

Second, investment spikes are the focus of most modern corporate finance theory. Typically, a theoretical model starts by specifying a setting in which a penniless entrepreneur is endowed with an indivisible investment project and assets in place (e.g. Myers and Majluf (1984) and Fulghieri and Lukin (2001)). Therefore, investment spikes provide a more appropriate

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<sup>5</sup>The examples are the firm-year observations (A,1) and (A,2).

<sup>6</sup>The examples are the firm-year observations (B,2) and (B,3).

setting for testing many theories, irrespective of their frequency. Third, investment spikes are interesting in their own right. According to Doms and Dunne (1998), in a 1987 Census of 358,567 manufacturing plants, the top 1000 plants (0.28%) account for 41% of the survey's total investment, whereas the bottom 308,567 plants (86.06%) account for only 6.5% of total investment (see Table II in Doms and Dunne (1998)). They also note that the investment spikes occur at critical points, such as change in ownership and change in industry (see Table III in Doms and Dunne (1998)).

## **2.2 Existing algorithms to identify investment spikes**

To restrict our attention to investment spikes, we need a “filter” to identify only investment spikes from the pool of both large investment episodes and routine replacement investments that firms regularly undertake. There is no selection bias as long as the estimates for financing patterns are interpreted as being conditional upon the spikes. Therefore, the question of how investment is financed can be precisely answered using the firm-level flow-of-funds data combined with a filtering device to identify investment spikes (see Mayer and Sussman (2005)). This new method which will be categorized as an example of “event studies” eliminates a potential bias caused by the merging of routine and non-routine investment periods. Nevertheless, designing a convincing filter is not as straightforward as it might seem. There have been two strands of research attempting to identify investment spikes, although the literature on this area is scarce compared with that on empirical and theoretical explanations of the lumpiness of investment. This shows that the empirical studies based on the assumption that

capital adjustments are frequent and continuous have not yet been revised, in spite of abundant evidence for lumpy investment.

### 2.2.1 Simple rules

The first strand of research uses simple rules such as absolute, relative, or combined spike criteria and includes Power (1994, 1998), Cooper *et al.* (1995, 1999), and Nilsen *et al.* (2009). Power (1994) has an extensive treatment of the definitions, causes and consequences of investment spikes. Nilsen *et al.* (2009) provide a summary of the definitions of investment spikes traditionally used in the literature. The following three definitions of investment spikes are found in the literature<sup>7</sup>:

(i) *Absolute spike criterion*: If investment rate<sup>8</sup> exceeds the absolute threshold, the investment is defined as an investment spike. The most commonly used threshold is 20% (see Cooper *et al.* (1999)). The absolute spike criterion focuses on large but potentially frequent investments. However, this criterion is not suitable for identifying sporadic bursts of investment that are not large in an absolute sense.

(ii) *Relative spike criterion*: If investment rate exceeds the median investment rate or normal investment rate by a factor which is generally set between 1.5 and 3, the investment is

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<sup>7</sup>Power (1998) also provides the definition of a multi-year investment spike. Some investment projects are so large they last more than one year. Thus, a single annual accounting period would not necessarily reflect the total expenditures necessary to complete the project. Furthermore, even a year-long project need not start at the beginning of an accounting year nor reach completion by the end of an accounting year. A multi-year spike occurs if absolute or relative spike criteria are satisfied for several consecutive years.

<sup>8</sup>The most commonly used measure of investment rates are “Total Investment to Total Assets Ratio” and “Fixed Investment to Fixed Capital Ratio”.

defined as an investment spike (see Power (1998)). The relative spike criterion focuses on unusual and potentially disruptive bursts of investment activity, although they may not be particularly large in an absolute sense. However, this criterion is not suitable for identifying smooth and potentially large expansions. Whited (2006) also follows this criterion.

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

## **2.2.2 Filters to identify investment spikes**

The second strand of research takes more proactive approaches in the sense that they design filters to capture investment spikes rather than apply a simple rule. Mayer and Sussman (2005) suggest 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 as defined in Equation 2.1. The filter suggested by Mayer and Sussman (2005) is similar to the relative spike in the sense that the investment is more likely to be categorized as an investment spike if the investment is significantly greater than the base-level investment. However, it is different from the simple relative spike criterion for the following reasons. First, the relevant range is the surrounding five-year period rather than the whole sample period. The surrounding five-year period might be more appropriate to judge whether the candidate investment is significantly greater than surrounding years because Mayer and Sussman (2005) use investment amounts data rather than investment rates data. Second, the final decision is based on a measure of the goodness-of-fit of each five-year investment sequence around a spike candidate to the benchmark spike pattern.

Bond *et al.* (2006) suggested two alternative filters defined on the five-year investment sequences. The first alternative simply selects a spike candidate as an investment spike if it is at least double the base level of investment. The second alternative regresses investment data for each five-year period on a constant, a linear trend, and a dummy variable for the middle year of the period. Then, a candidate investment is classified as an investment spike if the coefficient of the dummy variable is positive and statistically significant at the 5% level, regardless of the magnitude of the coefficient. The second filter proposed by Bond *et al.* (2006) has an advantage in that it uses a statistically interpretable threshold, i.e. a significance level such as 0.01, 0.05 and 0.10. A more detailed discussion of those filters presented in Mayer and Sussman (2005) and Bond *et al.* (2006) is provided below.

### A. Mayer–Sussman filter

Let  $I_{it}$  be the level of investment spending for firm  $i$  at time  $t$ , for  $i = 1, 2, \dots, N$  and  $t = 1, 2, \dots, T_i$ , where  $N$  represents the total number of firms in our whole sample. Let  $I^j$  be the  $j$ -th five-year investment sequence for  $j = 1, 2, \dots, J$ , where  $J$  represents the number of every possible complete five-year investment sequence that can be generated from our whole sample. The column vector  $I^j$ , for  $j = 1, 2, \dots, J$ , is equivalent to the vector  $(I^{j1}, I^{j2}, I^{j3}, I^{j4}, I^{j5})'$  where  $I^{j\tau}$ , for  $\tau = 1, 2, 3, 4, 5$  represents the investment data in the  $j$ -th column and  $\tau$ -th row of the  $5 \times J$  matrix of every possible five-year investment sequence.

The filter suggested by Mayer and Sussman (2005) produces a decision on whether an investment spike candidate is categorized as an investment spike or not based on the closeness of an actual investment sequence to a benchmark investment pattern. An investment spike candidate is defined as the third investment observation,  $I^{j3}$ , in each five-year event window with  $I^j = (I^{j1}, I^{j2}, I^{j3}, I^{j4}, I^{j5})'$ , for  $j = 1, 2, \dots, J$ . For each investment spike candidate,  $I^{j3}$ , the base level of investment  $b^j$ , for  $j = 1, 2, \dots, J$ , is calculated as the simple average for the four adjacent surrounding years:

$$b^j = \frac{(I^{j1} + I^{j2} + I^{j4} + I^{j5})}{4}. \quad (2.1)$$

A benchmark investment spike pattern is defined to be a five-year investment sequence that closely follows the pattern

$$(b^j, b^j, \gamma b^j, b^j, b^j)' \quad (2.2)$$

where  $b^j$  is the off-spike base level of investment, for  $j = 1, 2, \dots, J$ . The choice of  $\gamma$  is arbitrary but  $\gamma \geq 2$  was stipulated by Mayer and Sussman (2005).

For each  $I^j$ , for  $j = 1, 2, \dots, J$ , we construct a residual vector  $u^j = (u^{j1}, u^{j2}, u^{j3}, u^{j4}, u^{j5})'$ , for  $j = 1, 2, \dots, J$  where

$$u^{j\tau} = \begin{cases} \min(0, I^{j\tau} - 2b^j) & \text{for } \tau = 3 \\ I^{j\tau} - b^j & \text{for } \tau = 1, 2, 4, 5 \end{cases} \quad (2.3)$$

so that these residuals measure deviations from the benchmark spike pattern outlined in Equation (2.2). The criterion,  $ER^j$ , for  $j = 1, 2, \dots, J$ , is defined as

$$ER^j = \frac{\sqrt{u^{j'} u^j}}{5b^j} \quad (2.4)$$

where  $u^{j'} u^j$  represents the sum of squared residuals and  $b^j$  is strictly positive.

This criterion penalizes the squared deviations of actual investment from this pattern. The investment spike candidates,  $I^{j3}$ , for  $j = 1, 2, \dots, J$ , with low values are classified as investment spikes. The cut-off value is somewhat arbitrary, and Mayer and Sussman (2005) used 0.25 and Bond *et al.* (2006) used 0.15. The Mayer–Sussman filter is very intuitive but the filter has some shortcomings. First, the threshold is not only arbitrarily determined but also it is not statistically interpretable. Second, the Mayer–Sussman filter does not use any sort of detrending. If there is a linear trend in an investment sequence, the criterion over-penalizes the squared deviations from the benchmark spike pattern.

## B. Linear regression filter

Bond *et al.* (2006) suggested a filter based on a linear regression with a constant, a linear trend and a dummy variable for the middle year of a five-year event window. They classify as investment spikes any period for which the coefficient on this dummy variable is positive and statistically significant at the 5% significance level. This filter has a statistically interpretable threshold and takes a linear trend in the investment sequence into account.

The filter for single investment spikes processes every possible five-year sequences of investment data,  $I^j = (I^{j1}, I^{j2}, I^{j3}, I^{j4}, I^{j5})'$ , for  $j = 1, 2, \dots, J$ , and produces a dummy variable for investment spikes. As in the Mayer–Sussman filter, the investment spike candidate is defined as the third investment observation,  $I^{j3}$ , in each five-year event window with  $I^j = (I^{j1}, I^{j2}, I^{j3}, I^{j4}, I^{j5})'$ , for  $j = 1, 2, \dots, J$ . Whether the investment spike candidate  $I^{j3}$  is an investment spike or not is based on the sign and significance of the coefficient of a dummy variable for investment spike candidate in a regression of each five-year investment sequence on a constant, a linear trend, and a dummy variable for the investment spike candidate. That is, a candidate investment is classified as an investment spike if the coefficient of the dummy variable for the candidate investment is positive and statistically significant at a conventional level of significance, say 5%, regardless of the magnitude of the coefficient. A more detailed description of the filter is provided below.

First of all, each five-year sequence of investment data,  $I^j = (I^{j1}, I^{j2}, I^{j3}, I^{j4}, I^{j5})'$ , for  $j = 1, 2, \dots, J$ , is regressed on a constant, a linear trend, and a dummy variable for the investment spike candidate  $I^{j3}$ . The multiple linear regression for identifying single investment spikes

can be expressed compactly as

$$y = X\beta + \varepsilon \quad (2.5)$$

with the vectors  $y$ ,  $\beta$ , and  $\varepsilon$  and the matrix  $X$  specified as follows:

$$y = \begin{pmatrix} I^j1 \\ I^j2 \\ I^j3 \\ I^j4 \\ I^j5 \end{pmatrix} \quad (2.6)$$

$$X = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 1 & 3 & 1 \\ 1 & 4 & 0 \\ 1 & 5 & 0 \end{pmatrix} \quad (2.7)$$

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \quad (2.8)$$

and

$$\varepsilon = \begin{pmatrix} \varepsilon^{j1} \\ \varepsilon^{j2} \\ \varepsilon^{j3} \\ \varepsilon^{j4} \\ \varepsilon^{j5} \end{pmatrix} \quad (2.9)$$

In Equation (2.7), each of the three column vectors of the matrix  $X$ ,  $(1, 1, 1, 1, 1)'$ ,  $(1, 2, 3, 4, 5)'$ , and  $(0, 0, 1, 0, 0)'$  is used to model the effects of the constant, the linear trend and the dummy variable for the investment spike candidate, respectively. Therefore,  $\beta_1$ ,  $\beta_2$  and  $\beta_3$ , in Equation (2.8) represent the intercept, the coefficient for the time trend and the coefficient for the dummy variables for the investment spike candidate,  $I^{j3}$ , respectively.

The second step is to execute a one-sided  $t$ -test for  $\beta_3$ , the coefficient for the dummy variables for the investment spike candidate,  $I^{j3}$ . The null and alternative hypotheses are  $H_0 : \beta_3 = 0$  and  $H_1 : \beta_3 > 0$ , respectively. Under the null hypothesis, the statistic

$$t_3 = \frac{\hat{\beta}_3}{se_3} \quad (2.10)$$

follows a Student  $t$ -distribution with  $(T - K) = 2$  degrees of freedom, since  $T = 5$  and  $K = 3$ . The final decision about whether the investment spike candidate is an investment spike or not is made based on the result from the one-sided  $t$ -test at the 5% significance level. That is, a candidate investment is classified as an investment spike if the coefficient of the dummy variable for the candidate investment is positive and statistically significant at the 5%

significance level, regardless of the magnitude of the coefficient. Other significance levels such as 1% and 10% can be used.

## **2.3 Empirical literature on financing patterns**

### **2.3.1 Studies using aggregate data**

There has been a series of research after Mayer (1988) leading to a profound revision of academic thinking about the financing patterns of corporations in different countries (see Figure 2.1 for Mayer's (1988) empirical results). A major finding was that internal financing was the dominant source of financing in countries such as France, Germany, Japan, the UK and the USA. In addition, it was found that debt financing exercised a much more important role in external financing than equity financing. The most striking result is that net retirements of equity were observed in the US in 1980s. In addition, financing patterns were not very different among countries. Mayer's (1988) result is due to his use of national net-flow-of-funds data. This approach has advantages in that financing patterns are not distorted by *i*) degree of consolidation of accounts, *ii*) reciprocal arrangements between borrowers and lenders, and *iii*) compensating deposit requirements on borrowers, and inflation correction is provided by using flow rather than stock figures.

In line with Mayer's (1988) results, Corbett and Jenkinson (1997) confirmed the importance of internal financing in the UK, the US, Germany and Japan and the minor role of equity financing, concluding that the celebrated distinction between the market-based financial pattern

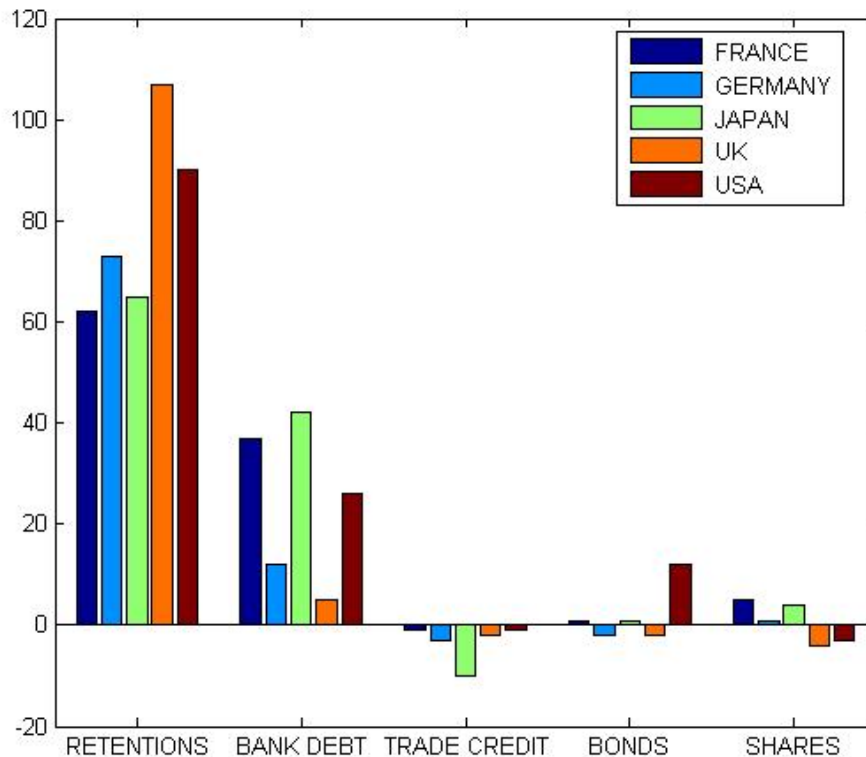


Figure 2.1: Net financing of private physical investment (Source: Mayer, 1988)

of the UK and the US and the bank-based pattern of Germany and Japan is inaccurate (see Table 2.2 for Corbett and Jenkinson's (1997) results based on US national accounting data). Corbett and Jenkinson (1997) provide some detailed discussion of some important issues, such as the comparison of stocks and flows and the advantages and disadvantages of national income accounting data over firm-level financial statement data. First, they emphasize that the flow of funds should be investigated to understand how investment has been funded. The argument for this is that investment is a flow concept and hence the most appropriate data are the associated flows of funds. Furthermore, they argue that the commonly used leverage ratios such as the ratio of debt to total capital are less relevant in understanding financing patterns

of investment. Finally, they suggest that the choice between national accounting data and company accounting data should follow our research question at hand. The national accounting data is more appropriate to answer the question of how domestic financial markets have performed in funding aggregate investment whereas the company accounting data is more appropriate to answer the question of how individual firms raise their spending in investment activities.

[Insert Table 2.2 Here.]

Rajan and Zingales (1995) also found only a minor role for equity issues in financing capital formation and again affirmed the relative importance of debt financing in external financing. They analyse the choice of financing with flow-of-funds data in addition to stock-based measures of capital structure. A problem with capital structure data is that it does not distinguish between internal equity and external equity, although the costs associated with these two forms of finance are very different (Myers and Majluf, 1984). One of their findings is that external finance is not higher than internal finance for the US, the UK, Japan and Canada. They argue that the reason why US firms increased their leverage despite little external finance is because external finance consists entirely of debt. Indeed, 102% of external finance was raised through net debt issuance, whereas -2% of external finance was raised through net equity issuance in the US in the 1980s (see Table 2.3 for the results).

[Insert Table 2.3 Here.]

However, Tirole (2006) argues that this does not mean that the volume of equity issues was negligible relative to that of debt issues. Rajan and Zingales (1995) report that, in their sample

of US firms for the 1984–1986 period, equity issuance amounted to 65% of external financing while equity reduction accounted for 68% of external financing, meaning that the net equity issuance was negative and basically all external financing was debt financing. External financing over the 1984–1986 period was typically small. External finance dependence computed as the ratio of the net external financing to the sum of cash flow from operations and net external financing amounted to 14% over the 1984–1986 period. Rajan and Zingales (2003) also report that the fraction of gross fixed capital formation raised via equity in 1999 was 12% in the US.

There has been a debate over the usefulness of the net-flow-of-funds approach since Hackethal and Schmidt's (2003) criticism of a large body of literature using the aggregate net flow of funds. In response to this, Corbett *et al.* (2005) defended the “net” flow approach by reemphasizing the purpose of aggregate financing pattern studies mentioned above and discussing potential problems with the “gross” flow-of-funds approach suggested in order to overcome a problem inherent in aggregate data by Hackethal and Schimidt (2003). This paper also recognized that a more important issue concerned with the use of aggregate flow-of-funds is the merging of routine and non-routine investments periods. To overcome this problem, Mayer and Sussman (2005) propose a filter for identifying investment spikes. Corbett *et al.* (2005) also recognize that aggregate studies cannot answer many of the questions that corporate finance theories are interested in addressing, such as, for example, financing of investment projects, acquisitions or financial distress. Finally, they suggest the use of firm-level flow-of-funds data combined with some filtering device to identify investment spikes in order to answer these sort of questions.

### **2.3.2 Studies using flow-of-funds data with a filtering technique**

There are not abundant studies which link investment spikes with firms' financing patterns. Unlike the findings of studies using aggregate data, Mayer and Sussman (2005) and Bond *et al.* (2006) found the importance of external sources such as debt and new equity in funding investment spikes. Note that, to some extent, this finding is inevitable. If the level of investment spending in periods identified as investment spikes typically exceeds the level of available internal funds, the difference must be financed using one or more of the external sources. However, it is also possible that a firm accumulates liquid assets for several years to pay for its investment spending and executes the lumpy investment project once it has sufficient cash. Therefore, it is still worthwhile to investigate how important external financing is in funding investment spikes. In addition, what sources of external finance are more commonly used is a more interesting question. Furthermore, it is also interesting to investigate the flow of funds before and after investment spikes.

[Insert Table 2.4 Here.]

Mayer and Sussman (2005) find that external sources of finance, and particularly debt, are much more important in financing corporate investment in periods when the firm's investment spending is unusually high. Using data for publicly traded non-financial US firms, they confirm that in most periods, most of the investment required for replacement and trend growth is financed internally, with very small contributions from both new equity and debt. Particularly for larger firms, the share of investment financed by debt is found to be much higher in periods characterized as investment spikes. They also find that debt finance is less important

in periods immediately after investment spikes, suggesting that debt–assets ratios adjust back towards some underlying target (see Table 2.4 for the flow-of-funds results reported in Mayer and Sussman (2005)).

Huang *et al.* (2007) take the same approach to examining the financing decisions of firms by evaluating the financing response of firms to large perturbations in cash flow requirements. Although the perturbations in cash flow are very different from those in investment, the financing patterns are very similar. Firms with larger and longer cash flow shortages tend to rely more on equity finance than debt finance. After the perturbations, firms gradually adjust their leverage back towards their previous level by repaying debt and issuing equity. They conclude that financing patterns during a perturbation are consistent with a pecking-order theory of finance, whereas the adjustment after a perturbation is consistent with a trade-off theory.

Similarly, Bond *et al.* (2006), using UK data, find that debt finance is more important in years of investment spikes than in normal periods, and also that debt finance is less important in the period immediately after investment spikes. They also find that differences in firm's technologies, measured through the presence of R&D programmes, Tobin's Q, or total factor productivity relative to industry norms, may be less important for explaining differences in financing patterns at the time of investment spikes than in normal periods.

## 2.4 Estimation of speed of leverage adjustment

A large body of literature such as Fama and French (2002), Flannery and Rangan (2006), Kayhan and Titman (2007), Lemmon *et al.* (2008), Huang and Ritter (2009), and Chang and Dasgupta (2009) study the speed of leverage adjustment to the target leverage, but differences in the estimated speed of adjustment are mainly due to the choice of estimation methods, as has been noted by Huang and Ritter (2009). Table 2.5, drawn from Huang and Ritter (2009), shows the estimated annual speed of adjustment toward target leverage per year in the existing empirical capital structure literature. The speed of adjustment is estimated as one minus the estimated coefficient on the lagged leverage ratio ( $1 - \hat{b}_1$ ) in a dynamic panel regression such as Equation (2.33) in Appendix 2.A.1. As in Lemmon *et al.* (2008) and Chang and Dasgupta(2009), the leverage half-life, which is the number of years required for a deviation from the target to be halved, is computed as  $\ln(0.5)/\ln(\hat{b}_1)$ .

[Insert Table 2.5 Here.]

Fama and French (2002) and Kayhan and Titman (2007) use an ordinary least squares (OLS) estimator and report that the speed of a capital structure adjustment is around 10%, reflecting a sluggish adjustment, whereas Flannery and Rangan (2006) use a Fixed Effects estimator (Within Groups estimator) and report that more than one third of the gap between last year's leverage and this year's target leverage is closed within a year, reflecting a prompt adjustment. Lemmon *et al.* (2008), who use System GMM estimator, report that the speed of adjustment is around 25% and Huang and Ritter (2009), using Long Differencing estimator, report that the speed of adjustment is around 17%. The results are consistent with the predictions of Nickell

(1981) and Bond (2002)<sup>9</sup>. In this setting, consistent estimates can be obtained using Generalized Method of Moments (GMM) estimators such as a difference GMM and/or a system GMM<sup>10</sup>. Appendix 2.A.1 provides details on a partial adjustment model with rational expectations, focusing on a derivation of a partial adjustment rule and an empirical specification to estimate the speed of adjustment.

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<sup>9</sup>A pooled OLS estimator is likely to produce  $\hat{b}_1$  that are biased upwards, indicating more persistence and lower capital adjustment speed (i.e. lower  $\hat{\gamma}$ ) than its true value. This is due to the fact that the unobserved firm effects  $\eta_i$  will necessarily be positively correlated with the leverage ratio in the previous period  $L_{i,t-1}$ . On the contrary, the fixed effects (FE) estimator is likely to generate  $\hat{b}_1$  that are biased downwards when the length of periods  $T$  is not large enough. This indicates less persistence of leverage or faster capital adjustment speed (i.e. higher  $\hat{\gamma}$ ) than the true value. The within transformation used to eliminate the unobserved firm-specific effects from the model causes the correlation between the transformed lagged dependent variable and the transformed error term to be negative. The correlation disappears as the number of time periods in the sample increases, but is likely to produce important biases in short panels. As a result, the estimated coefficients on all the explanatory variables  $b_2$  are also likely to be biased using both an OLS estimator and an FE estimator (see Nickell (1981) and Bond (2002) for more details on the short panel biases).

<sup>10</sup>The following summary is due to Bond *et al.* (2006a). “The difference GMM estimator, suggested by Anderson and Hsiao (1981) and developed by Arellano and Bond (1991), eliminates the unobserved firm effects by first-differencing the model. This process introduces shocks from the previous period into the error term of the transformed equations and therefore the transformed error term is correlated with the transformed lagged dependent variable. However, provided the shocks in the dynamic specification are serially uncorrelated, the lagged levels of the dependent variable from two or more years in the past are available as valid instrumental variables for the lagged dependent variable in the first-differenced equations. Other explanatory variable in the first-differenced equations may also need to be instrumented with past values, if the current levels of these variables are correlated with the previous year’s shock to the leverage ratio; they can act as valid instruments for themselves if there is no feedback from past shocks of this kind. Although difference GMM estimators are consistent provided the instruments are valid, the instruments become weak if the series are highly persistent (Blundell and Bond, 1998). In this case, the system GMM estimator, proposed by Arellano and Bover (1995) and Blundell and Bond (1998), is potentially more efficient than the difference GMM estimator. This estimator augments the system of equations in first-differences with additional equations in levels and uses the lagged first-difference of the dependent variable as instruments for the equations in levels. The second-order serial correlation test suggested by Arellano and Bond (1991) is used to test if the error term is serially correlated and the standard Sargan/Hansen test of over-identifying restrictions to test the validity of the instrument sets used.”

## 2.A Appendix

### 2.A.1 A partial adjustment model with rational expectations

#### A. Derivation of a partial adjustment rule

In this section, a partial adjustment model with rational expectations is described. The partial adjustment models used in Flannery and Rangan (2006) and Lemmon *et al.* (2008) are equivalent to assuming that observed exogenous variables follow random walks in the partial adjustment model with rational expectations. To derive a partial adjustment rule, I extend Kennan's (1979) empirical framework into a panel data setting by introducing an error component representing unobserved firm heterogeneity. Due to the existence of both unobserved heterogeneity and dynamics, an estimation procedure becomes quite complicated. Suppose that each firm  $i$ ,  $i \in \{1, 2, \dots, N\}$ , makes a sequence of capital structure decisions  $L_{it}$  designed to chase a stochastic target variable  $L_{it}^*$ . The actual leverage  $L_{it}$  is observed and the target leverage  $L_{it}^*$  is linearly related to observed exogenous variables related to the benefits and costs of various levels of leverage ratios  $X_{it}$ :

$$L_{it}^* = X_{it}'\alpha + U_{it}, \quad (2.11)$$

$$U_{it} = \mu_i + \delta_t + v_{it}, \quad (2.12)$$

where  $\alpha$  denotes a parameter vector reflecting the desired relationship between the vector  $X_{it}$  and  $L_{it}^*$ . The error term  $U_{it}$  consists of three components:  $\mu_i$  represents unobserved firm heterogeneity,  $\delta_t$  denotes white noise reflecting time effects, and  $v_{it}$  denotes further white noise reflecting the influence of omitted variables on  $L_{it}^*$ . It is assumed that  $U_{it}$  is realized before  $L_{it}$  is decided, which implies

$$E_t U_{t+s} = \begin{cases} \mu_i + \delta_t + v_{it} & \text{if } s = 0, \\ \mu_i & \text{if } s = 1, 2, 3, \dots, \end{cases}$$

since

$$E_t \mu_i = \begin{cases} \mu_i & \text{if } s = 0, \\ \mu_i & \text{if } s = 1, 2, 3, \dots, \end{cases}$$

$$E_t \delta_{t+s} = \begin{cases} \delta_t & \text{if } s = 0, \\ 0 & \text{if } s = 1, 2, 3, \dots, \end{cases}$$

and

$$E_t \nu_{i,t+s} = \begin{cases} \nu_{it} & \text{if } s = 0, \\ 0 & \text{if } s = 1, 2, 3, \dots. \end{cases}$$

The capital structure decision may be subject to disturbances such as mistakes or unexplained difficulties in implementing the planned leverage ratio. Let these disturbances be represented by  $V_{it}$ :

$$L_{it} = L_{it}^p + V_{it}, \quad (2.13)$$

$$V_{it} = \kappa_t + \varepsilon_{it}, \quad (2.14)$$

where  $L_{it}^p$  denotes the planned value of  $L_{it}$ . The error term  $V_{it}$  consists of two components: white noise  $\kappa_t$  which varies with time only<sup>11</sup> and white noise  $\varepsilon_{it}$  which varies with both firm and time. The error term  $V_{it}$  and its components are realized after  $L_{it}^p$  is selected and are assumed to have zero expectations:

$$E_t V_{i,t+s} = E_t \kappa_{t+s} = E_t \varepsilon_{i,t+s} = 0, \quad \forall s \geq 0. \quad (2.15)$$

Suppose each firm's financial manager's objective is to minimize the expected present value of a quadratic loss function:

$$\min_{L_{it}^p} E_t \sum_{t=1}^{\infty} \beta^t [\omega_{i1} (L_{it} - L_{it}^*)^2 + \omega_{i2} (L_{it} - L_{i,t-1})^2] \quad (2.16)$$

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<sup>11</sup>In some years, it might be easier or harder than in other years to implement the planned values due to financial market situations or changes in financial regulations.  $\kappa_t$  captures this possibility.

where  $\beta (= 1/(1+r))$  is a known and constant discount factor. The first component of this loss function is a disequilibrium cost, the second component is an adjustment cost, and the ratio  $\omega_i = \omega_{i1}/\omega_{i2}$  measures the relative importance of these costs, assuming  $\omega_{i2}$  is not zero. Each firm's decision is taken separately but the subscript  $i$  is included, first, to stress that the hyper-parameters such as  $\omega_{i1}$  and  $\omega_{i2}$  could be different across firms and, second, to make this clearly linked with the process for the stochastic target variable  $L_{it}^*$ .

Differentiation of (2.16) with respect to  $L_{it}^P$  gives the following first-order optimality condition for each firm  $i$ ,  $i \in \{1, 2, \dots, N\}$ :

$$\omega_i(L_{it}^P - E_t L_{it}^*) + (L_{it}^P - L_{i,t-1}) - \beta E_t \Delta L_{i,t+1} = 0 \quad (2.17)$$

where  $\Delta L_{i,t+1} \equiv L_{i,t+1} - L_{i,t}$  and  $E_t$  denotes the conditional expectations based on all information at time  $t$ .

In the deterministic case, when the future is known with certainty, the optimality condition can be written as:

$$\left(1 - \frac{1 + \beta + \omega_i}{\beta} L + \frac{1}{\beta} L^2\right) L_{i,t+1} = -\frac{\omega_i}{\beta} L_{it}^*, \quad t \geq 1, \quad (2.18)$$

where  $L$  is the lag operator. Let the roots of the quadratic expression in (2.18) be  $\lambda_i$  and  $\lambda'_i$ . It is easily seen that both roots are real. Also,

$$\begin{aligned} \lambda_i \lambda'_i &= \frac{1}{\beta} \\ \lambda_i + \lambda'_i &= \frac{1 + \beta + \omega_i}{\beta} \\ (\lambda_i - 1)(\lambda'_i - 1) &= \lambda_i \lambda'_i - (\lambda_i + \lambda'_i) + 1 = -\frac{\omega_i}{\beta} < 0 \end{aligned}$$

As a result, one root is less than unity and the other is greater, so let:

$$\lambda_i < 1 < \lambda'_i = \frac{1}{\beta \lambda_i}. \quad (2.19)$$

Now, the optimality condition (2.18) can be written as:

$$\begin{aligned}
(1 - \lambda_i L)(1 - \lambda'_i L)L_{i,t+1} &= -\frac{\omega_i}{\beta} L_{it}^* \\
(L^{-1} - \lambda'_i)(1 - \lambda_i L)L_{it} &= (1 - \lambda_i)(1 - \lambda'_i)L_{it}^*, \quad t \geq 2 \\
(1 - \lambda_i L)L_{it} &= (1 - \lambda_i) \frac{1 - \frac{1}{\lambda'_i}}{1 - \frac{1}{\lambda'_i} L^{-1}} L_{it}^*, \quad t \geq 2
\end{aligned} \tag{2.20}$$

Substituting  $\frac{1}{\lambda'_i} = \beta\lambda_i$  in (2.19) into (2.20) gives:

$$\begin{aligned}
(1 - \lambda_i L)L_{it} &= (1 - \lambda_i) \frac{1 - \lambda_i \beta}{1 - \lambda_i \beta L^{-1}} L_{it}^*, \quad t \geq 2 \\
&= (1 - \lambda_i) \tau_{it}, \quad t \geq 2
\end{aligned} \tag{2.21}$$

where the long-run target  $\tau_{it}$  is defined as follows:

$$\begin{aligned}
\tau_{it} &= \frac{1 - \lambda_i \beta}{1 - \lambda_i \beta L^{-1}} L_{it}^*, \quad t \geq 1 \\
&= (1 - \lambda_i \beta) \sum_{s=0}^{\infty} \lambda_i^s \beta^s L_{i,t+s}^*
\end{aligned} \tag{2.22}$$

It can also be shown that (2.21) holds for  $t = 1$ .

Thus, writing  $\gamma_i = 1 - \lambda_i$ , the optimal path satisfies the partial adjustment rule:

$$\Delta L_{it} = \gamma_i (\tau_{it} - L_{i,t-1}), \quad t \geq 1 \tag{2.23}$$

As shown in (2.22), the long-run target  $\tau_{it}$  is a geometrically weighted average of current and future values of the desired leverage ratios. The weights are entirely determined by the adjustment coefficient  $\gamma_i$  and by the discount factor  $\beta$ .

Now, by the certainty equivalence theorem, the solution of the stochastic optimization problem (2.16) is a partial adjustment rule as follows:

$$L_{it}^p = \gamma_i \tau_{it} + (1 - \gamma_i) L_{i,t-1} \tag{2.24}$$

where the long-run target is re-defined as:

$$\tau_{it} = (1 - \lambda_i \beta) \sum_{s=0}^{\infty} \lambda_i^s \beta^s E_t L_{i,t+s}^*, \quad (2.25)$$

and  $L_{i,t+s}^* = X'_{i,t+s} \alpha + \mu_i + \delta_{t+s} + \mathbf{v}_{i,t+s}$ .

So, the observed values of  $L_{it}$  will satisfy:

$$L_{it} = \gamma_i \tau_{it} + (1 - \gamma_i) L_{i,t-1} + \kappa_t + \varepsilon_{it}, \quad (2.26)$$

where

$$\tau_{it} = (1 - \lambda_i \beta) \sum_{s=0}^{\infty} \lambda_i^s \beta^s E_t X'_{i,t+s} \alpha + \mu_i + (1 - \lambda_i \beta) (\delta_t + \mathbf{v}_{it}). \quad (2.27)$$

## B. Empirical specification

Now the issue is how to estimate  $E_t X_{i,t+s}$  and this depends on what the stochastic process of  $X_{i,t+s}$  is like. We assume that  $X_{i,t+s}$  follows a random walk process. This is equivalent to assuming that expectation is formed statically in the rational sense. Let us assume that  $\beta = 1$  for simplicity. Then, (2.27) can be written as:

$$\tau_{it} = \gamma_i \sum_{s=0}^{\infty} (1 - \gamma_i)^s E_t X'_{i,t+s} \alpha + \mu_i + \gamma_i (\delta_t + \mathbf{v}_{it}), \quad (2.28)$$

where  $\gamma_i = (1 - \lambda_i)$ . Then,

$$\begin{aligned} L_{it} &= \gamma_i \left\{ \gamma_i \sum_{s=0}^{\infty} (1 - \gamma_i)^s E_t X'_{i,t+s} \alpha + \mu_i + \gamma_i (\delta_t + \mathbf{v}_{it}) \right\} + (1 - \gamma_i) L_{i,t-1} + \kappa_t + \varepsilon_{it} \\ &= (1 - \gamma_i) L_{i,t-1} + \gamma_i^2 \sum_{s=0}^{\infty} (1 - \gamma_i)^s E_t X'_{i,t+s} \alpha + \gamma_i \mu_i + \gamma_i^2 (\delta_t + \mathbf{v}_{it}) + \kappa_t + \varepsilon_{it} \\ &= (1 - \gamma_i) L_{i,t-1} + \gamma_i^2 \sum_{s=0}^{\infty} (1 - \gamma_i)^s E_t X'_{i,t+s} \alpha + \mu_i^* + \kappa_t^* + \varepsilon_{it}^*, \end{aligned} \quad (2.29)$$

where  $\mu_i^* = \gamma_i \mu_i$ ,  $\kappa_t^* = \kappa_t + \gamma_i^2 \delta_t$ , and  $\varepsilon_{it}^* = \varepsilon_{it} + \gamma_i^2 \nu_{it}$ . Assuming further that  $\gamma_i$  is constant across firms, i.e.  $\gamma_1 = \dots = \gamma_N = \gamma$ , we obtain

$$L_{it} = (1 - \gamma)L_{i,t-1} + \gamma^2 \sum_{s=0}^{\infty} (1 - \gamma)^s E_t X'_{i,t+s} \alpha + \mu_i^* + \kappa_t^* + \varepsilon_{it}^*, \quad (2.30)$$

where  $\mu_i^* = \gamma \mu_i$ ,  $\kappa_t^* = \kappa_t + \gamma^2 \delta_t$ , and  $\varepsilon_{it}^* = \varepsilon_{it} + \gamma^2 \nu_{it}$ .

If it is assumed that expectations are formed statically in the rational sense<sup>12</sup>,  $E_t X_{i,t+s} = X_{it}$  for all  $s \geq 0$ , and  $E_t X'_{i,t+s} \alpha = X'_{it} \alpha$  for all  $s \geq 0$ . Hence, the optimal decision rule can be written as follows:

$$L_{it} = (1 - \gamma)L_{i,t-1} + \gamma^2 \sum_{s=0}^{\infty} (1 - \gamma)^s X'_{it} \alpha + \mu_i^* + \kappa_t^* + \varepsilon_{it}^*. \quad (2.31)$$

This can be reduced to the following estimable equation:

$$L_{it} = (1 - \gamma)L_{i,t-1} + \gamma X'_{it} \alpha + \mu_i^* + \kappa_t^* + \varepsilon_{it}^*. \quad (2.32)$$

The coefficient  $\gamma$  denotes the speed of adjustment, which measures how fast the firm's actual leverage adjusts to the target leverage. It is expected to lie between 0 and 1, with a higher  $\gamma$  meaning a faster speed of adjustment. For example,  $\gamma = 1$  implies a 100% adjustment towards the target leverage ratio within a year, whereas  $\gamma = 0$  implies no adjustment.

### C. Estimation of the speed of adjustment

The error component  $\kappa_t^*$  can be dropped and instead time dummies can be included to capture the time effects. This can be re-written as the following standard dynamic panel regression

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<sup>12</sup>This is equivalent to assuming that  $X_{i,t+s}$  follows a random walk, in which case  $X_{i,t+s}$  can be written as follows:

$$X_{i,t+s} = X_{i,t+s-1} + e_{i,t+s},$$

where  $e_{i,t+s}$  is white noise. It is clear that expectation  $E_t X_{i,t+s} = E_t X_{it} = X_{it}$  for all  $s \geq 0$ . Nickell (1985) shows a number of examples in which different stochastic processes of expected values are generated from different specifications for the stochastic processes of actual values.

model:

$$L_{it} = b_1 L_{i,t-1} + b_2 X_{i,t} + \eta_i + \xi_{it} \quad (2.33)$$

for  $i = 1, \dots, N$  and  $t = 2, \dots, T$  where  $b_1 = (1 - \gamma)$  and  $b_2 = \gamma\alpha$ . Therefore, the speed of adjustment can be estimated as  $\widehat{\gamma} = 1 - \widehat{b}_1$ . Assume that  $\eta_i$  and  $\xi_{it}$  are independently distributed across  $i$  and have the familiar error components structure, in which:

$$E(\eta_i) = E(\xi_{it}) = E(\eta_i \xi_{it}) = 0 \text{ for } i = 1, \dots, N \text{ and } t = 2, \dots, T \quad (2.34)$$

and

$$E(\xi_{it} \xi_{is}) = 0 \text{ for } i = 1, \dots, N \text{ and } \forall t \neq s. \quad (2.35)$$

The speed of adjustment  $\gamma$  can be estimated consistently using the difference GMM suggested by Arellano and Bond (1991) and/or the system GMM suggested by Blundell and Bond (1998).

Table 2.1: Why is filtering required?

This table is a slightly modified version of Mayer and Sussman's (2005) hypothetical example. Consider two firms A and B that finance a project costing 300. Firm A is internally financed and accumulates liquid assets to pay for capital expenditure. Firm B is largely externally financed. That is, 200 out of 300 (two-thirds) is funded by external sources. Hence, considering A and B altogether, 200 out of 600 (one-third) is funded by external sources. Panel A describes the effects of aggregating observations in time-dimension. Time aggregation suggests that the external flow of funds to both firms is zero. Panel B shows the effects of aggregating all firm-year observations in the sample in both time- and cross-sectional dimensions. This aggregation also suggests that their investment amounts are only internally funded when in fact Firm B is actually externally financed. However, Panel C shows that the filtering can cure this problem. It is clear that only two firm-year observations, (A,3) and (B,1), are investment spikes in this hypothetical example. If we aggregate or average the flow of funds from only investment spikes sample, one-third of external financing is correctly captured.

Panel A. Two hypothetical firms								
Year	Firm A				Firm B			
	1	2	3	Aggr.	1	2	3	Aggr.
Total Investment	0	0	-300	-300	-300	0	0	-300
Internal Sources	+100	+100	+100	+300	+100	+100	+100	+300
Liquid Assets	-100	-100	+200	0	0	0	0	0
External Sources	0	0	0	0	+200	-100	-100	0

Panel B. Aggregation of firm-year observations				
Year	Firms A+B			
	1	2	3	Aggr.
Total Investment	-300	0	-300	-600
Internal Sources	+200	+200	+200	+600
Liquid Assets	-100	-100	+200	0
External Sources	+200	-100	-100	0

Panel C. Aggregation of filtered sample			
(Firm, Year)	Investment Spikes		
	(A,3)	(B,1)	Aggr.
Total Investment	-300	-300	-600
Internal Sources	+100	+100	+200
Liquid Assets	+200	0	+200
External Sources	0	+200	+200

Table 2.2: Net sources of finance (unit: %)—US national accounting data

This table summarizes Table 6 in Corbett and Jenkinson (1997). The following table is based on Flow-of-Funds Accounts (Sector Statements of Saving and Investment for Non-financial Corporate Enterprises) obtained from Federal Reserve System.

	1970-74	1975-79	1980-84	1985-89	1990-94
Internal finance	74.5	91.5	89.6	103.7	109.8
Bank finance	26.6	14.1	12.9	15.0	-4.5
Bond finance	15.7	14.9	10.9	24.8	10.4
New equity	7.3	0.7	-4.8	-29.6	-4.2
Trade credit	-2.8	-5.4	-1.7	-4.7	1.4
Other	-10.8	-8.7	-0.6	1.8	-6.1
Statistical adjustment	-10.4	-6.9	-6.4	-11.1	-6.8

Source: Corbett and Jenkinson (1997)

Table 2.3: Sources of external financing (1984-1991)—Firm-level data

This table summarizes Table IV in Rajan and Zingales (1995). The results are based on the Global Vantage Database. The figures for the various components of external financing are aggregated across all non-financial companies in the country and across all years, then normalized by the net external financing obtained by firms in the country during the period 1984–1991. External dependence is the ratio of net external financing to the sum of cashflow from operations and net external financing. Net debt financing is the sum of net short-term debt issuances and long-term debt issuances less long-term debt reduction. Net equity financing is the issue of both common and preferred stock and conversions of debt to equity less equity reduction.

Country	External Dependence	Composition of External Financing	
		Net Debt Issuance	Net Equity Issuance
United States	0.20	1.02	-0.02
Japan	0.50	0.80	0.20
United Kingdom	0.36	0.55	0.45
Canada	0.30	0.62	0.38

Source: Rajan and Zingales (1995)

Table 2.4: Flow of funds for filtered sample

This table summarizes Table 4 Panel A in Mayer and Sussman (2005). This table reports the flow of funds for the whole filtered sample (535 investment spikes) aggregated at project time  $\tau = -2$  to  $\tau = +2$ . All variables are normalized by the base-level investment  $b^j$  as defined in Equation (2.1). A positive sign indicates a source of funds and a negative sign indicates a use of funds so that all rows add up horizontally to zero. Firm size is measured by  $b^j$ , and the sample is split into three groups with approximately the same number of observations in each. The table reports arithmetic means for each size group.

Sub-sample	$\tau$	Obs.	$I$	Sources of Finance			
				<i>OPR</i>	<i>EQUITY</i>	<i>LTDEBT</i>	<i>OTHER</i>
Large firms	-2	179	-0.96	1.00	0.18	-0.18	-0.03
	-1	179	-1.00	1.20	-0.01	-0.03	-0.16
	<b>0</b>	<b>179</b>	<b>-2.71</b>	<b>1.04</b>	<b>0.01</b>	<b>1.03</b>	<b>0.63</b>
	+1	179	-1.04	1.13	0.04	-0.04	-0.09
	+2	179	-0.99	1.33	-0.32	-0.07	0.05
	Total	179	-6.71	5.69	-0.09	0.72	0.40
Medium-sized firms	-2	178	-0.94	1.02	0.52	-0.06	-0.54
	-1	178	-1.03	1.39	0.41	-0.16	-0.61
	<b>0</b>	<b>178</b>	<b>-2.85</b>	<b>1.36</b>	<b>0.20</b>	<b>1.17</b>	<b>0.12</b>
	+1	178	-1.05	1.25	0.07	-0.04	-0.23
	+2	178	-0.98	1.27	0.01	-0.08	-0.22
	Total	178	-6.85	6.29	1.20	0.84	-1.48
Small firms	-2	178	-0.96	0.85	2.06	-0.54	-1.41
	-1	178	-1.03	1.20	2.57	-0.75	-1.98
	<b>0</b>	<b>178</b>	<b>-3.81</b>	<b>0.78</b>	<b>2.56</b>	<b>0.64</b>	<b>-0.17</b>
	+1	178	-1.01	-0.07	0.59	-0.30	0.79
	+2	178	-0.99	0.13	1.12	-0.65	0.39
	Total	178	-7.81	2.89	8.90	-1.60	-2.38

Source: Mayer and Sussman (2005)

Table 2.5: Estimates of the speed of adjustment in empirical capital structure literature

This table shows the estimated annual speed of adjustment toward target leverage per year and the estimated leverage half-life (i.e. the number of years required for a deviation from target to be halved) in existing empirical capital structure research. The results are based on book leverage.

Paper	Fixed Effects	Estimation Method	Estimates	
			SOA	Half-Life
Fama and French (2002)	No	OLS	10% <sup>a</sup>	6.6 years
Kayhan and Titman (2007)	No	OLS	18% <sup>b</sup>	3.5 years
Flannery and Rangan (2006)	No	OLS	10%	6.6 years
Huang and Ritter (2009)	Yes	Within Groups Estimator <sup>c</sup>	34.2%	1.7 years
Lemmon <i>et al.</i> (2008)	Yes	Long Differencing Estimator <sup>d</sup>	17%	3.7 years
	Yes	System GMM <sup>e</sup>	25%	2.4 years

<sup>a</sup> Dividend-paying firms

<sup>b</sup> Non-dividend-paying firms

<sup>c</sup> a.k.a. Fixed Effects Estimator

<sup>d</sup> Hahn *et al.*'s (2007) Long Difference Instrumental Variables Estimation

<sup>e</sup> Blundell and Bond's (1998) Extended Generalized Method of Moments Estimator

Source: Huang and Ritter (2009)

## **Part II**

# **LUMPY INVESTMENT AND FINANCING PATTERNS**

# **Chapter 3**

## **Lumpy Investment and Filtering**

### **Techniques**

#### **3.1 Introduction**

Mayer and Sussman (2005) proposed a filter to identify investment spikes and investigated the flow of funds around investment spikes in an attempt to precisely answer how investment is financed. They also argue that investment spikes are more informative about corporate financing behaviours for the following reasons. First of all, investment spikes are interesting in their own right since a large proportion of investment is executed in lumps. Second, most corporate finance theory is developed for large and indivisible projects and should be tested on corresponding data. Finally, if firms switch investment regimes and the financing patterns are different across different regimes, then the power of the relevant tests can be enhanced by pre-

venting firms in repayment regimes from contaminating inferences about firms in investment regimes. In this case, pooling the data from two regimes will dilute the sample and obscure results rather than increase the efficiency of the estimation. Bond *et al.* (2006) also have also proposed a new filter based on a linear regression.

However, one potential problem with the existing two filters is that they are designed to capture only one type of lumpy investment pattern, namely  $(0,0,1,0,0)$ , where 1 denotes the year with an investment spike and 0 denotes the year with routine investment. Therefore, they can identify only subsets of large investment years by their construction. Some investment projects are so large that they last more than one year. Thus, a single annual accounting period would not necessarily reflect the total expenditures necessary to complete the project. Furthermore, even a year-long project need not start at the beginning of an accounting year nor reach completion by the end of an accounting year (see Power (1998) for a more detailed discussion on multi-year investment spikes). In this chapter, using several filters designed to identify two-year and three-year investment spikes<sup>1</sup>, I find strong evidence for the presence of multi-year investment spikes.

In this chapter, I propose the use of the Markov-switching filter in order to identify any conceivable patterns of lumpy investment including two-year and three-year investment spikes. The main idea is to apply a Markov-switching mean model to the investment rates detrended using Hodrick and Prescott's (1997) filter. The Gibbs-sampling algorithm is used to estimate unobserved state variables and model parameters, as it has several advantages over the classi-

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<sup>1</sup>Two-year and three-year investment spikes represent  $(0,0,1,1,0,0)$ -type and  $(0,0,1,1,1,0,0)$ -type investment spikes, respectively.

cal maximum likelihood approach. The biggest advantage of the Markov-switching approach is that it provides the statistical inference on the probability of the unobserved states such as investment spikes states. I estimate the filter using Compustat data over the period 1988 to 2007 for 504 firms without any missing values in the period. I find that some 86% of firms have lumpy investment using the filter with the 5% level of significance. I also categorize about 12% of firm-years in the sample as having investment spikes. I also show that the Markov-switching filter has some additional desirable statistical properties compared with the existing filters.

Note that the filtering technique has wide applicability across various economics and management disciplines where the objects of interests have lumpy dynamic patterns, for instance due to non-convex adjustment costs. This filter is applicable wherever the lumpiness comes from. In economics, the lumpy labour adjustments and lumpy capital adjustments are well-known examples. It is also probable that some specific types of those factors might have lumpy adjustment patterns as even more aggregated employment and capital stock have lumpy adjustment patterns. In management studies, there are lots of data series which have lumpy dynamic patterns. Examples include firms' R&D spending, firms' demand for IT facilities, and firms' electricity demand. Therefore, a filtering technique armed with a well-performing filter such as Markov-switching filter could be employed to answer various empirical research questions.

The rest of this chapter is organized as follows. Section 3.2 describes the data and variables and shows that the investment data in the sample is lumpy. Section 3.3 describes the Markov-

switching filter. Section 3.4 presents empirical results. Finally, Section 3.5 concludes.

## 3.2 Data and variables

### 3.2.1 Raw data and data cleaning

I use data from annual consolidated financial statements<sup>2</sup> of non-financial US companies reported in Standard and Poor's Compustat North America Fundamental Annual Dataset for the years 1988 to 2007<sup>3</sup>. I exclude firms whose Standard Industrial Classification (SIC)<sup>4</sup> code is greater than 5999 and smaller than 7000. That is, the firms whose main activity is financial services are dropped to construct the final sample.

All nominal items from the statement of cash flows and income statement and balance sheet items have been deflated to year 2000 dollars using the Gross Domestic Product (GDP) deflator obtained from the International Monetary Fund (IMF) database of country GDP deflators. I only use data from the firms whose fiscal years end in December because GDP deflators are calculated based on GDPs measured at the end of the calendar year<sup>5</sup>. Note that about 66% of US companies in the Compustat population have accounting periods that end in December.

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<sup>2</sup>The majority of companies report the consolidated financial statements, which include both parent and subsidiaries' accounts.

<sup>3</sup>Mayer and Sussman (2005) report that they could not use data prior to 1988 because the "statement of cash flows" replaced "cash statements by sources and uses of funds" from 1988 according to Financial Accounting Standards Boards (FASB) #5.

<sup>4</sup>The SIC, established in 1937, is being replaced by the six-digit North American Industry Classification System, released in 1997. However, certain US government departments and agencies, such as the Securities and Exchange Commission, still use the SIC codes (Source: Wikipedia).

<sup>5</sup>From the next chapter onwards, I use an interpolated GDP deflator if the fiscal year ends in other months than December without dropping those observations, resulting in a larger sample.

As long as there is no evidence that there is a clear difference in investment and financing patterns according to fiscal-year-end month, it is unlikely that there will be any potential sample selection bias due to this decision.

I also performed a minimum level of data cleaning. First, the duplicates checks were performed in such a way that one of the duplicate firm-year observations was dropped. Second, I drop observations if the capital stock estimated with the perpetual inventory method<sup>6</sup> is negative, or if the estimate is different from the book value (*ppent* in Compustat) by more than a factor of four. Third, I drop observations if total assets are negative. Finally, observations are dropped if any variable which constitutes the cash flow identity is missing.

### 3.2.2 Investment rate

The following two investment rates are found in the literature:

(i) *Total Investment to Total Assets Ratio* ( $I_{it}/A_{it}$ ): Total investment spending ( $I_{it}$ ) divided by total assets ( $A_{it}$ ).

(ii) *Fixed Investment to Capital Stock Ratio* ( $i_{it}/K_{it}$ ): Fixed investment spending ( $i_{it}$ ) divided by capital stock at replacement cost ( $K_{it}$ ).

“Total Investment ( $I_{it}$ )” is defined as the total investment spending from all types of investing activities such as net capital expenditures, acquisitions and other investing activities such as investment in equities or bonds which does not involve acquisitions. On the other hand,

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<sup>6</sup>The capital stock at replacement cost ( $K_{it}$ ) is estimated using the perpetual inventory method as outlined in Blundell *et al.* (1992).

“Fixed Investment ( $i_{it}$ )” is defined as net capital expenditures<sup>7</sup>. In this chapter, I use “Total Investment ( $I_{it}$ )” for the filters suggested by Mayer and Sussman (2005) and Bond *et al.* (2006) and “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )” and “Fixed Investment to Capital Stock Ratio ( $i_{it}/K_{it}$ )” for the Markov-switching filter. A detailed description of variables used in the construction of investment rates is provided in the Appendix 3.A.1.

### 3.2.3 Is firm-level investment lumpy?

Table 3.1 shows how lumpy both “Fixed Investment ( $i_{it}$ )” and “Total Investment ( $I_{it}$ )” are. All fixed investment ( $i_{it}$ ) and total investment ( $I_{it}$ ) of the firms with 20 non-missing observations are grouped into 20 groups based on the magnitude of each variable. For example, “Group 1” consists of the largest investment made by each company in its history, whereas “Group 20” consists of the smallest investment made by each company in its history. Although each group has an equal number of investment data, the proportions of each group in the total investment are markedly different. “Group 1” or the first 5% sample accounts for 10.40% and 16.69% in cases of fixed investment ( $i_{it}$ ) and total investment ( $I_{it}$ ) respectively. However, “Group 20” or

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<sup>7</sup>The following relation shows the relation between total investment and fixed investment. The items in italics represent Compustat item codes.

$$\begin{aligned}
 I_{it} &= -ivncf \\
 &= -(-ivch + siv + ivstch - capx + sppe - acq + ivaco) \\
 &= ivch - siv - ivstch + capx - sppe + acq - ivaco \\
 &= (capx - sppe) + acq + (ivch - siv - ivstch - ivaco) \\
 &= CE_{it} + AC_{it} + OI_{it}
 \end{aligned} \tag{3.1}$$

where *ivncf* denotes net cash flow from investing activities, *capx* capital expenditures, *sppe* sale of property, plant & equipment, *acq* acquisitions, *ivch* increase in investments, *siv* sale of investments, *ivstch* change in short-term investments, and *ivaco* other investing activities, respectively.  $CE_{it}$ ,  $AC_{it}$ , and  $OI_{it}$  also represent “net capital expenditure”, “acquisitions”, and “other investments”, respectively.

the last 5% sample accounts for 1.39% and -2.14% respectively. Note that dropping negative investment does not greatly change the results. Similarly, the first 25% sample accounts for 41.81% and 52.56% respectively. It seems that a high proportion of a firm's total investment over a period is concentrated into a small number of years.

[Insert Table 3.1 Here.]

Figure 3.1 shows the distributions of two investment rates such as fixed investment to capital stock and total investment to total assets. This shows that investment is quite skewed to the right because firms have near-zero investment quite often but a very high level of investment intermittently. This also suggests that for many firms a high proportion of total investment expenditure is concentrated into a single year, referred to as an investment spike.

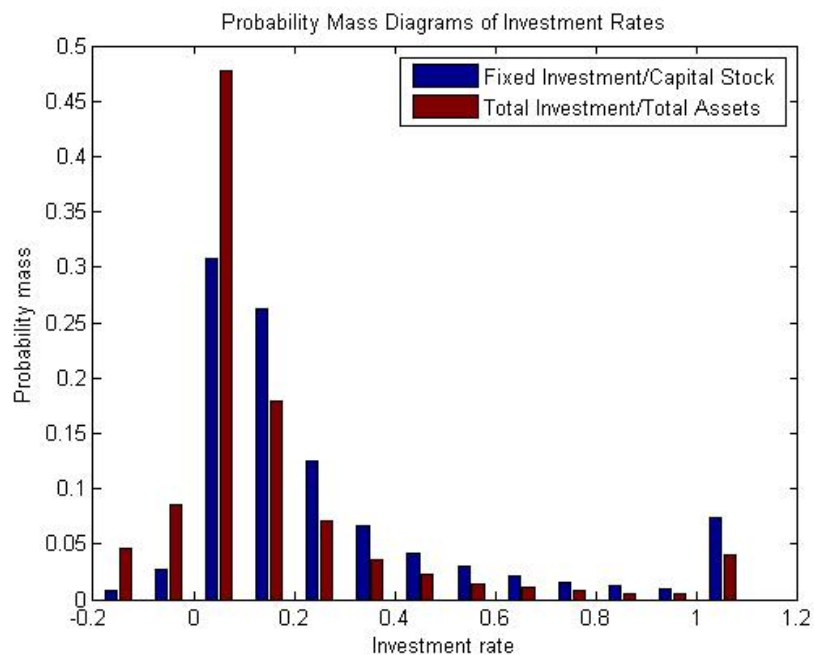


Figure 3.1: Distributions of two investment rates

### 3.3 The Markov-switching filter

The filters suggested by Mayer and Sussman (2005) and Bond *et al.* (2006) can capture only one type of lumpy investment pattern, such as (0,0,1,0,0). However, it is plausible that investment spending can have any possible pattern such as (0,1,0,1,0), (0,0,1,1,0,0), and (0,0,1,1,1,0,0). In fact, some investment projects are so large that they last more than one year. It is also plausible that some firms make unusually high level of investment for several consecutive years for other reasons such as severe competition within the industry. In these cases, one can say that those firms have multi-year investment spikes. To allow any imaginable lumpy investment patterns to be captured, I use a flexible model-based approach to identify investment spikes<sup>8</sup>. The basic idea of a new filter suggested in this section is to apply a Markov-switching mean model<sup>9</sup> to the detrended investment rates.

#### 3.3.1 Input series and detrending

The data used in this approach are two investment rates such as “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )” and “Fixed Investment to Capital Stock Ratio ( $i_{it}/K_{it}$ )” constructed as shown in section 3.2.2. Modelling these investment rates makes the Markov-switching model simpler and more intuitive compared to modelling fixed capital series or total assets series. Once the data is ready, I detrend the investment rates using the Hodrick-Prescott filter

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<sup>8</sup>Introducing a range of dummy variables in the framework of Bond *et al.* (2006) can be a partial solution to the arbitrary specification problem observed in Mayer and Sussman (2005) and Bond *et al.* (2006).

<sup>9</sup>One may consider a Markov-switching mean and variance model but I use a simpler model because this change will increase the number of parameters.

suggested by Hodrick and Prescott (1997). The detrending procedures are implemented separately for the time series of each individual firm  $i = 1, 2, \dots, N$  and therefore the subscript  $i$  is omitted for brevity.

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

$$y_t = \tau_t + c_t, \quad t = 1, 2, \dots, T \quad (3.2)$$

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

$$\min_{\{\tau_t\}_{t=1}^T} \sum_{t=1}^T (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (3.3)$$

where  $\lambda$  is the smoothing parameter<sup>10</sup>. The first term in the loss function penalizes the variance of  $c_t$ , while the second term penalizes the lack of smoothness in  $\tau_t$ . Having solved this minimization problem to arrive at an estimate of the trend, the cyclical component is defined as  $y_t - \tau_t$ .

Although there are some concerns<sup>11</sup> about the use of the Hodrick–Prescott filter, it is now the industry standard when it comes to detrending. As shown in King and Rebelo (1993), the Hodrick–Prescott filter has the ability to successfully detrend any series of an order of integration less than or equal to  $I(4)$ . The data used in the following Markov-switching model

<sup>10</sup>The Hodrick–Prescott filter was implemented using a MATLAB function *hpfilter* in MATLAB Econometrics Toolbox. I set the smoothing parameter as 100 as is recommended for annual data.

<sup>11</sup>See, for example, Harvey and Jaeger (1993) and Cogley and Nason (1994)

is the investment rates detrended using the Hodrick–Prescott filter. The cyclical components of the investment rates  $y_t, t = 1, 2, \dots, T$  are denoted as  $k_t, t = 1, 2, \dots, T$ . Figure 3.2 shows how Hodrick–Prescott detrending works for an example company.

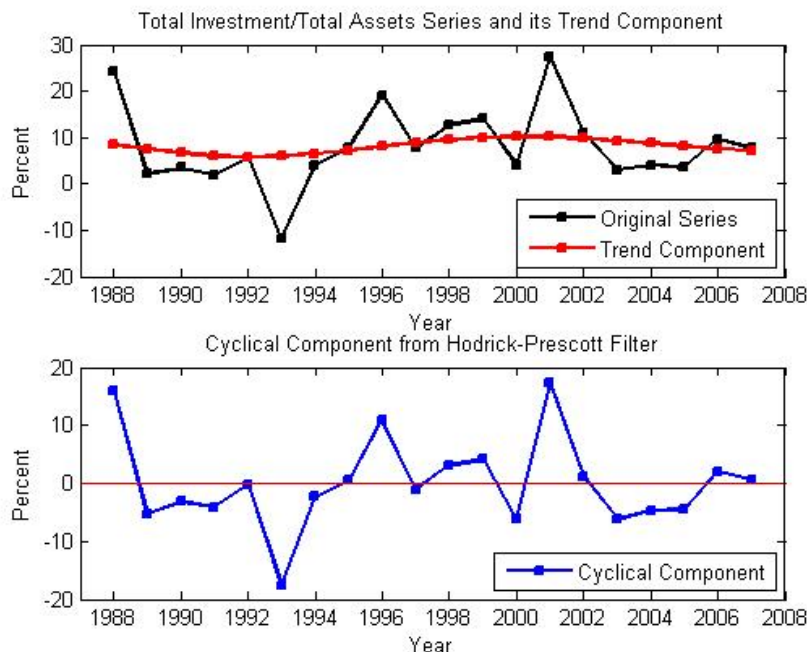


Figure 3.2: Hodrick–Prescott detrending for a standard firm with lumpy investment

### 3.3.2 Model specification

The Markov-switching model is considered a general approach to endogenous structural breaks and has been widely used in various empirical macroeconomics and finance research, including business cycle research, since the seminal work by Hamilton (1989) (see Kim and Nelson (1999)). Identifying investment spikes is in essence similar to identifying endogenous structural breaks in capital stock series or total assets series. The biggest advantage of the Markov-switching approach is that this approach provides the statistical inference on the

probability of unobserved states such as investment spikes states. The model used here is a simplified version of the Markov-switching mean model explained in Kim and Nelson (1999) following Albert and Chib (1993). It is assumed that the investment rates detrended using the Hodrick–Prescott filter are drawn from two normal distributions with different means and homoskedastic disturbances. As suggested by Albert and Chib (1993) for GDP growth rates, I use an  $AR(0)$  structure for the detrended investment rates. I detrend investment rates data using the Hodrick–Prescott filter<sup>12</sup> to make the  $AR(0)$  structure appropriate for the majority of firms in the sample. Therefore, this model is essentially a simplified version of Hamilton’s (1989) Markov-switching  $AR(p)$  model.

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

$$k_t = \mu_{S_t} + e_t \quad (3.4)$$

$$e_t \sim N(0, \sigma^2) \quad (3.5)$$

$$\mu_{S_t} = \mu_0 + \delta S_t \quad (3.6)$$

where  $\mu_1 = \mu_0 + \delta$  and  $\delta > 0$ . The unobserved Markov-switching variable  $S_t$  evolves according

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<sup>12</sup>Some firms might have investment rates of I(1). In this case, using a  $AR(0)$  structure without Hodrick–prescott detrending is not appropriate to model the investment rates.

to a two-state, first-order Markov-switching process with the following transition probabilities:

$$Pr[S_t = 0|S_{t-1} = 0] = q \quad (3.7)$$

$$Pr[S_t = 1|S_{t-1} = 1] = p \quad (3.8)$$

I assume that there are two regimes or two states: "State 0" and "State 1". "State 0" represents the regime of low investment and "State 1" represents the regime of high investment.

### 3.3.3 Estimation procedures

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

Therefore, I use the Bayesian Gibbs-sampling approach to estimate unobserved state variables along with parameters.

As mentioned earlier, the model's unknown parameters,<sup>13</sup>  $\mu_0$ ,  $\delta$ ,  $\sigma^2$ ,  $p$  and  $q$ , along with  $S_t$ ,  $t = 1, 2, \dots, T$ , are treated as random variables. For Bayesian inference about these  $(T + 5)$  variates, the following joint posterior density is required:

$$\begin{aligned}
f(\tilde{S}_T, \mu_0, \delta, \sigma^2, p, q | \tilde{k}_T) &= f(\mu_0, \delta, \sigma^2, p, q | \tilde{k}_T, \tilde{S}_T) f(\tilde{S}_T | \tilde{k}_T) \\
&= f(\mu_0, \delta, \sigma^2 | \tilde{k}_T, \tilde{S}_T) f(p, q | \tilde{k}_T, \tilde{S}_T) f(\tilde{S}_T | \tilde{k}_T) \\
&= f(\mu_0, \delta, \sigma^2 | \tilde{k}_T, \tilde{S}_T) f(p, q | \tilde{S}_T) f(\tilde{S}_T | \tilde{k}_T) \quad (3.9)
\end{aligned}$$

where  $\tilde{k}_T = [k_1 k_2 \dots k_T]'$  and  $\tilde{S}_T = [S_1 S_2 \dots S_T]'$ . Equation (3.9) assumes that, conditional on  $\tilde{S}_T$ , the transition probabilities  $p$  and  $q$  are independent of both the other parameters of the model and the data,  $\tilde{k}_T$ . Conditional on  $\tilde{S}_T$ , equations are simply a regression model with a known dummy variable,  $S_t$ . These conditioning features of the model allow us to employ the simulation tool of Gibbs-sampling for Bayesian inference.

To implement Gibbs-sampling<sup>14</sup>, I need to derive the distributions of the blocks of each of the above  $(T + 5)$  variates conditional on all the other blocks of variates. Thus, using arbitrary starting values for the parameters of the model, the following steps can be repeated until

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<sup>13</sup>The following density function is not affected by replacing  $\delta$  with  $\mu_1$  as  $\mu_1 = \mu_0 + \delta$ .

<sup>14</sup>The Gibbs-sampling procedures were implemented using MATLAB. I am grateful to Chang-Jin Kim for making GAUSS codes for important papers on Markov-switching models available through his web-pages. Kim and Nelson (1999) were extremely helpful when it comes to implementing Markov-switching models with both classical approaches and Gibbs-sampling procedures. I translated the GAUSS codes for Albert and Chib (1993) into MATLAB codes and modified the codes so that the model can be used to identify investment spikes.

convergence occurs. First, I generate a whole block of  $\tilde{S}_T$ <sup>15</sup>. Then, I generate the transition probabilities,  $p$  and  $q$ , from  $f(p, q | \tilde{S}_T)$ . Finally, I generate  $\mu_0, \delta, \sigma^2$  from  $f(\mu_0, \delta, \sigma^2 | \tilde{k}_T, \tilde{S}_T)$ . To constrain  $\delta > 0$ , I use rejection sampling. That is, if the generated value of  $\delta$  is less than or equal to 0, I discard draws. Whenever a legitimate  $\delta$  is generated, I transform it to  $\mu_1$  by simply adding  $\delta$  to  $\mu_0$ . Gibbs-sampling procedures produce the posterior probabilities of the investment-spike state ( $Pr[S_t = 1 | \tilde{k}_T]$ ). The probabilities are then calculated based on 10,000 draws after discarding the first 2,000 draws. Gibbs-sampling procedures also produce the marginal posterior distributions for the five unknown parameters,  $\mu_0, \mu_1, \sigma^2, p$  and  $q$ . The first 2,000 draws of Gibbs-sampling are discarded, and the analysis is based on the every fifth draw among the next 10,000 draws. For more detailed procedures of the Bayesian Gibbs-sampling, refer to Appendix 3.A.2 and Kim and Nelson (1999).

### 3.3.4 Picking investment spikes

Once Gibbs-sampling procedures are completed, the years with investment spikes can be identified. First, I check whether the Markov-switching model for a given firm satisfies the model selection criterion (*MSC*). The model selection criterion is based on the marginal posterior distributions for  $\mu_0$  and  $\mu_1$ ; *MSC* has a value of 1 if the  $(1 - \alpha)$  posterior band for  $\mu_0$ , where  $\alpha$  is the significance level, does not overlap with that for  $\mu_1$  and 0 otherwise. That is, the model satisfies the criteria only if the lower bound of  $\mu_1$  is greater than the upper bound of  $\mu_0$  since  $\mu_1 = \mu_0 + \delta$  and  $\delta > 0$ . This is equivalent to testing the null hypothesis  $H_0 : \delta = 0$  against

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<sup>15</sup>Following Carter and Kohn (1994) and Kim and Nelson (1998), I use Multi-move Gibbs-sampling.

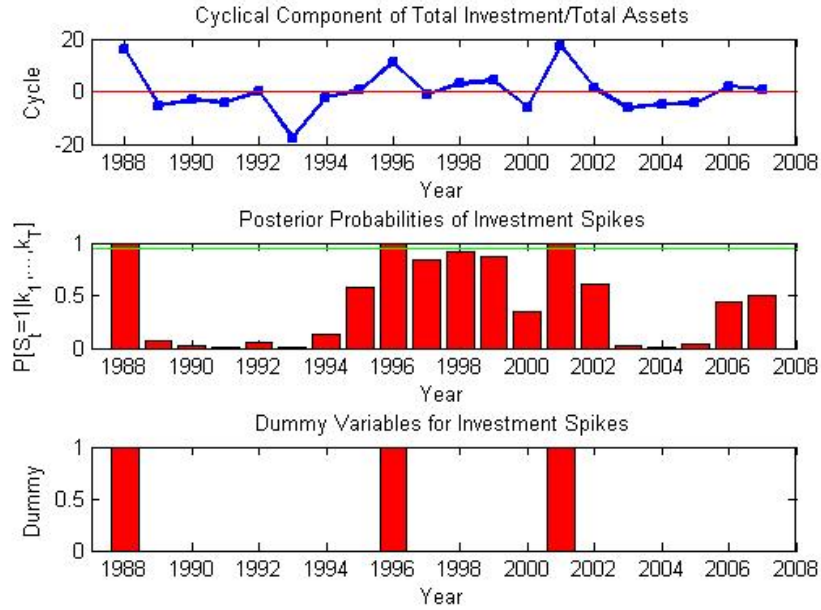


Figure 3.3: Markov-Switching filtering for a standard firm with lumpy investment

the alternative hypothesis  $H_1 : \delta > 0$ . The null hypothesis means that there are no investment spikes for the firm. The next step is to find years with investment spikes based on the posterior probabilities of the investment-spike state ( $Pr[S_t = 1 | \tilde{k}_T]$ ). I select the year as a year with an investment spike if  $Pr[S_t = 1 | \tilde{k}_T] > (1 - \alpha)$  where  $\alpha$  is the level of significance. Hence, at the 5% significance level, all the years where the probability of investment spikes is greater than 0.95 are identified as years with an investment spike.

### 3.4 Empirical analysis

In this section, I report the empirical results. First, I analyse what proportion of firms have lumpy investment. I then discuss the numbers of investment spikes identified by a range of

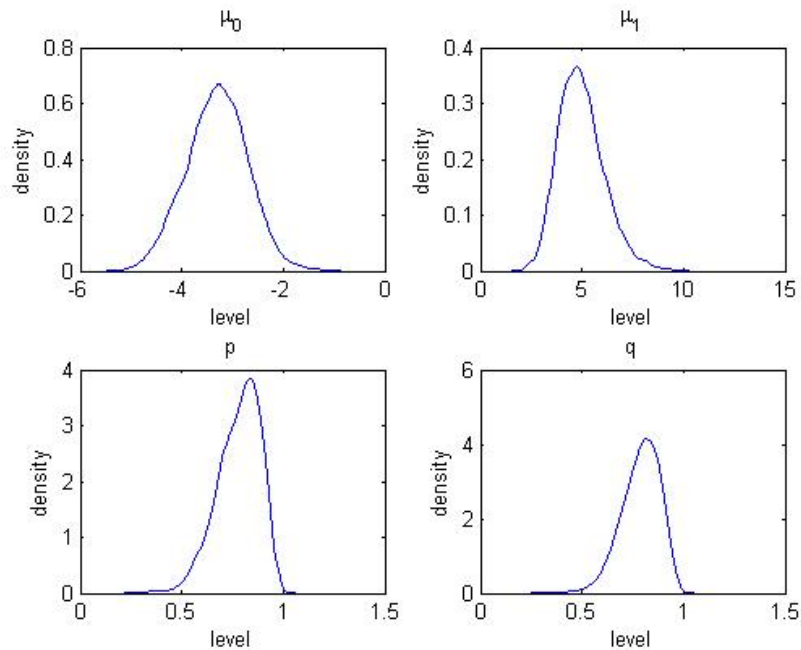


Figure 3.4: Posterior density of parameters for a standard firm with lumpy investment

filters and compare them using the match ratios derived from the  $2 \times 2$  table analysis. I then find evidence that there are a substantial number of multi-year investment spikes. Finally, I investigate which filters might be more appropriate to study the relationship between lumpy investment and business cycles, although this is not a focus of this chapter.

### 3.4.1 Proportion of firms having lumpy investment

#### A. A standard example

Let us review the above-mentioned procedures with an example firm. Table 3.2 summarizes the relevant statistics and outputs for the example firm. Panel A shows the output from the Hodrick–Prescott detrending procedure and the Markov-switching filter. The second column

is the original time series of “Total Investment to Total Assets Ratio”. The third and fourth columns represent the trend and cyclical components from Hodrick–Prescott detrending procedures, respectively. The cyclical component is used as the input of the Markov-switching model. The fifth column represents the probability of investment spikes conditional on all available data  $\tilde{k}_T = [k_1, \dots, k_T]'$ . The last column represents the dummy variable for investment spikes and hence the investments in the years with 1’s are designated as investment spikes. The significance level is given to be 5%, so the dummy variable has a value of 1 if the probability of investment spikes is greater than 0.95. Figures 3.2 and 3.3 graphically illustrate the same procedures with the same example firm.

[Insert Table 3.2 Here.]

Panel B shows the summary statistics for posterior distributions of five parameters. Columns five and six represent the 95% posterior bands for five parameters. Since the 95% posterior bands for  $\mu_0$  and  $\mu_1$  do not overlap, the Markov-switching model satisfies the model selection criteria. Hence, the results in Panel A are acceptable. In addition, the fourth column in Panel B represents the medians. The medians of  $\mu_0$  and  $\mu_1$  are  $-3.30\%$  and  $4.90\%$ . The medians of  $p$  and  $q$  are 0.7858 and 0.7992. This implies that both investment-spike state and low-investment state are quite persistent. Figure 3.4 shows posterior distributions of four parameters, such as  $\mu_0$ ,  $\mu_1$ ,  $p$  and  $q$ , using the Gaussian kernel density function.

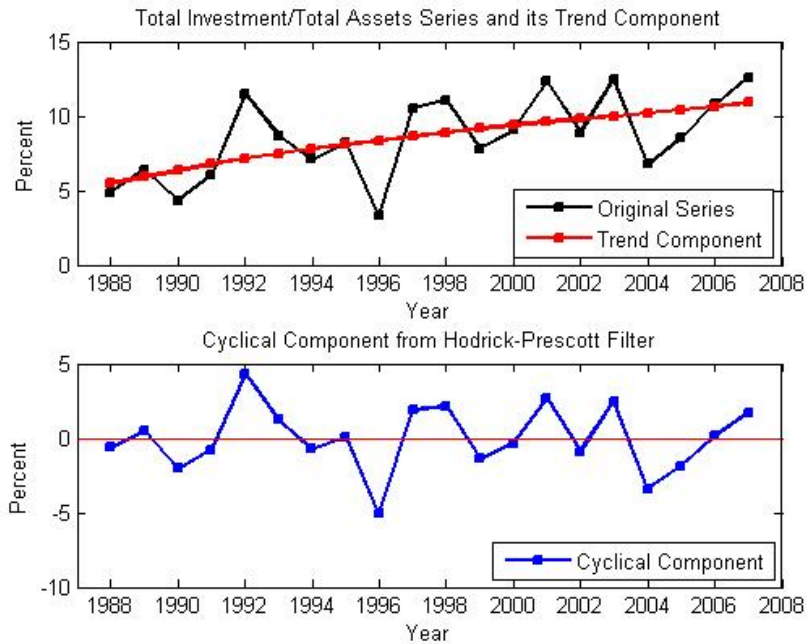


Figure 3.5: Hodrick–Prescott detrending for a firm with non-lumpy investment

### B. A non-standard example

Table 3.3 shows the relevant statistics and outputs from the Markov-switching filter with the data from a non-standard firm with a non-lumpy investment series. Panel A shows the output from the Hodrick–Prescott detrending procedure (see Figure 3.5) and Markov-switching filter (see Figure 3.6). Panel B shows the summary statistics for the posterior distributions of five parameters. Columns five and six represent the 95% posterior bands for five parameters. Since the 95% posterior bands for  $\mu_0$  and  $\mu_1$  overlap, the Markov-switching model does not satisfy the model selection criteria (see Figure 3.7). Therefore, the Markov-switching filter does not identify any investment spikes.

[Insert Table 3.3 Here.]

This type of non-standard example arises when the investment series is quite smooth or quite far from being lumpy. According to Table 3.4, at the 1%, 5%, and 10% levels of significance, 23.61%, 14.48%, and 11.31% of firms do not satisfy the model selection criteria because  $100(1 - \alpha)\%$  posterior bands for  $\mu_0$  and  $\mu_1$  overlap for those firms. Figure 3.5 shows that the trend in the investment rate is close to linear and the variation of the investment rate from this trend is not very large. Figure 3.6 shows that the posterior probability of investment changes over time and the probability does not exceed 95% at all. Furthermore, Figure 3.7 shows that the 95% posterior bands for  $\mu_0$  and  $\mu_1$  overlap. Therefore, there are no investment spikes in relation to this firm.

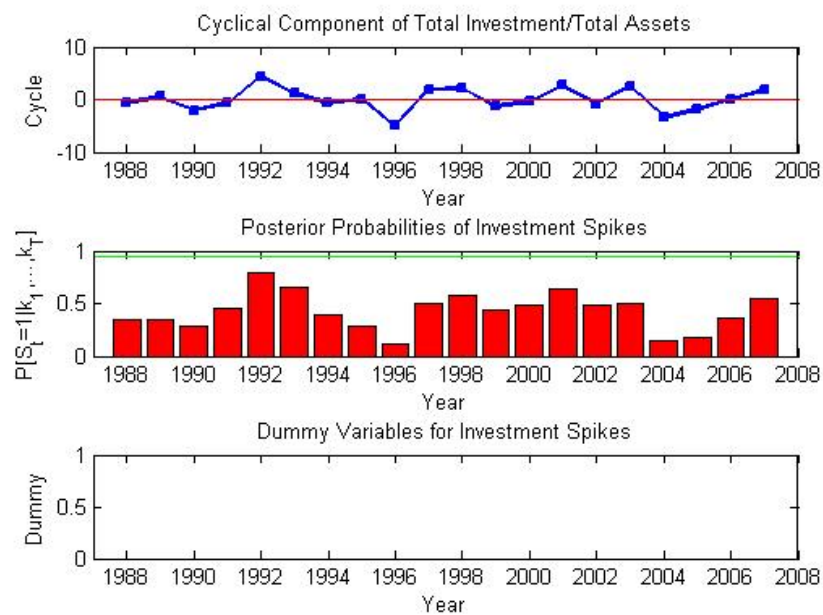


Figure 3.6: Markov-switching filtering for a firm with non-lumpy investment

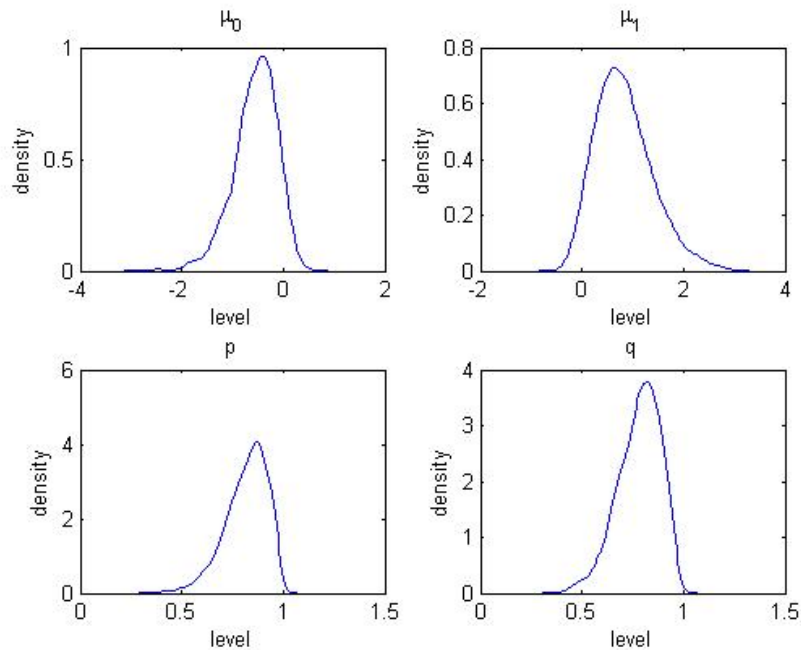


Figure 3.7: Posterior density of parameters for a firm with non-lumpy investment

### C. Summary of filtering results

Table 3.4 shows the summary of the Markov-switching filter with Hodrick–Prescott detrended data. The results are based on 20-year “Total Investment to Total Assets Ratio” data from 504 firms without missing values. Panel A shows how many firms satisfied the model selection criteria among the 504 firms. At 1%, 5% and 10% levels of significance, 76.39%, 85.52%, and 88.69% of firms satisfied the criteria. As expected, a higher proportion of firms meet the criteria when the significance level is higher. It seems that those firms which did not meet the criteria have generally less lumpy detrended investment rates. Panel B shows the means and standard deviations of the median of generated parameters according to the significance level. At a 5% level of significance, the means of  $\text{median}(\mu_0)$  and  $\text{median}(\mu_1)$  are -2.58 and 4.55 respectively. The difference is substantial. The means of  $\text{median}(p)$  and  $\text{median}(q)$  are 0.8010

and 0.7930<sup>16</sup>. This means that both states are highly persistent, which implies there should be a number of multi-year investment spikes and other persistent patterns of lumpy investment. Panel C shows the distribution of the number (proportion) of investment spikes by firm. At a 5% level of significance, the average number of investment spikes is 2.3526 among a total of 20 possible periods and therefore the average proportion of investment spikes is 11.76%.

[Insert Table 3.4 Here.]

### 3.4.2 Comparison of filters using match ratios

In this section, I compare a range of filters such as the Mayer–Sussman filter<sup>17</sup>, Regression-based filter, and Markov-switching filter with Hodrick–Prescott detrending. First, let us consider the numbers and proportions of investment spikes by each filter. The numbers of investment spikes are different depending on the threshold or level of significance. Table 3.5 shows the number of investment spikes identified by three different filters for three different thresholds. Panel A<sup>18</sup> shows the numbers and proportions of investment spikes identified by the Regression filter and the Mayer–Sussman filter for every possible complete five-year investment sequence. The data used for those two filters are “Total Investment ( $I_{it}$ )”. The numbers and proportions of investment spikes are presented according to thresholds or significance

<sup>16</sup>Terms such as  $\text{median}(\mu_0)$ ,  $\text{median}(\mu_1)$ ,  $\text{median}(p)$ , and  $\text{median}(q)$  represent the medians of the posterior distributions of the parameters  $\mu_0$ ,  $\mu_1$ ,  $p$ , and  $q$ , respectively. The medians are regarded as the point estimates of the parameters.

<sup>17</sup>In implementing the Mayer–Sussman filter, I use the investment data detrended using a linear regression on a constant and a linear trend.

<sup>18</sup>In Panel A, the results are from every possible complete five-year investment sequence that can be generated from the whole sample. Hence, the total number of five-year investment sequences,  $J$ , is 34,412. However, the sum of spikes and non-spikes in the Mayer–Sussman filter is 28,634, which is smaller than  $J$ , because the Mayer–Sussman filter requires a strictly positive base level of investment.

levels by filters. In panels A and B, the results are from every possible complete five-year investment sequence that can be generated from the firms satisfying the model selection criteria among 504 firms with 20 years of data. Panel C shows the numbers and proportions of investment spikes identified from the Markov-switching filter with Hodrick–Prescott detrending. Two investment rates such as “Fixed Investment/Capital Stock ( $i_{it}/K_{it}$ )” and “Total Investment/Total Assets ( $I_{it}/A_{it}$ )” are used for this filter. However, it should be noted that the proportion of investment spikes is not severely affected by the choice of input data. However, the results based on “Total Investment/Total Assets ( $I_{it}/A_{it}$ )” might be more comparable to the results based on the other two filters, which use “Total Investment ( $I_{it}$ )”.

[Insert Table 3.5 Here.]

Second, I perform the  $2 \times 2$  table analysis to see whether two different filters have a tendency to have a consistent classification. Let us denote a  $2 \times 2$  table as a  $2 \times 2$  matrix  $\mathbf{X}$ :

$$\mathbf{X} = \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix}$$

The elements  $a_{00}$  and  $a_{11}$  represent the numbers of observations classified identically by both filters whereas the elements  $a_{01}$  and  $a_{10}$  represent the numbers of observations classified differently by two filters. The *Match Ratio*  $MR$  is defined as follows:

$$MR = \frac{(a_{00} + a_{11})}{(a_{00} + a_{01} + a_{10} + a_{11})} \times 100 \quad (3.10)$$

		Mayer-Sussman			Regression filter			Markov-Switching		
		0.15	0.17	0.20	0.01	0.05	0.10	0.01	0.05	0.10
Mayer-Sussman	0.15	100.00%								
	0.17	96.65%	100.00%							
	0.20	89.57%	92.92%	100.00%						
Regression Filter	0.01	92.09%	88.95%	82.09%	100.00%					
	0.05	93.13%	90.63%	84.43%	95.26%	100.00%				
	0.10	93.04%	91.26%	85.88%	91.23%	95.97%	100.00%			
Markov-switching	0.01				91.72%	90.00%	88.13%	100.00%		
	0.05	84.99%	82.92%	78.07%	88.01%	87.34%	86.31%	94.78%	100.00%	
	0.10	83.08%	81.53%	77.49%	85.28%	85.22%	84.62%	90.96%	96.36%	100.00%

Figure 3.8: Comparison of filters using match ratios

Figure 3.8 shows the match ratios for all possible combinations of the three types of filter. One interesting finding is that all three filters match quite closely. In particular, the Mayer–Sussman filter with the linearly detrended data is very closely matched to the Regression filter designed to identify single-year investment spikes based on a linear regression. I could have had a higher match ratio by choosing another set of thresholds. However, the Regression filter has an advantage in the sense that it provides a statistically interpretable threshold, i.e. significance level. The significance level is interpreted as the probability of a Type 1 error. In addition, the Regression filter can correct the problems with the Mayer–Sussman filter when there is a linear trend in investment data. Another advantage is that the model can easily be extended to multi-year investment spikes or other lumpy investment patterns such as  $(0, 0, 1, 0, 1, 0, 0)$  by introducing relevant dummy variables<sup>19</sup>. The Markov-switching filter with Hodrick–Prescott detrending is quite closely matched with both the Regression filter and the Mayer–Sussman filter, although the match ratios with the Regression filter are slightly

<sup>19</sup>However, it should be noted that there are too many imaginable lumpy investment patterns and it is hard to integrate the results for various lumpy investment patterns. In spite of these problems, the Regression filters designed to identify two-year and three-year investment spikes are very useful to test whether there are multi-year investment spikes.

higher than those with the Mayer–Sussman filter. However, this analysis does not tell us which is the better filter out of the three. The potential problems inherent in both the Mayer–Sussman and Regression filters will be discussed in the following sections.

### **3.4.3 Presence of multi-year investment spikes**

In this section, I investigate if a significant number of multi-year investment spikes are identified. Extending the Regression filter to identify single-year investment spikes, I propose three versions of filters to identify two-year investment spikes and a filter for three-year investment spikes<sup>20</sup>. The first version of the filter for two-year investment spikes uses a joint dummy variable indicating the third and fourth investment data points among the six-year investment sequence and makes a final decision based on one  $t$ -test for the coefficient of the dummy variable. The second and third versions use two dummy variables indicating each of the third and fourth investment data points in a given six-year investment sequence. The second version makes a decision based on two  $t$ -tests for the coefficients of two dummy variables and signs of the coefficients of two dummy variables. The third version is based on an  $F$ -test for the joint significance of two coefficients for two dummy variables as well as the signs of the coefficients. The filter for three-year investment spikes is designed by simply extending the first filter for two-year investment spikes. Details on the filters for multi-year investment spikes are provided in Appendix 3.A.3.

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<sup>20</sup>Some investment projects are so large that they last more than one year. It is also plausible that some firms make unusually high level of investment for several consecutive years for other reasons, such as severe competition within the industry.

[Insert Table 3.6 Here.]

The filters explained above successfully capture a significant number of two-year and three-year investment spikes. Table 3.6 shows the number of multi-year investment spikes using the extended regression filters. Panel A<sup>21</sup> shows the number of two-year investment spikes by three different versions of the filters and Panel B<sup>22</sup> shows the number of three-year investment spikes identified by the Regression filter with one dummy variable and one t-test. This table provides very strong evidence that there are a large number of two-year and three-year investment spikes. It also implies that it is likely that there are other patterns of lumpy investment as well. Although the number of two-year investment spikes varies according to the filter used and the significance level, a significant number of two-year investment spikes are captured regardless. What is also interesting is that some three-year investment spikes are found.

Table 3.7 shows the relevant statistics and outputs from the Markov-switching filter with the data from an unusual firm with two two-year investment spikes. Since the 95% posterior bands for  $\mu_0$  and  $\mu_1$  do not overlap, the Markov-switching model satisfies the model selection criteria. Hence, the results in Panel A are acceptable. The medians of  $p$  and  $q$  are 0.7041 and 0.7521. This implies that both investment-spike state and low-investment state are quite persistent. Figure 3.9 also shows the same procedures graphically. Note that this firm has two single-year spikes and two two-year spikes.

[Insert Table 3.7 Here.]

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<sup>21</sup>The total number of all the possible complete six-year investment sequences generated from the whole sample,  $S$ , is 28,716.

<sup>22</sup>The total number of all the possible complete seven-year investment sequences generated from the whole sample,  $P$ , is 23,935.

The evidence for the presence of multi-year investment spikes suggests that the Mayer–Sussman filter and the Regression filter can capture only subsets of the years with large investment activities. Both filters assume there is only one lumpy investment pattern, namely  $(0,0,1,0,0)$ , and therefore they can identify only subsets of lumpy investments by their construction. This result makes necessary a new flexible filter allowing for various types of lumpy investment patterns, such as  $(0,1,0,0,0)$ ,  $(0,0,1,1,0,0)$ ,  $(0,0,1,1,1,0,0)$ ,  $(0,0,1,0,1,0,0)$ , and so forth. The Markov-switching filter has an advantage over the other filters in that the filter is flexible enough to capture any conceivable lumpy investment patterns, including those listed above.

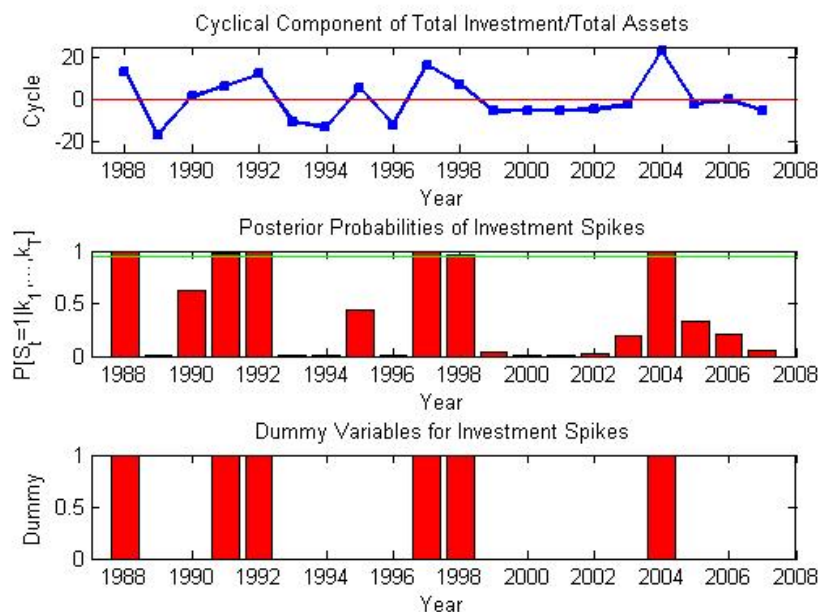


Figure 3.9: Markov-switching filtering for a firm with multi-year investment spikes

### 3.4.4 Proportion of firms with investment spikes and real GDP growth

Table 3.8 shows the proportion of firms with an investment spike by year and the correlation between the proportion and real GDP growth. Panel A shows what proportions of firms have an investment spike each year. These proportions vary depending on which filter and threshold are used. Panel B shows the correlations between the proportions of firms with an investment spike and current and lagged values of real GDP growth. The correlation analysis suggests that the proportions in the case of the investment spikes identified by the Markov-switching and Regression filters are quite highly positively correlated with the current and lagged values of real GDP growth. However, the proportions in the case of the Mayer–Sussman filter are only weakly positively correlated with lagged and current real GDP growth rates. Therefore, the correlation analysis also suggests that the Markov-switching filter and the Regression filter might be more appropriate than the Mayer–Sussman filter to study the relationship between lumpy investment and business cycles<sup>23</sup>.

[Insert Table 3.8 Here.]

Figure 3.10 shows that there is calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks in the case of the Markov-switching filter (Sig. Level=0.05). Some 9% of firms in the sample had an investment spike in 1991 with the lowest real GDP growth rate (-0.2%), whereas some 22% of firms in the sample had an investment spike in 1999 with the highest real GDP growth rate (4.8%). This is quite plausible because it is

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<sup>23</sup>This chapter will be extended to investigate whether financial crises or financial cycles in general have an impact on the incidence of investment spikes and whether a priori financially constrained firms are more likely to have lumpy investment patterns.

likely that more firms incur an investment spike in years with higher operating cash flows and higher availability of external finance. However, it seems that the proportions of firms with investment spikes are relatively less volatile with the Mayer–Sussman filter and the Regression filter. This might be partly because those two filters do not take into account multi-year spikes, which are more likely to occur during periods with more single-year investment spikes and less likely during periods with fewer single-year investment spikes. In Chapter 4, I investigate whether the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks is observed in the larger sample and whether the clustering of spikes has a significant effect on the reliability of the aggregated flow of funds around investment spikes.

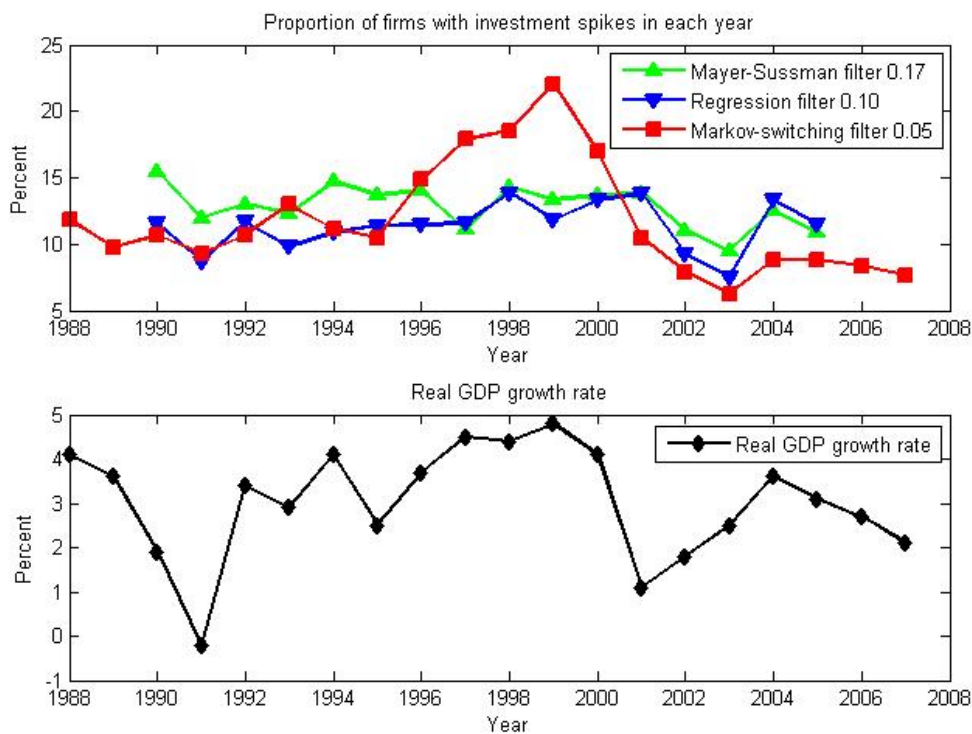


Figure 3.10: Proportion of firms with investment spikes and real GDP growth rate (1)

### 3.5 Conclusions

A filtering technique was first used by Mayer and Sussman (2005) in an attempt to precisely answer how investment is financed. The basic idea is that one can eliminate a potential bias caused by the merging of routine and non-routine investment periods by using the firm-level flow-of-funds data combined with a filtering device to identify investment spikes or years with unusually large investment activities. As Mayer and Sussman (2005) note, investment spikes are highly informative. First of all, investment spikes are interesting in their own right since a large proportion of investment is executed in lumps. Second, most corporate finance theory is developed for large and indivisible projects and should be tested on corresponding data. Most importantly, if firms switch investment regimes and the financing patterns are different across different regimes, then the power of tests can be enhanced by preventing firms in repayment regimes from contaminating inferences about firms in investment regimes. In this case, pooling the data from two regimes will dilute the sample and obscure results rather than increase the efficiency of the estimation.

To make the filtering technique implementable, a reliable filter is required. In this chapter, I show that the filters suggested by Mayer and Sussman (2005) and Bond *et al.* (2006) have some shortcomings by showing the strong evidence for the presence of multi-year investment spikes. Those two filters are based on the assumption that there is only one type of lumpy investment pattern, namely (0,0,1,0,0), and therefore they can identify only subsets of large investment years by their construction. Hence, I propose a new filter based on the Markov-switching mean model. One advantage of the Markov-switching approach is that it provides

the statistical inference on the probability of the unobserved states such as investment spikes states. In addition, I show that both the Markov-switching filter and the Regression filter might be appropriate to study the relationship between lumpy investment and business cycles. One reassuring result from the  $2 \times 2$  table analysis is that, broadly speaking, all three filters match quite closely. Although the Markov-switching filter has some advantages, it has an important disadvantage because it requires a longer period of investment data. Therefore, the Regression filter is used to identify investment spikes in Chapter 4.

A filtering technique armed with a reliable filter such as the Markov-switching filter and the Regression filter has wide applicability across various economics and management disciplines where the objects of interests have lumpy dynamic patterns, for instance due to non-convex adjustment costs. In Chapter 4, using the Regression filter, I show that the summary statistic of financing patterns is biased toward exaggerating the importance of internal resources in funding investment and neglecting the contribution of external financing, especially long-term debt financing, if the filtering technique is not used when investment is lumpy. In addition, I show that those findings are robust to the use of the Markov-switching filter suggested in this chapter. It is my expectation that the results of some previous studies which ignored the lumpiness of investment are at risk of being reversed by using a filtering technique.

## 3.A Appendix

### 3.A.1 Construction of variables

**Total Investment ( $I_{it}$ )** Total investment spending [*ivncf*] deflated to constant 2000 prices.

**Fixed Investment ( $i_{it}$ )** Net capital expenditures deflated to constant 2000 prices; calculated as the capital expenditures [*capx*] less the sale of property, plant and equipment [*spppe*].

**Total Assets ( $A_{it}$ )** Total assets [*at*] deflated to constant 2000 prices.

**Capital Stock ( $K_{it}$ )** The replacement cost of the capital stock is constructed using a standard perpetual inventory method with an assumed depreciation rate of 8%. The benchmark value is obtained from total net fixed assets [*ppent*].

**Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )** Total investment spending ( $I_{it}$ ) divided by Total assets ( $A_{it}$ ).

**Fixed Investment to Capital Stock Ratio ( $i_{it}/K_{it}$ )** Fixed investment spending ( $i_{it}$ ) divided by Capital stock at replacement cost ( $K_{it}$ ).

### 3.A.2 Review of Gibbs-sampling

As mentioned in 3.3.3, Gibbs-sampling procedures require repeating the following three steps using arbitrary starting values until convergence occurs. This section provides more detailed explanation of the three steps, but for more information see Kim and Nelson (1999).

**A. Generate the whole block of  $\tilde{S}_T$  from  $f(\tilde{S}_T | \mu_0, \delta, \sigma^2, p, q, \tilde{k}_T)$ .**

The Multi-move Gibbs-sampling first suggested by Carter and Kohn (1994) and implemented by Kim and Nelson (1998) is used. In Multi-move Gibbs-sampling,  $S_t, t = 1, 2, \dots, T$  are

simulated as a block from the following joint conditional distribution:

$$f(\tilde{S}_T | \mu_0, \delta, \sigma^2, p, q, \tilde{k}_T) \quad (3.11)$$

The following joint conditional density is derived by suppressing the conditioning on the model's parameters  $[\mu_0, \delta, \sigma^2, p, q]$ . The following derivation depends on the Markov property<sup>24</sup> of  $S_t$ .

$$\begin{aligned} f(\tilde{S}_T | \tilde{k}_T) &= f(S_1, S_2, \dots, S_T | \tilde{k}_T) \\ &= f(S_T | \tilde{k}_T) f(S_{T-1}, S_{T-2}, \dots, S_1 | S_T, \tilde{k}_T) \\ &= f(S_T | \tilde{k}_T) f(S_{T-1} | S_T, \tilde{k}_T) f(S_{T-2}, \dots, S_1 | S_T, S_{T-1}, \tilde{k}_T) \\ &= f(S_T | \tilde{k}_T) f(S_{T-1} | S_T, \tilde{k}_T) f(S_{T-2} | S_T, S_{T-1}, \tilde{k}_T) \cdots \\ &\quad f(S_1 | S_T, S_{T-1}, \dots, S_2, \tilde{k}_T) \\ &= f(S_T | \tilde{k}_T) f(S_{T-1} | S_T, \tilde{k}_{T-1}) f(S_{T-2} | S_{T-1}, \tilde{k}_{T-2}) \cdots f(S_1 | S_2, k_1) \\ &= f(S_T | \tilde{k}_T) \prod_{t=1}^{T-1} f(S_t | S_{t+1}, \tilde{k}_t) \end{aligned} \quad (3.12)$$

Hence, as Equation (3.12) suggests, I first need to generate  $S_T$  conditional on  $\tilde{k}_T$ . Then, I need to generate  $S_t$  conditional on  $\tilde{k}_t$  and the generated  $S_{t+1}$ , for  $t = T-1, T-2, \dots, 1$ . For this purpose, the following steps as in Kim and Nelson (1998) are employed:

**STEP 1** Generate  $f(S_t | \tilde{k}_t)$ , for  $t = 1, 2, \dots, T$ , by running Hamilton's (1989) basic filter. The last iteration of the basic filter provides us with  $f(S_T | \tilde{k}_T)$ , from which  $S_T$  is generated.

**STEP 2** Generate  $S_t$  conditional on  $\tilde{k}_t$  and the generated  $S_{t+1}$ , for  $t = T-1, T-2, \dots, 1$ , by

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<sup>24</sup>Conditional on  $S_{t+1}$ , no extra information is contained in  $[S_{t+2}, \dots, S_T]$  and  $[k_{t+1}, \dots, k_T]$

employing the following result:

$$\begin{aligned}
f(S_t|S_{t+1}, \tilde{k}_t) &= \frac{f(S_t, S_{t+1}|\tilde{k}_t)}{f(S_{t+1}|\tilde{k}_t)} \\
&= \frac{f(S_{t+1}|S_t, \tilde{k}_t)f(S_t|\tilde{k}_t)}{f(S_{t+1}|\tilde{k}_t)} \\
&= \frac{f(S_{t+1}|S_t)f(S_t|\tilde{k}_t)}{f(S_{t+1}|\tilde{k}_t)} \\
&\propto f(S_{t+1}|S_t)f(S_t|\tilde{k}_t)
\end{aligned} \tag{3.13}$$

where  $f(S_{t+1}|S_t)$  is the transition probability, and  $f(S_t|\tilde{k}_t)$  has been generated from Step 1. Now I am ready to generate  $S_t$ . First, I calculate  $Pr[S_t = 1|S_{t+1}, \tilde{k}_t]$  as follows:

$$Pr[S_t = 1|S_{t+1}, \tilde{k}_t] = \frac{f(S_{t+1}|S_t = 1)f(S_t = 1|\tilde{k}_t)}{\sum_{j=0}^1 f(S_{t+1}|S_t = j)f(S_t = j|\tilde{k}_t)}. \tag{3.14}$$

Then, I generate  $S_t$ ,  $t = T - 1, T - 2, \dots, 1$ , using a uniform distribution. That is, if a random number drawn from a uniform distribution is less than or equal to  $Pr[S_t = 1|S_{t+1}, \tilde{k}_t]$ , set  $S_t = 1$ . Otherwise, set  $S_t = 0$ .

## **B. Generate the transition probabilities, $p$ and $q$ , from $f(p, q|\tilde{S}_T)$ .**

The transition probabilities,  $p$  and  $q$ , are independent of the data  $\tilde{k}_T$  and the other parameters, conditional on  $\tilde{S}_T$ . Beta distribution is used as conjugate priors for the transition probabilities  $p$  and  $q$ .

### ***Prior Distribution***

I assume that the priors of the transition probabilities  $p$  and  $q$  are the following two independent beta distributions:

$$p \sim \text{beta}(\nu_{11}, \nu_{10}) \tag{3.15}$$

$$q \sim \text{beta}(\nu_{00}, \nu_{01}) \tag{3.16}$$

Then, the joint prior distribution can be written as follows:

$$g(p, q) \propto p^{\nu_{11}-1} (1-p)^{\nu_{10}-1} q^{\nu_{00}-1} (1-q)^{\nu_{01}-1} \quad (3.17)$$

where  $\nu_{ij}$ ,  $j = 0, 1$ , are known hyper-parameters of the priors.

### ***Likelihood Function***

The likelihood function for  $p$  and  $q$  is as follows:

$$L(p, q | \tilde{S}_T) = p^{\omega_{11}} (1-p)^{\omega_{10}} q^{\omega_{00}} (1-q)^{\omega_{01}} \quad (3.18)$$

where  $\omega_{ij}$  refers to the transitions from state  $i$  to  $j$ , which can be counted for given  $\tilde{S}_T = [S_1, S_2, \dots, S_T]$ .

### ***Posterior Distribution***

Combining the joint prior distribution and the likelihood function gives the following joint posterior distribution:

$$\begin{aligned} f(p, q | \tilde{S}_T) &= g(p, q) L(p, q | \tilde{S}_T) \\ &\propto p^{\nu_{11}-1} (1-p)^{\nu_{10}-1} q^{\nu_{00}-1} (1-q)^{\nu_{01}-1} p^{\omega_{11}} (1-p)^{\omega_{10}} q^{\omega_{00}} (1-q)^{\omega_{01}} \\ &= p^{\nu_{11}+\omega_{11}-1} (1-p)^{\nu_{10}+\omega_{10}-1} q^{\nu_{00}+\omega_{00}-1} (1-q)^{\nu_{01}+\omega_{01}-1} \end{aligned} \quad (3.19)$$

Therefore, the posterior distributions for  $p$  and  $q$  are given by the two independent beta distributions:

$$p | \tilde{S}_T \sim \text{beta}(\nu_{11} + \omega_{11}, \nu_{10} + \omega_{10}) \quad (3.20)$$

$$q | \tilde{S}_T \sim \text{beta}(\nu_{00} + \omega_{00}, \nu_{01} + \omega_{01}) \quad (3.21)$$

Now, I can generate  $p$  and  $q$  from the above posterior distributions.

**C. Generate  $\mu_0, \delta, \sigma^2$  from  $f(\mu_0, \delta, \sigma^2, [\tilde{k}_T, \tilde{S}_T])$ .**

**STEP 1: Generate  $\mu_0$  and  $\delta$ , conditional on  $\sigma^2, \tilde{S}_T$ , and  $\tilde{k}_T$ .**

Equations (3.4), (3.5), (3.6) can be rewritten as

$$k_t = \mu_0 + \delta S_t + e_t \quad (3.22)$$

where  $e_t \sim N(0, \sigma^2)$ . Dividing both sides of equation by  $\sigma$ , I get

$$y_t = \mu_0 x_{0t} + \delta x_{1t} + \varepsilon_t \quad (3.23)$$

where  $\varepsilon_t \sim i.i.d. N(0, 1)$ ,  $y_t = (k_t/\sigma)$ ,  $x_{0t} = (1/\sigma)$ ,  $x_{1t} = (S_t/\sigma)$ , and  $\varepsilon_t = (e_t/\sigma)$ . In matrix notation, I have

$$Y = X\tilde{\beta} + \xi \quad (3.24)$$

$$\xi \sim N(0, I_T) \quad (3.25)$$

where  $X = [x_0 \quad x_1]$  and  $\tilde{\beta} = [\mu_0 \quad \delta]'$ .

### ***Prior Distribution***

A normal prior is used for  $\tilde{\beta}$ .

$$\tilde{\beta} | \sigma^2 \sim N(b_0, \Sigma_0) \quad (3.26)$$

where  $b_0$  and  $\Sigma_0$  are known.

### ***Posterior Distribution***

Then, the posterior distribution is given by:

$$\tilde{\beta} | \sigma^2, \tilde{k}_T, \tilde{S}_T \sim N(b_1, \Sigma_1) \quad (3.27)$$

where  $b_1 = (\Sigma_0^{-1} + X'X)^{-1}(\Sigma_0^{-1}b_0 + X'Y)$  and  $\Sigma_1 = (\Sigma_0^{-1} + X'X)^{-1}$ .

Now I can draw  $\tilde{\beta} = [\mu_0 \quad \delta]'$  from the above multivariate posterior distribution. To constrain

$\delta > 0$ , I use rejection sampling. That is, if the generated value of  $\delta$  is less than or equal to 0, the draws are discarded. Otherwise, they are saved.

**STEP 2: Generate  $\sigma^2$ , conditional on  $\mu_0, \delta, \tilde{S}_T$ , and  $\tilde{k}_T$ .**

Equations (3.4), (3.5), and (3.6) can be rewritten as:

$$k_t = \mu_0 + \delta S_t + e_t \quad (3.28)$$

where  $e_t \sim N(0, \sigma^2)$ . In matrix notation, I have:

$$Y = X\tilde{\beta} + \xi \quad (3.29)$$

$$\xi \sim N(0, \sigma^2 I_T) \quad (3.30)$$

where  $X = [\tilde{1} \quad \tilde{S}_T]$  and  $\tilde{\beta} = [\mu_0 \quad \delta]'$ .

### ***Prior Distribution***

The natural conjugate prior for  $(1/\sigma^2)$  is the Gamma distribution.

$$\frac{1}{\sigma^2} \mid \mu_0, \delta \sim \Gamma\left(\frac{\alpha_0}{2}, \frac{\lambda_0}{2}\right) \quad (3.31)$$

### ***Posterior Distribution***

Then, the posterior distribution of  $1/\sigma^2$  is given by:

$$\frac{1}{\sigma^2} \mid \mu_0, \delta, \tilde{S}_T, \tilde{k}_T \sim \Gamma\left(\frac{\alpha_1}{2}, \frac{\lambda_1}{2}\right) \quad (3.32)$$

where

$$\alpha_1 = \alpha_0 + T \quad (3.33)$$

$$\lambda_1 = \lambda_0 + (Y - X\tilde{\beta})'(Y - X\tilde{\beta}) \quad (3.34)$$

### ***Prior Distribution***

Then, the prior distribution of  $\sigma^2$  is given by:

$$\sigma^2 \mid \mu_0, \delta \sim IG\left(\frac{\alpha_0}{2}, \frac{\lambda_0}{2}\right) \quad (3.35)$$

where  $IG$  represents the Inverse Gamma distribution.

### ***Posterior Distribution***

Then, the posterior distribution of  $\sigma^2$  is given by:

$$\sigma^2 \mid \mu_0, \delta, \tilde{S}_T, \tilde{k}_T \sim IG\left(\frac{\alpha_1}{2}, \frac{\lambda_1}{2}\right) \quad (3.36)$$

where

$$\alpha_1 = \alpha_0 + T \quad (3.37)$$

$$\lambda_1 = \lambda_0 + (Y - X\tilde{\beta})'(Y - X\tilde{\beta}) \quad (3.38)$$

$$= \lambda_0 + \sum_{t=1}^T (k_t - \mu_0 - \delta S_t)^2 \quad (3.39)$$

and  $T$  is equal to the sample size. From this posterior distribution, I can draw  $\sigma^2$ .

### **3.A.3 Algorithms to identify multi-year investment spikes**

Let  $I^s$  denote the  $s$ -th six-year investment sequence for  $s = 1, 2, \dots, S$ , where  $S$  represents the number of all possible complete six-year investment sequences that can be generated from our whole sample. The column vector  $I^s$ , for  $s = 1, 2, \dots, S$ , is equivalent to the vector  $(I^{s1}, I^{s2}, I^{s3}, I^{s4}, I^{s5}, I^{s6})'$ , where  $I^{s\tau}$ , for  $\tau = 1, 2, 3, 4, 5, 6$ , represents the investment data in the  $s$ -th column and  $\tau$ -th row of the  $6 \times S$  matrix of every possible six-year investment sequence. Similarly,  $I^p$  denotes the  $p$ -th seven-year investment sequence for  $p = 1, 2, \dots, P$ , where  $P$  represents the number of every possible complete seven-year investment sequence that can be generated from our whole sample. The column vector  $I^p$ , for  $p = 1, 2, \dots, P$ , is equivalent to the vector  $(I^{p1}, I^{p2}, I^{p3}, I^{p4}, I^{p5}, I^{p6}, I^{p7})'$  where  $I^{p\tau}$ , for  $\tau = 1, 2, 3, 4, 5, 6, 7$ , represents the in-

vestment data in the  $p$ -th column and  $\tau$ -th row of the  $7 \times P$  matrix of every possible seven-year investment sequence.

### A. Identifying two-year investment spikes with one dummy variable

First, each six-year sequence of investment data,  $I^s = (I^{s1}, I^{s2}, I^{s3}, I^{s4}, I^{s5}, I^{s6})'$  for  $s = 1, 2, \dots, S$  is regressed on a constant, a linear trend, and one specially designed dummy variable, where  $S$  denotes the total number of complete six-year investment sequences that can be generated from our whole sample. The dummy variable  $D_{34} = (0, 0, 1, 1, 0, 0)'$  is used to capture the extra explanatory power generated by the presence of both  $I^{s3}$  and  $I^{s4}$ . I define  $\{I^{s3}, I^{s4}\}$ , for  $s = 1, 2, \dots, S$ , as a joint two-year investment-spike candidate. The multiple linear regression for identifying investment spikes can be expressed compactly as:

$$y = X\beta + \varepsilon \quad (3.40)$$

with the same assumptions stated above and with the vectors  $y$ ,  $\beta$ , and  $\varepsilon$  and the matrix  $X$  specified as follows:

$$y = \begin{pmatrix} I^{s1} \\ I^{s2} \\ I^{s3} \\ I^{s4} \\ I^{s5} \\ I^{s6} \end{pmatrix} \quad (3.41)$$

$$X = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 1 & 3 & 1 \\ 1 & 4 & 1 \\ 1 & 5 & 0 \\ 1 & 6 & 0 \end{pmatrix} \quad (3.42)$$

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \quad (3.43)$$

and

$$\varepsilon = \begin{pmatrix} \varepsilon^{s1} \\ \varepsilon^{s2} \\ \varepsilon^{s3} \\ \varepsilon^{s4} \\ \varepsilon^{s5} \\ \varepsilon^{s6} \end{pmatrix} \quad (3.44)$$

The second step is to execute a one-sided  $t$ -test for  $\beta_3$ , the coefficient for the dummy variables for the joint two-year investment-spike candidates,  $\{I^{s3}, I^{s4}\}$ , for  $s = 1, 2, \dots, S$ . The null and alternative hypotheses are  $H_0 : \beta_3 = 0$  and  $H_1 : \beta_3 > 0$ , respectively. Under the null hypothesis, the statistic

$$t_3 = \frac{\hat{\beta}_3}{se_3} \quad (3.45)$$

follows a student  $t$ -distribution with  $(T - K) = 3$  degrees of freedom, since  $T = 6$  and  $K = 3$ .

The final decision is exactly the same as the case of one-year investment spikes.

## B. Identifying two-year investment spikes with two dummy variables

The second and third versions of the filters to identify two-year investment spikes use two dummy variables indicating each of the third and fourth investment data points in each six-year investment sequence  $I^s = (I^{s1}, I^{s2}, I^{s3}, I^{s4}, I^{s5}, I^{s6})'$  for  $s = 1, 2, \dots, S$ . The most important distinction from the first version is to use two dummy variables  $D_3 = (0, 0, 1, 0, 0, 0)'$  and  $D_4 = (0, 0, 0, 1, 0, 0)'$  rather than one dummy variable  $D_{34} = (0, 0, 1, 1, 0, 0)'$ . Accordingly, in both the second and third versions,  $X$  and  $\beta$  in the regression equation (3.49) are specified as follows:

$$X = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 1 & 2 & 0 & 0 \\ 1 & 3 & 1 & 0 \\ 1 & 4 & 0 & 1 \\ 1 & 5 & 0 & 0 \\ 1 & 6 & 0 & 0 \end{pmatrix} \quad (3.46)$$

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix} \quad (3.47)$$

However, the final decisions on whether a joint two-year investment-spike candidate,  $\{I^{s3}, I^{s4}\}$ , for  $s = 1, 2, \dots, S$ , is a two-year investment spike or not are different between the second and third versions of the filters. In the second version, two one-sided  $t$ -tests for  $\beta_3$  and  $\beta_4$  are executed where  $H_0 : \beta_k = 0$  and  $H_1 : \beta_k > 0$  for  $k = 3, 4$ , respectively. Under each null hypothesis, each of the statistics  $t_3 = \hat{\beta}_3/se_3$  and  $t_4 = \hat{\beta}_4/se_4$  has a Student  $t$ -distribution with  $(T - K) = 2$  degrees of freedom since  $T = 6$  and  $K = 4$ . A joint two-year investment-spike candidate,  $\{I^{s3}, I^{s4}\}$  for  $s = 1, 2, \dots, S$ , is classified as a two-year investment spike if both  $\beta_3$  and  $\beta_4$  are strictly positive and the two  $t$ -tests are rejected at the 5% significance level. For comparison

purposes, other significance levels such as 1% and 10% have also been considered.

In the third version, in addition to the two one-sided t-tests, a  $F$ -test with hypotheses  $H_0 : \beta_3 = \beta_4 = 0$  and  $H_1 : \beta_3 \neq 0$  or  $\beta_4 \neq 0$  is executed. Under the null hypothesis, the statistic

$$F = \frac{(RRSS - URSS)/R}{URSS/T - K} \quad (3.48)$$

where

$RRSS$  = Restricted Residual Sum of Squares

$URSS$  = Unrestricted Residual Sum of Squares

$T$  = number of samples

$K$  = number of explanatory variables including a constant

$R$  = number of restrictions

follows a  $F$ -distribution with degrees of freedom  $(R, T - K)$ . Here,  $URSS$  represents the residual sum of squares from a unrestricted regression of six investment sequences on a constant, a linear time trend, and two dummy variables as described above.  $RRSS$  represents the residual sum of squares from a restricted regression of six investment sequences on a constant and a linear time trend only. Hence, the number of restrictions,  $R$ , is 2. Hence, the test statistic  $F$  has a  $F$ -distribution with degrees of freedom  $(2, 2)$ . A joint two-year investment-spike candidate,  $\{I^{s3}, I^{s4}\}$  for  $s = 1, 2, \dots, S$ , is classified as a two-year investment spike if the null hypothesis of the  $F$ -test is rejected at the 5% significance level while both  $\beta_3$  and  $\beta_4$  are strictly positive and the two one-sided t-tests are rejected at the 5% significance level. For comparison purposes, other significance levels such as 1% and 10% have also been considered.

### C. Identifying three-year investment spikes with one dummy variable

First, each seven-year investment sequence,  $I^p = (I^{p1}, I^{p2}, I^{p3}, I^{p4}, I^{p5}, I^{p6}, I^{p7})'$  for  $p = 1, 2, \dots, P$  is regressed on a constant, a linear trend, and one specially designed dummy variable, where  $P$

denotes the total number of complete seven-year investment sequences that can be generated from our whole sample. The dummy variable  $D_{345} = (0, 0, 1, 1, 1, 0, 0)'$  is used to capture the extra explanatory power generated by the presence of  $I^{p3}$ ,  $I^{p4}$  and  $I^{p5}$ . I define  $\{I^{p3}, I^{p4}, I^{p5}\}$ , for  $p = 1, 2, \dots, P$ , as a joint triple investment spike candidate. The multiple linear regression for identifying investment spikes can be expressed compactly as

$$y = X\beta + \varepsilon \quad (3.49)$$

with the same assumptions stated above and with the vectors  $y$ ,  $\beta$ , and  $\varepsilon$  and the matrix  $X$  specified as follows:

$$y = \begin{pmatrix} I^{p1} \\ I^{p2} \\ I^{p3} \\ I^{p4} \\ I^{p5} \\ I^{p6} \\ I^{p7} \end{pmatrix} \quad (3.50)$$

$$X = \begin{pmatrix} 1 & 1 & 0 \\ 1 & 2 & 0 \\ 1 & 3 & 1 \\ 1 & 4 & 1 \\ 1 & 5 & 1 \\ 1 & 6 & 0 \\ 1 & 7 & 0 \end{pmatrix} \quad (3.51)$$

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} \quad (3.52)$$

and

$$\varepsilon = \begin{pmatrix} \varepsilon^{p1} \\ \varepsilon^{p2} \\ \varepsilon^{p3} \\ \varepsilon^{p4} \\ \varepsilon^{p5} \\ \varepsilon^{p6} \\ \varepsilon^{p7} \end{pmatrix} \quad (3.53)$$

The second step is to execute a one-sided  $t$ -test for  $\beta_3$ , the coefficient for the dummy variables for the joint three-year investment-spike candidates,  $\{I^{p3}, I^{p4}, I^{p5}\}$ , for  $p = 1, 2, \dots, P$ . The null and alternative hypotheses are  $H_0 : \beta_3 = 0$  and  $H_1 : \beta_3 > 0$ , respectively. Under the null hypothesis, the statistic

$$t_3 = \frac{\hat{\beta}_3}{se_3} \quad (3.54)$$

follows a student  $t$ -distribution with  $(T - K) = 4$  degrees of freedom, since  $T = 7$  and  $K = 3$ . The final decision is made in exactly the same way as in the case of one-year or two-year investment spikes.

Table 3.1: Lumpiness of investment

This table shows how lumpy both “Fixed Investment ( $i_{it}$ )” and “Total Investment ( $I_{it}$ )” are. All fixed investment ( $i_{it}$ ) and total investment ( $I_{it}$ ) of the firms with 20 non-missing observations are grouped into 20 groups based on the magnitude of each variable. For example, “Group 1” consists of the largest investment made by each company in its history, whereas “Group 20” consists of the smallest investment made by each company in its history. Note that dropping negative investments does not greatly change the results.

Group	N	Fixed Investment ( $i_{it}$ )			Total Investment ( $I_{it}$ )		
		Sum	Pct.	Cum.	Sum	Pct.	Cum.
1	504	437,641	10.40%	10.40%	960,453	16.69%	16.69%
2	504	387,274	9.20%	19.60%	647,605	11.26%	27.95%
3	504	340,414	8.09%	27.69%	529,714	9.21%	37.16%
4	504	312,002	7.41%	35.10%	469,140	8.15%	45.31%
5	504	282,257	6.71%	41.81%	416,815	7.24%	52.56%
6	504	263,434	6.26%	48.07%	371,037	6.45%	59.00%
7	504	243,586	5.79%	53.86%	341,211	5.93%	64.93%
8	504	225,982	5.37%	59.23%	305,117	5.30%	70.24%
9	504	208,756	4.96%	64.19%	279,139	4.85%	75.09%
10	504	194,084	4.61%	68.80%	254,924	4.43%	79.52%
11	504	181,018	4.30%	73.10%	229,940	4.00%	83.52%
12	504	167,176	3.97%	77.07%	213,684	3.71%	87.23%
13	504	157,491	3.74%	80.81%	190,885	3.32%	90.55%
14	504	148,272	3.52%	84.34%	174,732	3.04%	93.59%
15	504	139,149	3.31%	87.64%	153,337	2.67%	96.25%
16	504	129,734	3.08%	90.73%	132,217	2.30%	98.55%
17	504	121,447	2.89%	93.61%	105,430	1.83%	100.38%
18	504	113,285	2.69%	96.30%	79,227	1.38%	101.76%
19	504	96,874	2.30%	98.61%	21,704	0.38%	102.14%
20	504	58,663	1.39%	100.00%	-122,893	-2.14%	100.00%
Total	10,080	4,208,539	100.00%		5,753,418	100.00%	

Table 3.2: Markov-switching filter: A standard firm with lumpy investment

This table shows the relevant statistics and outputs from the Markov-switching filter with the data from a standard firm with lumpy investment. Panel A shows the output from the Hodrick–Prescott detrending procedure and the Markov-switching filter. The second column is the original time series of “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )”. The third and fourth columns represent the trend and cyclical components from the Hodrick-Prescott detrending procedures respectively. The cyclical component is used as the input of Markov-switching model. The fifth column represents the probability of investment spikes conditional on all available data  $\tilde{k}_T = \{k_1, \dots, k_T\}$ . The last column is the dummy variable for investment spikes and hence the years with 1’s have investment spikes. Panel B shows the summary statistics for the posterior distributions of five parameters.

Panel A. Results of the Markov-switching filter						
Year	Hodrick-Prescott			Markov-switching		
	Original	Trend	Cycle	$P[S_t = 1   \tilde{y}_T]$	$D_{Spike}$	
1988	24.27	8.45	15.82	1.00	1	
1989	2.16	7.45	-5.29	0.07	0	
1990	3.43	6.60	-3.17	0.03	0	
1991	1.90	6.02	-4.12	0.02	0	
1992	5.61	5.78	-0.17	0.06	0	
1993	-11.80	5.90	-17.70	0.00	0	
1994	4.06	6.43	-2.37	0.13	0	
1995	7.63	7.21	0.42	0.58	0	
1996	19.07	8.07	10.99	0.99	1	
1997	7.74	8.86	-1.12	0.84	0	
1998	12.55	9.50	3.05	0.92	0	
1999	14.00	9.94	4.07	0.87	0	
2000	3.97	10.13	-6.16	0.35	0	
2001	27.49	10.09	17.40	1.00	1	
2002	10.90	9.76	1.15	0.62	0	
2003	3.00	9.24	-6.24	0.03	0	
2004	3.98	8.68	-4.70	0.01	0	
2005	3.56	8.13	-4.57	0.04	0	
2006	9.64	7.61	2.03	0.43	0	
2007	7.78	7.11	0.68	0.49	0	

Panel B. Summary statistics for posterior distributions of parameters					
Parameter	Mean	Std. Dev.	Median	95% LB	95% UB
$\mu_0$	-3.3209	0.5958	-3.2969	-4.4859	-2.1867
$\mu_1$	5.0251	1.1540	4.8966	3.0568	7.5896
$\sigma^2$	64.0982	22.9892	59.2464	33.4443	123.8604
$p$	0.7757	0.1052	0.7858	0.5407	0.9417
$q$	0.7873	0.0960	0.7992	0.5720	0.9463

Table 3.3: Markov-switching filter: A non-standard firm with non-lumpy investment

This table shows the relevant statistics and outputs from the Markov-switching filter with the data from a non-standard firm with non-lumpy investment. Panel A shows the output from the Hodrick–Prescott detrending procedure and the Markov-switching filter. The second column is the original time series of “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )”. The third and fourth columns represent the trend and cyclical components from the Hodrick–Prescott detrending procedures respectively. The cyclical component is used as the input of the Markov-switching model. The fifth column represents the probability of investment spikes conditional on all available data  $\tilde{k}_T = \{k_1, \dots, k_T\}$ . The last column is the dummy variable for investment spikes and hence the years with 1’s have investment spikes. Panel B shows the summary statistics for the posterior distributions of five parameters.

Panel A. Results of the Markov-switching filter					
Year	Hodrick-Prescott			Markov-switching	
	Original	Trend	Cycle	$P[S_t = 1   \tilde{y}_T]$	$D_{Spike}$
1988	4.84	5.47	-0.63	0.34	0
1989	6.38	5.91	0.47	0.34	0
1990	4.31	6.34	-2.02	0.28	0
1991	6.00	6.76	-0.76	0.45	0
1992	11.48	7.16	4.32	0.79	0
1993	8.69	7.50	1.20	0.65	0
1994	7.07	7.79	-0.73	0.40	0
1995	8.17	8.06	0.10	0.28	0
1996	3.27	8.34	-5.07	0.12	0
1997	10.52	8.63	1.89	0.50	0
1998	11.05	8.90	2.15	0.58	0
1999	7.78	9.16	-1.38	0.44	0
2000	9.05	9.39	-0.34	0.50	0
2001	12.29	9.61	2.67	0.64	0
2002	8.88	9.80	-0.92	0.49	0
2003	12.48	9.98	2.49	0.50	0
2004	6.74	10.17	-3.42	0.16	0
2005	8.51	10.38	-1.87	0.18	0
2006	10.77	10.63	0.14	0.37	0
2007	12.61	10.90	1.70	0.54	0

Panel B. Summary statistics for posterior distributions of parameters					
Parameter	Mean	Std. Dev.	Median	95% LB	95% UB
$\mu_0$	-0.5535	0.4234	-0.5101	-1.5367	0.1434
$\mu_1$	0.8069	0.5518	0.7372	-0.0784	2.0946
$\sigma^2$	4.9791	1.7003	4.6998	2.5793	9.0891
$p$	0.8192	0.1048	0.8371	0.5769	0.9699
$q$	0.7830	0.1069	0.7947	0.5455	0.9500

Table 3.4: Markov-switching filter: Summary

This table shows the summary of the Markov-switching filter with Hodrick–Prescott detrending. This is based on the 20-year “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )” data for 504 firms without missing values. Panel A shows how many firms satisfied the model selection criteria. Panel B shows the means and standard deviations of the median of generated parameters according to the significance level. Panel C shows the distribution of the number and proportion of investment spikes made by each firm.

Panel A. Model selection criteria						
Model Selection Criteria	Sig. Level = 0.01		Sig. Level = 0.05		Sig. Level = 0.10	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
0: Fail	119	23.61	73	14.48	57	11.31
1: Pass	385	76.39	431	85.52	447	88.69
Total	504	100.00	504	100.00	504	100.00

Panel B. Summary of parameter estimates						
Median of:	Sig. Level = 0.01		Sig. Level = 0.05		Sig. Level = 0.10	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
$\mu_0$	-2.80	1.59	-2.58	1.63	-2.51	1.65
$\mu_1$	4.87	2.71	4.55	2.74	4.43	2.77
$\sigma^2$	155.69	643.56	153.25	625.83	150.21	619.85
$p$	0.7976	0.0403	0.8010	0.0395	0.8023	0.0393
$q$	0.7882	0.0494	0.7930	0.0516	0.7941	0.0518

Panel C. Number of investment spikes by firm						
No.(Prop.)	Sig. Level = 0.01		Sig. Level = 0.05		Sig. Level = 0.10	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
0 (0.00)	82	21.30	44	10.21	32	7.16
1 (0.05)	138	35.84	108	25.06	77	17.23
2 (0.10)	87	22.60	100	23.20	89	19.91
3 (0.15)	44	11.43	87	20.19	96	21.48
4 (0.20)	24	6.23	50	11.60	56	12.53
5 (0.25)	5	1.30	23	5.34	51	11.41
6 (0.30)	3	0.78	10	2.32	23	5.15
7 (0.35)	1	0.26	4	0.93	16	3.58
8 (0.40)	1	0.26	3	0.70	5	1.12
9 (0.45)	0	0.00	2	0.46	0	0.00
10 (0.50)	0	0.00	0	0.00	2	0.45
Total	385		431		447	
Avg. No. (Avg. Prop.)	1.5532 (0.0777)		2.3526 (0.1176)		2.9799 (0.1490)	

Table 3.5: Number of investment spikes by filters

This table shows the number of investment spikes identified by three different filters. The numbers and proportions of investment spikes are presented according to thresholds or significance levels by filters. “Total Investment ( $I_{it}$ )” is used to implement the Mayer–Sussman filter and the Regression filter, whereas “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )” and “Fixed Investment to Capital Stock Ratio ( $i_{it}/K_{it}$ )” are used to implement the Markov-switching filter. The results are based on the firms satisfying the model selection criteria.

Panel A. Results for the Mayer–Sussman filter							
Data	Threshold	Spikes		Non-spikes		Total	
		Number	Percent	Number	Percent	Number	Percent
$I_{it}$	0.15	650	(10.87%)	5,330	(89.13%)	5,980	(100%)
	0.17	888	(14.85%)	5,092	(85.15%)	5,980	(100%)
	0.20	1,362	(22.78%)	4,618	(77.22%)	5,980	(100%)
Panel B. Results for the Regression filter							
Data	Sig. Level	Spikes		Non-spikes		Total	
		Number	Percent	Number	Percent	Number	Percent
$I_{it}$	0.01	182	(2.67%)	6,634	(97.33%)	6,816	(100%)
	0.05	507	(7.44%)	6,309	(92.56%)	6,816	(100%)
	0.10	790	(11.59%)	6,026	(88.41%)	6,816	(100%)
Panel C. Results for the Markov-switching filter							
Data	Sig. Level	Spikes		Non-spikes		Total	
		Number	Percent	Number	Percent	Number	Percent
$I_{it}/A_{it}$	0.01	598	(7.77%)	7,102	(92.23%)	7,700	(100%)
	0.05	1,014	(11.76%)	7,606	(88.24%)	8,620	(100%)
	0.10	1,332	(14.90%)	7,608	(85.10%)	8,940	(100%)
$i_{it}/K_{it}$	0.01	538	(7.72%)	6,435	(92.28%)	6,973	(100%)
	0.05	979	(12.10%)	7,155	(87.9%)	8,094	(100%)
	0.10	1,336	(15.73%)	7,157	(84.27%)	8,493	(100%)

Table 3.6: Number of multi-year investment spikes

This table shows the number of multi-year investment spikes identified using the extended Regression filters. Panel A shows the number of two-year investment spikes by three different version of filters and Panel B shows the number of three-year investment spikes identified using the Regression filter with one dummy variable and one t-test.

Panel A. Two-year investment spikes							
Filter	Sig. Level	Spikes		Non-spikes		Total	
		Number	Percent	Number	Percent	Number	Percent
Regression filter	0.01	356	(1.24%)	28,360	(98.76%)	28,716	(100%)
with one dummy:	0.05	1,513	(5.27%)	27,203	(94.73%)	28,716	(100%)
One T-test	0.10	2,978	(10.37%)	25,738	(89.63%)	28,716	(100%)
Regression filter	0.01	153	(0.53%)	28,563	(99.47%)	28,716	(100%)
with two dummies:	0.05	633	(2.20%)	28,083	(97.80%)	28,716	(100%)
Two T-tests	0.10	1,177	(4.10%)	27,539	(95.90%)	28,716	(100%)
Regression filter	0.01	123	(0.43%)	28,593	(99.57%)	28,716	(100%)
with two dummies:	0.05	505	(1.76%)	28,211	(98.24%)	28,716	(100%)
1 F- and 2 T-tests	0.10	923	(3.21%)	27,793	(96.79%)	28,716	(100%)

Panel B. Three-year investment spikes							
Filter	Sig. Level	Spikes		Non-spikes		Total	
		Number	Percent	Number	Percent	Number	Percent
Regression filter	0.01	277	(1.16%)	23,658	(98.84%)	23,935	(100%)
with one dummy:	0.05	1,242	(5.19%)	22,693	(94.81%)	23,935	(100%)
One T-test	0.10	2,577	(10.77%)	21,358	(89.23%)	23,935	(100%)

Table 3.7: Markov-switching filter: A firm with multi-year investment spikes

This table shows the relevant statistics and outputs from the Markov-switching filter with the data from an unusual firm with two two-year investment spikes. Panel A shows the output from the Hodrick–Prescott detrending procedure and the Markov-switching filter. The second column is the original time series of “Total Investment to Total Assets Ratio ( $I_{it}/A_{it}$ )”. The third and fourth columns represent the trend and cyclical components from the Hodrick–Prescott detrending procedures respectively. The cyclical component is used as the input of the Markov-switching model. The fifth column represents the probability of investment spikes conditional on all available data  $\tilde{k}_T = \{k_1, \dots, k_T\}$ . The last column is the dummy variable for investment spikes and hence the investments in the years with 1’s are designated as investment spikes. Panel B shows the summary statistics for the posterior distributions of five parameters.

Panel A. Results of the Markov-switching filter					
Year	Hodrick–Prescott			Markov-switching	
	Original	Trend	Cycle	$P[S_t = 1 \tilde{y}_T]$	$D_{Spike}$
1988	37.40	24.19	13.20	0.99	1
1989	5.19	21.91	-16.72	0.00	0
1990	21.06	19.77	1.30	0.62	0
1991	23.92	17.71	6.20	0.98	1
1992	27.67	15.74	11.93	1.00	1
1993	3.35	13.87	-10.52	0.01	0
1994	-1.07	12.29	-13.36	0.00	0
1995	16.27	11.02	5.24	0.44	0
1996	-2.25	10.01	-12.26	0.01	0
1997	25.51	9.22	16.29	1.00	1
1998	15.60	8.50	7.10	0.97	1
1999	2.11	7.86	-5.75	0.05	0
2000	2.12	7.39	-5.28	0.01	0
2001	2.01	7.12	-5.10	0.01	0
2002	2.16	7.01	-4.86	0.02	0
2003	4.32	7.00	-2.68	0.20	0
2004	29.99	6.96	23.04	1.00	1
2005	4.45	6.73	-2.28	0.34	0
2006	6.12	6.39	-0.27	0.20	0
2007	0.74	6.00	-5.25	0.05	0

Panel B. Summary statistics for posterior distributions of parameters					
Parameter	Mean	Std. Dev.	Median	95% LB	95% UB
$\mu_0$	-5.0532	0.6621	-5.0094	-6.4760	-3.8249
$\mu_1$	8.4815	1.3703	8.5824	5.8143	10.9850
$\sigma^2$	111.1885	38.9755	103.1147	59.4055	203.8597
$p$	0.6986	0.1091	0.7041	0.4636	0.8845
$q$	0.7439	0.0972	0.7521	0.5412	0.9095

Table 3.8: Proportion of firms with an investment spike and GDP growth rate

This table shows the relationship between the proportion of firms with an investment spike and the GDP growth rate. Panel A shows what proportions of firms have an investment spike each year. These proportions are presented by the filters and thresholds. Panel B shows the correlations between the proportion of firms with an investment spike and current and lagged real GDP growth rates.

Panel A. Proportion of firms with an investment spike and real GDP growth rate ( $\Delta y_t$ )										
Year	Mayer–Sussman filter			Regression filter			Markov-switching filter			$\Delta y_t$
	0.15	0.17	0.20	0.01	0.05	0.10	0.01	0.05	0.10	
1988	N/A	N/A	N/A	N/A	N/A	N/A	8.57	11.83	15.44	4.1
1989	N/A	N/A	N/A	N/A	N/A	N/A	6.49	9.74	12.53	3.6
1990	11.18	15.46	25.28	2.87	7.43	11.55	5.71	10.67	12.98	1.9
1991	8.86	11.99	19.35	1.67	4.91	8.68	4.93	9.28	12.53	-0.2
1992	9.36	13.05	20.88	2.37	7.05	11.68	5.97	10.67	12.53	3.4
1993	8.75	12.29	19.43	2.09	5.90	9.82	9.35	12.99	15.43	2.9
1994	11.16	14.73	22.75	2.34	7.05	10.87	8.31	11.14	14.54	4.1
1995	9.94	13.69	22.12	2.37	7.10	11.38	7.53	10.44	12.98	2.5
1996	9.39	14.01	20.58	2.48	7.53	11.48	10.64	14.85	17.90	3.7
1997	8.39	11.11	18.54	2.44	7.20	11.59	11.17	17.87	21.25	4.5
1998	10.83	14.31	21.46	3.64	9.78	13.86	11.69	18.56	24.83	4.4
1999	9.24	13.33	19.32	3.02	7.87	11.84	12.73	22.04	26.62	4.8
2000	10.59	13.68	20.02	2.86	8.63	13.32	12.21	16.94	20.81	4.1
2001	10.70	13.83	20.09	3.56	9.06	13.82	7.79	10.44	13.42	1.1
2002	8.15	11.08	16.26	1.89	6.00	9.22	4.68	7.89	10.51	1.8
2003	7.27	9.49	14.59	1.59	4.99	7.55	3.90	6.26	7.61	2.5
2004	9.88	12.53	20.15	3.46	9.00	13.34	6.49	8.81	10.51	3.6
2005	8.06	10.90	19.14	3.19	7.53	11.52	6.23	8.81	11.19	3.1
2006	N/A	N/A	N/A	N/A	N/A	N/A	5.97	8.35	11.86	2.7
2007	N/A	N/A	N/A	N/A	N/A	N/A	4.94	7.66	12.53	2.1
Mean	9.48	12.84	20.00	2.62	7.31	11.35	7.77	11.76	14.90	3.04
SD	1.20	1.61	2.46	0.65	1.40	1.81	2.71	4.20	4.96	1.26

Panel B. Correlation between the proportion of firms with an investment spike and real GDP growth rate ( $\Delta y_t$ )										
$\rho$ with	Mayer–Sussman filter			Regression filter			Markov-switching filter			$\Delta y_t$
	0.15	0.17	0.20	0.01	0.05	0.10	0.01	0.05	0.10	
$\Delta y_t$	0.13	0.16	0.09	0.36	0.48	0.43	0.72	0.67	0.64	1.00
$\Delta y_{t-1}$	0.43	0.37	0.33	0.57	0.55	0.54	0.67	0.58	0.60	1.00

# Chapter 4

## Investment Spikes and Financing Patterns

### 4.1 Introduction

How do firms finance their exceptionally large investment activities?<sup>1</sup> To answer this question, I utilize a novel approach which uses the firm-level flow-of-funds data combined with a filtering device to identify years with unusually large investment activities or “*investment spikes*”<sup>2</sup>. Using US data, Mayer and Sussman (2005) find that the financing of investment around investment spikes is very different to the financing of investment at other times. Thus,

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<sup>1</sup>There is an established body of evidence that by far and away the dominant source of finance of firms across different countries and time periods is retained earnings (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this is primarily informative on how firms finance their routine, replacement investment rather than non-routine, expansion investment. In particular, the way in which firms meet exceptional financing needs in relation to unusually large investment opportunities is the subject of an emerging body of literature (see, for instance, DeAngelo *et al.* (2011)).

<sup>2</sup>Mayer and Sussman (2005) were the first to notice that summary statistics for financing patterns would overstate the importance of internal finance in funding firms’ investment activities. They proposed using the flow-of-funds approach combined with a filtering device designed to identify “years with unusually large investment activities”.

pooling data from two regimes of routine investment and non-routine investment dilutes the sample and obscures the results, without increasing the efficiency of the estimation (Mayer and Sussman, 2005). Using a structural estimation method, DeAngelo *et al.* (2011) analyse the financing decisions associated with investment spikes and find that, even when leverage is currently above average, large investment outlays are typically accompanied by substantial debt issuances that increase leverage, confirming Mayer and Sussman's (2005) major findings. By analysing the flow of funds before, during, and after investment spikes, one can investigate the financing patterns more precisely (Mayer and Sussman, 2005).

In this chapter, I examine the financing patterns around investment spikes with more recent data and a new filtering procedure suggested by Bond *et al.* (2006). First of all, I investigate the investment-weighted proportions of financing sources as shares of base-level investment for periods around 5,528 investment spikes, for which source-of-funds data are available for five-year event windows. This analysis confirms the finding of Mayer and Sussman (2005) that the financing of investment during an investment spike is very different from the financing of investment at other times<sup>3</sup>. In particular, the share of investment financed from internally generated funds (some 1.2 times the base-level investment) is much lower and the share of investment financed by long-term debt (some 2.5 times the base-level investment) is much

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<sup>3</sup>Unlike the findings of studies using aggregate data, Mayer and Sussman (2005) found the importance of external sources such as debt and new equity in funding investment spikes. Note that, to some extent, this finding is inevitable. If the level of investment spending in periods identified as investment spikes typically exceeds the level of available internal funds, the difference must be financed using one or more of the external sources. However, it is also possible that a firm accumulates liquid assets for several years to pay for its investment spending and executes the lumpy investment project once it has sufficient cash. Therefore, it is still worthwhile to investigate how important external financing is in funding investment spikes. Moreover, what sources of external finance are more commonly used is a very interesting question. It is also interesting to investigate the flow of funds before and after investment spikes.

higher<sup>4</sup>.

I then investigate whether there are significant differences in the financing of investment spikes for these sub-samples of US firms classified by firm size. The most striking finding is that small firms raise equity finance quite substantially during investment spikes, whereas large firms rely largely on debt finance during investment spikes. It is also quite surprising that small firms issue shares throughout the years around investment spikes. To further examine the heterogeneity of financing patterns, I investigate whether the financing patterns around investment spikes vary with the profitability of firms, level of future growth opportunities, tangibility of assets, R&D intensity and industry. Overall, firms with lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance when confronted with large investment requirements. However, the effects of those firm characteristics are not as strong as the effect of firm size on the financing patterns around investment spikes. In most industries, debt finance is the most important source of finance during investment spikes, followed by internal finance. Some contribution from equity finance at the time of an investment spike is also observed in most industries, whereas net retirement of equity is observed in several industries. Overall, there are no substantial differences in the financing of investment spikes across industries.

Moreover, I investigate whether investment spike characteristics entail differences in the financing of investment spikes. First, I investigate whether investment spikes involving acquisitions are funded differently from investment spikes involving capital expenditures. I find

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<sup>4</sup>This explains why the importance of internal finance is exaggerated if the full sample is used to calculate the summary statistics for financing patterns such as the investment-weighted financing proportions (see Mayer and Sussman (2005)).

that investment spikes involving acquisitions tend to be funded by a higher proportion of debt finance, although they also tend to be spikier (i.e. larger) than investment spikes involving only capital expenditures. I then investigate whether financing patterns vary according to the magnitude of investment spikes and find that financing patterns are substantially different in sub-groups based on the magnitude of investment spikes. Large firms tend to use only debt finance when they are confronted with relatively small investment spikes, but they tend to use more equity finance when they are confronted with relatively large investment spikes. It seems that this result is consistent with the pecking-order theory (Myers and Majluf, 1984). However, small firms tend to use more equity finance when they are confronted with relatively small investment spikes, but they tend to use more debt finance when they are confronted with relatively large investment spikes. This result seems to be consistent with the reverse pecking order which can be explained in a framework of Fulghieri and Lukin (2001)<sup>5</sup>. Mayer and Sussman (2005) find that large investment projects are predominantly financed with debt, in particular in large and profitable firms, and interpret this result as suggesting that corporate financing patterns are consistent with the pecking-order theory. However, it is surprising that the financing patterns of small firms are consistent with the reverse pecking order. Overall, my findings are more consistent with Mayer and Sussman's (2002) first draft.

I then investigate the relation between the level of initial leverage and the financing of investment spikes and find that the relation is not consistent with the classical trade-off theory

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<sup>5</sup>They show that, contrary to the pecking-order theory, when investors can produce information on the quality of the underlying firm at sufficiently low costs, firms may prefer to issue more information-sensitive security such as equity rather than less information-sensitive security such as risky debt. In their model, the expected dilution costs are the same for both debt and equity and the firm chooses the security that maximizes the probability of getting funding.

of debt, but quite consistent with the predictions of a dynamic trade-off theory augmented with investment spikes as proposed by DeAngelo *et al.* (2011)<sup>6</sup>. According to the classical trade-off theory of debt, it is expected that firms with higher initial leverage will use less debt in financing investment requirements in periods categorized as investment spikes and in normal periods. However, large firms tend to use more debt finance than equity finance in funding large investment projects, regardless of the level of initial leverage. In addition, small firms with lower initial leverage tend to use more equity finance but small firms with higher initial leverage tend to use more debt finance in order to meet large investment requirements, which is opposite to the prediction of the classical trade-off theory.

Some robustness tests are executed. I show that major empirical findings are robust to the use of different thresholds in the same filtering procedure and the use of the Markov-switching filter suggested in Chapter 3. I also show that two-year investment spikes identified by the Markov-switching filter are financed quite similarly to single-year investment spikes. Finally, I show that there is calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks when the Markov-switching filter is used and that the main findings are robust to the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks.

The rest of this chapter is organized as follows. In Section 4.2, I briefly discuss the data

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<sup>6</sup>DeAngelo *et al.* (2011) build a dynamic capital structure model in which firms deliberately but temporarily deviate from permanent leverage targets by issuing transitory debt to fund investment spikes. They then find that it explains firms' debt issuance/repayment decisions better than static trade-off models of capital structure, and that it can account for the leverage changes that accompany "investment spikes". In their model, firms have leverage targets as in static trade-off models, but managers sometimes choose to deviate from targets and subsequently seek to rebalance to meet targets by reducing debt with a lag determined in part by the time path of investment opportunities and earnings realizations.

and methodology. Section 4.3 presents empirical results and Section 4.4 provides results for various robustness tests. Finally, I conclude in Section 4.5.

## **4.2 Data and methodology**

### **4.2.1 Sample selection**

I use data from annual consolidated financial statements<sup>7</sup> of publicly traded US companies reported in Standard and Poor's Compustat North America Fundamental Annual Dataset for the years 1988 to 2007. The data starts from 1988 because the investigation of the financing patterns around investment spikes requires the use of firm-level flow-of-funds data, i.e. data from the cash-flow statements<sup>8</sup>. I exclude firms with an SIC code between 6000 and 6999 or between 4900 and 4999, i.e. firms whose main activity is financial services or regulated utilities are dropped to construct the final sample.

All nominal items from the statement of cash flows, income statement and balance sheet are deflated or inflated to year 2000 dollars using the GDP deflator obtained from the International Monetary Fund database of country GDP deflators. An interpolated GDP deflator is used if the fiscal year ends in other months than December. I also perform a minimum level of data cleaning. First, I drop observations if the firms are observed for less than five years.

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<sup>7</sup>The majority of US companies report the consolidated financial statements, which include both parent and subsidiaries accounts.

<sup>8</sup>Mayer and Sussman (2005), in their seminal paper on the use of a filtering technique and flow-of-funds approach in studies of financing patterns, report that they could not use data from before 1988 because the "cash statements by sources and uses of funds" was replaced by "statement of cash flows" in 1988 by the Financial Accounting Standards Boards #5.

Second, I drop observations if any variable which constitutes the cash-flow identity is missing. However, I replace the missing item with zero if at least one component of each financing source is reported because “missing” does not mean “unaccounted for”. For example, note that *LTDEBT*, the amount of long-term debt financing, can be calculated as “issuance of long-term debt (*dltis*)” less “reduction of long-term debt (*dltr*)”. It is clear that the firm-year observation should be deleted if both *dltis* and *dltr* are missing. However, if only one of the two components is missing then it is likely that that only “net issuance of long-term debt” is reported. In this case, it makes more sense to replace the missing item with zero rather than remove the firm-year observation. Finally, to reduce the effects of outliers and eradicate errors in the data, all variables in ratios are winsorized at the 1st and 99th percentiles, as in Flannery and Rangan (2006). Table 4.1 provides details of the Compustat items used to construct variables used in this chapter.

[Insert Table 4.1 Here.]

## **4.2.2 Algorithm to identify investment spikes**

This chapter uses a novel approach suggested by Mayer and Sussman (2005)<sup>9</sup>. They suggest that the question of how investment is financed can be precisely answered using the firm-level flow-of-funds data combined with a filtering device to identify investment spikes. This new approach eliminates a potential bias caused by the merging of routine and non-routine investment periods. The bias arises if investment is lumpy (i.e. firms’ regimes switch between high

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<sup>9</sup>Bond *et al.* (2006) and Huang *et al.* (2007) use a similar approach to study financing patterns.

investment and low investment), if financing patterns are markedly different across regimes, and if the data from two regimes are merged to make inferences on financing patterns. They argue that pooling data from two regimes dilutes the sample and obscures results, without increasing the efficiency of the estimation.

Mayer and Sussman (2005) also propose a simple and intuitive algorithm to identify investment spikes. However, the algorithm has an important disadvantage in that the threshold is arbitrary and not statistically interpretable. To overcome the problem, I utilize an algorithm used by Bond *et al.* (2006)<sup>10</sup>. The advantages of the new algorithm are that the threshold is statistically interpretable and that it works well when there is a trend in the investment sequence. Let the investment data,  $I_{i,t}$ , for  $i = 1, 2, \dots, N$  and  $t = 1, \dots, T_i$ , be defined as investment outlays on tangible assets, intangible assets and acquisitions (see Table 4.1 Panel A for the formula and the Compustat items used to measure  $I_{i,t}$ ). See below for more details on the algorithm.

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  $i = 1, 2, \dots, N$  and  $t = 3, \dots, (T_i - 2)$ , 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

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<sup>10</sup>They do use the algorithm suggested by Mayer and Sussman (2005), but also propose two new algorithms as a robustness test.

series<sup>11</sup>. The regression for identifying an investment spike can be expressed compactly as:

$$y = \mathbf{X}b + \varepsilon, \text{ where } \varepsilon \sim N(0, \sigma^2), \quad (4.1)$$

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

$$\mathbf{X} = [\mathbf{1} \quad \tau \quad \mathbf{D}_{\tau=0}] = \begin{pmatrix} 1 & -2 & 0 \\ 1 & -1 & 0 \\ 1 & 0 & 1 \\ 1 & +1 & 0 \\ 1 & +2 & 0 \end{pmatrix}, \quad (4.2)$$

$b = (\alpha_{it}, \beta_{it}, \delta_{it})'$ , 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  $\hat{b} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'y$ , it can be easily shown that:

$$\hat{\alpha}_{it} = \frac{I_{i,t-2} + I_{i,t-1} + I_{i,t+1} + I_{i,t+2}}{4}, \quad (4.3)$$

$$\hat{\beta}_{it} = \frac{-2I_{i,t-2} - I_{i,t-1} + I_{i,t+1} + 2I_{i,t+2}}{10}, \quad (4.4)$$

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<sup>11</sup>If  $T_i = 20$ ,  $16(= T_i - 4)$  regressions should be implemented for firm  $i$ . Therefore, a total of  $N(T_i - 4)$  regressions should be implemented. However, the following anatomy of a regression makes the algorithm simpler in the sense that the algorithm does not require the running of a large number of full regressions. In addition, the anatomy provides interesting measures, such as  $\hat{\alpha}_{it}$ ,  $\hat{\delta}_{it}$ , and  $\hat{\gamma}_{it}$ .

and

$$\widehat{\delta}_{it} = I_{i,t} - \widehat{\alpha}_{it}. \quad (4.5)$$

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

$$se(\widehat{\delta}_{it}) = \sqrt{\frac{5}{4}s^2}, \quad (4.6)$$

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

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

Under the null hypothesis, the statistic

$$t_{\widehat{\delta}_{it}} = \frac{\widehat{\delta}_{it}}{se(\widehat{\delta}_{it})} \quad (4.7)$$

follows a Student  $t$ -distribution with  $2(=n-k)$  degrees of freedom. The final decision is made based upon the result from the one-sided  $t$ -test at a conventional significance level of 5%. That is,  $I_{i,t}$  is classified as an investment spike if  $\widehat{\delta}_{it}$  is positive and statistically significant at the 5% significance level, regardless of the magnitude of the coefficient<sup>12</sup>. Alternatively, 1% or 10% significance levels can be used.

Note also that  $\tau \in \{-2, -1, 0, +1, +2\}$  denotes the time index in relation to an investment spike, and  $\widehat{\alpha}_{it}$  is equal to the base-level investment defined in Mayer and Sussman (2005). In addition, the magnitude of an investment spike as a factor of the base-level investment is

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<sup>12</sup>In other words, firm  $i$  has an investment spike in year  $t$  if  $t_{\widehat{\delta}_{it}} > t(0.95, df = 2)$ .

measured as:

$$\widehat{\gamma}_{it} = \frac{I_{i,t}}{\widehat{\alpha}_{it}}. \quad (4.8)$$

Repeating the procedures as many times as  $N(T_i - 4)$  will identify a total of  $J$  firm-years as those with an investment spike. For simplicity, the base-level investment and the relative magnitude of the  $j$ -th investment spike are denoted as  $BASE_j$  and  $GAMMA_j$ , for  $j \in \{1, 2, \dots, J\}$ , respectively. The procedures give a sample of 6,457 investment spikes, 9.56% of the 67,544 firm-year observations for which five consecutive years of investment data are observed. I restrict my attention to (*Low, Low, High, Low, Low*)-type investment spikes only, obtaining 6,424 investment spikes after dropping 33 investment spikes. The median  $GAMMA$  of 6,424 investment spikes is 3.42.

### 4.2.3 Aggregation of the flows of funds

After investment spikes are identified, I investigate the flow of funds according to the time index around investment spikes ( $\tau \in \{-2, -1, 0, +1, +2\}$ ). Following Mayer and Sussman (2005), I use the basic cash-flow identity linking investment spending to internally generated funds, long-term debt finance, new equity finance and other sources of funding:

$$I_{j\tau} \equiv OPR_{j\tau} + LTDEBT_{j\tau} + EQUITY_{j\tau} + OTHER_{j\tau}, \quad (4.9)$$

for  $j \in \{1, 2, \dots, J\}$  and  $\tau \in \{-2, -1, 0, +1, +2\}$ .  $I_{j\tau}$  measures investment outlays on tangible assets, intangible assets and acquisitions. It is worth noting that investment outlays are

recorded on a net basis. I treated sale of existing property, plant, and equipment (PPE) and sale of subsidiaries as a negative investment outlay, not as a source of finance<sup>13</sup>.  $OPR_{j\tau}$  measures after-tax cash flow from operating activities.  $LTDEBT_{j\tau}$  measures funds from issuances of long-term debt capital net of retirements.  $EQUITY_{j\tau}$  measures funds from issuances of ordinary and preferred shares net of retirements. The residual source of financing,  $OTHER_{j\tau}$ , is measured so as to ensure that the cash-flow identity holds. This category includes funds raised by “changes in cash, inventory, and security investments”, “changes in trade credit”, “changes in short-term debt”, and “other minor components”. I do not use more detailed breakdowns for this category because the sample size would decrease dramatically due to differences in accounting policy and degree of aggregation. Note also that a positive sign on the right-hand side of the identity denotes a source of funds, whereas a negative sign denotes a use of funds. Table 4.1 Panel A provides more details of the Compustat items used to measure these components of the identity.

The next step is to aggregate the flow of funds by sub-groups. In this chapter, I show the aggregate statistics of the flow of funds by sub-groups based on various firm characteristics, including firm size, industry, investment spike size, initial leverage, etc. To aggregate the flow of funds, I normalize the flow of funds using the base-level investment and then calculate the investment-weighted average of the normalized flow of funds. In the case of  $J$  large investment

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<sup>13</sup>It is noteworthy that the sources of finance cannot be broken down by such types of investment as net capital expenditures, acquisitions and other investments. The statement of cash flows does not provide information about how much long-term debt was used to fund an acquisition by a certain company in a certain year, even if it can tell us about how much long-term debt was used to fund all the investing activities of the firm in the year. Therefore,  $I_{j\tau}$  is defined as the sum of capital expenditures, acquisitions and other investment. However, one can study whether there are differences in funding capital expenditures and acquisitions using a dummy variable  $D_{acq}$ , which assigns 1 if the proportion of acquisition is greater than zero and 0 otherwise.

events in each sub-group, the aggregated sources of finance for each  $\tau$  are calculated as:

$$OPR_{\tau} = \sum_{j=1}^J \left( \frac{I_{j0}}{\sum_{j=1}^J I_{j0}} \right) \left( \frac{OPR_{j\tau}}{BASE_j} \right), \quad (4.10)$$

$$LTDEBT_{\tau} = \sum_{j=1}^J \left( \frac{I_{j0}}{\sum_{j=1}^J I_{j0}} \right) \left( \frac{LTDEBT_{j\tau}}{BASE_j} \right), \quad (4.11)$$

$$EQUITY_{\tau} = \sum_{j=1}^J \left( \frac{I_{j0}}{\sum_{j=1}^J I_{j0}} \right) \left( \frac{EQUITY_{j\tau}}{BASE_j} \right), \quad (4.12)$$

$$OTHER_{\tau} = \sum_{j=1}^J \left( \frac{I_{j0}}{\sum_{j=1}^J I_{j0}} \right) \left( \frac{OTHER_{j\tau}}{BASE_j} \right), \quad (4.13)$$

for  $\tau \in \{-2, -1, 0, +1, +2\}$ , where  $I_{j0}$  is the investment amounts during the  $j$ -th spike<sup>14</sup> and  $BASE_j$  is the base-level investment for the  $j$ -th spike. The aggregated measures for total assets and investment are constructed analogously. Note that investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics. Furthermore, the  $j$ -th investment spike is dropped if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment to minimize the effects of extreme values. These procedures leave 5,528 investment spikes with median *GAMMA* being 3.18.

[Insert Table 4.2 Here.]

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<sup>14</sup>Note that the weighting is based on investment amounts during investment spikes.

#### 4.2.4 Descriptive statistics

Table 4.2 shows the summary statistics of the major variables based on the investment spikes sample. How the investment spikes sample is constructed is described in Section 4.2.2 and Section 4.2.3. Panel A, Panel B and Panel C show summary statistics for large firms, medium-sized firms, and small firms, respectively. The total assets at the beginning of the year with an investment spike ( $TA_{j,\tau=-1}$ ) are used to group firms with an investment spike into “Small firms”, “Medium-sized firms” and “Large firms”. The thresholds used are the 33rd and 67th percentiles. The variables reported in this table are constructed as explained in Table 4.1 Panel B. The time index  $\tau$  represents the time in relation to an investment spike. For example,  $\tau = 0$  indicates the year categorized as an investment spike, whereas  $\tau = -1$  indicates the year before an investment spike.

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

[Insert Table 4.3 Here.]

## 4.3 Analysis of the flow of funds around investment spikes

### 4.3.1 How are investment spikes financed?

In this section, I investigate how investment spikes are financed by analysing the flow of funds around investment spikes. Table 4.3 shows the sources of finance expressed as a proportion of the base-level investment for periods around investment spikes. The aggregate statistics were constructed as described in Section 4.2.3.

Panel A shows the investment-weighted flows of funds around investment spikes for all firms in the large investment events sample. I confirm the finding of Mayer and Sussman (2005) that the financing of investment during a spike is very different from the financing of investment at other times. The share of investment financed from internally generated funds (some 1.2 times the base-level investment) is much lower and the share of investment financed by long-term debt (some 2.5 times the base-level investment) is much higher. The first of these results is inevitable. Because I focus on periods where the level of investment is likely to exceed internal cash flow, the share of investment that can possibly be financed from internally generated funds necessarily falls (Bond *et al.*, 2006). However, the second of the results is not inevitable and this is similar to the findings by Mayer and Sussman (2005). Note also that the share of investment financed by equity finance (some 0.3 times the base-level investment) is quite low. The column *TA* (Total Assets) shows that total assets increase by some 50% during an investment spike. In this sense, investment spikes can be regarded as periods of major expansion for firms.

Panel B reports the investment-weighted proportions of the flows of funds around investment spikes, separately for sub-samples of “large firms”, “medium-sized firms” and “small firms” based on the total assets at the beginning of the year with an investment spike ( $TA_{\tau=-1}$ ). There are significant differences in the financing of investment spikes for these sub-samples of US firms classified by firm size. The financing proportions for large firms are very similar to those of all firms with investment spikes. The most striking finding is that small firms raise equity finance quite substantially before, during and after investment spikes, whereas large firms rely largely on debt finance during investment spikes. It is also observed that the contribution of equity finance in funding investment spikes is negligible when it comes to large firms. In small firms, there is more equity finance with equity being issued frequently in small amounts.

Note also that small firms make huge operating losses and rely heavily on external finance (both debt finance and equity finance) during investment spikes. It is quite surprising that small firms issue shares before and after the years categorized as investment spikes as well. In addition, it should be noted that small firms tend to have larger investment spikes. On average, large firms increase their total assets by some 47% during an investment spike, while small firms increase their total assets by some 132% during an investment spike. Those results suggest that it might be important to control for various firm characteristics (including firm size) when studying financing patterns. Nevertheless, a flow-of-funds analysis is a very useful tool to describe financing patterns before, during and after investment spikes.

### 4.3.2 Heterogeneity in the financing of investment spikes

In this section, I investigate how the financing patterns of investment spikes vary according to firm characteristics and industry. In particular, I investigate the effects of the profitability of firms, level of future growth opportunities, tangibility of assets and R&D intensity. Table 4.1 Panel B describes how to construct variables representing firm characteristics. Table 4.4, Table 4.5, Table 4.6 and Table 4.7 report the investment-weighted flows of funds around investment spikes by the subgroups based on both firm size and each of those firm characteristics. Finally, I investigate whether there are substantial differences in the financing of investment spikes according to industry.

[Insert Table 4.4 Here.]

Table 4.4 shows the relation between profitability and the financing of investment spikes. The investment spikes are grouped into “High profitability” and “Low profitability” based on the median of earnings before interests and taxes to total assets ratios measured at the beginning of the years with an investment spike ( $EBIT\_TA_{\tau=-1}$ ). Panel A and Panel B show that firms with lower profitability tend to use more equity finance at the time of an investment spike. In particular, small firms with lower profitability tend to use lots of equity finance at the time of an investment spike. Although large firms in general rely more heavily on debt finance in the years categorized as investment spikes, large firms with lower profitability tend to use more equity finance than large firms with higher profitability. It is also observed that small firms tend to issue shares even in the periods before and after investment spikes. It is also noteworthy that small firms with low profitability tend to have very spiky investment spikes.

Those firms are presumably severely financially constrained and rely more on equity finance than other types of firms.

[Insert Table 4.5 Here.]

Table 4.5 shows the relation between future growth opportunities and the financing of investment spikes. The investment spikes are grouped into “High M/B” and “Low M/B” based on the median of market-to-book ratios measured at the beginning of the years with an investment spike ( $MV\_BV_{\tau=-1}$ ). Panel A shows that there is no significant difference between large firms with high market-to-book and large firms with low market-to-book. However, Panel B shows that the financing patterns of small firms with high market-to-book are very different from those of small firms with low market-to-book. Small firms with higher market-to-book tend to have significantly more spiky investment spikes and use a higher proportion of equity finance.

[Insert Table 4.6 Here.]

Table 4.6 shows the relation between tangibility of assets and the financing of investment spikes. The investment spikes are grouped into “High tangibility” and “Low tangibility” based on the median of fixed-assets-to-total-assets ratios measured at the beginning of the years with an investment spike ( $FA\_TA_{\tau=-1}$ ). Panel A shows that the financing patterns of large firms with more tangible assets are not significantly different from those of large firms with fewer tangible assets. However, Panel B shows that small firms with fewer tangible assets tend to use more equity finance than small firms with more tangible assets. Note also that firms with fewer tangible assets tend to have more spiky investment spikes, which might be attributed to

the difficulty of obtaining external finance in normal periods.

[Insert Table 4.7 Here.]

Table 4.7 shows the relation between R&D intensity and the financing of investment spikes. The investment spikes are grouped into “High R&D intensity” and “Low R&D intensity” based on the median of R&D expenses-to-total assets ratios measured at the beginning of the years with an investment spike ( $RD\_TA_{\tau=-1}$ ). Panel A shows that the financing patterns of large firms with higher R&D intensity are not significantly different from those of large firms with lower R&D intensity. However, Panel B shows that small firms with higher R&D intensity tend to rely on more equity finance than small firms with lower R&D intensity. What is surprising is that small firms with lower R&D intensity tend to use more debt finance than small firms with higher R&D intensity, although those firms tend to have more spiky investment spikes. Overall, firms with lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance when confronted with large investment requirements.

[Insert Table 4.8 Here.]

Table 4.8 shows that the shares of finance during investment spikes are almost homogeneous across industries. In most industries, debt finance is the most important source of finance during investment spikes, followed by internal finance. Some contribution of equity finance at the time of an investment spike is also observed in most industries, whereas net retirement of equity is observed in several industries. For firms in construction-related, tobacco, or petrol refining industries, internally generated funds are slightly more important than debt finance at

the time of an investment spike, although debt finance is quite important as well. In the case of the leather industry, the most important source of finance was equity finance but this result might be attributed to the small sample size ( $N=27$ ). I conclude that there are no substantial differences in the financing of investment spikes across industries.

[Insert Table 4.9 Here.]

### **4.3.3 Spike characteristics and the financing of investment spikes**

In this section, I investigate whether investment spike characteristics make a difference in the financing of investment spikes. First, I investigate whether investment spikes involving acquisitions are funded differently from investment spikes involving capital expenditures. The financing patterns of acquisitions and those of capital expenditures are compared in Table 4.9. Investment spikes are classified as acquisitions if acquisitions are involved in that year ( $D_{AQC} > 0$ ), while they are classified as capital expenditures otherwise. In both Panel A and Panel B, it is observed that investment spikes involving acquisitions tend to be more spiky (i.e. larger) than investment spikes involving only capital expenditures. Therefore, it is expected that more equity finance will be involved in funding investment spikes involving acquisitions, as expected by the pecking-order theory (Myers and Majluf, 1984). However, additional investment requirements at the time of acquisitions tend to be funded by additional debt finance. In particular, small firms rely more on equity finance to finance capital expenditures, but they rely more on debt finance to finance acquisitions. These financing patterns among small firms are consistent with a reverse pecking order which can be predicted under endogenous infor-

mation production in a framework of Fulghieri and Lukin (2001), because it seems that equity finance is considered first among external finance sources.

[Insert Table 4.10 Here.]

Second, I investigate whether the financing patterns vary according to the magnitude of investment spikes. Table 4.10 and Table 4.11 show that financing patterns are substantially different in sub-groups based on  $GAMMA_j$  or the magnitude of investment spikes. According to Table 4.10, large firms tend to use only debt finance when they are confronted with relatively small investment spikes, but they tend to use more equity finance when they are confronted with relatively large investment spikes. It seems that this result is consistent with the pecking-order theory (Myers and Majluf, 1984). However, Table 4.11 shows that small firms tend to use more equity finance when they are confronted with relatively small investment spikes but more debt finance when they are confronted with relatively large investment spikes. This result seems to be consistent with the reverse pecking order as predicted by Fulghieri and Lukin (2001). Mayer and Sussman (2005) find that large investment projects are predominantly financed with debt, in particular in large and profitable firms, and interpret this result as suggesting that corporate financing patterns are consistent with the pecking-order theory. However, it is surprising that the financing patterns of small firms are rather consistent with the reverse pecking order. Overall, my findings are more consistent with Mayer and Sussman's (2002) first draft.

[Insert Table 4.11 Here.]

#### **4.3.4 Initial leverage and the financing of investment spikes**

In this section, the relation between the level of initial leverage and the financing of investment spikes is investigated. Table 4.12 and Table 4.13 show the investment-weighted flows of funds around investment spikes undertaken by large firms and small firms, respectively. According to the classical trade-off theory of debt, it is expected that firms with higher initial leverage will use less debt in financing investment requirements in periods categorized as investment spikes and in normal periods. However, Table 4.12 shows that initial leverage does not make significant differences in the financing of investment spikes in the case of large firms. That is, large firms tend to use more debt finance than equity finance in funding large investment projects regardless of the level of initial leverage.

[Insert Table 4.12 Here.]

Table 4.13 shows that the relation between the level of initial leverage and the financing of investment spikes undertaken by small firms is opposite to the prediction of the classical trade-off theory of debt. This table reveals that small firms with lower initial leverage tend to use more equity finance but small firms with higher initial leverage tend to use more debt finance in order 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 then, the financing of investment spikes cannot be fully explained using a classical trade-off theory of debt.

[Insert Table 4.13 Here.]

Despite some differences in financing patterns between large firms and small firms, the relation between the level of initial leverage and the financing of investment spikes is quite consistent with the predictions of a dynamic trade-off theory augmented with investment spikes as outlined by DeAngelo *et al.* (2011). DeAngelo *et al.* (2011) build a dynamic capital structure model in which firms deliberately but temporarily deviate from permanent leverage targets by issuing transitory debt to fund investment. They then find that it explains firms' debt issuance/repayment decisions better than static trade-off models of capital structure, and that it can account for the leverage changes that accompany "investment spikes". In their model, firms have leverage targets as in static trade-off models, but managers sometimes choose to deviate from targets and subsequently seek to rebalance to targets by reducing debt with a lag determined in part by the time path of investment opportunities and earnings realizations. The major components of their model are highly consistent with Mayer and Sussman's (2005) argument and the major empirical findings.

[Insert Table 4.14 Here.]

## **4.4 Robustness tests**

In this section, some robustness tests are executed. First, I investigate whether the financing of investment spikes is different depending on the significance level in the Regression filter. Regardless of significance level (1%, 5% and 10%), external finance becomes more important than internal finance at the time of an investment spike and debt finance is more important

than equity finance. In addition, a small proportion of equity finance is observed at the time of an investment spike too. See Table 4.14 for details.

[Insert Table 4.15 Here.]

Second, I investigate whether major findings on the financing of investment spikes are robust to the use of the Markov-switching filter suggested in Chapter 3. Table 4.15 Panel A reports the flow of funds around (0,0,1,0,0)-type investment spikes identified by the Markov-switching filter with the 5% level of significance. The results are based on the sample consisting of the firms for which investment rates are observed for the period 1988–2007, 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. Just as in the case of the Regression filter, external finance becomes very important at the time of investment spikes. More importantly, long-term debt is the most important source of finance, while the contribution of equity finance is quite small. Table 4.15 Panel B reports the flow of funds around (0,0,1,1,0,0)-type investment spikes identified by the Markov-switching filter. This analysis confirms that two-year investment spikes identified by the Markov-switching filter are financed quite similarly to single-year investment spikes. Again, external finance becomes very important at the time of investment spikes and debt finance is much more important than equity finance in funding two-year investment spikes.

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

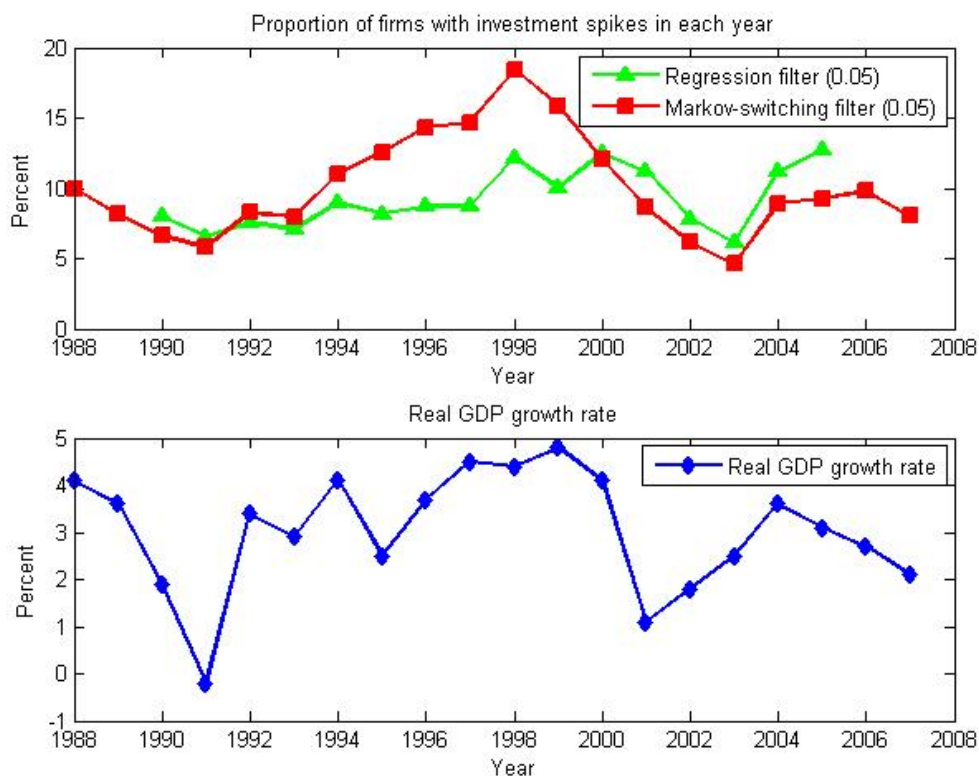


Figure 4.1: Proportion of firms with investment spikes and real GDP growth rate (2)

funds around investment spikes. Figure 4.1 shows that, unlike when the Regression filter (Sig. Level=0.05) is used, there is calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks when the Markov-switching filter (Sig. Level=0.05) is used. For instance, 5.81% of firms in the sample had an investment spike in 1991 (i.e. a recession year), whereas 18.40% of firms in the sample had an investment spike in 1998 (i.e. a boom year). It is also noteworthy that the proportion of firms with investment spikes in 1999 (15.87%) is slightly lower than that in 1998 which is a peak in real GDP growth rate. The lower proportion in 1999 could be due to firms' expectations about adverse future business conditions. According to Table 4.16, the sample contains a significantly larger number of

investment spikes in 1998 (i.e. 147 spikes) than in 1991 (i.e. 47 spikes).

[Insert Table 4.16 Here.]

To investigate whether the reliability of the aggregated flow of funds is affected by the calendar-time-dependent clustering, I examine if the flow of funds in a boom year (e.g. 1998) is significantly different from that in a recession year (e.g. 1991). Table 4.16 shows that the financing patterns around investment spikes in 1998 are not very different from the financing patterns around investment spikes in 1991. In both years, external finance is more important than internal finance at the time of an investment spike and debt finance is more important than both internal finance and equity finance at the time of an investment spike. In addition, some equity finance is used at the time of an investment spike.

However, there are some minor differences between the flow of funds around spikes in 1998 and the flow of funds around spikes in 1991, because investment spikes in 1998 tend to be spikier than those in 1991 and more internally generated funds are available around 1998. In 1998, a higher proportion of external finance, both debt and equity, is used at the time of an investment spike. While net repayment of debt and net retirement of equity are observed in periods after spikes in 1998, some additional borrowing and equity issuances are observed in periods after spikes in 1991. Note that the financing patterns in the two years are quite similar to the (averaged) financing patterns reported in Table 4.3 Panel A and Table 4.15 Panel A. Therefore, I conclude that the main findings reported in this chapter are robust to the calendar-time-dependent clustering of investment spikes generated by macroeconomic shocks.

## 4.5 Conclusions

Many studies hold that the dominant source of finance for firms across different countries and time periods is retained earnings (see Mayer (1988), Corbett and Jenkinson (1997), and Rajan and Zingales (1995)). However, this is primarily indicative of how firms finance their routine, replacement investment rather than non-routine, expansion investment. In particular, the way in which firms meet exceptional financing needs in relation to unusually large investment opportunities is the subject of an emerging body of literature, which includes DeAngelo *et al.* (2011).

Above all, I confirm the finding of Mayer and Sussman (2005) that the financing of investment during an investment spike is very different from the financing of investment at other times with more recent data and a filtering procedure suggested by Bond *et al.* (2006). It is confirmed that the share of investment financed by external sources is much higher than the share of investment financed from internally generated funds. More importantly, I find that the share of investment financed by long-term debt is much higher than the share of investment financed from equity finance. I also find that small firms raise equity finance quite substantially during investment spikes, whereas large firms rely largely on debt finance during investment spikes. In addition, firms with lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance when confronted with large investment requirements. However, the effects of those firm characteristics are not as strong as the effect of firm size on the financing of investment spikes. It seems that there are no substantial differences in the financing of investment spikes across industries.

Furthermore, I find that investment spikes involving acquisitions tend to be funded by a higher proportion of debt finance, although they tend to be spikier than investment spikes involving only capital expenditures. One of the most striking findings is that financing patterns are substantially different in sub-groups based on the magnitude of investment spikes. Large firms tend to use only debt finance when they are confronted with relatively small investment spikes, but they tend to use more equity finance when they are confronted with relatively large investment spikes. However, small firms tend to use more equity finance when they are confronted with relatively small investment spikes, but they tend to use more debt finance when they are confronted with relatively large investment spikes. It seems that the financing patterns of large firms are consistent with the pecking-order theory (Myers and Majluf, 1984), whereas the financing patterns of small firms are consistent with the reverse pecking order which can be predicted with endogenous information production (Fulghieri and Lukin, 2001).

Finally, the analysis of the relation between initial leverage and the financing of investment spikes suggests that financing patterns are not consistent with the classical trade-off theory of debt, but quite consistent with the predictions of a dynamic trade-off theory augmented with investment spikes as outlined in DeAngelo *et al.* (2011). According to the classical trade-off theory of debt, it is expected that firms with higher initial leverage will use less debt in financing their investment requirements in periods categorized as investment spikes and in normal periods. However, large firms tend to use more debt finance than equity finance in funding large investment projects regardless of the level of initial leverage. In addition, small firms with lower initial leverage tend to use more equity finance but small firms with higher

initial leverage tend to use more debt finance in order to meet large investment requirements, which is opposite to the prediction of the classical trade-off theory.

Table 4.1: Definition of variables

The table shows definitions for the variables used in the study. Panel A describes the variables used in the cash-flow identity whereas Panel B describes the other variables used in this chapter. The items in the cash-flow identity are defined similarly to Mayer and Sussman (2005). Unless otherwise stated, all the Compustat variables are measured at the end of year  $t$ . The variables in ratios are winsorized at the 1st and 99th percentiles. The italicized codes in the brackets ([ ]) represent the item codes in Compustat North America.

Panel A. Variables in cash-flow identity		
Abbreviation	Description	Formula
<i>I</i>	Total investment spending	Capital expenditures [ <i>capx</i> ] - Sale of property, plant, and equipment [ <i>spppe</i> ] + Acquisitions [ <i>aqc</i> ]
<i>OPR</i>	Internally generated funds	Income before extraordinary items [ <i>ibc</i> ] + Depreciation and amortization [ <i>dpc</i> ] - Cash dividends [ <i>dv</i> ]
<i>LTDEBT</i>	Long-term debt finance	Issuance of long-term debt [ <i>dltis</i> ] - Retirement of long-term debt [ <i>dltr</i> ]
<i>EQUITY</i>	Equity finance	Sale of common and preferred stock [ <i>sstk</i> ] - Purchase of common and preferred stocks [ <i>prstk</i> ]
<i>OTHER</i>	Other types of finance	$I - OPR - LTDEBT - EQUITY$
Panel B. Other variables		
Abbreviation	Description	Formula
<i>LEV</i>	Market leverage	$(\text{Total long-term debt } [dltt] + \text{Total short-term debt } [dlc]) / (\text{Total long-term debt } [dltt] + \text{Total short-term debt } [dlc] + \text{Close price at the end of calendar year } [prcc\_c] \times \text{Number of common shares outstanding } [csho])$
<i>BLEV</i>	Book leverage	$(\text{Total long-term debt } [dltt] + \text{Total short-term debt } [dlc]) / \text{Total assets } [at]$
<i>LnTA</i>	Firm size	Natural logarithm of Total assets [ <i>at</i> ]
<i>EBIT_TA</i>	Profitability	$(\text{Income before extraordinary items } [ib] + \text{Total interest and related expenses } [xint] + \text{Total income taxes } [txt]) / \text{Total assets at the beginning of the year } [at_{t-1}]$
<i>MV_BV</i>	Market-to-Book	$(\text{Total long-term debt } [dltt] + \text{Total debt in current liabilities } [dlc] + \text{Liquidation value of preferred stock } [pstkl] + \text{Close price at the end of calendar year } [prcc\_c] \times \text{Number of common shares outstanding } [csho]) / \text{Total assets } [at]$
<i>FA_TA</i>	Tangibility of assets	$\text{Total property, plant and equipment } [ppent] / \text{Total assets } [at]$
<i>RD_TA</i>	R&D intensity	$\text{R\&D expenses } [xrd] / \text{Total assets at the beginning of the year } [at_{t-1}]$
<i>D_AQC</i>	Dummy variable for acquisitions	1 if a firm reports positive acquisitions [ <i>aqc</i> ], and 0 otherwise.

Table 4.2: Summary statistics: Investment spikes sample

This table reports the summary statistics for the investment spikes sample. Section 4.2.2 and Section 4.2.3 describe how the investment spikes sample is constructed. Panel A, Panel B and Panel C show large firms, medium-sized firms, and small firms, respectively. The total assets at the beginning of the year with an investment spike ( $TA_{j,\tau=-1}$ ) are used to group firms with an investment spike into “Small firms”, “Medium-sized firms” and “Large firms”. The thresholds used are the 33rd and 67th percentiles. The variables reported below are constructed as explained in Table 4.1 Panel B. The time index  $\tau$  represents the time in relation to an investment spike. For example,  $\tau = 0$  indicates the year categorized as an investment spike, whereas  $\tau = -1$  indicates the year before an investment spike.

Panel A. Large firms						
Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ( $\tau = 0$ )	1708	0.297	0.220	0.123	0.262	0.428
Market leverage ( $\tau = -1$ )	1680	0.226	0.195	0.076	0.180	0.328
Book leverage ( $\tau = 0$ )	1819	0.325	0.216	0.188	0.307	0.429
Book leverage ( $\tau = -1$ )	1818	0.278	0.218	0.131	0.253	0.367
Total assets ( $\tau = -1$ )	1824	5518	16413	672	1369	3733
Log total assets ( $\tau = -1$ )	1824	7.523	1.255	6.510	7.222	8.225
Profitability ( $\tau = -1$ )	1763	0.123	0.111	0.070	0.117	0.171
Market-to-Book ( $\tau = -1$ )	1671	1.799	1.725	0.957	1.343	2.033
Assets tangibility ( $\tau = -1$ )	1821	0.333	0.216	0.161	0.286	0.473
R&D intensity ( $\tau = -1$ )	1824	0.025	0.055	0.000	0.000	0.025
Panel B. Medium-sized firms						
Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ( $\tau = 0$ )	1797	0.242	0.246	0.020	0.167	0.404
Market leverage ( $\tau = -1$ )	1765	0.162	0.208	0.002	0.069	0.259
Book leverage ( $\tau = 0$ )	1875	0.257	0.246	0.039	0.221	0.399
Book leverage ( $\tau = -1$ )	1875	0.197	0.237	0.008	0.122	0.306
Total assets ( $\tau = -1$ )	1880	167	91	88	146	233
Log total assets ( $\tau = -1$ )	1880	4.969	0.557	4.473	4.980	5.452
Profitability ( $\tau = -1$ )	1724	0.098	0.410	0.062	0.125	0.203
Market-to-Book ( $\tau = -1$ )	1764	2.323	3.514	0.924	1.434	2.383
Assets tangibility ( $\tau = -1$ )	1879	0.260	0.209	0.095	0.202	0.369
R&D intensity ( $\tau = -1$ )	1880	0.062	0.144	0.000	0.000	0.063
Panel C. Small firms						
Variable	N	Mean	SD	Q1	Median	Q3
Market leverage ( $\tau = 0$ )	1759	0.199	0.227	0.012	0.109	0.322
Market leverage ( $\tau = -1$ )	1660	0.126	0.188	0.001	0.036	0.176
Book leverage ( $\tau = 0$ )	1821	0.215	0.235	0.022	0.164	0.341
Book leverage ( $\tau = -1$ )	1821	0.174	0.288	0.003	0.079	0.251
Total assets ( $\tau = -1$ )	1824	21	15	8	18	32
Log total assets ( $\tau = -1$ )	1823	2.684	1.003	2.071	2.887	3.470
Profitability ( $\tau = -1$ )	1690	-0.087	0.756	-0.082	0.075	0.176
Market-to-Book ( $\tau = -1$ )	1659	2.652	3.476	0.898	1.576	3.005
Assets tangibility ( $\tau = -1$ )	1823	0.219	0.207	0.070	0.151	0.288
R&D intensity ( $\tau = -1$ )	1823	0.097	0.191	0.000	0.011	0.113

Table 4.3: Firm size and the flow of funds around investment spikes

This table summarizes the flow of funds around investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes for all firms in the investment spikes sample. Panel B shows the investment-weighted flow of funds around an investment spike by firm size. The total assets at the beginning of the year with an investment spike ( $TA_{j,\tau=-1}$ ) are used to group firms with an investment spike into “Small firms”, “Medium-sized firms” and “Large firms”. The thresholds used are the 33rd and 67th percentiles. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Flow of funds: All firms with investment spikes								
Sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
All firms	-2	5,528	13.71	0.8897	1.0676	0.0711	-0.0349	-0.2141
	-1	5,528	15.14	0.9662	1.1608	0.1366	-0.0181	-0.3132
	<b>0</b>	<b>5,528</b>	<b>22.61</b>	<b>5.2423</b>	<b>1.2149</b>	<b>2.4558</b>	<b>0.3425</b>	<b>1.2291</b>
	+1	5,528	22.42	1.0957	1.2307	-0.0940	-0.0185	-0.0225
	+2	5,528	22.74	1.0484	1.2835	-0.1250	-0.2055	0.0954
Panel B. Flow of funds by sub-samples based on firm size								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
Large firms	-2	1,824	13.89	0.9010	1.0916	0.0781	-0.0697	-0.1991
	-1	1,824	15.28	0.9703	1.1759	0.1504	-0.0914	-0.2646
	<b>0</b>	<b>1,824</b>	<b>22.48</b>	<b>5.0109</b>	<b>1.2376</b>	<b>2.2781</b>	<b>0.2319</b>	<b>1.2633</b>
	+1	1,824	22.28	1.0886	1.2630	-0.0923	-0.0473	-0.0347
	+2	1,824	22.61	1.0401	1.3027	-0.1303	-0.2371	0.1048
Medium-sized firms	-2	1,880	11.06	0.7425	0.8038	-0.0325	0.4123	-0.4412
	-1	1,880	13.03	0.9143	1.0391	-0.0662	0.8854	-0.9440
	<b>0</b>	<b>1,880</b>	<b>23.61</b>	<b>8.2132</b>	<b>1.0190</b>	<b>4.8705</b>	<b>1.4911</b>	<b>0.8326</b>
	+1	1,880	23.57	1.1763	0.9996	-0.1473	0.2967	0.0273
	+2	1,880	23.98	1.1669	1.1627	0.0284	0.1302	-0.1544
Small firms	-2	1,824	10.75	0.5893	0.0464	-0.0202	0.9485	-0.3853
	-1	1,824	13.74	0.8369	0.1917	-0.0600	2.3411	-1.6360
	<b>0</b>	<b>1,824</b>	<b>31.86</b>	<b>11.7976</b>	<b>-0.1463</b>	<b>6.4843</b>	<b>5.5176</b>	<b>-0.0580</b>
	+1	1,824	30.71	1.3747	-1.0699	0.1064	1.2107	1.1275
	+2	1,824	30.08	1.1990	-0.2143	-0.6250	1.2235	0.8148

Table 4.4: Profitability and the flow of funds around investment spikes

This table shows the relation between profitability and the financing of investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes of large firms in the investment spikes sample, while Panel B shows those for small firms in the investment spikes sample. Profitability ( $EBIT\_TA$ ) as defined in Table 4.1 Panel B is used to group firms with an investment spike into “High profitability” and “Low profitability”. The median is used as a threshold. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Large firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High profitability	-2	943	12.06	0.8841	1.2006	0.0978	-0.1146	-0.2997
	-1	943	13.41	0.9761	1.3494	0.2043	-0.1931	-0.3845
	<b>0</b>	<b>943</b>	<b>20.76</b>	<b>5.4551</b>	<b>1.3950</b>	<b>2.5653</b>	<b>0.1439</b>	<b>1.3508</b>
	+1	943	20.89	1.0815	1.4468	-0.1127	-0.0417	-0.2109
	+2	943	21.28	1.0582	1.3869	-0.0442	-0.2730	-0.0114
Low profitability	-2	820	16.49	0.9403	0.9183	0.0538	0.0156	-0.0473
	-1	820	17.83	0.9784	0.8913	0.0874	0.0528	-0.0531
	<b>0</b>	<b>820</b>	<b>22.75</b>	<b>4.0625</b>	<b>1.0968</b>	<b>1.8217</b>	<b>0.3417</b>	<b>0.8023</b>
	+1	820	22.12	1.0925	0.8345	0.0095	-0.0598	0.3083
	+2	820	22.32	0.9888	1.1415	-0.2395	-0.1896	0.2763
Panel B. Small firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High profitability	-2	683	10.26	0.5928	1.0868	-0.1003	0.3065	-0.7002
	-1	683	14.04	0.9137	1.9152	-0.3352	1.8844	-2.5507
	<b>0</b>	<b>683</b>	<b>29.00</b>	<b>9.6109</b>	<b>1.2937</b>	<b>5.7408</b>	<b>2.5976</b>	<b>-0.0212</b>
	+1	683	29.33	1.3040	0.7908	-0.2293	0.6239	0.1187
	+2	683	29.25	1.1894	0.6233	-0.4066	0.4433	0.5294
Low profitability	-2	1,007	10.86	0.5754	-0.7868	0.0734	1.2927	-0.0038
	-1	1,007	13.12	0.7606	-1.2024	0.1603	2.6012	-0.7985
	<b>0</b>	<b>1,007</b>	<b>34.61</b>	<b>14.2161</b>	<b>-1.1580</b>	<b>7.6280</b>	<b>7.9140</b>	<b>-0.1679</b>
	+1	1,007	32.38	1.4455	-2.3252	0.3546	1.5946	1.8216
	+2	1,007	31.29	1.2185	-0.7634	-0.8491	1.8619	0.9692

Table 4.5: Growth opportunities and the flow of funds around investment spikes

This table shows the relation between future growth opportunities and the financing of investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes of large firms in the investment spikes sample, while Panel B shows those for small firms in the investment spikes sample. The level of future growth opportunities measured by market-to-book ratios ( $MV\_BV$ ) as defined in Table 4.1 Panel B is used to group firms with an investment spike into “High M/B” and “Low M/B”. The median is used as a threshold. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Large firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High M/B	-2	758	11.13	0.8879	1.1883	0.0746	-0.1539	-0.2212
	-1	758	12.76	0.9531	1.3095	0.2711	-0.1535	-0.4741
	<b>0</b>	<b>758</b>	<b>22.40</b>	<b>5.5426</b>	<b>1.2592</b>	<b>2.7334</b>	<b>0.2326</b>	<b>1.3174</b>
	+1	758	22.17	1.1129	1.2867	-0.1667	-0.0756	0.0684
	+2	758	22.51	1.0462	1.3505	-0.2929	-0.2752	0.2637
Low M/B	-2	913	16.90	0.9359	1.0208	0.0722	-0.0116	-0.1455
	-1	913	18.18	0.9817	1.2091	0.0192	-0.0612	-0.1854
	<b>0</b>	<b>913</b>	<b>23.10</b>	<b>4.1401</b>	<b>1.2923</b>	<b>1.8070</b>	<b>0.1382</b>	<b>0.9027</b>
	+1	913	22.97	1.0596	1.2137	-0.0970	-0.0588	0.0017
	+2	913	23.35	1.0228	1.2650	-0.0545	-0.2432	0.0555
Panel B. Small firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High M/B	-2	905	9.15	0.5825	-0.1636	0.0738	1.2084	-0.5361
	-1	905	12.96	0.8574	0.0478	-0.0930	3.2156	-2.3130
	<b>0</b>	<b>905</b>	<b>34.55</b>	<b>14.3888</b>	<b>0.0881</b>	<b>8.9040</b>	<b>5.4721</b>	<b>-0.0753</b>
	+1	905	33.79	1.2936	-0.8151	-0.1894	1.7627	0.5355
	+2	905	33.49	1.2665	-0.6364	-0.9292	1.6342	1.1978
Low M/B	-2	754	15.64	0.7134	0.6732	-0.1687	0.4804	-0.2715
	-1	754	17.18	0.8972	0.8842	-0.0673	0.9348	-0.8544
	<b>0</b>	<b>754</b>	<b>25.90</b>	<b>7.3338</b>	<b>0.5966</b>	<b>4.1940</b>	<b>0.7429</b>	<b>1.8003</b>
	+1	754	25.52	1.2013	0.3939	-0.0237	0.5075	0.3236
	+2	754	25.36	1.1880	0.9479	-0.4988	0.4038	0.3352

Table 4.6: Assets tangibility and the flow of funds around investment spikes

This table shows the relation between tangibility of assets and the financing of investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes of large firms in the investment spikes sample, while Panel B shows those for small firms in the investment spikes sample. Tangibility of assets ( $FA\_TA$ ) as defined in Table 4.1 Panel B is used to group firms with an investment spike into “High tangibility” and “Low tangibility”. The median is used as a threshold. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Large firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High tangibility	-2	1,188	11.85	0.9026	1.0292	0.0509	-0.0662	-0.1114
	-1	1,188	12.76	0.9927	1.0294	0.0703	-0.0638	-0.0433
	<b>0</b>	<b>1,188</b>	<b>17.85</b>	<b>4.1738</b>	<b>1.1266</b>	<b>1.8974</b>	<b>0.2249</b>	<b>0.9249</b>
	+1	1,188	17.57	1.0791	1.1344	0.0337	-0.0130	-0.0760
	+2	1,188	18.12	1.0257	1.2224	-0.0227	-0.1108	-0.0632
Low tangibility	-2	633	19.74	0.9009	1.2634	0.1478	-0.0836	-0.4267
	-1	633	22.27	0.9048	1.5785	0.3373	-0.1726	-0.8385
	<b>0</b>	<b>633</b>	<b>35.39</b>	<b>7.3769</b>	<b>1.5418</b>	<b>3.3031</b>	<b>0.2460</b>	<b>2.2860</b>
	+1	633	35.55	1.1137	1.6242	-0.4008	-0.1028	-0.0069
	+2	633	35.20	1.0806	1.5207	-0.4063	-0.6013	0.5675
Panel B. Small firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High tangibility	-2	655	8.15	0.6691	0.0925	-0.0239	0.4820	0.1186
	-1	655	9.61	1.0091	0.1701	0.1065	1.0574	-0.3249
	<b>0</b>	<b>655</b>	<b>19.53</b>	<b>7.0138</b>	<b>-0.1484</b>	<b>4.2402</b>	<b>2.7455</b>	<b>0.1765</b>
	+1	655	18.98	1.1872	-0.6153	0.0543	0.8920	0.8562
	+2	655	18.29	1.1346	-0.2184	-0.5102	0.9456	0.9176
Low tangibility	-2	1,168	12.88	0.5502	0.0155	-0.0182	1.3033	-0.7503
	-1	1,168	17.04	0.7400	0.2126	-0.1786	3.3098	-2.6037
	<b>0</b>	<b>1,168</b>	<b>40.87</b>	<b>15.1704</b>	<b>-0.1593</b>	<b>8.2462</b>	<b>7.2451</b>	<b>-0.1615</b>
	+1	1,168	39.20	1.4461	-1.4566	0.1471	1.4601	1.2956
	+2	1,168	38.53	1.2637	-0.2721	-0.8547	1.4535	0.9369

Table 4.7: R&D intensity and the flow of funds around investment spikes

This table shows the relation between R&D intensity and the financing of investment spikes. Panel A shows the investment-weighted flows of funds around investment spikes of large firms in the investment spikes sample, while Panel B shows those for small firms in the investment spikes sample. R&D intensity ( $RD\_TA$ ) as defined in Table 4.1 Panel B is used to group firms with an investment spike into “High R&D intensity” and “Low R&D intensity”. The median is used as a threshold. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Large firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High R&D intensity	-2	869	15.33	0.9113	1.2454	0.0805	-0.1004	-0.3142
	-1	869	16.58	0.9799	1.2701	0.0966	-0.1718	-0.2149
	<b>0</b>	<b>869</b>	<b>23.80</b>	<b>5.0469</b>	<b>1.3017</b>	<b>2.0113</b>	<b>0.0612</b>	<b>1.6727</b>
	+1	869	23.63	1.0823	1.4097	-0.0188	-0.0365	-0.2721
	+2	869	24.10	1.0264	1.4013	-0.0811	-0.2628	-0.0310
Low R&D intensity	-2	955	11.63	0.8848	0.8500	0.0744	-0.0214	-0.0181
	-1	955	13.24	0.9552	1.0280	0.2350	0.0350	-0.3428
	<b>0</b>	<b>955</b>	<b>20.40</b>	<b>4.9543</b>	<b>1.1368</b>	<b>2.6973</b>	<b>0.5002</b>	<b>0.6199</b>
	+1	955	20.18	1.0984	1.0323	-0.2079	-0.0644	0.3385
	+2	955	20.27	1.0616	1.1478	-0.2076	-0.1968	0.3182
Panel B. Small firms								
Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High R&D intensity	-2	972	13.18	0.6372	-0.0851	-0.0511	1.5059	-0.7325
	-1	972	17.33	0.8848	0.0220	-0.0315	3.4979	-2.6036
	<b>0</b>	<b>972</b>	<b>31.82</b>	<b>8.6531</b>	<b>-1.2292</b>	<b>3.5008</b>	<b>6.4826</b>	<b>-0.1010</b>
	+1	972	30.89	1.3295	-1.9274	0.3428	1.9241	0.9901
	+2	972	30.49	1.1484	-0.8042	-0.3079	1.6033	0.6573
Low R&D intensity	-2	851	8.94	0.5540	0.1441	0.0026	0.5359	-0.1286
	-1	851	11.09	0.8013	0.3181	-0.0810	1.4844	-0.9202
	<b>0</b>	<b>851</b>	<b>31.90</b>	<b>14.1267</b>	<b>0.6564</b>	<b>8.6949</b>	<b>4.8042</b>	<b>-0.0288</b>
	+1	851	30.57	1.4083	-0.4356	-0.0686	0.6826	1.2298
	+2	851	29.78	1.2364	0.2207	-0.8617	0.9426	0.9348

Table 4.8: Industry and the financing of investment spikes

This table summarizes the sources of finance during investment spikes according to industry groups as suggested by Mayer and Sussman (2005). 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 industry. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Code	Industry	Obs.	$I$	Sources of Finance			
				$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
1	Agriculture	25	7.1103	1.6302	4.6206	0.1427	0.7167
2	Mining	41	4.5041	1.0400	2.8844	0.4187	0.1610
3	Oil and gas extraction	171	3.1392	1.0016	1.3930	0.1332	0.6113
4	Construction related	77	5.5388	2.2443	1.1211	0.2565	1.9169
5	Food	179	8.3089	1.4247	3.4282	-0.1091	3.5650
6	Tobacco	13	8.0665	2.0079	1.7870	-0.6028	4.8743
7	Textile	60	7.2628	1.5922	5.6900	0.1547	-0.1741
8	Apparel	65	5.0227	1.7260	2.9513	0.1144	0.2311
9	Lumber and wood	30	8.3215	1.6528	5.9876	0.2918	0.3894
10	Furniture and fixture	40	4.2263	1.2043	2.3572	-0.1780	0.8428
11	Paper	82	4.5678	1.2398	2.3143	0.0253	0.9883
12	Printer and publishing	115	7.9845	1.5801	4.5578	-0.3575	2.2041
13	Chemicals	406	7.2875	0.8017	3.6273	-0.0826	2.9412
14	Petrol refining	46	2.0382	1.2941	0.3878	0.0090	0.3473
15	Rubber and plastic	89	5.8741	1.2283	4.0502	0.0859	0.5098
16	Leather	27	4.7401	2.1742	1.4988	4.0417	-2.9746
17	Stone and concrete	49	4.5622	1.6158	1.7645	0.5407	0.6412
18	Primary metal	118	4.3832	1.0938	2.0510	0.5269	0.7110
19	Other metal	104	5.1424	1.1324	3.4007	0.1352	0.4740
20	Machinery	360	5.2253	1.4948	1.5942	0.2750	1.8613
21	Electrical products	553	4.1524	1.4511	1.7025	0.7400	0.2588
22	Transportation equipment	148	4.5286	1.4585	2.0678	0.4225	0.5799
23	Other: Watches, photos	439	7.3400	1.3224	3.1640	0.4900	2.3636
24	Miscellaneous products	74	5.7917	1.7804	2.5254	0.4455	1.0404
25	Transportation services	123	2.5468	0.7775	1.1506	0.2116	0.4072
26	Communication	241	3.8668	0.7897	1.9612	0.7714	0.3445
27	Wholesale	268	7.9007	1.7582	4.0852	1.3647	0.6926
28	Retail	374	4.0039	1.2092	1.8020	0.3033	0.6894
29	Other services	1151	7.0834	1.4397	3.9582	0.6724	1.0131
30	Other	60	3.7760	1.6036	1.5774	0.4906	0.1044
	Total	5,528	5.2423	1.2149	2.4558	0.3425	1.2291

Table 4.9: 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. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Large firms								
Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
Capital expenditures	-2	722	13.27	0.8483	1.0276	0.0430	-0.0266	-0.1957
	-1	722	14.37	0.9998	1.1324	0.1173	0.0314	-0.2813
	<b>0</b>	<b>722</b>	<b>16.57</b>	<b>1.9065</b>	<b>1.1373</b>	<b>0.3795</b>	<b>0.0747</b>	<b>0.3151</b>
	+1	722	16.54	1.0806	1.1231	0.1459	-0.0876	-0.1009
	+2	722	17.06	1.0713	1.2266	0.0079	-0.1927	0.0296
Acquisitions	-2	1,102	14.21	0.9283	1.1248	0.0963	-.0920	-0.2008
	-1	1,102	15.75	0.9551	1.1985	0.1676	-.1550	-0.2560
	<b>0</b>	<b>1,102</b>	<b>25.53</b>	<b>6.6171</b>	<b>1.2895</b>	<b>3.2604</b>	<b>0.3133</b>	<b>1.7539</b>
	+1	1,102	25.26	1.0927	1.3353	-0.2156	-.0265	-0.0005
	+2	1,102	25.48	1.0239	1.3421	-0.2018	-.2601	0.1437
Panel B. Small firms								
Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
Capital expenditures	-2	1,158	12.29	0.6787	-0.1174	-0.0748	1.2768	-0.4059
	-1	1,158	15.41	0.9999	-0.1622	-0.1056	2.7656	-1.4979
	<b>0</b>	<b>1,158</b>	<b>25.11</b>	<b>6.0732</b>	<b>-1.5381</b>	<b>2.6983</b>	<b>5.5309</b>	<b>-0.6178</b>
	+1	1,158	23.19	1.2489	-2.7270	0.4341	1.3014	2.2403
	+2	1,158	22.52	1.0725	-0.6614	-0.3473	1.8151	0.2661
Acquisitions	-2	666	9.84	0.5372	0.1420	0.0116	0.7569	-0.3733
	-1	666	12.77	0.7418	0.3983	-0.0334	2.0934	-1.7165
	<b>0</b>	<b>666</b>	<b>35.81</b>	<b>15.1386</b>	<b>0.6661</b>	<b>8.6939</b>	<b>5.5099</b>	<b>0.2688</b>
	+1	666	35.10	1.4482	-0.1027	-0.0848	1.1577	0.4780
	+2	666	34.49	1.2728	0.0466	-0.7871	0.8783	1.1350

Table 4.10: Spike size and the flow of funds around investment spikes I—Large firms

This table shows the investment-weighted flows of funds around investment spikes that large firms undertake according to the magnitude of investment spikes. The magnitudes of investment spikes are measured by  $GAMMA_j$  as defined in Section 4.2.2.  $Q1$ ,  $Q2$  and  $Q3$  represent the 1st, 2nd and 3rd quartiles of  $GAMMA_j$ , respectively. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
$GAMMA_j < Q1$	-2	629	13.47	0.8896	1.0748	0.0727	-0.0797	-0.1781
	-1	629	14.50	0.9771	1.1568	0.0794	-0.0743	-0.1847
	<b>0</b>	<b>629</b>	<b>16.16</b>	<b>1.5489</b>	<b>1.1872</b>	<b>0.2781</b>	<b>-0.0602</b>	<b>0.1436</b>
	+1	629	16.38	1.0469	1.1620	0.1455	-0.1369	-0.1237
	+2	629	16.79	1.0864	1.2522	0.0295	-0.2701	0.0747
$Q1 \leq GAMMA_j < Q2$	-2	466	12.21	0.8657	0.9066	0.0486	-0.0184	-0.0710
	-1	466	13.26	0.9190	1.0584	0.0111	-0.0433	-0.1073
	<b>0</b>	<b>466</b>	<b>19.04</b>	<b>2.6033</b>	<b>1.1197</b>	<b>0.8791</b>	<b>0.1236</b>	<b>0.4810</b>
	+1	466	19.18	1.1220	1.2796	0.0973	-0.1370	-0.1178
	+2	466	19.93	1.0933	1.2730	0.0201	-0.2007	0.0008
$Q2 \leq GAMMA_j < Q3$	-2	375	12.54	0.7775	1.0149	0.0669	-0.0074	-0.2969
	-1	375	14.44	0.9481	1.1327	0.1309	0.0010	-0.3164
	<b>0</b>	<b>375</b>	<b>19.41</b>	<b>4.0961</b>	<b>1.2423</b>	<b>2.0122</b>	<b>0.1022</b>	<b>0.7394</b>
	+1	375	19.61	1.1566	1.2549	-0.0463	-0.0183	-0.0337
	+2	375	21.09	1.1177	1.2899	0.0056	-0.2253	0.0475
$GAMMA_j \geq Q3$	-2	354	16.43	1.0126	1.2949	0.1129	-0.1338	-0.2614
	-1	354	18.15	1.0145	1.3111	0.3453	-0.2007	-0.4412
	<b>0</b>	<b>354</b>	<b>33.83</b>	<b>11.1798</b>	<b>1.3792</b>	<b>5.6942</b>	<b>0.7117</b>	<b>3.3948</b>
	+1	354	32.71	1.0695	1.3664	-0.5246	0.1021	0.1256
	+2	354	31.93	0.9034	1.3884	-0.4996	-0.2353	0.2499

Table 4.11: Spike size and the flow of funds around investment spikes II—Small firms

This table shows the investment-weighted flows of funds around investment spikes that small firms undertake according to the magnitude of investment spikes. The magnitudes of investment spikes are measured by  $GAMMA_j$  as defined in Section 4.2.2.  $Q1$ ,  $Q2$  and  $Q3$  represent the 1st, 2nd and 3rd quartiles of  $GAMMA_j$ , respectively. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in each sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
$GAMMA_j < Q1$	-2	311	9.70	0.7516	0.4889	-0.1059	0.7243	-0.3557
	-1	311	11.52	0.8818	0.6599	0.0036	1.2407	-1.0224
	<b>0</b>	<b>311</b>	<b>14.11</b>	<b>1.7474</b>	<b>0.6376</b>	<b>0.1259</b>	<b>1.4899</b>	<b>-0.5059</b>
	+1	311	15.92	1.1294	0.4397	0.2693	0.5739	-0.1535
	+2	311	16.91	1.2372	0.7751	-0.0664	0.5830	-0.0545
$Q1 \leq GAMMA_j < Q2$	-2	434	10.88	0.6588	0.4006	-0.1032	0.7793	-0.4179
	-1	434	13.20	0.8224	0.6101	-0.4222	2.0709	-1.4364
	<b>0</b>	<b>434</b>	<b>18.20</b>	<b>2.6555</b>	<b>0.3323</b>	<b>0.9087</b>	<b>1.6994</b>	<b>-0.2849</b>
	+1	434	18.90	1.2060	0.2629	0.2815	0.8015	-0.1399
	+2	434	20.06	1.3129	0.6902	0.1987	0.7881	-0.3641
$Q2 \leq GAMMA_j < Q3$	-2	507	10.53	0.6427	0.1666	-0.0666	0.9556	-0.4128
	-1	507	13.05	0.8859	0.3196	-0.1380	2.0626	-1.3583
	<b>0</b>	<b>507</b>	<b>20.52</b>	<b>4.1841</b>	<b>-0.3362</b>	<b>1.7636</b>	<b>2.7249</b>	<b>0.0317</b>
	+1	507	22.10	1.1915	-0.3199	0.7276	0.8886	-0.1048
	+2	507	22.96	1.2799	-0.4223	0.3183	1.2519	0.1320
$GAMMA_j \geq Q3$	-2	572	10.93	0.5322	-0.1381	0.0277	1.0135	-0.3709
	-1	572	14.41	0.8159	-0.0139	0.0465	2.6495	-1.8662
	<b>0</b>	<b>572</b>	<b>41.64</b>	<b>18.1157</b>	<b>-0.2839</b>	<b>10.3960</b>	<b>7.9866</b>	<b>0.0170</b>
	+1	572	38.62	1.5153	-1.8586	-0.1931	1.5098	2.0571
	+2	572	36.81	1.1366	-0.4703	-1.2492	1.3950	1.4612

Table 4.12: Initial leverage and the flow of funds around investment spikes I—Large firms

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

Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
$LEV_{j,\tau=-1} < Q1$	-2	159	14.04	0.6505	1.7579	-0.0897	-0.3880	-0.6297
	-1	159	16.03	0.7457	2.1276	-0.0845	-0.1695	-1.1280
	<b>0</b>	<b>159</b>	<b>23.68</b>	<b>5.3360</b>	<b>2.1250</b>	<b>1.5120</b>	<b>-0.3314</b>	<b>2.0304</b>
	+1	159	25.90	1.2153	2.4101	0.0567	-0.5077	-0.7437
	+2	159	26.71	1.3885	1.4510	0.3596	-1.2744	0.8523
$Q1 \leq LEV_{j,\tau=-1} < Q2$	-2	352	10.70	0.8153	1.1990	0.0721	-0.1449	-0.3110
	-1	352	12.41	0.8739	1.3212	0.0117	-0.1840	-0.2750
	<b>0</b>	<b>352</b>	<b>23.42</b>	<b>5.4698</b>	<b>1.2069</b>	<b>2.4180</b>	<b>0.0902</b>	<b>1.7547</b>
	+1	352	23.70	1.1581	1.5660	-0.1981	-0.0669	-0.1428
	+2	352	24.56	1.1526	1.5383	-0.0110	-0.2209	-0.1538
$Q2 \leq LEV_{j,\tau=-1} < Q3$	-2	612	13.60	0.9902	1.0613	0.0786	-0.0653	-0.0844
	-1	612	14.96	1.0199	1.2194	0.1778	-0.1840	-0.1932
	<b>0</b>	<b>612</b>	<b>20.59</b>	<b>4.4161</b>	<b>1.2787</b>	<b>2.1962</b>	<b>0.0449</b>	<b>0.8963</b>
	+1	612	20.18	1.0430	1.1104	-0.2375	-0.0384	0.2085
	+2	612	19.93	0.9468	1.2185	-0.4044	-0.2850	0.4177
$LEV_{j,\tau=-1} \geq Q3$	-2	557	16.92	0.9254	0.9828	0.0798	0.0011	-0.1383
	-1	557	18.49	0.9947	1.1470	0.2793	0.0635	-0.4951
	<b>0</b>	<b>557</b>	<b>24.72</b>	<b>4.8630</b>	<b>1.2026</b>	<b>2.2612</b>	<b>0.5077</b>	<b>0.8916</b>
	+1	557	24.22	1.0715	1.0353	0.0376	-0.0375	0.0360
	+2	557	24.90	1.0084	1.2236	-0.0858	-0.1283	-0.0011

Table 4.13: Initial leverage and the flow of funds around investment spikes II—Small firms

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

Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
$LEV_{j,\tau=-1} < Q1$	-2	567	12.46	0.5169	-0.0184	-0.0785	1.6116	-0.9978
	-1	567	17.15	0.8637	0.3323	-0.3792	4.3660	-3.4554
	<b>0</b>	<b>567</b>	<b>32.54</b>	<b>9.9586</b>	<b>-0.8406</b>	<b>3.8484</b>	<b>5.7515</b>	<b>1.1993</b>
	+1	567	31.52	1.4627	-1.5155	-0.0470	1.8910	1.1341
	+2	567	30.60	1.1568	-1.3078	0.2134	1.1812	1.0700
$Q1 \leq LEV_{j,\tau=-1} < Q2$	-2	512	9.83	0.7010	0.1431	0.0099	0.9558	-0.4077
	-1	512	12.41	0.8461	0.2696	-0.2287	2.2483	-1.4431
	<b>0</b>	<b>512</b>	<b>26.94</b>	<b>9.4537</b>	<b>-0.1883</b>	<b>5.9045</b>	<b>3.3327</b>	<b>0.4049</b>
	+1	512	27.26	1.2471	-0.3900	0.0574	1.3224	0.2574
	+2	512	27.58	1.2057	-0.2463	-0.8549	1.6767	0.6302
$Q2 \leq LEV_{j,\tau=-1} < Q3$	-2	293	12.90	0.6957	0.7358	-0.1151	0.3235	-0.2485
	-1	293	14.91	0.9669	0.9479	0.0654	0.8221	-0.8684
	<b>0</b>	<b>293</b>	<b>25.17</b>	<b>7.3166</b>	<b>0.5846</b>	<b>3.8605</b>	<b>1.7320</b>	<b>1.1394</b>
	+1	293	25.88	1.1747	0.3582	-0.0169	0.7919	0.0415
	+2	293	25.05	1.1627	0.8630	-0.4325	0.5315	0.2006
$LEV_{j,\tau=-1} \geq Q3$	-2	288	11.66	0.5640	-0.0435	0.1038	0.1887	0.3151
	-1	288	12.98	0.7697	0.0887	0.5747	0.2918	-0.1855
	<b>0</b>	<b>288</b>	<b>41.86</b>	<b>22.7404</b>	<b>2.8180</b>	<b>16.8774</b>	<b>3.5457</b>	<b>-0.5007</b>
	+1	288	39.12	1.2482	1.1829	-0.7098	0.5264	0.2488
	+2	288	39.59	1.4181	1.9275	-1.9125	0.5186	0.8846

Table 4.14: Significance level and the flow of funds around investment spikes

This table summarizes the flow of funds around investment spikes according to the significance level of the Regression filter. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the spikes sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Sig. Level	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
1%	-2	2,278	14.78	0.9264	1.1696	0.0106	-0.0573	-0.1965
	-1	2,278	16.19	0.9242	1.2442	0.1299	-0.0960	-0.3540
	<b>0</b>	<b>2,278</b>	<b>27.52</b>	<b>7.8074</b>	<b>1.3005</b>	<b>3.8739</b>	<b>0.5243</b>	<b>2.1087</b>
	+1	2,278	27.25	1.0979	1.4111	-0.2688	0.0092	-0.0536
	+2	2,278	27.34	1.0516	1.3849	-0.2422	-0.1845	0.0933
5%	-2	5,528	13.71	0.8897	1.0676	0.0711	-0.0349	-0.2141
	-1	5,528	15.14	0.9662	1.1608	0.1366	-0.0181	-0.3132
	<b>0</b>	<b>5,528</b>	<b>22.61</b>	<b>5.2423</b>	<b>1.2149</b>	<b>2.4558</b>	<b>0.3425</b>	<b>1.2291</b>
	+1	5,528	22.42	1.0957	1.2307	-0.0940	-0.0185	-0.0225
	+2	5,528	22.74	1.0484	1.2835	-0.1250	-0.2055	0.0954
10%	-2	8,004	13.20	0.8872	1.0063	0.0852	-0.0241	-0.1802
	-1	8,004	14.65	0.9823	1.1337	0.1288	0.0023	-0.2825
	<b>0</b>	<b>8,004</b>	<b>20.97</b>	<b>4.4254</b>	<b>1.1710</b>	<b>2.0097</b>	<b>0.2587</b>	<b>0.9861</b>
	+1	8,004	20.87	1.0908	1.1241	-0.0215	-0.0414	0.0296
	+2	8,004	21.34	1.0397	1.2813	-0.0699	-0.1943	0.0226

Table 4.15: Markov-switching filter and the flow of funds around investment spikes

This table reports the flow of funds around investment spikes identified by the Markov-switching filter with the 5% level of significance. Panel A reports the flow of funds around (0,0,1,0,0)-type investment spikes, whereas Panel B reports the flow of funds around (0,0,1,1,0,0)-type investment spikes. The results are based on the sample consisting of the firms for which investment rates are observed for the period 1988–2007, 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. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all the investment spikes in the spikes sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Single-year investment spikes								
Investment pattern	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
(0,0,1,0,0)-type	-2	1,290	10.95	0.8793	1.0312	0.0972	-0.1681	-0.0810
	-1	1,290	11.86	1.0121	0.9993	0.0944	-0.1527	0.0711
	<b>0</b>	<b>1,290</b>	<b>19.99</b>	<b>5.4408</b>	<b>1.2393</b>	<b>2.6082</b>	<b>0.1376</b>	<b>1.4557</b>
	+1	1,290	20.08	1.1251	1.2641	0.0291	-0.0425	-0.1257
	+2	1,290	20.90	0.9836	1.3853	0.0366	-0.2044	-0.2339
Panel B. Two-year investment spikes								
Investment pattern	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
(0,0,1,1,0,0)-type	-2	230	8.12	0.7379	0.8741	-0.0517	-0.0655	-0.0190
	-1	230	9.05	0.9951	1.1653	-0.0856	-0.1415	0.0569
	<b>0<sup>§</sup></b>	<b>230</b>	<b>15.08</b>	<b>3.6436</b>	<b>1.1195</b>	<b>1.9920</b>	<b>0.0351</b>	<b>0.4970</b>
	+1	230	16.48	1.2030	1.1344	-0.4201	0.2041	0.2846
	+2	230	17.26	1.0640	1.1800	-0.2340	-0.0631	0.1812

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

Table 4.16: Markov-switching filter and the effect of calendar-time-dependent clustering

This table reports the flow of funds around (0,0,1,0,0)-type investment spikes that happened in a boom year and in a recession year, respectively. The Markov-switching filter with the 5% level of significance is used to identify investment spikes. The results are based on the sample consisting of the firms for which investment rates are observed for the period 1988–2007, 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. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all the investment spikes in the spikes sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Panel A. Single-year investment spikes in a boom year								
Spike year	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
1998	-2	147	9.89	0.8250	0.9037	0.0569	-0.1659	0.0302
	-1	147	12.48	1.0032	1.2038	0.3404	-0.1474	-0.3936
	<b>0</b>	<b>147</b>	<b>24.08</b>	<b>7.8706</b>	<b>1.2471</b>	<b>5.2023</b>	<b>0.9133</b>	<b>0.5080</b>
	+1	147	23.43	1.2580	1.5381	-0.6757	-0.3538	0.7493
	+2	147	23.58	0.9139	1.3659	-0.2078	-0.0545	-0.1897
Panel B. Single-year investment spikes in a recession year								
Spike year	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
1991	-2	47	7.50	0.8068	0.7721	0.1583	-0.0183	-0.1054
	-1	47	8.42	1.1541	0.7494	0.2285	0.0264	0.1498
	<b>0</b>	<b>47</b>	<b>10.76</b>	<b>2.2888</b>	<b>0.7816</b>	<b>1.2613</b>	<b>0.0840</b>	<b>0.1620</b>
	+1	47	11.21	1.1747	0.8130	0.2789	0.0734	0.0094
	+2	47	11.58	0.8644	0.5196	0.0558	0.1210	0.1680

## **Part III**

# **SHARE LIQUIDITY AND FINANCING PATTERNS**

# **Chapter 5**

## **Share Liquidity and the Financing of Investment Spikes**

### **5.1 Introduction**

The share market is often characterized by the liquidity of shares. Share liquidity is crucial to market participants because it entails transaction costs to them. However, there is not a lot of literature on the effect of share liquidity on corporate financing decisions. Lipson and Mortal (2009) examine the cross-sectional relation between leverage and liquidity and find that liquidity accounts for a significant part of the variation in leverage. Similarly, Frieder and Martell (2006) show that share liquidity has a significant impact on leverage, even after taking the endogeneity of share liquidity into account. However, whether the liquidity of shares makes any difference in financing firms' unusually large investment activities has not been

investigated at all<sup>1</sup>.

First, I examine whether the financing of investment spikes varies with share liquidity using the same data and methodology of Chapter 4. Specifically, I investigate whether there are significant differences in the financing of investment spikes for these sub-samples of US firms classified by share liquidity<sup>2</sup> measured in the year before investment spikes. The most important finding is that low-liquidity firms tend to raise substantial amounts of new equity finance during investment spikes, whereas high-liquidity firms tend not to rely on new equity issuances. Even in the periods before and after investment spikes, low-liquidity firms tend to issue some new equity but high-liquidity firms tend to buy back existing shares. All these results imply that share liquidity seems to have a positive effect on the propensity to raise debt finance during investment spikes.

I then investigate how strongly firm size and share liquidity are linked. The main finding is that shares of small firms tend to be less liquid and shares of large firms tend to be more liquid, although the share liquidity of medium-sized firms is symmetrically distributed. This partly explains why the financing patterns of high-liquidity (low-liquidity) firms are similar to those of large (small) firms. This analysis motivated me to investigate the effect of share liquidity on the propensity to raise debt finance more thoroughly<sup>3</sup>. Nevertheless, it is an intriguing finding that firms with less liquid shares tend to rely more heavily on equity to finance investment

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<sup>1</sup>Mayer and Sussman (2005) emphasize that one can study corporate finance patterns more precisely by investigating the flow of funds around investment spikes (see Chapter 4 for details).

<sup>2</sup>In this chapter, Hasbrouck's (2009) Gibbs-spread measure and Amihud's (2002) price impact measure are used as liquidity proxies.

<sup>3</sup>I investigate the effect of share liquidity on the flow of funds around investment spikes in this chapter, while I investigate the effect of share liquidity on the change in leverage during an investment spike in Chapter 6.

spikes.

Finally, I investigate whether firms' classifications as high liquidity and low liquidity are stable over the period of this study using the Markov-switching mean models (proposed in Chapter 3) applied to share illiquidity measures. Using demeaned Gibbs spread measures and demeaned Amihud's measures of 760 firms without any missing values in the years 1988-2007, I find that the probability of sticking to the low-liquidity state ( $p = Pr[S_t = 1 | S_{t-1} = 1]$ ) and the probability of sticking to the high-liquidity state ( $q = Pr[S_t = 0 | S_{t-1} = 0]$ ) are sufficiently high. Therefore, I conclude that share liquidity could be regarded as a slowly changing firm characteristic.

The structure of the remainder of the chapter is as follows. Section 5.2 describes measures for share liquidity and Section 5.3 presents empirical results for the relation between share liquidity and the financing of investment spikes. Section 5.4 discusses the relation between share liquidity and firm size and Section 5.5 provides evidence on the persistence of firms' classifications as high liquidity and low liquidity. Finally, Section 5.6 concludes.

## **5.2 Measures for share liquidity**

The market microstructure research has shown that liquidity captures the costs associated with information asymmetry (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985), as well as the direct trading costs such as fees or taxes and the costs associated with inventory (Garman, 1976; Ho and Stoll, 1981). Despite the difficulty of defining market liquidity, Kyle

(1985) suggests that market liquidity encompasses a number of the transactional properties of markets, including “tightness”, “depth”, and “resiliency”. “Tightness” refers to the cost of turning over a position in a short period of time and is often measured by the reciprocal of the bid-ask spread. “Depth” refers to the ability of the market to absorb quantities without having a large impact on price and is often measured by the reciprocal of the price impact. “Resiliency” refers to the speed with which prices tend to converge towards the underlying liquidation value of the commodity.

Recently, there has been some research testing whether the available liquidity proxies can capture the actual transaction costs of market participants. Goyenko *et al.* (2009) provide a comprehensive survey of liquidity measures and run “horseraces” involving a wide range of proxies for both price impact and bid-ask spread. In addition, based on several performance metrics such as cross-sectional correlation, time-series correlation, mean bias and the root mean squared error, they provide a list of low-frequency measures appropriate for applied research based on the closeness of low-frequency measures with high-frequency measures of transaction costs. They report that Holden’s (2009) measure performs the best among the spread measures, whereas Amihud’s (2002) measure performs the best among the price impact measures. Similarly, Hasbrouck (2009) compares several indirect measures of liquidity to measures of spreads and price impact constructed with the Trades and Quotes (TAQ) database, finding that the Gibbs sampler estimate of the Roll (1984) model suggested by Hasbrouck (2009) is the best measure of effective trading costs and the Amihud (2002) measure is the best measure of price impact. Amihud (2002) shows that his illiquidity measure is positively

and strongly related to two microstructure estimates of illiquidity, such as Kyle's (1985)  $\lambda$ , the price impact measure, and  $\psi$ , the fixed-cost component related to the bid-ask spread suggested by Brennan and Subrahmanyam (1996).

In this chapter, I use two liquidity measures: Hasbrouck's (2009) Gibbs-spread measure and Amihud's (2002) price impact measure. I do not use the Holden measure because this is computationally intensive. One major advantage that those two measures have over some other liquidity measures is that they can be computed over more extensive sample periods than liquidity measures that require the TAQ data, because they are calculated using CRSP data (Butler and Wan, 2010). The TAQ data are only available back to 1993, whereas this study needs data for the period 1988 to 2007<sup>4</sup>.

The first measure is Hasbrouck's (2009) Gibbs-spread measure. He introduces a Gibbs sampler estimation of the Roll (1984) model using prices from all days in each year. In his model, the "efficient price" ( $m_t$ ) is assumed to follow a Gaussian random walk:

$$m_t = m_{t-1} + u_t, \tag{5.1}$$

where  $u_t \sim N(0, \sigma_u^2)$ . The transaction price is given by:

$$p_t = m_t + cq_t, \tag{5.2}$$

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<sup>4</sup>Nevertheless, the liquidity measures calculated using TAQ data such as the relative spread are regarded as one of the best proxies for share liquidity. Therefore, they are often used as benchmark liquidity measures to evaluate liquidity proxies calculated using low-frequency data (see Goyenko *et al.* (2009) and Fang *et al.* (2009)).

where  $c$  is the effective cost parameter and  $q_t$  is the trade direction indicator, which takes the value +1 (for a buy) or -1 (for a sale) with equal probability. The disturbance,  $u_t$ , reflects public information and is assumed to be uncorrelated with  $q_t$ . The transaction prices are observed but  $q_t$  and  $m_t$  are not. Taking first-differences gives:

$$\Delta p_t = m_t + cq_t - (m_{t-1} + cq_{t-1}) = c\Delta q_t + u_t, \quad (5.3)$$

Note that this equation would be a simple linear regression if  $\Delta q_t$  were known. However,  $\Delta q_t$  is unobserved. In this situation, a Bayesian method called Gibbs sampling provides a way to estimate the model parameters  $\{c, \sigma_u^2\}$  along with the latent buy/sell indicators  $q = \{q_1, q_2, \dots, q_T\}$ , where  $T$  is the number of days in the year. The parameter  $c$  estimated for firm  $i$  during year  $y$  gives us the effective trading cost for firm  $i$  during year  $y$ ,  $Gibbs_{iy}$ . I use the SAS programming codes on Joel Hasbrouck's website without any modification. To see the economic significance of the measure, I normalized the Gibbs spread measure so that its mean equals 0 and its standard deviation equals 1.

The second measure is the price impact measure developed by Amihud (2002), which captures the "daily price response associated with one dollar of trading volume." Specifically, he uses the following ratio:

$$Amihud_{iy} = \frac{1}{D_{iy}} \sum_{d=1}^{D_{iy}} \left( \frac{|R_{iyd}|}{DVOL_{iyd}} \right), \quad (5.4)$$

where  $D_{iy}$  is the number of days for which data are available for stock  $i$  in year  $y$ ,  $R_{iyd}$  is firm  $i$ 's stock return on day  $d$  in year  $y$ , and  $DVOL_{iyd}$  is firm  $i$ 's dollar volume on day  $d$  in year

y. The average is calculated over all positive-volume days, since the ratio is undefined for zero-volume days. The Amihud measure is also normalized so that its mean equals 0 and its standard deviation equals 1.

[Insert Table 5.1 Here.]

### **5.3 Share liquidity and the financing around investment spikes**

In this section, I investigate whether the financing around investment spikes varies with share liquidity. Table 5.1 and Table 5.2 show the investment-weighted flows of funds around investment spikes by the subgroups based on Hasbrouck's Gibbs-spread measure and Amihud's price impact measure, respectively. Both tables show that in the period surrounding investment spikes, low-liquidity firms are net issuers of equity while high-liquidity firms are net purchasers. At the time of the investment spike, both high- and low-liquidity firms increase their use of both debt and equity financing. High-liquidity firms increase their use of equity financing by cutting back on equity repurchases while low-liquidity firms increase equity issuance. It is also noteworthy that both high- and low-liquidity firms increase their use of residual financing sources, although this is not a focus of this study.

[Insert Table 5.2 Here.]

However, low-liquidity firms tend to have somewhat higher investment requirements during investment spikes on average<sup>5</sup>, whereas low-liquidity firms tend to have substantially lower

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<sup>5</sup>Table 5.1 shows that high-liquidity firms increase total assets by some 43% whereas low-liquidity firms increase total assets by some 88%. Based on *GAMMA* as defined in Chapter 4, low-liquidity firms (*GAMMA* =

operating cash flows throughout the periods around investment spikes. Therefore, I do not draw any conclusions at this point regarding the effect of share liquidity on the propensity to raise debt finance, as other factors for financing decisions are not controlled for<sup>6</sup>. However, it is an important finding that firms with lower share liquidity raise more equity to finance exceptional external financing requirements in the period surrounding investment spikes.

## 5.4 Relation between firm size and share liquidity

In this section, I investigate how strongly firm size and share liquidity are linked by counting the number of investment spikes by firm size and share liquidity. The total assets measured at the beginning of the year with an investment spike ( $TA_{j,\tau=-1}$ ) are used to group firms with an investment spike into “Small firms”, “Medium-sized firms” and “Large firms”. The thresholds used are the 33rd and 67th percentiles. Investment spikes are grouped into five sub-groups based on the quintiles of the Hasbrouck’s Gibbs-spread measure ( $Gibbs_{j,\tau=-1}$ ) in Panel A and based on the quintiles of Amihud’s price impact measure ( $Amihud_{j,\tau=-1}$ ) in Panel B. The main finding from this analysis is that the shares of small firms tend to be less liquid, whereas the shares of large firms tend to be more liquid<sup>7</sup>. This explains why the financing patterns of high-liquidity firms are similar to those of large firms, whereas the financing patterns of low-liquidity firms are similar to those of small firms. Therefore, it is worth investigating whether

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9.77) tend to have spikier investment spikes than high-liquidity firms ( $GAMMA = 4.83$ ).

<sup>6</sup>In Chapter 6, I investigate the effect of share liquidity on the change in leverage during an investment spike controlling for various factors such as firm size, profitability and spike size.

<sup>7</sup>However, there are some large firms with low share liquidity and some small firms with high liquidity. In addition, the share liquidity of medium-sized firms is symmetrically distributed.

the effect of share liquidity vanishes when firm size is controlled for. Similarly, it is also worth investigating whether the effect of firm size vanishes when share liquidity is controlled for.

[Insert Table 5.3 Here.]

In Table 5.1 and Table 5.2, it can be seen that the magnitude of investment spikes is quite different between high-liquidity firms and low-liquidity firms. In Chapter 6, I investigate whether the effect of share liquidity exists even after controlling for the magnitude of investment spikes and other firm characteristics in a regression framework. Nevertheless, it is an intriguing finding that firms with less liquid shares tend to rely more heavily on equity to finance investment spikes.

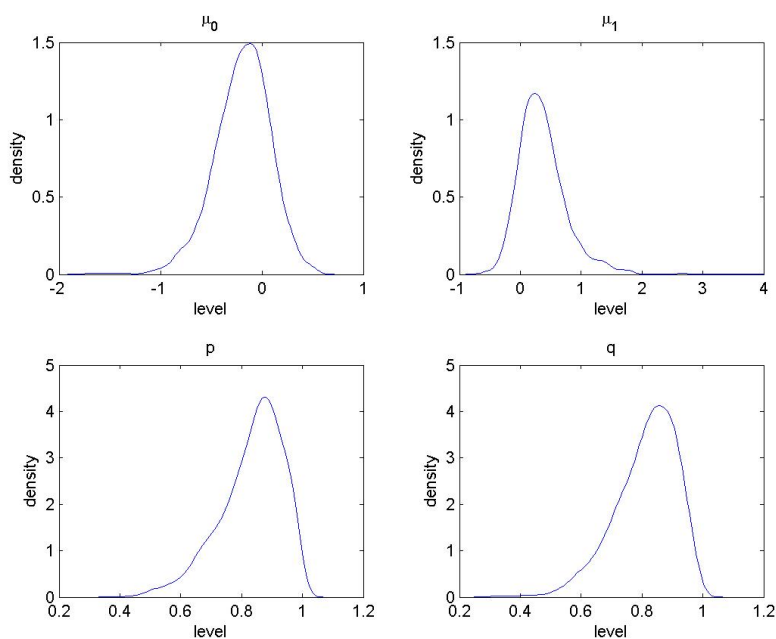


Figure 5.1: Posterior density of parameters in a Markov-switching model for a typical firm

## 5.5 Testing persistence of share liquidity measures

In this section, I investigate whether firms' classifications as high-liquidity firms and low-liquidity firms are stable over the period of this study. If a typical firm's classification is stable over time, share liquidity can be treated as a (persistent or slowly changing) firm characteristic. However, if a typical firm switches between the two classifications frequently, share liquidity could be regarded as a (time-varying) year characteristic rather than a (persistent) firm characteristic. As a test of persistence of the two classifications, I investigate whether the probability of sticking to the low-liquidity state ( $p = Pr[S_t = 1 | S_{t-1} = 1]$ ) and the probability of sticking to the high-liquidity ( $q = Pr[S_t = 0 | S_{t-1} = 0]$ ) are sufficiently high in the Markov-switching mean models (proposed in Chapter 3) applied to share illiquidity measures.

[Insert Table 5.4 Here.]

Table 5.4 reports the summary statistics of (firm-specific) parameter estimates from the Markov-switching mean models applied to demeaned Gibbs spread measures and demeaned Amihud's measures of 760 firms without any missing values in the years 1988-2007. According to Panel A<sup>8</sup> which summarizes parameter estimates from the Markov-switching models with Gibbs spread measures, the cross-sectional means (medians) of point estimates for the probability of sticking to the low-liquidity state ( $p = Pr[S_t = 1 | S_{t-1} = 1]$ ) and the probability of sticking to the high-liquidity state ( $q = Pr[S_t = 0 | S_{t-1} = 0]$ ) are 0.8610 (0.8570) and 0.8547 (0.8409), respectively. Figure 5.1 also shows that the medians of  $p$  and  $q$ , in a Markov-

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<sup>8</sup>Panel B which summarizes parameter estimates from the Markov-switching models applied to Amihud's measures also shows that the cross-sectional means (medians) of point estimates for the probability of sticking to the low-liquidity state ( $p = Pr[S_t = 1 | S_{t-1} = 1]$ ) and the probability of sticking to the high-liquidity state ( $q = Pr[S_t = 0 | S_{t-1} = 0]$ ) are 0.8528 (0.8498) and 0.8449 (0.8333), respectively.

switching model applied to a typical firm's Gibbs spread measures, are sufficiently high. Note that  $Pr[p < 0.5]$  and  $Pr[q < 0.5]$  are quite low. This analysis shows that the states of high liquidity and low liquidity are highly persistent. Therefore, I conclude that share liquidity could be regarded as a slowly changing firm characteristic because it seems that firms' classification as high liquidity and low liquidity are stable over time.

## 5.6 Conclusion

In this chapter, I have explored the heterogeneity in financing patterns by share liquidity, in particular around the time of an investment spike. Using the same approach as Chapter 4, I find that that in the period surrounding investment spikes, low-liquidity firms are net issuers of equity while high-liquidity firms are net purchasers. At the time of the investment spike, both high- and low-liquidity firms increase their use of both debt and equity financing. High-liquidity firms increase their use of equity financing by cutting back on equity repurchases while low-liquidity firms increase equity issuance. All these results imply that share liquidity seems to have a positive effect on the propensity to raise debt finance. In addition, I find that small firms tend to have less liquid shares, while large firms tend to have more liquid shares. However, it is worth investigating whether the effect of share liquidity vanishes when firm size and other firm characteristics are controlled for. These issues are carefully examined in Chapter 6. Finally, I find evidence on the persistence of firms' classifications as high liquidity and low liquidity using the Markov-switching mean model proposed in Chapter 3.

Table 5.1: Share liquidity and the flow of funds around investment spikes—*Gibbs*

This table shows the investment-weighted flows of funds around investment spikes by the subgroups based on Hasbrouck’s Gibbs-spread measure ( $Gibbs_{j,\tau=-1}$ ). Firms with this measure below the 20th percentile are categorized as “High liquidity”, firms with this measure greater than or equal to the 40th percentile and below the 60th percentile are categorized as “Medium liquidity”, and firms with this measure greater than or equal to the 80th percentile are categorized as “Low liquidity”. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the spikes sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Sub-sample	$\tau$	Obs.	TA	I	Sources of Finance			
					OPR	LTDEBT	EQUITY	OTHER
High liquidity	-2	745	13.63	0.9341	1.1474	0.0888	-0.1973	-0.1048
	-1	745	14.89	0.8933	1.3158	0.1005	-0.2485	-0.2744
	<b>0</b>	<b>745</b>	<b>21.30</b>	<b>4.8313</b>	<b>1.3718</b>	<b>2.5391</b>	<b>-0.0764</b>	<b>0.9967</b>
	+1	745	21.54	1.0927	1.4635	-0.1895	-0.2651	0.0838
	+2	745	22.33	1.0799	1.6120	-0.2683	-0.3724	0.1086
Medium liquidity	-2	746	13.73	0.8816	0.8040	0.1629	0.1614	-0.2468
	-1	746	15.26	0.9681	1.1341	-0.0356	0.3438	-0.4743
	<b>0</b>	<b>746</b>	<b>21.95</b>	<b>4.6881</b>	<b>1.3535</b>	<b>2.4558</b>	<b>0.6149</b>	<b>0.2639</b>
	+1	746	21.87	1.0731	1.1032	-0.1056	0.1206	-0.0451
	+2	746	22.85	1.0772	1.2482	-0.1290	-0.0553	0.0134
Low liquidity	-2	745	12.94	0.6766	0.6302	0.0614	0.5343	-0.5492
	-1	745	14.55	0.7996	0.7685	-0.0751	0.6871	-0.5809
	<b>0</b>	<b>745</b>	<b>27.31</b>	<b>9.7684</b>	<b>0.3523</b>	<b>5.6882</b>	<b>1.5327</b>	<b>2.1953</b>
	+1	745	26.49	1.4661	0.5394	-0.1548	0.8399	0.2416
	+2	745	24.43	1.0578	0.4443	-0.5281	0.6721	0.4696

Table 5.2: Share liquidity and the flow of funds around investment spikes—*Amihud*

This table shows the investment-weighted flows of funds around investment spikes by the subgroups based on Amihud’s price impact measure ( $Amihud_{j,\tau=-1}$ ). Firms with this measure below the 20th percentile are categorized as “High liquidity”, firms with this measure greater than or equal to the 40th percentile and below the 60th percentile are categorized as “Medium liquidity”, and firms with this measure greater than or equal to the 80th percentile are categorized as “Low liquidity”. The reported summary statistics are the flow of funds and total assets, first normalized by the base-level investment and then weighted by the proportion of investment spending during an investment spike to total investment spending throughout all investment spikes in the spikes sample. I drop the  $j$ -th investment spike if any of  $OPR_{j,\tau}/BASE_j$  or  $OTHER_{j,\tau}/BASE_j$  falls outside the  $[-40,40]$  segment. Investment spikes with any missing values in the cash-flow identity during the five-year event window ( $\tau \in \{-2, -1, 0, +1, +2\}$ ) are not used to construct the aggregate statistics.

Sub-sample	$\tau$	Obs.	$TA$	$I$	Sources of Finance			
					$OPR$	$LTDEBT$	$EQUITY$	$OTHER$
High liquidity	-2	745	14.42	0.9228	1.2096	0.0928	-0.2082	-0.1714
	-1	745	15.70	0.9433	1.4176	0.1532	-0.2795	-0.3480
	<b>0</b>	<b>745</b>	<b>22.06</b>	<b>4.6679</b>	<b>1.4207</b>	<b>2.3733</b>	<b>-0.0953</b>	<b>0.9692</b>
	+1	745	22.35	1.0862	1.3462	-0.1912	-0.2129	0.1441
	+2	745	22.80	1.0476	1.5261	-0.1810	-0.4433	0.1457
Medium liquidity	-2	746	13.23	0.8201	0.8399	-0.0516	0.3520	-0.3203
	-1	746	15.05	1.0037	0.9969	0.1459	0.5550	-0.6941
	<b>0</b>	<b>746</b>	<b>24.01</b>	<b>6.9411</b>	<b>1.2593</b>	<b>3.9041</b>	<b>1.1982</b>	<b>0.5795</b>
	+1	746	24.12	1.0878	1.1267	-0.3255	0.1738	0.1128
	+2	746	24.09	1.0884	1.2388	-0.1359	-0.0145	-0.0000
Low liquidity	-2	745	14.20	0.7390	0.7915	-0.1068	0.1676	-0.1134
	-1	745	14.59	0.8047	0.9088	-0.2308	0.1515	-0.0248
	<b>0</b>	<b>745</b>	<b>26.53</b>	<b>9.1646</b>	<b>0.9746</b>	<b>5.1052</b>	<b>1.0460</b>	<b>2.0388</b>
	+1	745	26.48	1.3650	1.2186	-0.0382	0.7553	-0.5706
	+2	745	23.88	1.0913	0.9998	-0.9484	0.5941	0.4457

Table 5.3: Firm size and share liquidity: Frequency analysis

This table reports the number of investment spikes by firm size and share liquidity. The total assets measured at the beginning of the year with an investment spike ( $TA_{j,\tau=-1}$ ) is used to group firms with an investment spike into “Small firms”, “Medium-sized firms” and “Large firms”. The thresholds used are the 33rd and 67th percentiles. Investment spikes are grouped into five sub-groups based on the quintiles of the Hasbrouck’s Gibbs spread measure ( $Gibbs_{j,\tau=-1}$ ) in Panel A and based on the quintiles of Amihud’s price impact measure ( $Amihud_{j,\tau=-1}$ ) in Panel B.

Panel A. Firm size and share liquidity based on Gibbs spread						
Firm size	Share liquidity					Total
	1: Highest	2	3	4	5: Lowest	
Small firms	12	53	156	291	558	1,070
Medium-sized firms	184	318	391	397	178	1,468
Large firms	549	374	199	57	9	1,188
Total	745	745	746	745	745	3,726

Panel B. Firm size and share liquidity based on Amihud’s measure						
Firm size	Share liquidity					Total
	1: Highest	2	3	4	5: Lowest	
Small firms	0	30	150	333	557	1,070
Medium-sized firms	72	360	478	378	180	1,468
Large firms	673	355	118	34	8	1,188
Total	745	745	746	745	745	3,726

Table 5.4: Testing persistence of share liquidity measures using Markov-switching models

This table reports the summary statistics of parameter estimates from the Markov-switching mean models applied to demeaned Gibbs spread measures and demeaned Amihud's measures of 760 firms without any missing values in the years 1988-2007. The numbers reported in this table represent cross-sectional moments of point estimates (or medians in posterior distributions) of five model parameters. The Markov-switching mean models proposed in Chapter 3 are used in this study.

Panel A. Summary of parameter estimates from the Markov-switching models with Gibbs spread (N=760)

Cross-sectional moments	Point estimates (or medians in posterior distributions) of:				
	$\mu_0$	$\mu_1$	$\sigma^2$	$p$	$q$
Mean	-1.9792	3.5353	66.9908	0.8610	0.8547
Standard deviation	2.2144	4.0204	158.7396	0.0235	0.0353
Q1	-2.8894	0.6435	1.7097	0.8466	0.8288
Median	-1.0524	1.7919	7.8068	0.8570	0.8409
Q3	-0.3975	5.0880	47.7300	0.8766	0.8797

Panel B. Summary of parameter estimates from the Markov-switching models with Amihud's measure (N=760)

Cross-sectional moments	Point estimates (or medians in posterior distributions) of:				
	$\mu_0$	$\mu_1$	$\sigma^2$	$p$	$q$
Mean	-0.5395	1.4658	86.2547	0.8528	0.8449
Standard deviation	1.0287	2.9136	454.2036	0.0159	0.0276
Q1	-0.3193	0.2581	0.0963	0.8468	0.8304
Median	-0.1517	0.2681	0.1025	0.8498	0.8333
Q3	-0.1429	0.7825	1.6757	0.8530	0.8448

## **Chapter 6**

# **Does Liquidity Increase the Propensity to Raise Debt Finance?**

### **6.1 Introduction**

The pecking-order theory of Myers (1984) is one of the most influential theories of corporate financing decisions in the literature. Based on Myers and Majluf's (1984) argument that asymmetric information problems drive corporate financing decisions, Myers (1984) argues that if managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Therefore, it is predicted that firms will use equity issuances to meet large external financing needs only as a last resort, after less information-sensitive financing sources such as internal cash and debt have been exhausted. Thus, firms with less liquid shares or more severe asymmetric information problems

are likely to raise more debt finance (Bharath *et al.*, 2009)<sup>1</sup>. Similarly, Lipson and Mortal (2009) and Frieder and Martell (2006) argue that firms with more liquid shares are likely to raise more equity finance because those firms have lower costs for raising equity capital (Butler *et al.*, 2005).

However, there are some reasons to believe that share liquidity has a *positive* effect on the propensity to raise debt finance. Although it seems obvious that firms with more liquid shares incur lower costs when raising equity capital, there are good reasons to believe that firms with more liquid shares have lower costs for raising debt capital as well (Butler and Wan, 2010). One of the most promising rationales as to why firms with more liquid shares have lower borrowing costs is based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2009). Firms with more liquid shares are less likely to have problems arising from asymmetric information between informed investors including firm managers and uninformed investors. Therefore, firms with more liquid shares are likely to have more informative share prices. In addition, it is likely that there is more publicly available information on high-liquidity firms because those firms are followed by a relatively large number of financial analysts and the shares of those firms are owned by a relatively large number of financial institutions. Therefore, banks can monitor those firms more efficiently by supplementing their own information with publicly available information such as share prices. Due to the lower monitoring costs, banks would thus propose

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<sup>1</sup>Majority of empirical studies focused on testing the main prediction of the pecking-order theory and the evidence is mixed (Shyam-Sunder and Myers, 1999; Fama and French, 2002; Frank and Goyal, 2003). Unlike conventional studies, Bharath *et al.* (2009) attempt to evaluate the core assumption of the pecking-order theory, finding that asymmetric information affects the capital structure decisions of US firms over the sample period 1973-2002. According to their estimation, for every dollar of financing deficit to cover, firms in the highest asymmetric information decile issue 30 cents of debt more than firms in the lowest decile.

lower borrowing costs to high-liquidity firms. Despite the existence of conflicting arguments on the effect of liquidity on the propensity to raise debt finance, this issue has not received sufficient attention from researchers in empirical corporate finance.

To answer those questions, I utilize a novel approach which focuses on the years with unusually large investment activities or “*investment spikes*”. Using the US data, Mayer and Sussman (2005) find that the financing of investment around investment spikes is very different from the financing of investment at other times. Thus, pooling data from two regimes of routine investment and non-routine investment dilutes the sample and obscures the results, without increasing the efficiency of the estimation (Mayer and Sussman, 2005). Therefore, by focusing on the firm-years categorized as investment spikes, one can investigate whether share liquidity affects financing patterns more precisely. In Chapter 5, I have found that firms with less liquid shares tend to rely more heavily on equity finance to finance investment spikes, using the approach suggested in Chapter 4. In this chapter, I aim to examine whether share liquidity increases the propensity to raise debt finance after controlling for the size of investment spikes and various firm characteristics, and through which mechanisms this works.

First of all, I investigate whether share liquidity has a positive effect on abnormal borrowing at the time of an investment spike. To answer the question, I use a dynamic leverage change model in which the dependent variable is the change in leverage during an investment spike and the right-hand side variables include a lagged leverage, various firm characteristics, share liquidity, industry dummies, and year dummies<sup>2</sup>. This model is equivalent to the reduced-form

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<sup>2</sup>“A change in leverage during an investment spike” is an excellent proxy for the propensity to raise debt finance because it reflects the significance of debt finance in funding a large investment requirement. A change in leverage during a routine investment period would reflect the rate of leverage adjustment rather than the

partial adjustment model which is often used to estimate the speed of adjustment of actual leverage to target leverage (Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007; Leary and Roberts, 2005; Lemmon *et al.*, 2008; Huang and Ritter, 2009). To make a clear distinction between share liquidity as a determinant of target leverage and share liquidity as a determinant of abnormal borrowing at the time of an investment spike, I use an empirical specification with the following three key variables: 1) the basic liquidity terms in the dynamic leverage models, telling us about the effect of share liquidity on target leverage ratios; 2) a measure of spike size, telling us about abnormal borrowing when faced with an investment spike; and 3) an interaction term between spike size and share liquidity, telling us about the effect of share liquidity on this abnormal borrowing. Using this framework, I show that share liquidity has a positive effect on abnormal borrowing when faced with an investment spike, meaning that high-liquidity firms have a higher propensity to raise debt finance. Under the conditional independence assumption (CIA)<sup>3</sup>, this finding has a causal interpretation that a given firm would have a higher propensity to raise debt finance during an investment spike if the firm had a higher level of share liquidity.

Some robustness tests are then executed. First, I investigate whether the positive effect of share liquidity on the propensity to raise debt finance or abnormal borrowing during an investment spike remains, after controlling for the effects of various firm characteristics such as firm size, initial leverage, and profitability. This study also finds that firms with higher initial propensity to raise debt finance. By restricting attention to a leverage change during an investment spike, one can investigate the factors affecting the propensity to raise debt finance more precisely and implement more reasonable dynamic models with intuitive interpretations.

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<sup>3</sup>See Angrist and Pischke (2009) and Section 6.5.1 for further details on CIA.

leverage have a lower propensity to raise debt finance, while firms with higher profitability, higher market-to-book, and higher R&D intensity have a higher level of abnormal borrowing during an investment spike. Strikingly, both firm size and tangibility of assets do not have a significant effect on abnormal borrowing during an investment spike, although they have a significant effect on target leverage. Even after controlling for the effects of various firm characteristics, share liquidity has a significant positive effect on the propensity to raise debt finance. Second, I show that the positive effect of share liquidity on the propensity to raise debt finance is robust to the use of various leverage measures, including a book leverage measure. Finally, one could argue that the positive effect of share liquidity on the propensity to raise debt finance is driven by the use of the investment spikes sample instead of the whole sample. To test this possibility, I implement a dynamic leverage change model on the whole sample, finding that the financing patterns during the investment spike periods are distinct from those in normal periods and that share liquidity has a positive effect on the propensity to raise debt finance during the investment spike periods. I therefore conclude that the main results are not just driven by the use of the investment spikes sample, although the years categorized as investment spikes have distinct features and those years are more appropriate to study financing patterns, in particular the composition of external finance. Based on various robustness tests, I conclude that high-liquidity firms do indeed have a higher propensity to raise debt finance.

Having established the positive effect of share liquidity on the propensity to raise debt finance, I turn to the assessment of the mechanisms through which share liquidity increases

this propensity. To assess whether each of the two mechanisms works, I first compare the observed correlation coefficients between share liquidity and key variables in each mechanism with the correlation coefficients predicted in different mechanisms. Then, I check whether the coefficient of an interaction term between a spike size measure and a dummy variable for high-liquidity firms vanishes when a key variable and an interaction term between the spike size measure and a dummy variable based on the key variable are included as explanatory variables in the regression. This study shows that the information spillover and credit ratings arguments are well supported. Those two arguments provide interesting explanations as to why high-liquidity firms have a propensity to raise debt finance. Firms with more liquid shares are less likely to have severe asymmetric information problems between informed investors including managers and uninformed investors. Thus, high-liquidity firms are likely to have more informative share prices. In addition, more information on high-liquidity firms is produced because those firms are followed by a large number of financial analysts and the shares of those firms are owned by many financial institutions. Hence, Banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices and propose lower loan spreads to high-liquidity firms. Moreover, high-liquidity firms tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, high-liquidity firms have lower costs of raising debt finance in subsequent periods and are likely to raise relatively more debt finance to finance large investment requirements.

Finally, I investigate what drives the inconsistent liquidity effects in static and dynamic regressions<sup>4</sup>. Some of the existing literature such as the studies by Bharath *et al.* (2009), Lipson

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<sup>4</sup>The static leverage equation does not include lagged leverage as an explanatory variable, whereas the dy-

and Mortal (2009) and Fang *et al.* (2009), which use static leverage-level regressions (i.e. leverage models without lagged leverage as an explanatory variable), find that there is a negative relation between share liquidity and leverage level. Regardless of the choice of estimation methods or the choice of liquidity measures, I also find a negative relation between share liquidity and leverage level in static leverage regressions. However, I find a positive effect of share liquidity on leverage in dynamic regressions with lagged leverage as an explanatory variable. Similarly, this study also finds that two liquidity measures have significant positive correlations with change in leverage, while they have significant negative correlations with lagged leverage. This puzzling correlation structure could arise if lagged leverage decreases share liquidity and share liquidity has a positive effect on the change in leverage. Therefore, the negative relation between share liquidity and leverage in static regressions could be driven by the causality running from lagged leverage, which is highly correlated with contemporary leverage, to share liquidity. Using the omitted variables bias (OVB) formula, I show that both relations can hold at the same time. These arguments are consistent with a theory predicting that lagged leverage has a negative effect on share liquidity<sup>5</sup> and the main empirical findings that share liquidity has a positive effect on the propensity to raise debt finance as measured by

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dynamic leverage equation includes lagged leverage as an explanatory variable.

<sup>5</sup>Lesmond *et al.* (2008) propose a theory on the effect of leverage change on share liquidity by extending the Kyle (1985) model. In addition, they show that leverage-increasing firms experience an increase of 1% in the bid-ask spread and leverage-decreasing firms experience a decrease of 2% in the bid-ask spread. In Appendix 6.A.1, I propose a theory on the effect of the initial leverage by extending Kyle's (1985) single-period trading model. Using the model, I show that Kyle's  $\lambda$ , which measures the price impact or the sensitivity of the market price to the total order flow when the total order flow goes up by one unit, increases monotonically with initial leverage. This might be because the insider is expected to have more concentrated private information when firms have higher initial leverage, as evidenced from its effects on the variance of the *ex post* liquidation value of each share. Kyle (1985) notes that market makers compensate themselves for bad trades due to the adverse selection of insiders by making the market less liquid. Similarly, this analysis shows that, when firms have higher leverage, market makers respond more sensitively to bad trades due to the adverse selection of informed traders. See Appendix 6.A.1 for more details.

the change in leverage.

The structure of the remainder of this chapter is as follows. In Section 6.2, I discuss various arguments as to how share liquidity affects the propensity to raise debt finance. Section 6.3 describes the sample selection procedures, the algorithm to identify investment spikes, the variables used in this study, and the descriptive statistics. Section 6.4 presents the results from the analysis of the incidence of investment spikes. Section 6.5 presents the issues in research design and main empirical results. Section 6.6 discusses the inconsistent liquidity effects in static and dynamic leverage models. Finally, Section 6.7 provides conclusions.

## **6.2 Share liquidity and the propensity to raise debt finance**

Beginning with work by Bagehot (1971), share liquidity or liquidity of stock market has been viewed not only as a reflection of the direct trading costs such as fees or taxes and the costs associated with inventory (Garman, 1976; Ho and Stoll, 1981), but also as a reflection of adverse selection due to the presence of better-informed traders in a stock market (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). Despite the difficulty of defining market liquidity, Kyle (1985) suggests that market liquidity encompasses a number of the transactional properties of markets, including “tightness” and “depth”<sup>6</sup>. Empirical market microstructure literature including Goyenko *et al.* (2009) and Hasbrouck (2009) provide a comprehensive survey of liquidity measures and run “horseraces” involving a wide range of proxies for both

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<sup>6</sup>“Tightness” refers to the cost of turning over a position in a short period of time and is often measured by the reciprocal of the bid-ask spread. “Depth” refers to the ability of the market to absorb quantities without having a large impact on price and is often measured by the reciprocal of the price impact.

price impact and bid-ask spread. Goyenko *et al.* (2009) report that Holden's (2009) measure performs the best among the spread measures whereas Amihud's (2002) measure performs the best among the price impact measures based on the closeness of low-frequency measures with high-frequency measures of bid-ask spread and price impact. Similarly, Hasbrouck (2009) finds that the Gibbs sampler estimate of the Roll (1984) model suggested by Hasbrouck (2009) performs the best among the spread measures and the Amihud's (2002) measure performs the best among the price impact measures.

In this study, two liquidity measures such as Amihud's (2002) measure and Hasbrouck's (2009) Gibbs-spread measure are used as proxies for the extent of asymmetric information. Amihud (2002) shows that his illiquidity measure is positively and strongly related to Kyle's (1985)  $\lambda$  which is affected by the volatility of a private information shock or the degree of asymmetric information. Hasbrouck (2009) also shows that his Gibbs-spread measure is positively and strongly correlated with the effective spread constructed with Trade and Quote (TAQ) data. It is often believed that the width of the effective spread provides an indication of the severity of asymmetric information problems (Odders-White and Ready, 2006). Bharath *et al.* (2009) also use some liquidity measures among others to construct a composite index of adverse selection for each firm using a principal component analysis<sup>7</sup>.

Why do we care about the relationship between the degree of asymmetric information as

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<sup>7</sup>Bharath *et al.* (2009) also recognize that the nature of information asymmetry in the secondary market (i.e. in the market microstructure context) is somewhat different from that of information asymmetry in the primary market (i.e. in the corporate finance context). Asymmetric information in the corporate context is a matter between firm managers and market participants. However, asymmetric information in the microstructure context is a matter between a larger category of agents (informed traders) and the rest of the market (uninformed traders). Nevertheless, market microstructure measures of information asymmetry including well-performing liquidity measures can be used as "imperfect" proxies for the financial markets' perception of the information advantage held by firm managers.

measured by share liquidity and the propensity to raise debt finance? One of the most influential theories of corporate financing decisions, the pecking-order theory of Myers (1984), is based on a core assumption that asymmetric information drives corporate financing decisions (Myers and Majluf, 1984). Myers (1984) argues that if managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Therefore, it is predicted that firms will use equity issuances to meet large exceptional financing needs only as a last resort, after less information-sensitive financing sources such as internal cash and debt have been exhausted. In other words, firms with more severe asymmetric problems are more likely to raise more debt finance according to the pecking-order theory. This suggests that share liquidity will have a *negative* effect on the propensity to raise debt finance<sup>8</sup>.

There are some other existing studies which predict a negative effect of share liquidity on the propensity to raise debt finance, although share liquidity measures are not used as proxies for the extent of asymmetric information (Lipson and Mortal, 2009; Frieder and Martell, 2006). Some of the asset-pricing literature, including the studies by Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005), show that investors are willing to pay more for high-liquidity shares and require a premium for bearing the costs of illiquidity. Although the secondary-market returns might be closely linked with the primary-market costs of equity finance in equilibrium, it is

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<sup>8</sup>Majority of empirical studies focused on testing the main prediction of the pecking-order theory and the evidence is mixed (Shyam-Sunder and Myers, 1999; Fama and French, 2002; Frank and Goyal, 2003). Unlike conventional studies, Bharath *et al.* (2009) attempt to evaluate the core assumption of the pecking-order theory, and find that asymmetric information affects the capital structure decisions of US firms over the sample period 1973-2002. According to their estimation, for every dollar of financing deficit to cover, firms in the highest asymmetric information decile issue 30 cents of debt more than firms in the lowest decile.

not clear whether secondary-market liquidity would have parallel effects on secondary-market returns and the primary-market costs of equity capital. However, Butler *et al.* (2005) show that the costs of issuing equity measured by gross fees paid to investment banks are significantly lower for high-liquidity firms when other factors are controlled for. Based on these premises, Lipson and Mortal (2009) and Frieder and Martell (2006) derive the hypothesis that firms with more liquid shares would use relatively less debt finance because those firms would find it more attractive to issue equity relative to other financing options.

However, there are some reasons to believe that share liquidity has a *positive* effect on the propensity to raise debt finance. Although it seems obvious that firms with more liquid shares incur lower costs when raising equity capital, there are good reasons to believe that firms with more liquid shares have lower costs for raising debt capital as well (Butler and Wan, 2010)<sup>9</sup>. There are several rationales as to why firms with more liquid shares have lower borrowing costs. The most promising one is based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2009). Firms with more liquid shares are less likely to have problems arising from asymmetric information between informed investors including firm managers and uninformed investors. Therefore, firms with more liquid shares are likely to have more informative share prices. In addition, it is likely that there is more publicly available information on high-liquidity firms because those firms are followed by a relatively large number of financial analysts and the shares

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<sup>9</sup>Butler and Wan (2010) investigate whether there are liquidity differences between debt issuers and matched firms, finding that debt issuers have significantly higher share liquidity. They also study the long-run stock performance of debt issuers, finding that the under-performance of debt issuers disappears when a liquidity factor is included in the model for expected returns.

of those firms are owned by a relatively large number of financial institutions. Therefore, banks can monitor those firms more efficiently by supplementing their own information with publicly available information such as share prices. Due to the lower monitoring costs, banks would thus propose lower borrowing costs to high-liquidity firms. Sunder (2004) also shows that firms' borrowing costs decrease with measures of information production in the stock market. Furthermore, high-liquidity firms have stronger bargaining power on the conditions of loan contracts as they have equity financing as a quite attractive outside option. Therefore, it is expected that share liquidity will have a positive effect on the propensity to raise debt finance. Sunder (2004) and Saunders and Steffen (2009) provide some empirical evidence. Sunder (2004) reports that one standard deviation decrease in relative bid-ask spread reduces the borrowing costs by over 18 basis points on average. Saunders and Steffen (2009), using UK data, also show that private firms have substantially higher borrowing costs than public firms. Going public increases the availability of equity market information that banks use to determine loan rates. Other arguments related to the loan costs disadvantage of private firms are also quite similar to those on the loan costs disadvantage of firms with less liquid shares.

Another argument explaining why firms with more liquid shares have lower costs of debt capital is based on the shared information content in credit ratings and liquidity measures. Oders-White and Ready (2006) show that credit ratings are poorer when adverse selection risk measured by various share illiquidity measures is higher and that adverse selection measures can be used to predict future ratings changes. Therefore, it is likely that firms with lower share liquidity incur higher costs when raising debt finance in subsequent periods. In this case,

low-liquidity firms would be less likely to raise debt finance. Furthermore, as credit ratings information is available to banks, firms with low share liquidity are more likely to be credit rationed in the sense that they cannot obtain the loan that they want even though they are willing to pay the interest that the banks require, perhaps even a higher interest<sup>10</sup>. In this case, firms with less liquid shares are more likely to use new equity finance, as this might be the only available option to meet external financing needs.

In the next section, I describe the sample selection procedures, the variables used in this study, and the descriptive statistics.

## **6.3 Data and methodology**

### **6.3.1 Sample selection**

I use data from annual consolidated financial statements<sup>11</sup> of publicly traded US companies reported in Standard and Poor's Compustat North America Fundamental Annual Dataset for the years 1988 to 2007. The data starts from 1988 because I investigate the financing patterns

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<sup>10</sup>There are, broadly speaking, two explanations for credit rationing: the adverse selection explanation and the moral-hazard explanation. Both explanations start from the observation that an interest rate increase has no effect on the firm in the event of bankruptcy as long as the firm is protected by limited liability. The adverse selection explanation is that, in a situation where banks cannot directly tell good and bad firms apart, a higher interest rate tends to attract low-quality firms because low-quality firms are more likely to default on their loan and therefore are less affected by a rise in the interest rate than high-quality firms. Therefore, banks may want to keep interest rates low in order to attract a better sample of borrowers. The moral-hazard explanation is that the reduced stake in the case of a high interest rate may demotivate the borrowing firms so that they pursue projects with high private benefits, neglect the projects, or engage in outright fraud. Therefore, banks may want to keep interest rates low in order to motivate the borrowing firms (Tirole, 2006).

<sup>11</sup>The majority of US companies report the consolidated financial statements, which include both parent and subsidiaries accounts.

around investment spikes and it requires the use of firm-level flow-of-funds data, i.e. the data from the cash-flow statements<sup>12</sup>. I also use the stock market data from Center for Research in Security Prices (CRSP) to construct two liquidity measures such as Amihud's (2002) price impact measure and Hasbrouck's (2009) Gibbs spread measure. The S&P Long-Term Issuer Credit Ratings Database and Thomson-Reuters Institutional Holdings (13F) Database<sup>13</sup> are also obtained through Wharton Research Data Services (WRDS). I exclude firms with a Standard Industrial Classification (SIC) code between 6000 and 6999 or between 4900 and 4999, meaning the firms whose main activity is financial services or regulated utilities are dropped to construct the final sample.

All nominal items from the statement of cash flows, income statement and balance sheet are deflated or inflated to year 2000 dollars using the Gross Domestic Product (GDP) deflator obtained from the International Monetary Fund database of country GDP deflators. An interpolated GDP deflator is used if the fiscal year ends in other months than December. I also perform a minimum level of data cleaning. First, I drop observations if the firms are observed for less than five years. Second, I drop observations if any variable which constitutes the cash-flow identity is missing. However, I replace the missing item with zero if at least one component of each financing source is reported because "missing" does not mean "unaccounted for". For example, note that that *LTDEBT*, the amount of long-term debt financing, can be calculated as "issuance of long-term debt (*dltis*)" less "reduction of long-term

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<sup>12</sup>Mayer and Sussman (2005), in their seminal paper on the use of a filtering technique and flow-of-funds approach in studies of financing patterns, report that they could not use the data prior to 1988 because the "statement of cash flows" replaced "cash statements by sources and uses of funds" from 1988 by FASB (Financial Accounting Standards Boards) #5.

<sup>13</sup>This database is also known as the CDA/Spectrum 3 4 database, and contains ownership information by institutional managers with \$100 million or more in assets under management.

debt (*dltr*)". It is clear that the firm-year observation should be deleted if both of *dltis* and *dltr* are missing. However, if only one of the two components is missing then it is likely that that only "net issuance of long-term debt" is reported. In this case, it makes more sense to replace the missing item with zero rather than remove the firm-year observation. Finally, to reduce the effects of outliers and eradicate errors in the data, all variables in ratios used in the baseline regression specification are winsorized at the 1st and 99th percentiles, as in Flannery and Rangan (2006).

### **6.3.2 Algorithm to identify investment spikes**

Mayer and Sussman (2005) propose a simple and intuitive algorithm to identify investment spikes. However, the algorithm has one important disadvantage in that the threshold is arbitrary and not statistically interpretable. To overcome the problem, I utilize an algorithm used by Bond *et al.* (2006). The advantages of the new algorithm are that the threshold is statistically interpretable and that it works well when there is a trend in the investment sequence. See Section 4.2.2 for more details on the algorithm. Repeating the procedures as many times as possible will identify a total of  $J$  firm-years as those with an investment spike. For simplicity, the base-level investment and the relative magnitude of the  $j$ -th investment spike are denoted as  $BASE_j$  and  $GAMMA_j$ , for  $j \in \{1, 2, \dots, J\}$ , respectively. The procedures give a sample of 6,457 investment spikes, 9.56% of the 67,544 firm-year observations for which five consecutive years of investment data are observed. I restrict my attention to (*Low, Low, High, Low, Low*)-type investment spikes only, obtaining 6,424 investment spikes

after dropping 33 investment spikes. The median *GAMMA* of 6,424 investment spikes is 3.42.

### 6.3.3 Construction of variables

#### A. Major variables

The dependent variable in the baseline specification (Table 6.5) is defined as the change in market leverage during an investment spike<sup>14</sup> ( $\Delta LEV_{j,\tau=0}$ ), where the market leverage is defined as:

$$LEV = \frac{\text{Total liabilities}}{\text{Total liabilities} + \text{Market value of equity}}. \quad (6.1)$$

As a robustness test, the following two alternative leverage measures<sup>15</sup> are used in this study:

$$MLEV = \frac{\text{Total long-term debt} + \text{Total short-term debt}}{\text{Total long-term debt} + \text{Total short-term debt} + \text{Market value of equity}}, \quad (6.2)$$

$$BLEV = \frac{\text{Total long-term debt} + \text{Total short-term debt}}{\text{Total assets}}. \quad (6.3)$$

<sup>14</sup>The change in leverage during an investment spike is an excellent proxy for the propensity to raise debt finance because it reflects the significance of debt finance in funding a large investment requirement. The change in leverage during the routine investment period would reflect the rate of leverage adjustment rather than the propensity to raise debt finance. By restricting attention to a leverage change during an investment spike, one can investigate the factors involved in the propensity to raise debt finance more precisely and implement more reasonable dynamic models with intuitive interpretations. Welch (2011) argues that the correlation between issuing activities and capital structure changes is “either insignificant or outright perverse”. It is highly likely that Welch’s argument is correct during routine investment periods. However, during non-routine investment periods, issuing activities and capital structure changes are highly significantly correlated. In the spikes sample, the correlation between  $LTDEBT_{j,\tau=0}/BASE_j$  and  $\Delta LEV_{j,\tau=0}$  is positive (correlation coefficient=0.0774) and significant at the 1% level of significance (p-value=0.0000).

<sup>15</sup>*MLEV* is an alternative market leverage measure, while *BLEV* is a book leverage measure. The three measures are defined as in Flannery and Rangan (2006). However, Welch (2011) argues that future research should avoid “financial debt to total assets ratio” such as *BLEV*. He argues that the measure would be problematic in the sense that non-financial liabilities are considered as equity rather than debt.

The liquidity of shares is measured by multiplying either Hasbrouck's Gibbs spread or Amihud's price impact by  $(-1)$ . The liquidity measure based on Hasbrouck's Gibbs spread and the liquidity measure based on Amihud's price impact are denoted as  $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ , respectively. The higher  $LIQ_{j,\tau=-1}^G$  or  $LIQ_{j,\tau=-1}^A$ , the higher share liquidity. To investigate whether high-liquidity firms use more abnormal borrowing during an investment spike, I include a spike size measure ( $SPIKESIZE_{j,\tau=0}$ ) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) in the regression equation. The spike size measure ( $SPIKESIZE_{j,\tau=0}$ ) measures abnormal investment as a proportion of market assets at the beginning of the year, where abnormal investment is calculated as spike investment less base-level investment.  $D\_HLIQ_{j,\tau=-1}^G$  and  $D\_HLIQ_{j,\tau=-1}^A$  represent the dummy variable for high-liquidity firms based on Hasbrouck's Gibbs spread and that based on Amihud's price impact, respectively. To investigate whether acquisitions tend to be funded differently from capital expenditures, the dummy variable for acquisitions ( $D\_AQC_{j,\tau=0}$ ) is also included in the regression equation.

The control variables used in this study is very similar to those used in Flannery and Rangan (2006), Lemmon *et al.* (2008) and Rajan and Zingales (1995). These controls include the one-lagged leverage ( $LEV_{j,\tau=-1}$ ), the natural logarithm of total assets ( $LnTA_{j,\tau=-1}$ ), the ratio of earnings before interests and taxes to total assets ( $EBIT\_TA_{j,\tau=-1}$ ), market-to-book ratio ( $MV\_BV_{j,\tau=-1}$ ), tangibility of assets ( $FA\_TA_{j,\tau=-1}$ ), and research and development (R&D) expenses as a proportion of total assets ( $RD\_TA_{j,\tau=-1}$ ). In addition, both industry and year

dummies are included. The industry median leverage is not included because it causes a multi-collinearity problem when it is included along with industry dummies. The companies in the sample are allocated to 43 industries based on SIC following Fama and French (1997). They classify all firms into 48 industries but four of them belong to financial services and one of them belongs to regulated utilities. Table 6.1 Panel A and Panel B present more detailed formulas with Compustat item codes required to construct the variables mentioned in this section.

[Insert Table 6.1 Here.]

## **B. Additional variables**

Some additional variables are used to investigate how share liquidity increases the propensity to raise debt finance. The correlations between the two liquidity measures ( $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ ) and the key variables in the information spillover and credit ratings mechanisms such as the number of institutional managers for each firm-year ( $NUMMGRS$ ) and a modified Altman's Z-score ( $MALTMANZ$ ) are reported in Table 6.3 Panel C. Furthermore, the results of the regressions used to evaluate the information spillover and the credit ratings mechanisms are reported in Table 6.10 and Table 6.11, respectively.

To test the information spillover mechanism, the number of institutional managers for each firm-year ( $NUMMGRS$ ) is constructed.  $NUMMGRS$  is used as a proxy for the amount of public information produced in the share market. The data obtained from WRDS is based on

the reports filed by institutional investment managers (Form 13F)<sup>16</sup>. *NUMMGRS* is calculated as the number of institutional investors who filed Form 13F for each firm-year.

Altman's Z-score is often used to measure a firm's probability of default or adverse selection risk. Since Altman's Z-score already contains a measure of leverage, I construct a modified version of Altman's Z-score without leverage following Graham *et al.* (1998) and Chava *et al.* (2009). The formula is as follows:

$$\begin{aligned}
 MALTMANZ = & 1.0 \left( \frac{\text{Net sales}}{\text{Total assets}} \right) + 1.2 \left( \frac{\text{Working capital}}{\text{Total assets}} \right) + 1.4 \left( \frac{\text{Retained earnings}}{\text{Total assets}} \right) \\
 & + 3.3 \left( \frac{\text{Earnings before interest and taxes}}{\text{Total assets}} \right) \qquad (6.4)
 \end{aligned}$$

### 6.3.4 Descriptive statistics

Table 6.2 shows the summary statistics of the major variables based on the whole sample and the investment spikes sample. Panel A reports summary statistics for the whole sample, whereas Panel B reports summary statistics for the investment spikes sample. The whole sample denotes the sample after data-cleaning procedures. The investment spikes sample is constructed following the procedures described in Section 6.3.2. The firm characteristics variables measured in the year before investment spikes have similar means and medians to those in the whole sample. This suggests that the firms in the subsample are not significantly different from the firms in the whole sample.

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<sup>16</sup>See <http://www.sec.gov/answers/form13f.htm> for more details on the reporting requirements and the definition of institutional managers.

[Insert Table 6.2 Here.]

However, the following differences should be noted. First, the mean and median of leverage changes during investment spikes are 7.3% and 5.0%, whereas the mean and median of leverage changes in the whole sample are as low as 1.4% and 0.6%, respectively. Second, it is noteworthy that the leverage level at the beginning of the year with an investment spike (28.5%) is about 7% lower than the long-run average leverage level observed in the whole sample (35.9%), while the leverage level at the end of the year with an investment spike (35.4%) is very close to the long-run average leverage level. Although further investigation is required, it seems that firms adjust leverage in anticipation of large investment events. Another possibility is that firms with lower initial leverage tend to be included in the investment spikes sample. This evidence provides a justification for using a dynamic leverage model with lagged leverage. Third, the means and medians of  $Amihud_{it}$  are slightly lower for the investment spikes sample than for the whole sample, whereas the means and medians of  $Gibbs_{it}$  are almost the same. It might be the case that slightly more liquid firms are included in the investment spikes sample. Therefore, I investigate whether share liquidity has a statistically significant effect on the incidence of investment spikes in Section 6.4.

[Insert Table 6.3 Here.]

Table 6.3 presents Pearson correlation coefficients between change in leverage, lagged leverage, two liquidity measures, and the major control variables used in the baseline specification. Panel A shows those for the whole sample, while Panel B shows those for the investment spikes sample. Panel C reports the correlations between the two share liquidity measures

( $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ ) and the key variables in the mechanisms through which share liquidity increases the propensity to raise debt finance. The results in Panel C are discussed in relation to the correlations predicted by those mechanisms in Section 6.5.3.

It should be noted that, in the whole sample, the two liquidity measures ( $LIQ_{i,t-1}^G$  and  $LIQ_{i,t-1}^A$ ) have significantly positive correlations with the change in leverage ( $\Delta LEV_{it}$ ), while they have significantly negative correlations with lagged leverage ( $LEV_{i,t-1}$ ). Even in the investment spikes sample, the two liquidity measures ( $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ ) are significantly positively correlated with the change in leverage during an investment spike ( $\Delta LEV_{j,\tau=0}$ ), while they are significantly negatively correlated with lagged leverage ( $LEV_{j,\tau=-1}$ ). Although they do not reflect partial correlations, these results are quite puzzling. This result appears to imply that the level of leverage prior to an investment spike ( $LEV_{j,\tau=-1}$ ) has a negative effect on the liquidity of shares ( $LIQ_{j,\tau=-1}^G$  or  $LIQ_{j,\tau=-1}^A$ ), which might have a positive effect on the leverage change during an investment spike ( $\Delta LEV_{j,\tau=0}$ ), although this causal link needs to be investigated more carefully.

In addition, it is also noteworthy that, in the case of the investment spikes sample, only initial leverage ( $LEV_{j,\tau=-1}$ ) and two liquidity measures ( $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ ) are significantly correlated with the change in leverage during an investment spike ( $\Delta LEV_{j,\tau=0}$ ). This implies that both initial leverage and share liquidity might have much more significant effects on the funding pattern during an investment spike than any other firm characteristics. It seems that high-leverage firms have a lower propensity towards raising debt finance as predicted by the trade-off argument, while high-liquidity firms have a higher propensity to raise debt finance.

This chapter investigates whether those relationships hold even after controlling for various firm characteristics, investment characteristics, industry effects, and year effects.

## 6.4 Share liquidity and the incidence of investment spikes

Before investigating whether the financing of investment around investment spikes varies with the share liquidity of firms, I first investigate whether share liquidity helps to explain the incidence of investment spikes. Recall that, in Table 6.2, the sample means of two illiquidity measures (*Gibbs* and *Amihud*) are slightly lower in the investment spikes sample than in the whole sample. Firms with more liquid shares may be more likely to have better access to external finance and therefore have the kinds of investment opportunities that appear in the data as investment spikes.

This hypothesis is not supported. Table 6.4 reports the OLS and probit regression models in which the dependent variable is a binary dummy variable  $D\_SPIKE_{it}$  equal to one if the firm-year is categorized as an investment spike and zero otherwise. The liquidity measures based on Hasbrouck's Gibbs spread ( $LIQ_{i,t-1}^G$ ) or the liquidity measure based on Amihud's price impact ( $LIQ_{i,t-1}^A$ ) are used as a proxy of share liquidity in each regression. The control variables include the lagged leverage ( $LEV_{i,t-1}$ ), the natural logarithm of total assets ( $LnTA_{i,t-1}$ ), the ratio of earnings before interests and taxes to total assets ( $EBIT\_TA_{i,t-1}$ ), market-to-book ratio ( $MV\_BV_{i,t-1}$ ), tangibility of assets ( $FA\_TA_{i,t-1}$ ), and R&D expenses as a proportion of total assets ( $RD\_TA_{i,t-1}$ ). In addition, both industry and year dummies are included. Neither

$LIQ_{i,t-1}^G$  nor  $LIQ_{i,t-1}^A$  helps to explain the incidence of investment spikes. This suggests that distinctive features of the financial behaviour of high-liquidity firms may *not* be attributed to a higher or lower frequency of investment spikes.

However, firms with lower initial leverage and firms with a lower proportion of tangible assets are significantly more likely to have investment spikes. Larger firms are significantly more likely to have investment spikes in the regressions with  $LIQ_{i,t-1}^A$ , whereas that is not the case in the regressions with  $LIQ_{i,t-1}^G$ . This suggests that investment spikes are endogenous. In particular, the effect of initial leverage on the incidence of investment spikes is negative and significant at the 1% level. This implies that highly leveraged firms might pass over or delay some large investment opportunities, which seems to be evidence for the debt-overhang problem. To deal with this endogeneity problem, I include the initial leverage<sup>17</sup> together with various firm characteristics in the regressions in Section 6.5.

[Insert Table 6.4 Here.]

## **6.5 Effect of liquidity on the propensity to raise debt finance**

In this section, the effect of share liquidity on the propensity to raise debt finance and the mechanisms through which share liquidity affects the propensity to raise debt finance are investigated in a regression framework. The various arguments stated in Section 6.2 give rise

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<sup>17</sup>The primary motivation for including the lagged leverage in the regression equation in which the dependent variable is the change in leverage during an investment spike is to deal with this endogeneity problem. However, it should be noted that the model is in essence equivalent to a partial adjustment model. This will be detailed in Section 6.5.

to the following hypotheses:

**H1. High-liquidity firms have a higher propensity to raise debt finance.**

**H1A. (*Information spillover*)** Firms with more liquid shares are less likely to have severe asymmetric information problems between informed investors including managers and uninformed investors. Thus, high-liquidity firms are likely to have more informative share prices. In addition, more information on high-liquidity firms is produced because those firms are followed by a large number of financial analysts and the shares of those firms are owned by many financial institutions. Banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices and propose lower loan spreads to high-liquidity firms (Sunder, 2004; Saunders and Steffen, 2009).

**H1B. (*Credit ratings*)** Firms with less liquid shares or higher adverse selection risk have poorer credit ratings. Thus, firms with less liquid shares incur higher costs when raising debt finance in subsequent periods (Odders-White and Ready, 2006). In addition, as credit ratings information is available to banks, low-liquidity firms have a higher cost of debt or are more likely to be credit rationed.

**H2. High-liquidity firms have a lower propensity to raise debt finance.**

**H2A. (*Asymmetric information*)** If managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Thus, firms will use equity issuances only as a last resort, after less information-sensitive sources such as internal cash and debt have been exhausted. Firms with less liquid shares or more severe asymmetric information problems are likely to raise more debt finance

(Myers, 1984; Myers and Majluf, 1984; Bharath *et al.*, 2009).

**H2B. (*Liquidity premium*)** Investors are willing to pay more for highly liquid shares and require a liquidity premium for bearing the costs of illiquidity (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Pastor and Stambaugh, 2003; and Acharya and Pedersen, 2005). There is empirical evidence that high-liquidity firms have lower costs for raising equity capital (Butler *et al.*, 2005). Based on these premises, Lipson and Mortal (2009) and Frieder and Martell (2006) argue that firms with more liquid shares are likely to raise more equity finance.

### **6.5.1 Baseline regression: specifications and results**

To investigate whether share liquidity has a positive or negative effect on abnormal borrowing at the time of an investment spike, the change in leverage during an investment spike is regressed on a lagged leverage, a liquidity measure, a spike size measure and several other variables.

#### **A. Issues in empirical research design**

In this section, I consider two dynamic leverage change models: one with a measure of spike size and an interaction term between spike size and share liquidity and the other without those variables. First, consider a specification without spike size-related variables defined as

follows:

$$\Delta LEV_{j,\tau=0} = \alpha + \beta LEV_{j,\tau=-1} + X'_{j,\tau=-1}\gamma + \delta LIQ_{j,\tau=-1} + IND_k + YR_t + \varepsilon_j, \quad (6.5)$$

where the dependent variable measures the increase in leverage during an investment spike ( $\Delta LEV_{j,\tau=0} = LEV_{j,\tau=0} - LEV_{j,\tau=-1}$ ).  $LEV_{j,\tau=-1}$  represents the lagged leverage or the leverage level at the beginning of the year with an investment spike.  $X_{j,\tau=-1}$  represents a  $5 \times 1$  column vector filled with the values of the control variables measured for  $j$ -th spike during the year before an investment spike ( $\tau = -1$ ). The control variables are firm size ( $LnTA$ ), profitability ( $EBIT\_TA$ ), market-to-book ratio ( $MV\_BV$ ), tangibility of assets ( $FA\_TA$ ), and R&D intensity ( $RD\_TA$ ).  $LIQ_{j,\tau=-1}$  represents either the liquidity measure based on Hasbrouck's (2009) Gibbs spread ( $LIQ^G_{j,\tau=-1}$ ) or the liquidity measure based on Amihud's (2002) price impact ( $LIQ^A_{j,\tau=-1}$ ). An industry fixed effect for industry  $k$  ( $IND_k$ ), and a year fixed effect for year  $t$  ( $YR_t$ ) are also included. For simplicity, industry dummies and year dummies are used to capture these effects. See Table 6.1 Panel A for detailed formulas with the Compustat item codes required to construct the variables used in the regressions.

One may wonder why I do not use the following specification without lagged leverage as an explanatory variable:

$$\Delta LEV_{j,\tau=0} = \alpha + X'_{j,\tau=-1}\gamma + \delta LIQ_{j,\tau=-1} + IND_k + YR_t + \varepsilon_j. \quad (6.6)$$

There are several reasons. The first reason is that the incidence of investment spikes is some-

what endogenous. It was shown in Section 6.4 that high-leverage firms have a lower incidence of investment spikes. Although the incidence of spikes is very weakly explained by the lagged leverage and other firm characteristics ( $R^2 = 0.0214$ ), it is very important to make sure that all the differences in funding patterns should not be attributed to the differences in starting leverage. The second reason is that the exclusion of lagged leverage might exaggerate a positive relation between share liquidity and the change in leverage during an investment spike as predicted by the OVB formula<sup>18</sup>.

Note that Equation (6.5) is equivalent to the reduced-form partial adjustment model<sup>19</sup> which is often used to estimate the speed of adjustment (*SOA*) of actual leverage to target leverage (Fama and French, 2002; Flannery and Rangan, 2006; Kayhan and Titman, 2007; Leary and Roberts, 2005; Lemmon *et al.*, 2008; Huang and Ritter, 2009). Note also that  $\delta$  should be interpreted as “*SOA*  $\times$  *Sensitivity of Target Leverage to Share Liquidity*”. However, as long as *SOA* is positive,  $\delta$  could be roughly interpreted as the effect of share liquidity on target leverage. Although  $\delta$  captures the effect of share liquidity on target or normal leverage ratios,  $\delta$  does not capture whether share liquidity increases abnormal borrowing at the time of an investment spike.

In designing an empirical specification, I make a clear distinction between share liquidity as

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<sup>18</sup>Consider a simple OLS regression without control variables such as:

$$\Delta LEV_{j,\tau=0} = \alpha + \beta LIQ_{j,\tau=-1} + \varepsilon_j,$$

where  $\varepsilon_j = \gamma LEV_{j,\tau=-1} + e_j$ . In this case, the OVB formula says  $\beta^{short} = \beta^{long} + \gamma \delta_{LEV_{j,\tau=-1}, LIQ_{j,\tau=-1}}$ , where  $\delta_{LEV_{j,\tau=-1}, LIQ_{j,\tau=-1}}$  is the slope coefficient in the regression of  $LEV_{j,\tau=-1}$  on  $LIQ_{j,\tau=-1}$ . It is expected that  $\gamma$  is negative and  $\delta_{LEV_{j,\tau=-1}, LIQ_{j,\tau=-1}}$  is negative. To verify this, see Table 6.3 Panel B. Therefore,  $\beta^{short} > \beta^{long}$ , meaning that the exclusion of lagged leverage exaggerates a positive relation between  $LIQ_{j,\tau=-1}$  and  $\Delta LEV_{j,\tau=0}$ . See Angrist and Pischke (2009) for further details on the OVB formula.

<sup>19</sup>See Section 2.4 for a derivation of the reduced-form partial adjustment model.

a determinant of target leverage and share liquidity as a determinant of abnormal borrowing at the time of an investment spike. In the empirical specification, the basic liquidity terms in the dynamic leverage models tell us about the effect of share liquidity on target leverage ratios, a measure of spike size tells us about abnormal borrowing when faced with an investment spike, and an interaction term between spike size and share liquidity tells us about the effect of share liquidity on this abnormal borrowing.

Formally, the baseline specification with a measure of spike size and an interaction term between spike size and share liquidity is defined as follows:

$$\begin{aligned} \Delta LEV_{j,\tau=0} = & \alpha + \beta LEV_{j,\tau=-1} + X'_{j,\tau=-1} \gamma + \delta LIQ_{j,\tau=-1} + \pi D\_AQC_{j,\tau=0} \quad (6.7) \\ & + \theta_L SPIKESIZE_{j,\tau=0} + \theta_D SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1} \\ & + IND_k + YR_t + \varepsilon_j, \end{aligned}$$

where  $\Delta LEV_{j,\tau=0}$ ,  $LEV_{j,\tau=-1}$ ,  $X_{j,\tau=-1}$ , and  $LIQ_{j,\tau=-1}$  are defined as in Equation (6.5). To investigate whether acquisitions tend to be funded differently to capital expenditures, a dummy variable for acquisitions ( $D\_AQC_{j,\tau=0}$ ) is also included in the regression equation.  $D\_AQC_{j,\tau=0}$  is 1 if a firm reports positive acquisitions during the year categorized as an investment spike and 0 otherwise. To investigate whether high-liquidity firms use more abnormal borrowing during an investment spike, a spike size measure ( $SPIKESIZE_{j,\tau=0}$ ) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) are included in the regression equation.

Section 6.3.3 and Table 6.1 Panel B provides details on how to construct those variables.  $\theta_L$  represents the propensity to raise debt finance of low-liquidity firms, whereas  $\theta_H (= \theta_L + \theta_D)$  represents the propensity to raise debt finance of high-liquidity firms. Hypothesis **H1** is supported if  $\theta_D > 0$ , whereas Hypothesis **H2** is supported if  $\theta_D < 0$ .

[Insert Table 6.5 Here.]

## B. Results from baseline regression specifications

Table 6.5 reports the results of the regressions designed to investigate whether high liquidity firms have higher abnormal borrowing during investment spikes, as well as whether high-liquidity firms have higher target leverage ratios. First of all, the main effect of interest, the coefficient of an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ), is positive and significant at the 1% level of significance (See columns (2) and (4) in Table 6.5.). These results support the Hypothesis **H1**, since share liquidity has a positive effect on abnormal borrowing during an investment spike. The results appear economically significant as well.  $\theta_H = 0.242$  and  $\theta_L = 0.162$  in the case of the liquidity measure based on the Gibbs spread, while  $\theta_H = 0.249$  and  $\theta_L = 0.164$ . This suggests that firms with higher share liquidity tend to use substantially more debt finance when they are faced with unusually large investment requirements.

However, Table 6.5 shows that high-liquidity firms do not have significantly higher tar-

get leverage ratios than low-liquidity firms<sup>20</sup>. In column (1), the coefficient of the liquidity measure based on Hasbrouck's Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) is positive and significant at the 1% level, but its significance vanishes in column (2) in which investment spike characteristics are included. In columns (3) and (4), the coefficient of the liquidity measure based on Amihud's price impact ( $LIQ_{j,\tau=-1}^A$ ) is positive but insignificant. Therefore, there are minimal differences between high-liquidity firms and low-liquidity firms, all else being equal.

Some of the explanatory variables contained in the vector  $X_{j,\tau=-1}$  are significant. It should be noted that they are determinants of the target leverage ratio<sup>21</sup>. The following analysis is based on columns (2) and (4). First, the coefficient on firm size ( $LnTA_{\tau=-1}$ ) is negative and significant at the 1% level in both columns. This suggests that, after controlling for other factors, large firms tend to have lower target leverage ratios on average. Second, the coefficient of  $EBIT\_TA_{j,\tau=-1}$  is negative and significant at the 5% level in both columns. This suggests that more profitable firms tend to have somewhat lower target leverage ratios on average. Third, the coefficient on market-to-book ratio ( $MV\_BV_{\tau=-1}$ ) is negative and significant at the 5% level in both columns. This suggests that firms with more future growth opportunities tend to have somewhat lower target leverage ratios on average. Finally, the coefficient on tangibility of assets ( $FA\_TA_{\tau=-1}$ ) is positive and significant at the 1% level in both columns.

<sup>20</sup>In Table 6.9, I run similar regressions in the whole sample. In this case, within-firm variation as well as cross-sectional variation is also explored. Therefore, using the whole sample, we can better evaluate whether the increase in share liquidity induces the increase in target leverage ratio. However, it should be noted at this point that the models based on the investment spikes sample provide a sharper inference on the effect of share liquidity on the propensity to raise debt finance as emphasized in Chapter 4.

<sup>21</sup>The coefficient of lagged leverage is negative and significant at the 1% level in the dynamic leverage change models reported in columns (1)-(4). The speed of adjustment is estimated to be 0.173 in the case of column (1). This suggests that firms also show mean reverting behaviours or target adjustment behaviours during investment spikes.

Firms with higher tangibility of assets or a higher proportion of fixed assets tend to have higher target leverage ratios on average. This is because they have relatively more collateral to pledge against and therefore have better access to bank loans.

It is also interesting that the coefficients of  $D\_AQC$  have positive signs in all regressions, meaning that investment spikes involving acquisitions tend to be more debt-financed compared with investment spikes with capital expenditures only. This is notable because the size of investment spikes, initial leverage of firms, and other firm characteristics are controlled for. Although the results are not tabulated, it can also be seen that the coefficients of  $SPIKESIZE$  have positive signs and the coefficients of  $SPIKESIZESQ(= SPIKESIZE \times SPIKESIZE)$  have negative signs, meaning that there is a convex relation between the changes in leverage during an investment spike and abnormal investment during the spike<sup>22</sup>. This appears to support the pecking-order theory, although formal testing of pecking-order theory goes beyond the scope of this study.

I conclude that high-liquidity firms tend to have a higher propensity to raise debt finance or higher abnormal borrowing during an investment spike. Under Conditional Independence Assumption (CIA)<sup>23</sup>, this finding has a causal interpretation that a given firm would have a

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<sup>22</sup>However, the coefficient of  $SPIKESIZESQ$  is not very large, although it is significantly different from zero at 1%. So, the relation might be close to a linear relation.

<sup>23</sup>Causality means different things to different people, but many researchers tend to believe that a conditional expectation function (CEF) is causal, when it describes differences in average potential outcomes for a fixed reference population (Angrist and Pischke, 2009). The causal relation between the leverage change during an investment spike (or the propensity to raise debt finance) and share liquidity can be defined as the functional relationship that describes what leverage change a given firm would make during an investment spike if the firm had different levels of share liquidity. In other words, the causal relationship between the leverage change and liquidity tells us what leverage change firms have, on average, if they could either change their share liquidity in a perfectly controlled environment or change their liquidity randomly so that firms with different levels of share liquidity would be otherwise comparable. However, CIA is not directly testable. Therefore, I do not strongly argue that this regression has a causal interpretation. However, recall that the incidence of investment spikes is

higher propensity to raise debt finance during the investment spike if the firm had a higher level of share liquidity.

[Insert Table 6.6 Here.]

## 6.5.2 Robustness tests

### A. Controlling for the effects of firm characteristics on abnormal borrowing during an investment spike

In this section, I investigate whether the positive effect of share liquidity on the propensity to raise debt finance or abnormal borrowing during an investment spike remains after controlling for the effects of various firm characteristics, such as firm size, initial leverage, and profitability. Table 6.6 and Table 6.7 show that the positive effect of share liquidity on the propensity to raise debt finance is robust to the inclusion of interaction terms to capture the effects of various firm characteristics. As the results in both tables are very similar, the following analysis is based on Table 6.6, which uses the liquidity measure based on the Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) as the measure of share liquidity.

First of all, column (1) shows that the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$ )

is not affected at all, after inclusion of an interaction term between the spike size measure and

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not significantly affected by share liquidity, as shown in Section 6.4. Therefore, it might be more likely that CIA is less problematic when we focus on unusually large investment years and we control for various factors that affect the incidence of investment spikes such as initial leverage. Note that this causal interpretation is useful to derive some practical implications from this empirical finding.

a dummy variable for large firms ( $SPIKESIZE_{j,\tau=0} \times D\_LARGE_{j,\tau=-1}$ ). In Chapter 4, it was shown that there are substantial differences in funding patterns between large firms and small firms. In addition, in Chapter 5, it was also shown that the financing patterns of large firms are similar to those of high-liquidity firms, whereas the financing patterns of small firms are similar to those of low-liquidity firms. For those reasons, one might surmise that the effects attributed to share liquidity could be driven by firm size. However, this result shows that this is not the case. Furthermore, the effect of share liquidity ( $\theta_D = 0.101$ ) is larger than that in column (2) of Table 6.5 ( $\theta_D = 0.080$ ). This means that the effect of share liquidity on the propensity to raise debt finance is stronger when firm size is controlled for.

Second, columns (2)-(4) show that the effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$ ) is reduced to some extent but still positive and significant, when an interaction term between the spike size measure and a dummy variable for high-leverage firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLEV_{j,\tau=-1}$ ), an interaction term between the spike size measure and a dummy variable for high-profitability firms ( $SPIKESIZE_{j,\tau=0} \times D\_HPRF_{j,\tau=-1}$ ), or an interaction term between the spike size measure and a dummy variable for high market-to-book firms ( $SPIKESIZE_{j,\tau=0} \times D\_HMB_{j,\tau=-1}$ ) is included in the regression equation. Column (2) shows that highly leveraged firms have a lower propensity to raise debt finance, while columns (3)-(4) show that firms with high profitability and higher growth opportunities tend to use more abnormal borrowing during investment spikes. It should be noted that firms with higher profitability and higher market-to-book tend to have lower target leverage ratios. This suggests that firms with higher profitability

and future growth opportunities use relatively more debt finance when substantial amounts of external finance is required, although they have lower target leverage ratios. On the contrary, firms with lower profitability and future growth opportunities use relatively less debt finance and more equity finance when external finance is required. This result is consistent with the pecking-order theory suggested by Myers and Majluf (1984).

Third, columns (5)-(6) show that the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$ ) is not reduced almost at all, when an interaction term between the spike size measure and a dummy variable for firms with high assets tangibility ( $SPIKESIZE_{j,\tau=0} \times D\_HTAN_{j,\tau=-1}$ ) or an interaction term between the spike size measure and a dummy variable for firms with high R&D intensity ( $SPIKESIZE_{j,\tau=0} \times D\_HRD_{j,\tau=-1}$ ) is included in the regression. Note that asset tangibility does not have a significant effect on abnormal borrowing during a spike, while R&D intensity has a weakly significant positive effect on the propensity to raise debt finance. It is also noteworthy that firms with higher tangibility of assets tend to have higher target leverage ratios. This suggests that tangibility of assets does not have a significant effect on the propensity to raise debt finance, although firms with higher tangibility of assets tend to have higher target leverage ratios.

Finally, the regression result reported in column (7) is based on the specification with all the interaction terms used in columns (1)-(6) included at once. This specification does not change the findings explained above. Firms with higher initial leverage have a lower propensity to raise debt finance, while firms with higher profitability, higher market-to-book, and higher

R&D intensity have a higher propensity to raise debt finance. Even after controlling for those effects, share liquidity has a significant positive effect on the propensity to raise debt finance. Therefore, I conclude that **H1** is supported after controlling for the effects of various firm characteristics. Table 6.7, which uses the liquidity measure based on the Amihud measure ( $LIQ_{j,\tau=-1}^A$ ) as a measure of share liquidity, shows almost identical results.

[Insert Table 6.7 Here.]

## B. Using various definitions of leverage ratios

In this section, I investigate whether the positive effect of share liquidity on the propensity to raise debt finance is robust to the use of various leverage measures. Two alternative leverage measures,  $MLEV$  and  $BLEV$  (as defined in Section 6.3.3), are used for this purpose. Table 6.8 reports the regression results. The dependent variable is the change in alternative market leverage during an investment spike ( $\Delta MLEV_{j,\tau=0}$ ) in columns (1)-(2), whereas the dependent variable is the change in book leverage during an investment spike ( $\Delta BLEV_{j,\tau=0}$ ) in columns (3)-(4). Accordingly,  $MLEV_{j,\tau=-1}$  is used as a lagged leverage ratio in columns (1)-(2), whereas  $BLEV_{j,\tau=-1}$  is used in columns (3)-(4). In all models, the coefficient of an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) is positive and significant at the 1% level of significance. These results support Hypothesis **H1**, since share liquidity has a positive effect on abnormal borrowing at the time of an investment spike. It is noteworthy that, in columns (1) and (3), the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$

is somewhat larger than that in column (2) of Table 6.5. Note also that the liquidity measures do not have any significant effect on target leverage in all columns. I therefore conclude that firms with higher share liquidity tend to use substantially more debt finance when they are faced with unusually large investment requirements, although share liquidity does not have a significant effect on target leverage. The positive effect of share liquidity on the propensity to raise debt finance is robust to the choice of leverage measures.

[Insert Table 6.8 Here.]

### **C. Using the whole sample rather than the investment spikes sample**

One would suspect that a positive effect from share liquidity on the change in leverage is driven by the use of the investment spikes sample instead of the whole sample. Therefore, I test this possibility by implementing a dynamic leverage change model similar to Equation (6.5) and Equation (6.7) with the whole sample. Table 6.9 reports the results for the regressions designed to investigate whether share liquidity has a positive effect on target leverage and abnormal borrowing during an investment spike in the whole sample. The dependent variables in all regressions are the change in leverage ( $\Delta LEV_{it}$ ). The liquidity measure based on the Gibbs spread is used as a measure of liquidity in columns (1)-(4), whereas the liquidity measure based on the Amihud measure is used in columns (5)-(8). Odd-numbered columns present the OLS estimation results, whereas even-numbered columns present the FE regression results. All the models reported in columns (1)-(8) have a dummy variable for a year with investment spikes ( $D\_SPIKE_{it}$ ) to see if more debt finance is used

in the year with investment spikes compared with other periods. The models reported in columns (3), (4), (7), and (8) include a spike size measure ( $SPIKESIZE_{it}$ ) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $(SPIKESIZE \times D\_HLIQ^G)_{it}$  or  $(SPIKESIZE \times D\_HLIQ^A)_{it}$ ), as well as a dummy variable for acquisitions ( $D\_AQC_{it}$ ). Table 6.1 Panel B provides details on how to construct those variables. Note that the spike size measure ( $SPIKESIZE_{it}$ ) and its interaction terms ( $(SPIKESIZE \times D\_HLIQ^G)_{it}$  or  $(SPIKESIZE \times D\_HLIQ^A)_{it}$ ) have a value of zero if the firm-year is not categorized as an investment spike. The industry dummies defined as in Fama and French's (1997) study and year dummies are included in each regression.

[Insert Table 6.9 Here.]

The results of this analysis are summarized as follows. First, note that a dummy variable for a year with investment spikes ( $D\_SPIKE_{it}$ ) is positive and significant at the 1% level, regardless of model specifications and estimation methods. This suggests that a substantial amount of debt finance is raised during a year with investment spikes. Based on column (1), on average firms increase leverage in such a year by about 6.1% points more than in normal periods. Second, the effect of share liquidity on target leverage<sup>24</sup> is positive and significant at the 1% level, regardless of model specifications and estimation methods. It seems that share liquidity has a positive and significant effect on target leverage in normal periods, whereas that is not the case if we focus on a year with investment spikes. However, the magnitude of the effect is not so large. Third, the coefficients of  $D\_AQC$  have positive signs regardless of

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<sup>24</sup>Note that the models used in Table 6.9 are the reduced form of the partial adjustment models.

estimation methods, meaning that investment spending involving acquisitions tends to be more debt-financed compared with investment spending with capital expenditures only. Finally, an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $(SPIKESIZE \times D\_HLIQ^G)_{it}$  or  $(SPIKESIZE \times D\_HLIQ^A)_{it}$ ) is positive and significant at the 1% level, regardless of the estimation method used. In addition, the magnitude of the positive effect of share liquidity is very similar to that found in the investment spikes sample. This analysis also shows that the addition of investment spikes information increases the explanatory power of the model. Note that R-squared increases from 0.186 (column (1)) to 0.202 (column (3)) and the coefficients of all additional variables are significant at the 1% level.

In summary, financing patterns during investment spike periods are distinct from those in normal periods and share liquidity has a positive effect on the propensity to raise debt finance during investment spike periods. I find that the results in the previous section are not just driven by the use of the investment spikes sample, although the years with investment spikes have distinct features and those years are more appropriate for studying financing patterns, in particular the composition of external finance. Various robustness tests confirm that **H1** is well supported. I therefore conclude that high-liquidity firms have a higher propensity to raise debt finance.

### 6.5.3 How does liquidity increase the propensity to raise debt finance?

Having established the positive effect of share liquidity on the propensity to raise debt finance, I turn to the assessment of the mechanisms through which share liquidity increases the propensity to raise debt finance. To assess whether each of the two mechanisms works, I compare the observed correlation coefficients between share liquidity measure ( $LIQ_{j,\tau=-1}^G$  and  $LIQ_{j,\tau=-1}^A$ ) and the two key variables<sup>25</sup> with the correlation coefficients predicted in those mechanisms. Then, I check whether the significance of the coefficient of an interaction term<sup>26</sup> between a spike size measure ( $SPIKESIZE_{j,\tau=0}$ ) and a dummy variable for high-liquidity firms ( $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) vanishes when a key variable and an interaction term between the spike size measure and a dummy variable based on the key variable are included as explanatory variables in the regression.

First, the *information spillover mechanism (H1A)* is based on the argument that banks can monitor high-liquidity firms more efficiently by supplementing their own information with more informative stock prices, as more public information is available for those firms and such information spills over into the debt market (Sunder, 2004; Saunders and Steffen, 2009). Although the amount of public information prevailing in the stock market is hard to measure, it is proxied by the number of institutional managers for each firm-year ( $NUMMGRS$ ). The information spillover mechanism predicts that the shares of high-liquidity firms are owned by a larger number of institutional managers. Table 6.3 Panel C shows that  $NUMMGRS$  is posi-

<sup>25</sup>The key variables used are  $MALTMANZ$  for the credit ratings mechanism and  $NUMMGRS$  for the information spillover mechanism. Those variables are defined in Section 6.3.3.

<sup>26</sup>Recall that this was defined as  $\theta_D$  in Section 6.5.1.

tively correlated with two liquidity measures at the 1% level, as predicted by this mechanism.

[Insert Table 6.10 Here.]

Table 6.10 reports the results of the regression models designed to evaluate the information spillover mechanism. I investigate whether the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) is attenuated after the inclusion of the number of institutional managers ( $NUMMGRS_{j,\tau=-1}$ ) as a proxy for the information produced in the stock market and the inclusion of an interaction term between the spike size measure and a dummy variable for firms with high information production ( $SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$ ). As before, the regressions reported in columns (1) and (3) use the same sample as in the regressions reported in columns (2) and (4). The findings are summarized as follows. First, note that the positive effect of share liquidity on the propensity to raise debt finance vanishes when additional variables related to information production in the share market are included in the regression. In the case of both liquidity measures, the magnitude of  $\theta_D$  gets smaller and its significance disappears. Second, the coefficients of  $SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$  are positive but not significant at the 10% level in columns (2) and (4). Third, the coefficients of  $NUMMGRS_{j,\tau=-1}$  in columns (2) and (4) are not significant at the 10% level, meaning that the amount of the information prevailing in stock market does not have a positive effect on target leverage. The information spillover mechanism is hard to test directly<sup>27</sup>, but these re-

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<sup>27</sup>Note that this is not a test of whether share market information has been transferred to the debt market, but rather a test of whether firms with more information prevailing in the share market have a higher propensity to raise debt finance and whether the effect of information production on debt finance nullifies the effect of share liquidity on debt finance.

sults are consistent with the information spillover mechanism. Thus, based on both correlation analysis and regression analysis, I conclude that the information spillover mechanism works.

Second, the *credit rating mechanism* (**H1B**) is based on the argument that both credit ratings and share liquidity capture the same adverse selection risk, although they are measured in different markets, i.e. the debt market and the equity market (Odders-White and Ready, 2006). A modified Altman's Z-score (*MALTMANZ*) is often used to measure adverse selection risk instead of credit ratings data<sup>28</sup>. Thus, the credit ratings mechanism predicts a positive correlation between share liquidity and *MALTMANZ*. Table 6.3 Panel C shows that correlations between *MALTMANZ* and both liquidity measures are positive and significant at the 1% level in the investment spikes sample. Chava *et al.* (2009) also show that *MALTMANZ* has a significantly negative effect on the loan spread, after controlling for various firm and loan characteristics.

[Insert Table 6.11 Here.]

Table 6.11 reports the results of the regressions designed to evaluate the credit rating mechanism. I investigate whether the positive effect of share liquidity on abnormal borrowing during an investment spike (or the coefficient of  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ ) is attenuated after the inclusion of an interaction term between the spike size measure and a dummy variable for firms with high credit ratings ( $SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$ ). To make sure that fair comparisons are made, the regressions reported in columns (1) and (3) use the same sample as the regressions in columns (2) and (4)<sup>29</sup>. The

<sup>28</sup>A dummy variable for an investment-grade bond is highly correlated with the modified Altman's Z-score.

<sup>29</sup>Although the regressions reported in columns (1) and (3) do not include  $MALTMANZ_{j,\tau=-1}$  and

findings are summarized as follows. First, note that the positive effect of share liquidity on the propensity to raise debt finance is attenuated when additional variables related to credit ratings are included in the regression. In the case of both liquidity measures, the magnitude of  $\theta_D$  gets smaller and its significance gets weaker.  $\theta_D$  is significant only at the 10% level in the case of the liquidity measure based on the Gibbs spread, whereas  $\theta_D$  is not significant in case of the liquidity measure based on the Amihud's price impact. Second, the coefficients of  $SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$  are significant at the 10% level and 5% level in columns (2) and (4). This suggests that credit ratings reflecting adverse selection risk have a significant effect on the propensity to raise debt finance. Third, the coefficients of  $MALTMANZ_{j,\tau=-1}$  in columns (2) and (4) are significant at the 10%, meaning that credit ratings reflecting adverse selection risk have a positive effect on target leverage as well, although this effect is not very strong. Overall, it seems that share liquidity captures the adverse selection risk reflected in credit ratings. Thus, based on both correlation analysis and regression analysis, I conclude that the credit ratings mechanism works.

In this section, I show that the credit ratings mechanism and information spillover mechanism work. Those two mechanisms provide interesting explanations as to why high-liquidity firms have a propensity to raise debt finance. High-liquidity firms are less likely to have severe asymmetric information problems between informed investors including managers and uninformed investors. Thus, high-liquidity firms are likely to have more informative share prices.

In addition, more information on high-liquidity firms is available because those firms are fol-

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$SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$  as explanatory variables, I use the data of the firms for which those variables are not missing.

lowed by a large number of financial analysts and the shares of those firms are owned by many financial institutions. Banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices. Hence, high-liquidity firms face a lower cost of debt and are likely to have a higher propensity to raise debt finance. Moreover, high-liquidity firms also tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, high-liquidity firms incur lower costs when raising debt finance in subsequent periods and are likely to raise relatively more debt finance to finance large investment requirements.

## 6.6 Inconsistent liquidity effects in leverage models

Why are the liquidity effects different in static and dynamic leverage regressions? Some of the existing literature which used static leverage-level regressions (i.e. leverage models without lagged leverage as an explanatory variable) find that there is a negative relation between share liquidity and leverage level<sup>30</sup>. As a consistency check, I provide comparisons of the effects of share liquidity in static and dynamic leverage-level regressions<sup>31</sup>. Table 6.12 reports the results of static and dynamic regression models with one of the two liquidity measures, estimated using either OLS or FE regressions. Regardless of the choice of estimation methods or the

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<sup>30</sup>See Bharath *et al.* (2009), Lipson and Mortal (2009) and Fang *et al.* (2009). Note that Fang *et al.* (2009) define leverage as the market value of equity divided by the book value of assets. Furthermore, they do not focus on firms' financing decisions as leverage is treated only as a component of market-to-book ratio, their main object of interest. However, they also report the results of static leverage models.

<sup>31</sup>The static leverage equation does not include lagged leverage as an explanatory variable, whereas the dynamic leverage equation includes lagged leverage as an explanatory variable. Note that the leverage change equation with lagged leverage is equivalent to the leverage-level equation with lagged leverage. Both equations are actually the reduced-form specifications of the partial adjustment model.

choice of liquidity measures, the coefficients of liquidity measures are negative and significant at the 1% level in static regressions, whereas the coefficients are positive and significant at the 1% level in dynamic regressions<sup>32</sup>.

What can explain the puzzle of inconsistent liquidity effects in static and dynamic leverage models? Before answering this question, recall that two liquidity measures have significant positive correlations with change in leverage, while they have significant negative correlations with lagged leverage in both the whole sample and the investment spikes sample. This correlation structure could arise if lagged leverage decreases share liquidity and share liquidity has a positive effect on the change in leverage. Therefore, the negative relation between  $LIQ_{i,t-1}$  and  $LEV_{it}$  in static regressions could be driven by the causality running from  $LEV_{i,t-1}$ , which is highly correlated with  $LEV_{it}$ , to  $LIQ_{i,t-1}$ . One could argue that there is a direct causal effect from  $LIQ_{i,t-1}$  to  $LEV_{it}$ . If so, the effect of liquidity on leverage might be largely related to the effect of liquidity on the market value of equity. The static leverage model is likely to capture the mechanical effect of liquidity on leverage rather than the marginal effect of liquidity on the propensity to raise debt finance. However, a dynamic leverage model might be able to capture the effect of liquidity on the propensity to raise debt finance, as the reduced-form partial adjustment model allows us to capture the effect of liquidity on target leverage<sup>33</sup>.

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<sup>32</sup>Although not reported here, the coefficients of liquidity measures in the leverage change model without lagged leverage as an explanatory variable are also positive and significant at the 1% level. It is striking that the liquidity measures have positive signs in dynamic models, whereas the liquidity measures have negative signs in static leverage models. Fang *et al.* (2009) report the results of the regression of “a change in leverage surrounding decimalization” on “a change in share liquidity surrounding decimalization” and “changes in other control variables surrounding decimalization”. Note that their underlying equation is equivalent to the static leverage-level equation, resulting in no difference in the signs of the liquidity effect. The decimalization event may not be an appropriate natural experiment as long as a true model is the dynamic leverage-level model or dynamic leverage change model.

<sup>33</sup>The coefficient of liquidity measures in the dynamic leverage model should be interpreted as

[Insert Table 6.12 Here.]

More formally, the puzzle could be partly resolved using the OVB formula. Assume that the true economic relation should include  $LEV_{i,t-1}$  in the regression of  $LEV_{it}$  and the coefficient of  $LIQ_{i,t-1}$  is  $\beta$ . Now assume that the estimated coefficient of  $LIQ_{i,t-1}$  from a regression without  $LEV_{i,t-1}$  is  $\hat{\beta}$ . In this case, the OVB formula<sup>34</sup> says:

$$p \lim \hat{\beta} = \beta + \gamma \cdot \frac{Cov(LIQ_{i,t-1}, LEV_{i,t-1})}{Var(LIQ_{i,t-1})}, \quad (6.8)$$

where  $\gamma$  is the coefficient of  $LEV_{i,t-1}$  in the true economic relation. Note that the asymptotic bias is likely to be negative, given that  $\gamma > 0$  and  $Cov(LIQ_{i,t-1}, LEV_{i,t-1}) < 0$ . The former holds because leverage is persistent, while the latter holds because firms with higher leverage will have lower share liquidity, as predicted by the theory presented in Appendix 6.A.1. Note also that  $\hat{\beta} < 0$  in the static leverage models of Table 6.12. This implies that the true effect of  $LIQ_{i,t-1}$  or  $\beta$  could be either negative but larger than  $\hat{\beta}$  or positive. This explains why  $\beta > 0$  in dynamic leverage models. I therefore conclude that the results of both static leverage models and dynamic leverage models are robust and can hold at the same time. However, I will leave it to the reader's own judgement to decide which model offers more reasonable, interesting, and intuitive interpretations.

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*"Speed of Adjustment (SOA) × Sensitivity of Target Leverage to Share Liquidity"*.

<sup>34</sup>See Roberts and Whited (2011) and Angrist and Pischke (2009) for details.

## 6.7 Conclusions

A conventional view in corporate finance predicts a *negative* effect of share liquidity on the propensity to raise debt finance. Based on Myers and Majluf's (1984) argument that asymmetric information problems drive corporate financing decisions, Myers (1984) argues that if managers know more than the rest of the market about their firms' value, the market penalizes the issuance of information-sensitive securities such as equities. Therefore, it is predicted that firms will use equity issuances to meet large exceptional financing needs only as a last resort, after less information-sensitive financing sources such as internal cash and debt have been exhausted. Thus, firms with less liquid shares or more severe asymmetric information problems are likely to raise more debt finance (Bharath *et al.*, 2009). Similarly, Lipson and Mortal (2009) and Frieder and Martell (2006) argue that firms with more liquid shares are likely to raise more equity finance because those firms have lower costs for raising equity capital (Butler *et al.*, 2005).

However, there are some reasons to believe that share liquidity has a *positive* effect on the propensity to raise debt finance. Although it seems obvious that firms with more liquid shares incur lower costs when raising equity capital, there are good reasons to believe that firms with more liquid shares have lower costs for raising debt capital as well (Butler and Wan, 2010). One of the most promising rationales as to why firms with more liquid shares have lower borrowing costs is based on the spillover of the information produced in the stock market into the debt market (Sunder, 2004; Saunders and Steffen, 2009). Despite the existence of conflicting arguments on the effect of liquidity on the propensity to raise debt finance, this issue has

not received sufficient attention from researchers in empirical corporate finance. This study investigates whether share liquidity has a positive, negative, or no effect on the propensity to raise debt finance as measured by abnormal borrowing at the time of an investment spike. This study also explores the distinct mechanisms through which share liquidity increases the propensity to raise debt finance.

This study shows that share liquidity has a positive effect on the propensity to raise debt finance. Using an empirical specification which makes a clear distinction between share liquidity as a determinant of target leverage and share liquidity as a determinant of abnormal borrowing at the time of an investment spike, I find that share liquidity has a positive effect on abnormal borrowing when faced with an investment spike, meaning that high-liquidity firms have a higher propensity to raise debt finance. Those results are robust to a control for the effects of various firm characteristics, the use of various leverage measures, and the use of a whole sample combined with investment spike characteristics. Thus, I conclude that high-liquidity firms have a higher propensity to raise debt finance. Under the conditional independence assumption, this has a causal interpretation that a given firm would have a higher propensity to raise debt finance during an investment spike if the firm had a higher level of share liquidity.

The underlying mechanisms through which this works are then investigated. This study finds evidence supporting the information spillover and credit ratings mechanisms. Those mechanisms provides interesting explanations as to why high-liquidity firms have a higher propensity to raise debt finance. Firms with more liquid shares are less likely to have se-

vere asymmetric information problems between informed investors including managers and uninformed investors. Thus, those firms are likely to have more informative share prices. In addition, more information on high-liquidity firms is produced because those firms are followed by a large number of financial analysts and the shares of those firms are owned by many financial institutions. Hence, banks can monitor those firms more efficiently by supplementing their own information with more informative stock prices. High-liquidity firms will also have stronger bargaining power on the conditions of loan contracts, as they also have equity financing as a quite attractive outside option. Hence, high-liquidity firms face a lower cost of debt and are likely to have a higher propensity to raise debt finance. Moreover, high-liquidity firms tend to have a lower adverse selection risk, which will be reflected in future credit ratings. Thus, high-liquidity firms have lower costs of raising debt finance in subsequent periods and are likely to raise relatively more debt finance to finance large investment requirements.

This study also identifies a puzzle regarding the inconsistent effects of share liquidity in static and dynamic leverage models and resolves it. The puzzle is that there is a negative relation between share liquidity and the level of leverage in static leverage regressions, while there is a positive relation between share liquidity and leverage in dynamic leverage regressions. Some existing literature, such as the research by Bharath *et al.* (2009), Lipson and Mortal (2009) and Fang *et al.* (2009) which use static leverage level regressions (i.e. leverage models without lagged leverage as an explanatory variable), find that there is a negative relation between share liquidity and leverage level. Regardless of the choice of estimation methods or the choice of liquidity measures, I also find a negative relation between share liq-

uidity and leverage level in static leverage regressions. Similarly, this study also finds that two liquidity measures have significant positive correlations with change in leverage, while they have significant negative correlations with lagged leverage. This puzzling correlation structure could arise if lagged leverage decreases share liquidity and share liquidity has a positive effect on the change in leverage. Therefore, the negative relation between share liquidity and leverage in static regressions could be driven by the causality running from lagged leverage, which is highly correlated with contemporary leverage, to share liquidity. Using the OVB formula, I show that both relations can hold at the same time. These arguments are consistent with a theory predicting that lagged leverage has a negative effect on share liquidity and the main empirical findings that share liquidity has a positive effect on the propensity to raise debt finance as measured by the change in leverage.

The results have some practical implications on the management of share liquidity and level of debt. First, as long as debt is a preferred source of finance, it would be beneficial for a firm to keep share liquidity high, in particular if the firm is planning a large investment project. If a firm has high share liquidity, the firm might be able to attract more financial analysts and institutional investors. This could be done by improving investor relations, providing relevant information to the share market, spending wisely on advertising, going public if the firm is a private firm, and so on. Thus, more public information regarding the firm will be available to potential investors. Therefore, it will be less costly for banks to monitor such a firm as banks can supplement their own information with more informative stock prices. In addition, a firm with higher share liquidity will have a stronger bargaining power with the banks so

that it can have better terms and conditions for a loan contract. This study therefore shows why an equity market star is usually a debt market star as well. Second, a firm might benefit from strategically managing the debt level in a dynamic context considering future investment needs, as high leverage has a negative effect on share liquidity. It might be optimal for a firm to keep leverage low until shares are sufficiently liquid in anticipation of an investment spike, raise debt finance at favourable conditions at the time of an investment spike, and repay debt gradually after an investment spike. The current level of debt might have a significant effect on the availability and conditions of future external finance through the effect of share liquidity on the costs of debt finance. If a firm cannot borrow at reasonable conditions to finance unusually large investment activities, the shareholders should be ready to give up their ownership to a third party. Otherwise, the firm might have to forgo investment opportunities, making the firm less competitive in the long run.

## 6.A Appendix

### 6.A.1 A theory on the effect of leverage on liquidity

Consider a batch auction in which traders submit “market orders”, i.e. quantities to buy or sell regardless of what the price turns out to be. Assume that trading takes place on the last day of year 0 only. Assume that the value of the firm on the last day of year  $-1$  is given as:

$$V_{-1} = D_{-1} + E_{-1}, \quad (6.9)$$

where  $D_{-1}$  and  $E_{-1}$  are the amounts of debt and equity on the last day of year  $-1$ , respectively. The firm value on the last day of year  $-1$  can be also written as:

$$V_{-1} = \frac{C}{r}, \quad (6.10)$$

where  $C$  is perpetual free cash flows and  $r$  is the weighted average cost of capital (WACC), reflecting the risk of the firm’s businesses. Assume that there are no taxes and the firm survives forever.

The firm value on the last day of year 0,  $\tilde{V}$ , is forecast as  $V^U = V_{-1}(1 + \delta)$  by uninformed traders but forecast as  $V^I = V_{-1}(1 + \delta + \tilde{\epsilon})$  by a single informed trader, where  $\delta$  is a zero mean random shock which is “*common knowledge*” on the last day of year 0 and  $\tilde{\epsilon}$  is a random shock distributed normally with mean 0 and variance  $\sigma_{\tilde{\epsilon}}^2$  and is observed by a single informed trader only. Hence, the *ex post* liquidation value of the firm’s equity is

$$\tilde{E} = \tilde{V} - D_{-1} = V_{-1}(1 + \delta + \tilde{\epsilon}) - D_{-1}. \quad (6.11)$$

Assuming further that the price of a share on the last day of year  $-1$  is 1, i.e.  $p_{-1} = 1$ , such that  $E_{-1} = n \cdot p_{-1} = n$  where  $n$  is the number of shares outstanding, it can be shown that the

*ex post* liquidation value of a share of the firm is

$$\tilde{p} = \frac{\tilde{E}}{n} = p_\delta + \left(1 + \frac{D_{-1}}{E_{-1}}\right) \tilde{\epsilon}, \quad (6.12)$$

where

$$p_\delta = 1 + \left(1 + \frac{D_{-1}}{E_{-1}}\right) \delta. \quad (6.13)$$

Therefore, the variance of the *ex post* liquidation value of each share,  $\sigma_p^2$ , is monotonically increasing in the initial debt-to-equity ratio,  $D_{-1}/E_{-1}$ , meaning that the insider is expected to have more private information when the initial leverage is high.

As in Kyle (1985), the quantity traded by noise traders, denoted by  $\tilde{u}$ , is normally distributed with mean zero and variance  $\sigma_u^2$ . The random variables  $\tilde{p}$  and  $\tilde{u}$  are independently distributed. The quantity traded by the insider is denoted  $\tilde{x}$  and the market price set by the market maker is denoted  $\tilde{m}$ . As the market maker cannot observe the source of the orders, the information on the total order size ( $\tilde{u} + \tilde{x}$ ) is important to the market maker. The more positive the total order size, the more likely it is that  $\tilde{x}$  is large due to the insider knowing that  $\tilde{p}$  is greater than  $p_\delta$ . So, the market maker would tend to set  $\tilde{m}$  higher than otherwise. Thus, the pricing rule of the market maker is a function of  $(\tilde{u} + \tilde{x})$ . For simplicity, assume a linear function such that  $\tilde{m} = M(\tilde{u} + \tilde{x}) = \mu + \lambda(\tilde{u} + \tilde{x})$ . The insider chooses  $x$  to maximize his expected end-of-period profits,  $\tilde{\pi}$ , given the knowledge of the true value of a share,  $p$ , and the pricing rule of the market maker, i.e.  $M(u + x)$ . Hence, if the market maker uses a linear pricing rule, the optimal strategy for the insider is a linear trading rule. Thus, let us assume a linear function such as  $x = \alpha + \beta p$ . Solving for a linear equilibrium gives the following equilibrium price

$$m = p_\delta + \frac{\sigma_p}{2\sigma_u}(u + x), \quad (6.14)$$

where the equilibrium order submitted by the insider is  $x = \sigma_u/\sigma_p(p - p_\delta)$ . Hence, the Kyle's  $\lambda$  is given as

$$\lambda = \frac{\sigma_p}{2\sigma_u} = \frac{\left(\frac{V_{-1}}{E_{-1}}\right) \sigma_\epsilon}{2\sigma_u}. \quad (6.15)$$

This means that, given  $\sigma_\varepsilon$  (i.e. standard deviation of a private information shock) and  $\sigma_u$  (i.e. standard deviation of the quantity of noise trading), firms with higher initial leverage (i.e. higher  $V_{-1}/E_{-1}$ ), will have a higher price impact or lower share liquidity than firms with lower initial leverage.

Table 6.1: Variable definitions

The table shows the definitions of variables used in the study. Panel A describes the variables used in regressions whereas Panel B describes the variables related to investment spikes. The definitions of variables used in baseline regressions closely follow those of Flannery and Rangan (2006), Lemmon *et al.* (2008), and Rajan and Zingales (1995). Unless otherwise stated, all the Compustat variables are measured at the end of year  $t$ . The variables in ratios are winsorized at the 1-st and 99-th percentiles. The italicized codes in the brackets ([ ]) represent the item codes in Compustat North America.

Panel A. Variables used in regressions		
Abbreviation	Description	Formula
<i>LEV</i>	Market leverage	Total liabilities [ $lt$ ] / (Total liabilities [ $lt$ ] + Close price at the end of calendar year [ $prcc\_c$ ] $\times$ Number of common shares outstanding [ $csho$ ])
$\Delta LEV$	Change in market leverage	$LEV_t - LEV_{t-1}$
<i>LnTA</i>	Firm size	Natural logarithm of Total assets [ $at$ ]
<i>EBIT_TA</i>	Profitability	(Income before extraordinary items [ $ib$ ] + Total interest and related expenses [ $xint$ ] + Total income taxes [ $txt$ ]) / Total assets at the beginning of the year [ $at_{t-1}$ ]
<i>MV_BV</i>	Market-to-Book	(Total long-term debt [ $dltt$ ] + Total debt in current liabilities [ $dltc$ ] + Liquidation value of preferred stock [ $pstk$ ]) + Close price at the end of calendar year [ $prcc\_c$ ] $\times$ Number of common shares outstanding [ $csho$ ] / Total assets [ $at$ ]
<i>FA_TA</i>	Tangibility of assets	Total property, plant and equipment [ $ppent$ ] / Total assets [ $at$ ]
<i>RD_TA</i>	R&D intensity	R&D expenses [ $xrd$ ] / Total assets at the beginning of the year [ $at_{t-1}$ ]
<i>LIQ<sup>G</sup></i>	Liquidity based on <i>Gibbs</i>	(-1) $\times$ Standardized Hasbrouck's Gibbs spread or - <i>Gibbs</i>
<i>LIQ<sup>A</sup></i>	Liquidity based on <i>Amihud</i>	(-1) $\times$ Standardized Amihud's price impact or - <i>Amihud</i>
Panel B. Variables related to investment spikes		
Abbreviation	Description	Formula
<i>D_AQC</i>	Dummy variable for acquisitions	1 if a firm reports positive acquisitions [ $aqc$ ], and 0 otherwise.
<i>D_HLIQ<sup>G</sup></i>	High liquidity dummy based on Hasbrouck's (2009) Gibbs spread	1 if $LIQ_{j,\tau=-1}^G$ is greater than its sample median, and 0 otherwise.
<i>D_HLIQ<sup>A</sup></i>	High liquidity dummy based on Amihud's (2002) price impact	1 if $LIQ_{j,\tau=-1}^A$ is greater than its sample median, and 0 otherwise.
<i>SPIKESIZE</i>	Abnormal investment as a proportion of market assets at the beginning of the year with an investment spike	$(I_{\tau=0} - BASE) / (\text{Total liabilities at the beginning of the year } [lt_{\tau=-1}] + \text{Close price at the beginning of calendar year } [prcc\_c_{\tau=-1}] \times \text{Number of common shares outstanding } [csho_{\tau=-1}])$ ; <i>SPIKESIZE</i> and its interaction terms with <i>D_HLIQ<sup>G</sup></i> or <i>D_HLIQ<sup>A</sup></i> have a value of zero if the firm-year is not categorized as an investment spike.

Table 6.2: Summary statistics

Panel A reports summary statistics for the whole sample whereas Panel B reports summary statistics for the investment spikes sample. Section 6.3.2 describes how the investment spikes sample is constructed. The variables are defined as in Table 6.1. The summary statistics of *Gibbs* and *Amihud* before standardization are reported. The identifier  $i$  represents the firm code, whereas the identifier  $j$  represents the investment spike code. The time index  $t$  represents the fiscal year reported in Compustat, whereas the time index  $\tau$  represents the time in relation to an investment spike. For example,  $\tau = 0$  indicates the year categorized as an investment spike, whereas  $\tau = -1$  indicates the year before an investment spike. The subscripts  $(i, t)$  are used in the whole sample, whereas the subscripts  $(j, \tau)$  are used in the investment spikes sample.

Panel A. Summary statistics: Whole sample						
Variable	N	Mean	SD	Q1	Median	Q3
$\Delta LEV_{it}$	89936	0.014	0.148	-0.047	0.006	0.074
$LEV_{it}$	103093	0.359	0.259	0.137	0.313	0.541
$LnTA_{it}$	117471	4.558	2.630	2.842	4.551	6.306
$TA_{it}$	117870	1970	11865	17	94	545
$EBIT\_TA_{it}$	100807	-0.108	0.787	-0.063	0.068	0.143
$MV\_BV_{it}$	102400	2.669	5.367	0.840	1.282	2.308
$FA\_TA_{it}$	117210	0.281	0.238	0.090	0.210	0.414
$RD\_TA_{it}$	112278	0.071	0.171	0.000	0.000	0.062
$Gibbs_{it}$	66922	0.014	0.017	0.004	0.007	0.017
$Amihud_{it}$	66922	5.835	43.991	0.009	0.112	1.379

Panel B. Summary statistics: Investment spikes sample						
Variable	N	Mean	SD	Q1	Median	Q3
$\Delta LEV_{j,\tau=0}$	5872	0.073	0.150	-0.005	0.050	0.141
$LEV_{j,\tau=0}$	6123	0.354	0.242	0.147	0.319	0.527
$LEV_{j,\tau=-1}$	5905	0.285	0.227	0.094	0.232	0.429
$LnTA_{j,\tau=-1}$	6415	4.729	2.376	3.117	4.672	6.295
$TA_{j,\tau=-1}$	6424	1666	9114	22	107	541
$EBIT\_TA_{j,\tau=-1}$	5964	-0.078	0.844	0.008	0.101	0.175
$MV\_BV_{j,\tau=-1}$	5878	2.827	4.756	0.954	1.516	2.746
$FA\_TA_{j,\tau=-1}$	6406	0.249	0.217	0.076	0.184	0.360
$RD\_TA_{j,\tau=-1}$	6418	0.090	0.203	0.000	0.002	0.082
$Gibbs_{j,\tau=-1}$	4103	0.013	0.016	0.004	0.007	0.016
$Amihud_{j,\tau=-1}$	4103	4.563	46.450	0.009	0.093	0.851

Table 6.3: Correlation matrix for variables used in regression analysis

This table shows the correlation matrix between the major variables used in this study. Panel A is based on the whole sample, whereas Panel B is based on the investment spikes sample. Definitions of variables used in panels A and B are in Table 1 Panel A. Panel C shows the correlation coefficients between the two share liquidity measures and additional variables defined in Section 6.3.3 calculated in the investment spikes sample. The time index  $\tau$  represents the time in relation to an investment spike. Pearson correlation coefficients are reported. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

Panel A. Correlation matrix: Whole sample								
	$\Delta LEV_{it}$	$LEV_{i,t-1}$	$LnTA_{i,t-1}$	$EBIT\_TA_{i,t-1}$	$MV\_BV_{i,t-1}$	$FA\_TA_{i,t-1}$	$RD\_TA_{i,t-1}$	$LIQ_{i,t-1}^G$
$LEV_{i,t-1}$	-0.2652***							
$LnTA_{i,t-1}$	-0.0196***	0.1766***						
$EBIT\_TA_{i,t-1}$	-0.0436***	0.0743***	0.3754***					
$MV\_BV_{i,t-1}$	0.0742***	-0.2804***	-0.3963***	-0.5343***				
$FA\_TA_{i,t-1}$	-0.0211***	0.2177***	0.2318***	0.1092***	-0.1178***			
$RD\_TA_{i,t-1}$	0.0326***	-0.2946***	-0.2218***	-0.4572***	0.2965***	-0.2407***		
$LIQ_{i,t-1}^G$	0.0709***	-0.1899***	0.5298***	0.1432***	0.0724***	0.0079*	-0.0115***	
$LIQ_{i,t-1}^A$	0.0513***	-0.1092***	0.1623***	0.0297***	0.0422***	-0.0157***	0.0217***	0.5445***

Panel B. Correlation matrix: Investment spikes sample								
	$\Delta LEV_{j,\tau=0}$	$LEV_{j,\tau=-1}$	$LnTA_{j,\tau=-1}$	$EBIT\_TA_{j,\tau=-1}$	$MV\_BV_{j,\tau=-1}$	$FA\_TA_{j,\tau=-1}$	$RD\_TA_{j,\tau=-1}$	$LIQ_{j,\tau=-1}^G$
$LEV_{j,\tau=-1}$	-0.2279***							
$LnTA_{j,\tau=-1}$	0.0086	0.2212***						
$EBIT\_TA_{j,\tau=-1}$	0.0085	0.1181***	0.3264***					
$MV\_BV_{j,\tau=-1}$	-0.0083	-0.3371***	-0.3270***	-0.4858***				
$FA\_TA_{j,\tau=-1}$	0.0184	0.2669***	0.2547***	0.1347***	-0.1551***			
$RD\_TA_{j,\tau=-1}$	-0.0154	-0.3309***	-0.2372***	-0.5698***	0.3381***	-0.2675***		
$LIQ_{j,\tau=-1}^G$	0.0553***	-0.1563***	0.5201***	0.1075***	0.0726***	0.0294*	-0.0228	
$LIQ_{j,\tau=-1}^A$	0.0510***	-0.1009***	0.1292***	0.0237	0.0355**	-0.0401**	0.0131	0.5974***

Panel C. Correlation coefficients between share liquidity and additional variables		
	$MALTMANZ_{j,\tau=-1}$	$NUMMGRS_{j,\tau=-1}$
$LIQ_{j,\tau=-1}^G$	0.1204***	0.3680***
$LIQ_{j,\tau=-1}^A$	0.0496***	0.1080***

Table 6.4: Share liquidity and the incidence of investment spikes

This table shows OLS and probit regression results in which the dependent variable is a dummy variable  $D\_SPIKE_{it}$  equal to one if the firm-year is categorized as an investment spike, and zero otherwise. All explanatory variables are defined as in Table 6.1 Panel A. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	OLS		Probit	
	$D\_SPIKE_{it}$ (1)	$D\_SPIKE_{it}$ (2)	$D\_SPIKE_{it}$ (3)	$D\_SPIKE_{it}$ (4)
<i>INTERCEPT</i>	<b>0.161***</b> (0.030)	<b>0.158***</b> (0.030)	<b>-0.920***</b> (0.166)	<b>-0.940***</b> (0.166)
<i>LEV<sub>i,t-1</sub></i>	<b>-0.084***</b> (0.008)	<b>-0.088***</b> (0.008)	<b>-0.547***</b> (0.051)	<b>-0.575***</b> (0.050)
<i>LnTA<sub>i,t-1</sub></i>	<b>0.001</b> (0.001)	<b>0.001*</b> (0.001)	<b>0.004</b> (0.006)	<b>0.010**</b> (0.005)
<i>EBIT_TA<sub>i,t-1</sub></i>	<b>0.009</b> (0.006)	<b>0.009</b> (0.006)	<b>0.049</b> (0.032)	<b>0.051</b> (0.032)
<i>MV_BV<sub>i,t-1</sub></i>	<b>0.002*</b> (0.001)	<b>0.002*</b> (0.001)	<b>0.006</b> (0.004)	<b>0.006</b> (0.004)
<i>FA_TA<sub>i,t-1</sub></i>	<b>-0.060***</b> (0.009)	<b>-0.060***</b> (0.009)	<b>-0.371***</b> (0.058)	<b>-0.374***</b> (0.058)
<i>RD_TA<sub>i,t-1</sub></i>	<b>0.000</b> (0.016)	<b>0.001</b> (0.016)	<b>-0.010</b> (0.088)	<b>-0.006</b> (0.088)
<i>LIQ<sup>G</sup><sub>i,t-1</sub></i>	<b>0.002</b> (0.002)		<b>0.018</b> (0.014)	
<i>LIQ<sup>A</sup><sub>i,t-1</sub></i>		<b>-0.003</b> (0.002)		<b>-0.017</b> (0.012)
Observations	38,656	38,656	38,656	38,656
(Pseudo) R-squared	0.013	0.013	0.0214	0.0214

Table 6.5: Effects of share liquidity on the propensity to raise debt finance

This table reports the results of the regressions designed to investigate whether share liquidity increases abnormal borrowing during an investment spike. The dependent variable is the change in leverage during an investment spike ( $\Delta LEV_{j,\tau=0}$ ). The explanatory variables are defined as in Table 6.1 Panel A. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) is used as a measure of liquidity in columns (1)-(2), whereas the liquidity measure based on Amihud's (2002) price impact ( $LIQ_{j,\tau=-1}^A$ ) is used in columns (3)-(4). Odd-numbered columns present the regression results without investment spike characteristics, whereas even-numbered columns present the regression results with investment spike characteristics. One of the following interaction terms are used in columns (2) and (4), respectively:  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ . Table 6.1 Panel B describes how to construct  $D\_AQC_{j,\tau=0}$ ,  $SPIKESIZE_{j,\tau=0}$ ,  $D\_HLIQ_{j,\tau=-1}^G$ , and  $D\_HLIQ_{j,\tau=-1}^A$ . The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	Liquidity based on <i>Gibbs</i>		Liquidity based on <i>Amihud</i>	
	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)
<i>INTERCEPT</i>	<b>0.117***</b> (0.030)	<b>0.077***</b> (0.024)	<b>0.109***</b> (0.030)	<b>0.076***</b> (0.024)
$LEV_{j,\tau=-1}$	<b>-0.173***</b> (0.013)	<b>-0.184***</b> (0.012)	<b>-0.181***</b> (0.013)	<b>-0.187***</b> (0.013)
$LnTA_{j,\tau=-1}$	<b>-0.005***</b> (0.001)	<b>-0.005***</b> (0.001)	<b>-0.003**</b> (0.001)	<b>-0.004***</b> (0.001)
$EBIT\_TA_{j,\tau=-1}$	<b>-0.019***</b> (0.006)	<b>-0.016**</b> (0.006)	<b>-0.019***</b> (0.006)	<b>-0.015**</b> (0.006)
$MV\_BV_{j,\tau=-1}$	<b>-0.003***</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.003***</b> (0.001)	<b>-0.002**</b> (0.001)
$FA\_TA_{j,\tau=-1}$	<b>0.059***</b> (0.015)	<b>0.051***</b> (0.013)	<b>0.060***</b> (0.015)	<b>0.052***</b> (0.014)
$RD\_TA_{j,\tau=-1}$	<b>-0.059***</b> (0.022)	<b>-0.024</b> (0.021)	<b>-0.058***</b> (0.022)	<b>-0.024</b> (0.021)
$LIQ_{j,\tau=-1}^G$	<b>0.010***</b> (0.004)	<b>0.006</b> (0.004)		
$LIQ_{j,\tau=-1}^A$			<b>0.005</b> (0.003)	<b>0.003</b> (0.003)
$D\_AQC_{j,\tau=0}$		<b>0.023***</b> (0.005)		<b>0.024***</b> (0.005)
$SPIKESIZE_{j,\tau=0}$		<b>0.162***</b> (0.017)		<b>0.164***</b> (0.017)
$SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$		<b>0.080***</b> (0.022)		
$SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$				<b>0.085***</b> (0.023)
Observations	3,728	3,728	3,728	3,728
R-squared	0.174	0.281	0.173	0.281

Table 6.6: Controlling for other firm characteristics—Gibbs spread measure

This table reports the results of the regressions designed to investigate whether the effect of share liquidity on abnormal borrowing during an investment spike remains after controlling for firm characteristics. The same variables used in column (2) of Table 6.5 are used in each model. Additionally, the interaction terms between  $SPIKESIZE_{j,\tau=0}$  and the following dummy variables are used:  $D\_LARGE_{j,\tau=-1}$  (*large firms dummy*);  $D\_HLEV_{j,\tau=-1}$  (*high-leverage firms dummy*);  $D\_HPRF_{j,\tau=-1}$  (*high profitability dummy*);  $D\_HMB_{j,\tau=-1}$  (*high market-to-book dummy*);  $D\_HTAN_{j,\tau=-1}$  (*high assets tangibility dummy*); and  $D\_HRD_{j,\tau=-1}$  (*high R&D intensity dummy*). The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)	$\Delta LEV_{j,\tau=0}$ (6)	$\Delta LEV_{j,\tau=0}$ (7)
<i>INTERCEPT</i>	<b>0.075***</b> (0.025)	<b>0.065***</b> (0.024)	<b>0.074***</b> (0.024)	<b>0.071***</b> (0.024)	<b>0.075***</b> (0.024)	<b>0.076***</b> (0.024)	<b>0.063**</b> (0.025)
$LEV_{j,\tau=-1}$	<b>-0.183***</b> (0.012)	<b>-0.161***</b> (0.013)	<b>-0.177***</b> (0.013)	<b>-0.171***</b> (0.013)	<b>-0.184***</b> (0.012)	<b>-0.183***</b> (0.012)	<b>-0.152***</b> (0.013)
$LnTA_{j,\tau=-1}$	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.005***</b> (0.001)	<b>-0.005***</b> (0.001)	<b>-0.005***</b> (0.001)	<b>-0.005***</b> (0.001)	<b>-0.004***</b> (0.001)
$EBIT\_TA_{j,\tau=-1}$	<b>-0.016**</b> (0.006)	<b>-0.014**</b> (0.006)	<b>-0.020***</b> (0.006)	<b>-0.015**</b> (0.006)	<b>-0.015**</b> (0.006)	<b>-0.016**</b> (0.006)	<b>-0.019***</b> (0.006)
$MV\_BV_{j,\tau=-1}$	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002***</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)
$FA\_TA_{j,\tau=-1}$	<b>0.052***</b> (0.013)	<b>0.051***</b> (0.013)	<b>0.052***</b> (0.014)	<b>0.051***</b> (0.013)	<b>0.058***</b> (0.015)	<b>0.052***</b> (0.013)	<b>0.049***</b> (0.015)
$RD\_TA_{j,\tau=-1}$	<b>-0.023</b> (0.021)	<b>-0.016</b> (0.021)	<b>-0.028</b> (0.021)	<b>-0.019</b> (0.021)	<b>-0.023</b> (0.021)	<b>-0.026</b> (0.021)	<b>-0.024</b> (0.021)
$LIQ_{j,\tau=-1}^G$	<b>0.006</b> (0.004)	<b>0.006*</b> (0.004)	<b>0.006*</b> (0.004)	<b>0.006*</b> (0.004)	<b>0.006</b> (0.004)	<b>0.006</b> (0.004)	<b>0.006*</b> (0.004)
$D\_AQC_{j,\tau=0}$	<b>0.023***</b> (0.005)	<b>0.022***</b> (0.005)	<b>0.022***</b> (0.005)	<b>0.022***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.022***</b> (0.005)	<b>0.021***</b> (0.005)
$SPIKESIZE_{j,\tau=0}$	<b>0.168***</b> (0.019)	<b>0.224***</b> (0.030)	<b>0.128***</b> (0.017)	<b>0.144***</b> (0.016)	<b>0.175***</b> (0.022)	<b>0.148***</b> (0.017)	<b>0.132***</b> (0.034)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HLIQ_{j,\tau=-1}^G$	<b>0.101***</b> (0.027)	<b>0.074***</b> (0.023)	<b>0.051**</b> (0.024)	<b>0.061**</b> (0.025)	<b>0.080***</b> (0.022)	<b>0.081***</b> (0.022)	<b>0.044*</b> (0.027)
$SPIKESIZE_{j,\tau=0}$ $\times D\_LARGE_{j,\tau=-1}$	<b>-0.032</b> (0.028)						<b>-0.011</b> (0.024)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HLEV_{j,\tau=-1}$		<b>-0.092***</b> (0.029)					<b>-0.057***</b> (0.027)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HPRF_{j,\tau=-1}$			<b>0.090***</b> (0.025)				<b>0.088***</b> (0.022)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HMB_{j,\tau=-1}$				<b>0.085***</b> (0.033)			<b>0.057*</b> (0.030)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HTAN_{j,\tau=-1}$					<b>-0.021</b> (0.025)		<b>0.015</b> (0.024)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HRD_{j,\tau=-1}$						<b>0.049*</b> (0.028)	<b>0.055**</b> (0.023)
Observations	3,728	3,728	3,728	3,728	3,728	3,728	3,728
R-squared	0.282	0.287	0.288	0.286	0.282	0.283	0.297

Table 6.7: Controlling for other firm characteristics—Amihud price impact measure

This table reports the results of the regressions designed to investigate whether the effect of share liquidity on abnormal borrowing during an investment spike remains after controlling for firm characteristics. The same variables used in column (4) of Table 6.5 are used in each model. Additionally, the interaction terms between  $SPIKESIZE_{j,\tau=0}$  and the following dummy variables are used:  $D\_LARGE_{j,\tau=-1}$  (*large firms dummy*);  $D\_HLEV_{j,\tau=-1}$  (*high-leverage firms dummy*);  $D\_HPRF_{j,\tau=-1}$  (*high profitability dummy*);  $D\_HMB_{j,\tau=-1}$  (*high market-to-book dummy*);  $D\_HTAN_{j,\tau=-1}$  (*high assets tangibility dummy*); and  $D\_HRD_{j,\tau=-1}$  (*high R&D intensity dummy*). The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)	$\Delta LEV_{j,\tau=0}$ (5)	$\Delta LEV_{j,\tau=0}$ (6)	$\Delta LEV_{j,\tau=0}$ (7)
<i>INTERCEPT</i>	<b>0.075***</b> (0.024)	<b>0.064***</b> (0.024)	<b>0.073***</b> (0.024)	<b>0.069***</b> (0.024)	<b>0.075***</b> (0.024)	<b>0.076***</b> (0.024)	<b>0.061**</b> (0.024)
$LEV_{j,\tau=-1}$	<b>-0.186***</b> (0.013)	<b>-0.164***</b> (0.013)	<b>-0.181***</b> (0.012)	<b>-0.175***</b> (0.013)	<b>-0.187***</b> (0.013)	<b>-0.187***</b> (0.013)	<b>-0.156***</b> (0.013)
$LnTA_{j,\tau=-1}$	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>-0.003**</b> (0.001)
$EBIT\_TA_{j,\tau=-1}$	<b>-0.015**</b> (0.006)	<b>-0.013**</b> (0.006)	<b>-0.019***</b> (0.006)	<b>-0.015**</b> (0.006)	<b>-0.014**</b> (0.006)	<b>-0.015**</b> (0.006)	<b>-0.018***</b> (0.006)
$MV\_BV_{j,\tau=-1}$	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)
$FA\_TA_{j,\tau=-1}$	<b>0.053***</b> (0.014)	<b>0.053***</b> (0.014)	<b>0.053***</b> (0.014)	<b>0.052***</b> (0.013)	<b>0.058***</b> (0.015)	<b>0.053***</b> (0.014)	<b>0.049***</b> (0.015)
$RD\_TA_{j,\tau=-1}$	<b>-0.024</b> (0.021)	<b>-0.016</b> (0.021)	<b>-0.028</b> (0.021)	<b>-0.020</b> (0.021)	<b>-0.023</b> (0.021)	<b>-0.027</b> (0.021)	<b>-0.024</b> (0.021)
$LIQ^A_{j,\tau=-1}$	<b>0.004</b> (0.003)	<b>0.004</b> (0.003)	<b>0.003</b> (0.003)	<b>0.004</b> (0.003)	<b>0.004</b> (0.003)	<b>0.003</b> (0.003)	<b>0.003</b> (0.003)
$D\_AQC_{j,\tau=0}$	<b>0.024***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.021***</b> (0.005)
$SPIKESIZE_{j,\tau=0}$	<b>0.169***</b> (0.019)	<b>0.226***</b> (0.030)	<b>0.125***</b> (0.017)	<b>0.145***</b> (0.016)	<b>0.175***</b> (0.022)	<b>0.151***</b> (0.017)	<b>0.129***</b> (0.034)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HLIQ^A_{j,\tau=-1}$	<b>0.100***</b> (0.030)	<b>0.082***</b> (0.023)	<b>0.063**</b> (0.025)	<b>0.065**</b> (0.026)	<b>0.085***</b> (0.023)	<b>0.085***</b> (0.023)	<b>0.058**</b> (0.027)
$SPIKESIZE_{j,\tau=0}$ $\times D\_LARGE_{j,\tau=-1}$	<b>-0.022</b> (0.030)						<b>-0.013</b> (0.025)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HLEV_{j,\tau=-1}$		<b>-0.093***</b> (0.029)					<b>-0.059**</b> (0.027)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HPRF_{j,\tau=-1}$			<b>0.093***</b> (0.024)				<b>0.092***</b> (0.022)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HMB_{j,\tau=-1}$				<b>0.086**</b> (0.033)			<b>0.055*</b> (0.030)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HTAN_{j,\tau=-1}$					<b>-0.018</b> (0.026)		<b>0.018</b> (0.025)
$SPIKESIZE_{j,\tau=0}$ $\times D\_HRD_{j,\tau=-1}$						<b>0.045</b> (0.029)	<b>0.053**</b> (0.024)
Observations	3,728	3,728	3,728	3,728	3,728	3,728	3,728
R-squared	0.281	0.287	0.288	0.285	0.281	0.282	0.296

Table 6.8: Robustness tests—Various definitions of leverage

This table reports the results of the regressions designed to investigate whether the effect of liquidity on the propensity to raise debt finance is robust to the use of various leverage measures. The dependent variable is the change in alternative market leverage during an investment spike ( $\Delta MLEV_{j,\tau=0}$ ) in columns (1)-(2), whereas the dependent variable is the change in book leverage during an investment spike ( $\Delta BLEV_{j,\tau=0}$ ). See Section 6.3.3 for how to construct the alternative market leverage and book leverage. The explanatory variables are defined as in Table 6.1 Panel A. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) is used as a measure of liquidity in columns (1) and (3), whereas the liquidity measure based on Amihud's (2002) price impact ( $LIQ_{j,\tau=-1}^A$ ) is used in columns (2) and (4). One of the following interaction terms are used in columns (2) and (4), respectively:  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^G$  or  $SPIKESIZE_{j,\tau=0} \times D\_HLIQ_{j,\tau=-1}^A$ . Table 6.1 Panel B describes how to construct  $D\_AQC_{j,\tau=0}$ ,  $SPIKESIZE_{j,\tau=0}$ ,  $D\_HLIQ_{j,\tau=-1}^G$ , and  $D\_HLIQ_{j,\tau=-1}^A$ . The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	Alternative Market Leverage		Book Leverage	
	$\Delta MLEV_{j,\tau=0}$ (1)	$\Delta MLEV_{j,\tau=0}$ (2)	$\Delta BLEV_{j,\tau=0}$ (3)	$\Delta BLEV_{j,\tau=0}$ (4)
<i>INTERCEPT</i>	<b>0.032</b> (0.026)	<b>0.036</b> (0.026)	<b>0.036</b> (0.027)	<b>0.046*</b> (0.027)
<i>MLEV<sub>j,τ=-1</sub></i>	<b>-0.157***</b> (0.014)	<b>-0.156***</b> (0.014)		
<i>BLEV<sub>j,τ=-1</sub></i>			<b>-0.271***</b> (0.043)	<b>-0.268***</b> (0.042)
<i>LnTA<sub>j,τ=-1</sub></i>	<b>-0.004***</b> (0.001)	<b>-0.004***</b> (0.001)	<b>0.002</b> (0.002)	<b>0.001</b> (0.002)
<i>EBIT_TA<sub>j,τ=-1</sub></i>	<b>-0.005</b> (0.005)	<b>-0.005</b> (0.005)	<b>0.004</b> (0.007)	<b>0.004</b> (0.007)
<i>MV_BV<sub>j,τ=-1</sub></i>	<b>-0.002***</b> (0.001)	<b>-0.002***</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002***</b> (0.001)
<i>FA_TA<sub>j,τ=-1</sub></i>	<b>0.073***</b> (0.014)	<b>0.075***</b> (0.014)	<b>0.086***</b> (0.018)	<b>0.089***</b> (0.019)
<i>RD_TA<sub>j,τ=-1</sub></i>	<b>-0.027</b> (0.017)	<b>-0.028*</b> (0.017)	<b>-0.002</b> (0.022)	<b>-0.004</b> (0.022)
<i>LIQ<sub>j,τ=-1</sub><sup>G</sup></i>	<b>0.001</b> (0.004)		<b>-0.005</b> (0.005)	
<i>LIQ<sub>j,τ=-1</sub><sup>A</sup></i>		<b>0.003</b> (0.002)		<b>0.002</b> (0.002)
<i>D_AQC<sub>j,τ=0</sub></i>	<b>0.021***</b> (0.005)	<b>0.021***</b> (0.005)	<b>0.013***</b> (0.005)	<b>0.014***</b> (0.005)
<i>SPIKESIZE<sub>j,τ=0</sub></i>	<b>0.204***</b> (0.021)	<b>0.210***</b> (0.021)	<b>0.202***</b> (0.021)	<b>0.210***</b> (0.021)
<i>SPIKESIZE<sub>j,τ=0</sub> × D_HLIQ<sub>j,τ=-1</sub><sup>G</sup></i>	<b>0.098***</b> (0.025)		<b>0.100***</b> (0.026)	
<i>SPIKESIZE<sub>j,τ=0</sub> × D_HLIQ<sub>j,τ=-1</sub><sup>A</sup></i>		<b>0.088***</b> (0.026)		<b>0.082***</b> (0.027)
Observations	3,725	3,725	3,730	3,730
R-squared	0.308	0.306	0.312	0.310

Table 6.9: Robustness tests—Use of whole sample

The regressions are designed to investigate whether share liquidity has a positive effect on target leverage and abnormal borrowing during an investment spike in the whole sample. The dependent variables are the change in leverage ( $\Delta LEV_{it}$ ). All the models reported in columns (1)–(8) include a dummy for the year with investment spikes ( $D\_SPIKE_{it}$ ). The models reported in columns (3), (4), (7), and (8) include a spike size measure ( $SPIKESIZE_{it}$ ) and an interaction term between the spike size measure and a dummy variable for high-liquidity firms ( $(SPIKESIZE \times D\_HLIQ^G)_{it}$  or  $(SPIKESIZE \times D\_HLIQ^A)_{it}$ ) as well as a dummy variable for acquisitions ( $D\_AQC_{it}$ ). The industry dummies and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*\*) (\*) indicate significance at 1% (5%) (10%) (10%) two-tailed tests.

VARIABLES	Liquidity based on <i>Gibbs</i>				Liquidity based on <i>Amihud</i>			
	$\Delta LEV_{it}$ (1)	$\Delta LEV_{it}$ (2)	$\Delta LEV_{it}$ (3)	$\Delta LEV_{it}$ (4)	$\Delta LEV_{it}$ (5)	$\Delta LEV_{it}$ (6)	$\Delta LEV_{it}$ (7)	$\Delta LEV_{it}$ (8)
<i>INTERCEPT</i>	<b>0.123***</b> (0.010)	<b>-0.077***</b> (0.011)	<b>0.117***</b> (0.009)	<b>-0.091***</b> (0.011)	<b>0.117***</b> (0.010)	<b>-0.086***</b> (0.011)	<b>0.111***</b> (0.009)	<b>-0.099***</b> (0.011)
<i>LEV<sub>t,t-1</sub></i>	<b>-0.157***</b> (0.004)	<b>-0.446***</b> (0.008)	<b>-0.156***</b> (0.004)	<b>-0.440***</b> (0.008)	<b>-0.162***</b> (0.004)	<b>-0.459***</b> (0.008)	<b>-0.161***</b> (0.003)	<b>-0.452***</b> (0.008)
<i>LnTA<sub>t,t-1</sub></i>	<b>0.000</b> (0.000)	<b>0.036***</b> (0.002)	<b>-0.001</b> (0.000)	<b>0.037***</b> (0.002)	<b>0.002***</b> (0.000)	<b>0.039***</b> (0.002)	<b>0.001**</b> (0.000)	<b>0.040***</b> (0.002)
<i>EBIT_TA<sub>t,t-1</sub></i>	<b>-0.023***</b> (0.003)	<b>-0.019***</b> (0.003)	<b>-0.023***</b> (0.003)	<b>-0.018***</b> (0.003)	<b>-0.022***</b> (0.003)	<b>-0.018***</b> (0.003)	<b>-0.022***</b> (0.003)	<b>-0.017***</b> (0.003)
<i>MV_BV<sub>t,t-1</sub></i>	<b>-0.001***</b> (0.000)	<b>-0.000</b> (0.000)	<b>-0.001***</b> (0.000)	<b>-0.000</b> (0.000)	<b>-0.001***</b> (0.000)	<b>-0.000</b> (0.000)	<b>-0.001***</b> (0.000)	<b>-0.000</b> (0.000)
<i>FA_TA<sub>t,t-1</sub></i>	<b>0.008**</b> (0.004)	<b>0.062***</b> (0.011)	<b>0.010**</b> (0.004)	<b>0.060***</b> (0.011)	<b>0.008**</b> (0.004)	<b>0.063***</b> (0.011)	<b>0.010**</b> (0.004)	<b>0.061***</b> (0.011)
<i>RD_TA<sub>t,t-1</sub></i>	<b>-0.055***</b> (0.006)	<b>-0.037***</b> (0.009)	<b>-0.048***</b> (0.006)	<b>-0.033***</b> (0.009)	<b>-0.054***</b> (0.006)	<b>-0.034***</b> (0.009)	<b>-0.047***</b> (0.006)	<b>-0.031***</b> (0.009)
<i>LIQ<sup>G</sup><sub>t,t-1</sub></i>	<b>0.007***</b> (0.001)	<b>0.012***</b> (0.002)	<b>0.006***</b> (0.001)	<b>0.011***</b> (0.002)				
<i>LIQ<sup>A</sup><sub>t,t-1</sub></i>					<b>0.005***</b> (0.002)	<b>0.007***</b> (0.002)	<b>0.004**</b> (0.002)	<b>0.007***</b> (0.002)
<i>D_SPIKE<sub>it</sub></i>	<b>0.061***</b> (0.002)	<b>0.049***</b> (0.002)	<b>0.028***</b> (0.002)	<b>0.018***</b> (0.002)	<b>0.062***</b> (0.002)	<b>0.049***</b> (0.002)	<b>0.028***</b> (0.002)	<b>0.019***</b> (0.003)
<i>D_AQC<sub>it</sub></i>			<b>0.013***</b> (0.001)	<b>0.009***</b> (0.002)			<b>0.013***</b> (0.001)	<b>0.008***</b> (0.002)
<i>SPIKESIZE<sub>it</sub></i>			<b>0.174***</b> (0.017)	<b>0.163***</b> (0.017)			<b>0.178***</b> (0.017)	<b>0.169***</b> (0.017)
$(SPIKESIZE \times D\_HLIQ^G)_{it}$			<b>0.079***</b> (0.021)	<b>0.089***</b> (0.021)				
$(SPIKESIZE \times D\_HLIQ^A)_{it}$							<b>0.078***</b> (0.022)	<b>0.081***</b> (0.023)
Number of firms	5,976	5,976	5,953	5,953	5,976	5,976	5,953	5,953
Firm fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	38,598	38,598	38,351	38,351	38,598	38,598	38,351	38,351
R-squared	0.186	0.331	0.202	0.343	0.185	0.330	0.201	0.342

Table 6.10: Testing the information spillover mechanism

This table reports the results of the regressions designed to investigate through the information spillover mechanism whether share liquidity increases abnormal borrowing during an investment spike. The dependent variable is the change in leverage during an investment spike ( $\Delta LEV_{j,\tau=0}$ ). The explanatory variables are defined as in Table 6.1 Panel A and Panel B. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) is used as a measure of liquidity in columns (1)-(2), whereas the liquidity measure based on Amihud's (2002) price impact ( $LIQ_{j,\tau=-1}^A$ ) is used in columns (3)-(4). Odd-numbered columns present the regression results without  $NUMMGRS_{j,\tau=-1}$  (Number of institutional managers) and  $SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$  (Interaction between abnormal investment and the dummy for high number of institutional managers) in the subsample in which those variables are observed. Section 6.3.3 describes how to construct  $NUMMGRS_{j,\tau=-1}$  and  $D\_HNMGRS_{j,\tau=-1}$ . On the contrary, even-numbered columns present the regression results with those variables included in the right-hand side of the equation. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	Liquidity based on <i>Gibbs</i>		Liquidity based on <i>Amihud</i>	
	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)
<i>INTERCEPT</i>	<b>0.038</b> (0.026)	<b>0.043</b> (0.027)	<b>0.040</b> (0.026)	<b>0.042</b> (0.026)
$LEV_{j,\tau=-1}$	<b>-0.159***</b> (0.013)	<b>-0.155***</b> (0.014)	<b>-0.153***</b> (0.013)	<b>-0.152***</b> (0.014)
$LnTA_{j,\tau=-1}$	<b>-0.005***</b> (0.002)	<b>-0.007***</b> (0.003)	<b>-0.005***</b> (0.001)	<b>-0.006**</b> (0.003)
$EBIT\_TA_{j,\tau=-1}$	<b>-0.018*</b> (0.010)	<b>-0.018*</b> (0.010)	<b>-0.016*</b> (0.009)	<b>-0.016*</b> (0.009)
$MV\_BV_{j,\tau=-1}$	<b>-0.003***</b> (0.001)	<b>-0.003***</b> (0.001)	<b>-0.003***</b> (0.001)	<b>-0.003***</b> (0.001)
$FA\_TA_{j,\tau=-1}$	<b>0.045***</b> (0.015)	<b>0.046***</b> (0.015)	<b>0.044***</b> (0.014)	<b>0.045***</b> (0.014)
$RD\_TA_{j,\tau=-1}$	<b>-0.017</b> (0.022)	<b>-0.017</b> (0.022)	<b>-0.017</b> (0.022)	<b>-0.017</b> (0.022)
$LIQ_{j,\tau=-1}^G$	<b>0.014**</b> (0.006)	<b>0.015***</b> (0.006)		
$LIQ_{j,\tau=-1}^A$			<b>0.041***</b> (0.009)	<b>0.042***</b> (0.009)
$D\_AQC_{j,\tau=0}$	<b>0.023***</b> (0.005)	<b>0.023***</b> (0.005)	<b>0.024***</b> (0.005)	<b>0.024***</b> (0.005)
$SPIKESIZE_{j,\tau=0}$	<b>0.179***</b> (0.023)	<b>0.178***</b> (0.023)	<b>0.181***</b> (0.022)	<b>0.179***</b> (0.022)
$SPIKESIZE_{j,\tau=0} \times D\_H LIQ_{j,\tau=-1}^G$	<b>0.063**</b> (0.027)	<b>0.040</b> (0.033)		
$SPIKESIZE_{j,\tau=0} \times D\_H LIQ_{j,\tau=-1}^A$			<b>0.071***</b> (0.026)	<b>0.041</b> (0.038)
$NUMMGRS_{j,\tau=-1}$		<b>0.000</b> (0.000)		<b>0.000</b> (0.000)
$SPIKESIZE_{j,\tau=0} \times D\_HNMGRS_{j,\tau=-1}$		<b>0.038</b> (0.031)		<b>0.039</b> (0.039)
Observations	2,891	2,891	2,891	2,891
R-squared	0.303	0.304	0.307	0.307

Table 6.11: Testing the credit ratings mechanism

This table reports the results of the regressions designed to investigate through the credit ratings mechanism whether share liquidity increases abnormal borrowing during an investment spike. The dependent variable is the change in leverage during an investment spike ( $\Delta LEV_{j,\tau=0}$ ). The explanatory variables are defined as in Table 6.1 Panel A and Panel B. The liquidity measure based on Hasbrouck's (2009) Gibbs spread ( $LIQ_{j,\tau=-1}^G$ ) is used as a measure of liquidity in columns (1)-(2), whereas the liquidity measure based on Amihud's (2002) price impact ( $LIQ_{j,\tau=-1}^A$ ) is used in columns (3)-(4). Odd-numbered columns present the regression results without  $MALTMANZ_{j,\tau=-1}$  (Modified Altman's Z-score) and  $SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$  (Interaction between abnormal investment and the dummy for high  $MALTMANZ_{j,\tau=-1}$ ) in the subsample in which those variables are observed. Section 6.3.3 describes how to construct  $MALTMANZ_{j,\tau=-1}$  and  $D\_HMALTZ_{j,\tau=-1}$ . Even-numbered columns present the regression results with those variables included in the right-hand side of the equation. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	Liquidity based on <i>Gibbs</i>		Liquidity based on <i>Amihud</i>	
	$\Delta LEV_{j,\tau=0}$ (1)	$\Delta LEV_{j,\tau=0}$ (2)	$\Delta LEV_{j,\tau=0}$ (3)	$\Delta LEV_{j,\tau=0}$ (4)
<i>INTERCEPT</i>	<b>-0.077***</b> (0.023)	<b>-0.073***</b> (0.023)	<b>-0.082***</b> (0.023)	<b>-0.077***</b> (0.023)
$LEV_{j,\tau=-1}$	<b>-0.197***</b> (0.022)	<b>-0.196***</b> (0.022)	<b>-0.207***</b> (0.022)	<b>-0.205***</b> (0.022)
$LnTA_{j,\tau=-1}$	<b>-0.005**</b> (0.002)	<b>-0.005**</b> (0.002)	<b>-0.003</b> (0.002)	<b>-0.003</b> (0.002)
$EBIT\_TA_{j,\tau=-1}$	<b>-0.012</b> (0.007)	<b>-0.015**</b> (0.007)	<b>-0.010</b> (0.007)	<b>-0.014*</b> (0.007)
$MV\_BV_{j,\tau=-1}$	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002**</b> (0.001)	<b>-0.002*</b> (0.001)
$FA\_TA_{j,\tau=-1}$	<b>0.054**</b> (0.025)	<b>0.057**</b> (0.025)	<b>0.053**</b> (0.025)	<b>0.057**</b> (0.025)
$RD\_TA_{j,\tau=-1}$	<b>-0.011</b> (0.025)	<b>-0.015</b> (0.025)	<b>-0.012</b> (0.025)	<b>-0.017</b> (0.025)
$LIQ_{j,\tau=-1}^G$	<b>0.008*</b> (0.004)	<b>0.008*</b> (0.004)		
$LIQ_{j,\tau=-1}^A$			<b>0.003</b> (0.003)	<b>0.003</b> (0.003)
$D\_AQC_{j,\tau=0}$	<b>0.022***</b> (0.007)	<b>0.021***</b> (0.007)	<b>0.023***</b> (0.007)	<b>0.022***</b> (0.007)
$SPIKESIZE_{j,\tau=0}$	<b>0.158***</b> (0.029)	<b>0.119***</b> (0.028)	<b>0.164***</b> (0.029)	<b>0.119***</b> (0.027)
$SPIKESIZE_{j,\tau=0} \times D\_H LIQ_{j,\tau=-1}^G$	<b>0.114***</b> (0.037)	<b>0.083*</b> (0.044)		
$SPIKESIZE_{j,\tau=0} \times D\_H LIQ_{j,\tau=-1}^A$			<b>0.110**</b> (0.046)	<b>0.082</b> (0.051)
$MALTMANZ_{j,\tau=-1}$		<b>0.001*</b> (0.000)		<b>0.001*</b> (0.000)
$SPIKESIZE_{j,\tau=0} \times D\_HMALTZ_{j,\tau=-1}$		<b>0.095*</b> (0.049)		<b>0.104**</b> (0.049)
Observations	1,707	1,707	1,707	1,707
R-squared	0.292	0.299	0.289	0.296

Table 6.12: Inconsistent liquidity effects in static and dynamic leverage models

This table reports the results for various regressions based on the whole sample. The dependent variables in all regressions are the levels of leverage ( $LEV_{it}$ ). (Note that the dynamic leverage models are equivalent to the leverage change models with lagged leverage in the right-hand side of the equation.) The liquidity measure based on Hasbrouck's (2009) Gibbs spread is used as a measure of liquidity in columns (1)-(4) whereas the liquidity measure based on Amihud's (2002) price impact is used in columns (5)-(8). Odd-numbered columns present the OLS estimation results whereas even-numbered columns present the FE regression results. The industry dummies as defined by Fama and French (1997) and year dummies are included in each regression. The robust standard errors are reported in parentheses. The star signs such as \*\*\* (\*\*\*) (\*) indicate significance at 1% (5%) (10%) two-tailed tests.

VARIABLES	Liquidity based on <i>Gibbs</i>							
	Static Model				Dynamic Model			
	$LEV_{it}$ (1)	$LEV_{it}$ (2)	$LEV_{it}$ (3)	$LEV_{it}$ (4)	$LEV_{it}$ (5)	$LEV_{it}$ (6)	$LEV_{it}$ (7)	$LEV_{it}$ (8)
<i>INTERCEPT</i>	<b>0.316***</b> (0.017)	<b>0.100***</b> (0.013)	<b>0.066***</b> (0.009)	<b>0.010</b> (0.008)	<b>0.389***</b> (0.017)	<b>0.138***</b> (0.013)	<b>0.060***</b> (0.009)	<b>0.000</b> (0.008)
$LEV_{i,t-1}$			<b>0.855***</b> (0.003)	<b>0.594***</b> (0.007)			<b>0.849***</b> (0.003)	<b>0.582***</b> (0.006)
$LnTA_{i,t-1}$	<b>0.027***</b> (0.001)	<b>0.052***</b> (0.003)	<b>-0.001***</b> (0.000)	<b>0.030***</b> (0.002)	<b>0.015***</b> (0.001)	<b>0.045***</b> (0.003)	<b>0.000</b> (0.000)	<b>0.032***</b> (0.001)
$EBIT\_TA_{i,t-1}$	<b>-0.124***</b> (0.005)	<b>-0.066***</b> (0.005)	<b>-0.029***</b> (0.002)	<b>-0.024***</b> (0.003)	<b>-0.137***</b> (0.005)	<b>-0.071***</b> (0.005)	<b>-0.028***</b> (0.002)	<b>-0.023***</b> (0.003)
$MV\_BV_{i,t-1}$	<b>-0.028***</b> (0.001)	<b>-0.012***</b> (0.001)	<b>-0.000</b> (0.000)	<b>-0.000</b> (0.000)	<b>-0.030***</b> (0.001)	<b>-0.013***</b> (0.001)	<b>-0.000</b> (0.000)	<b>-0.000</b> (0.000)
$FA\_TA_{i,t-1}$	<b>0.097***</b> (0.006)	<b>0.186***</b> (0.015)	<b>0.004</b> (0.003)	<b>0.063***</b> (0.010)	<b>0.103***</b> (0.006)	<b>0.192***</b> (0.015)	<b>0.004</b> (0.003)	<b>0.064***</b> (0.010)
$RD\_TA_{i,t-1}$	<b>-0.282***</b> (0.011)	<b>-0.112***</b> (0.013)	<b>-0.062***</b> (0.006)	<b>-0.041***</b> (0.008)	<b>-0.310***</b> (0.012)	<b>-0.124***</b> (0.013)	<b>-0.061***</b> (0.006)	<b>-0.039***</b> (0.008)
$LIQ_{i,t-1}^G$	<b>-0.056***</b> (0.002)	<b>-0.032***</b> (0.002)	<b>0.006***</b> (0.001)	<b>0.011***</b> (0.001)				
$LIQ_{i,t-1}^A$					<b>-0.026***</b> (0.005)	<b>-0.011***</b> (0.003)	<b>0.004***</b> (0.001)	<b>0.005***</b> (0.002)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,060	53,060	53,059	53,059	53,060	53,060	53,059	53,059
R-squared	0.355	0.165	0.758	0.408	0.330	0.153	0.758	0.407
Number of firms	6,809	6,809	6,809	6,809	6,809	6,809	6,809	6,809

## **Part IV**

# **CONCLUDING REMARKS**

# Chapter 7

## Conclusions and Extensions

In this thesis, I have focused on the subject of investment spikes and the financing behaviour of firms. It has been well established that by far and away the dominant source of finance of firms across different countries and time periods is retained earnings. However, the empirical results reflect how firms finance their routine, replace investment rather than their occasional major expansion investment. By analysing the firm-level flow of funds data around investment spikes, Mayer and Sussman (2005) have found that the financing of investment during spike periods is very different from the financing of investment at other times. For most firms, debt has been found to be much more important than equity and internally generated funds for meeting large investment requirements. In particular, the way in which firms meet exceptional financing needs in relation to unusually large investment requirements is the subject of an emerging body of literature, including DeAngelo *et al.* (2011). This thesis makes substantial contributions to this literature. In this chapter, I summarise its major contributions and outline

promising directions for future research.

## 7.1 Lumpy investment and financing patterns (Part II)

Mayer and Sussman (2005) proposed a filter to identify investment spikes and investigated the flow of funds around investment spikes in an attempt to precisely answer how investment is financed. They also argue that investment spikes are more informative about corporate financing behaviours for the following reasons. First of all, investment spikes are interesting in their own right since a large proportion of investment is executed in lumps. Second, most corporate finance theory is developed for large and indivisible projects and should be tested on corresponding data. Finally, if firms switch investment regimes and the financing patterns are different across different regimes, then the power of the relevant tests can be enhanced by preventing firms in repayment regimes from contaminating inferences about firms in investment regimes. In this case, pooling the data from two regimes will dilute the sample and obscure results rather than increase the efficiency of the estimation. Bond *et al.* (2006) also have also proposed a new filter based on a linear regression.

However, one potential problem with the existing two filters is that they are designed to capture only one type of lumpy investment pattern, namely (0,0,1,0,0), and therefore they can identify only subsets of large investment years by their construction. In Chapter 3, I have proposed the use of the Markov-switching filter in order to identify any conceivable patterns of lumpy investment including two-year and three-year investment spikes. Using

the extended Regression filter and the Markov-switching filter, I have found strong evidence for the presence of multi-year investment spikes. Although the Markov-switching filter has more desirable statistical properties, it is reassuring that all three filters match quite closely based on the  $2 \times 2$  table analysis. Unlike the Markov-switching filter, the Regression filter can be applied to a larger sample because it requires only a five-year period of investment data. Therefore, the Regression filter is used to identify investment spikes in Chapter 4. A filtering technique with a properly reliable filter has wide applicability across various economics and management disciplines, as long as the objects of interest have lumpy dynamic patterns. It is my expectation that the results of some previous studies, which ignored the lumpiness of investment, are at risk of being reversed by using a filtering technique.

In Chapter 4, I have found that the financing of investment during an investment spike is very different from that at other times, using more recent data and a filtering procedure suggested by Bond *et al.* (2006). Specifically, external financing, in particular debt finance, is very important in financing the firm-years categorized as investment spikes, confirming the finding of Mayer and Sussman (2005). It has also been found that two-year investment spikes identified by the Markov-switching filter are financed in quite similar ways to single-year investment spikes. Again, external finance becomes very important at the time of investment spikes and debt finance is much more important than equity finance in funding two-year investment spikes. In addition, it has been found that firms with a smaller size, lower profitability, more future growth opportunities, fewer tangible assets and more R&D spending tend to use more equity finance when confronted with large investment requirements. However, it seems

that the financing of investment spikes is quite homogeneous across industries. Furthermore, I have also found that investment spikes involving acquisitions tend to be funded by a higher proportion of debt finance.

One striking finding is that the financing patterns of large firms are consistent with the pecking-order theory (Myers and Majluf, 1984), whereas the financing patterns of small firms are consistent with the reverse pecking order which can be predicted with endogenous information production (Fulghieri and Lukin, 2001). Large firms tend to use only debt finance when they are confronted with relatively small investment spikes, but they tend to use more equity finance when they are confronted with relatively large investment spikes. On the other hand, small firms tend to use more equity finance when they are confronted with relatively small investment spikes, but more debt finance when they are confronted with relatively large investment spikes. Another important finding is that the financing of investment spikes is more consistent with the predictions of a dynamic trade-off theory augmented with investment spikes as suggested by DeAngelo *et al.* (2011) rather than a classical counterpart. Unlike our expectation that firms with higher initial leverage will use lots of equity in financing investment spikes, large firms tend to use more debt finance than equity finance in funding large investment projects, regardless of the level of initial leverage. Furthermore, small firms with lower initial leverage tend to use more equity finance but small firms with higher initial leverage tend to use more debt finance in order to finance investment spikes, which is opposite to the prediction of the classical trade-off theory.

## **7.2 Share liquidity and financing patterns (Part III)**

An investigation of the literature regarding the effect of share liquidity on the factors involved in the propensity to raise debt finance has revealed that the views are divided into two groups. The majority predict a positive effect of share liquidity on the propensity to raise debt finance, a view based on credit ratings, information spillover, shareholder rights, activist exit, and debt trade-off. Yet some of them predict a negative effect of share liquidity on the propensity to raise debt finance, a view based on liquidity premium, information-production cost, and shareholder activism. However, no comprehensive empirical studies have been done to investigate this topic. I have investigated whether share liquidity has a positive effect on the propensity to raise debt finance, and through which channels share liquidity increases the propensity to raise debt finance.

In Chapter 5, I have found that low-liquidity firms tend to raise substantial amounts of new equity finance during investment spikes, whereas high-liquidity firms tend not to rely on new equity issuances. These findings are based on the approach employed in Chapter 4. Even in the periods before and after investment spikes, low-liquidity firms tend to issue some new equity but high-liquidity firms tend to buy back existing shares. In Chapter 6, I have found that share liquidity has a positive effect on abnormal borrowing when faced with an investment spike. Those results are robust to a control for the effects of various firm characteristics, the use of various leverage measures, and the use of a whole sample combined with investment spike characteristics. Chapter 5 shows that small firms tend to have less liquid shares, whereas large firms tend to have more liquid shares. However, it has been found that

there is little information in firm size controlling for share liquidity, suggesting that financing patterns previously attributed to firm size may in fact reflect differences in share liquidity. In addition, I have found that firms with more liquid shares also tend to have higher target leverage ratios. One interpretation of these patterns is that information spillovers from the presence of more informative share prices allow firms with more liquid shares to borrow on more favourable terms in normal times, as well as to obtain additional debt finance at lower costs when confronted with unusually large investment opportunities.

A puzzle regarding the inconsistent effects of share liquidity in static and dynamic leverage models is identified and resolved in Chapter 6. The puzzle is that there is a negative relation between share liquidity and the level of leverage in static leverage regressions, while there is a positive relation between share liquidity and leverage in dynamic leverage regressions. I argue that this puzzling situation could arise if lagged leverage decreases share liquidity and share liquidity has a positive effect on the change in leverage. Therefore, the negative relation between share liquidity and leverage in static regressions could be driven by the causality running from lagged leverage, which is highly correlated with contemporary leverage, to share liquidity. Using the OVB formula, I show that both relations can hold at the same time. These arguments are consistent with a theory predicting that lagged leverage has a negative effect on share liquidity and the main empirical finding that share liquidity has a positive effect on the propensity to raise debt finance as measured by the change in leverage.

## 7.3 Future research

There are many interesting ways in which this line of research could be extended. First, the relationship between investment expenditure and deviations from normal or target leverage ratios could also be analysed more generally, exploring whether similar patterns are found for a broader sub-sample of observations, beyond the relatively rare events that are currently classified as an investment spikes.

Second, it has been observed that small firms issue substantial amounts of equity at the time of an investment and at other times quite frequently. However, it has not been systematically studied whether they issue shares because it is optimal to issue shares or because debt finance is not available to them at the time of an investment spike. In relation to this issue, it is worth investigating whether privately placed equity rather than publicly placed equity is largely used at the time of an investment spike. A large use of private equity at the time of an investment spike may mean a change of ownership through the interventions of activists. Although this project is also at an early stage, this line of investigation will uncover answers to issues that have not been understood by previous research in empirical corporate finance.

Third, one aspect of my results which I have not fully explored is heterogeneity in the type of investment spikes. My current results suggest that debt finance is more important when the spike is associated with an acquisition, rather than capital expenditures. This could be studied further, allowing for heterogeneity within the set of acquisitions (e.g. within sector or across sectors; within the US or international).

Finally, it is worth investigating whether the liquidity of shares has an impact on the target adjustment behaviours of leverage, i.e. whether share liquidity affects the speed of leverage adjustment. Although this project is at an early stage, I have observed that there are conflicting theoretical predictions regarding the effect of share liquidity on the speed of leverage adjustment. A pilot study shows that firms with liquid shares tend to have a lower speed of adjustment, which seems to be consistent with the liquidity-augmented trade-off theory of debt. The empirical model used to estimate the speed of adjustment is a reduced-form partial adjustment model (i.e. a dynamic panel data model) and this research will reveal important issues regarding the estimation of the speed of leverage adjustment (see Section 2.4).

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