VERY PRELIMINARY

Projects are Largely External and Mostly Debt Financed: A New Approach to Testing Capital Structure

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1 Introduction

How do firms finance investment?

There are two approaches that the literature takes to answering this question. The first is to look at aggregate statistics and the second to analyse panels of firms. The studies based on aggregate data suggest that the answer is almost exclusively from own internally generated funds. To the extent that they resort to external sources, firms do so primarily from banks, rarely from bond markets (except in North America) and even more rarely from equity markets. These observations are consistent with pecking order theories of finance, which rank internal sources of finance ahead of debt finance, which in turn is ahead of new equity sources.

The panel data studies address a different set of issues. They are primarily concerned with the relation between capital structure and the characteristics of firms and industries. They point to the importance of industry in so far as capital structure displays greater similarity within than across industries. This is consistent with the view that optimal capital structures are determined by firms' underlying characteristics (such as the volatility of their income streams, the ratio of their intangible to tangible assets and their tax positions). These display greater uniformity within than across industries.

Both sets of studies suffer from significant problems. Firstly, most financing activity is associated with routine replacement rather than expansion of the capital stock. The fact that internal funds are the normal source of finance does not mean that they are the main source of non-routine investment, any more than the fact that IQs of around 100 are normal does not mean that IQs of 100 are the most significant.

As a consequence, both sets of empirical studies provide weak evidence on the way in which investment is funded and weak tests of underlying theories of capital structures. As Harris and Raviv (1990) note, existing empirical studies "have identified a large number of *potential* determinants of capital structure. The empirical work so far has not, however, sorted out which of these are important in various contexts…..The empirical work is largely consistent with the theory, although there are a few instances where the evidence seems to contradict certain models. These inconsistencies cannot, however, be regarded as conclusive, because the empirical studies were not designed specifically to test the models and were, therefore not careful about satisfying the *ceteris paribus* conditions…….With regard to further empirical work, it seems essential that empirical studies concentrate on testing particular models or classes of models in an attempt to discover the most important determinants of capital structure in given environments." (Harris and Raviv (1990), p. 3).

We take up Harris and Raviv's challenge by following a different procedure from previous studies. Firstly, we use disaggregate rather than aggregate data. In fact, we operate at the level of projects or collections of projects.

Secondly, we look at what happens out of rather than in steady state. We are interested in the financing of unusually large projects - shocks rather than routine investment. This approach is informative about new investment activities in a way in which neither the aggregate nor panel data studies can be.

Specifically, we construct a filter for identifying firms that display "investment peaks" – distinct sharp one-off increases in investment. We look at the financing of firms around and during the peaks. We then examine whether there is a relation between financing patterns before, after and during the peak and the characteristics of firms.

This methodology allows a variety of questions that are central to corporate finance to be addressed. Do firms finance spikes in investment from retentions, debt or new equity? Does debt finance precede new equity? Do firms accumulate cash balances prior to large investment expenditures? Do large firms use more or less bank finance than small firms? Are small firms excluded from new equity sources?

As we will describe in the following sections, these questions bear directly on existing theories about corporate finance. For example, the pecking order hypothesis has clear implications for the order in which finance should raised. The information theories bear directly on differences in financing of large and small firms.

Some quite striking results emerge. First, while in steady state, firms may raise little external financing, in response to investment shocks they raise a large amount. Large investment expenditures are not financed out of accumulated reserves.

Second, debt is the dominant source of external finance. This is consistent with aggregate financing results but this is predominantly a large company result. Surprisingly, small listed companies rely heavily on new equity sources.

Examining the sequencing of financing reveals several other striking results. The use of debt finance comes after new equity issues. Companies do not appear to exhaust debt finance before they go to stock markets. On the contrary, they use debt after accessing equity markets. Furthermore, the fact that large companies finance large projects out of debt and small companies out of new equity means that the life cycle development of firm financing is from stock markets to debt not vice versa.

Examining the relation of financing patterns to firm characteristics, we find that existing capital structure is a poor predictor of forms of financing. There is therefore little consistency in financing patterns over time.

These observations have important implications for theories and conventional views of corporate finance. First, they provide little support for pecking order theories. Firms do not work up the pecking order from debt to new equity. While debt is an important source of external finance, it does not precede new equity finance either sequentially in the financing of particular projects or over the life cycle of firms. Debt rather than new equity meet the large financing requirements of large firms.

Second, they do not support capital structure models based on firm characteristics. For example, according to tax or information theories, firms' choice of finance should be influenced by largely invariant characteristics of the firm. We find that there is no stability in firms' financing patterns.

Third, life cycle and information theories that suggest that firms graduate from debt to new equity are exactly contrary to what is observed. Firms initially finance large investments from new equity and then turn to debt markets.

What can explain these results? We will argue that they point to the importance of collateral in allowing firms to access debt markets. Debt finance does not precede equity because firms require collateral before they can raise debt and the reliance of small firms on equity finance reflects the fact that they have insufficient collateral with which to secure adequate debt finance. New equity finance is therefore comparatively expensive but only for firms that have the collateral with which to raise debt finance

In section 2 we set out four hypotheses on firms' financing pattern based on theories of corporate finance and past empirical studies. In section 3, we describe the data and methodology that we have employed. In section 4, we describe forms of financing of large projects and in section 5, we perform cross-section regressions of financing ratios on characteristics of firms. In section 6, we evaluate the results in light of the predictions of the four hypotheses.

2 Hypotheses

Much existing work on corporate financing is based on aggregate sources and uses of funds data. Table 1 records the type of results that others have reported. It shows that Our starting point is the recognition that aggregating flow-of-fund accounts across time and companies, like in Table 1, so as to track down investment funding is misleading. The numerical example in Table 2 explains why. Both company A and company B invest in a 'lumpy' project an amount of 150. Firm A is borrowing constrained. Hence, it retains earning for two years and then finance internally. Firm B borrows and then repays out of its earning. Aggregating across time, however, makes the two firms observationally equivalent. Now consider a third firm, whose investment is not lumpy at all, so it can spread the same amount of investment along three years. That firm may prefer to finance internally, not because it is borrowing constrained, but simply because external finance is slightly more costly than internal finance. In short, Table 1 ignores two important effects:

- Aggregating over time, positive and negative flows cancel out, which is where the hart of the matter is.
- Investment funding ratios are may be highly non-linear in the relative scale of investment. Aggregating small and large 'projects' average out the interesting effect.

To overcome these problems, we program our filter to detect investment spikes and line them up along 'project-time' zero. We can then test our first hypothesis:

H1: *Project finance is largely internal.*

As we shall see below. H1 is rejected up-front. We can then address the question in of how projects are financed, and particularly how the patterns of finance change across different types of firms. We are especially interested in the hypothesis, which is commonly associated with Diamond (), according to which small firms tend to rely on debt finance and move, as they grow, towards equity finance. Namely, *H2*: *As firm size increases, project-finance moves from debt to equity.*

The special structure of our sample allows us to construct more precise tests of some of the capital-structure theories that have been suggested. Maybe the most famous of these is the pecking-order theory. Within our sample it has the following implication. If a company has issued equity shortly before the spike, it must have signalled its low type. Actually, that company must have exhausted its debt capacity and has no choice but to keep on issuing equity. We write down a borrowing equation () by

(1) $\mathrm{DEBT}_0 = (a + b{\cdot}x)\mathrm{I}_0 + g{\cdot}\mathrm{OPR}_0,$

where DEBT is the flow of borrowing, I is investment and OPR is earning from operation. The subscript refers to project time τ=-2,...2, where 0 is the time where investment takes place. Then,

H3: *According to the pecking-order theory,*

$$a=0, \qquad b=1, \qquad x = \begin{cases} 0 & if \quad EQUITY_{-1} > 0 \\ 1 & otherwise \end{cases} .$$

Another idea that got much attention in the literature is the trade-of theory. In that case, x is a vector of characteristics that is supposed to be correlated with the underlying agency problems. For example: *R&D* is related to asset tangibility and thus to the value of liquidated assets; industry affiliation is related to the opportunities for over-investment (mature industries have less such opportunities), *etc.*[1]. The main weakness of this approach is that x is typically a very dirty proxy for the 'real thing' the theory is accounting for. Our data provides a way by which we can get around the 'dirty proxy' problem, because static leverage at t-2 is a sufficient statistic for all those factors taken together. Hence,

H4: *According to the trade-off theory, x is past* (*namely* t=-2) *static leverage and* a=g=0, and b=1.

Since we reject both H3 and H4, it is worth while stating an hypothesis which is not rejected.

H5: *Projects are largel debt financed, while losses are largely equity financed.*

The importance of H5 is that it helps to reconcile our findings with earlier ones. One of the main observations made by supporters of the pecking-order theory is that announcements about new debt tend to have a positive price effect, while announcements about new equity tend to have a negative price effect. H5 is consistent with observation. Also, one of the important observations by supporters of the trade-off theory is the great deal similarity in capital structure that exists within industries. H5 would relate the result to a similar industry-history of profit and investment.

3. Data

[1] See Harris and Raviv ().

In this section we describe the 'raw data', on which we have operated with our filter to derive the sample of investment spikes. We use the flow-of-funds accounts of non-financial COMPUSTAT (North America) companies, for the yeas 1988-1998, deflated appropriately to account for inflation. All the companies are publicly traded, although some are not listed in any one of the major exchanges; they are traded in the over-the-counter market only. At this point the sample had more than eleven thousand companies.

We have deleted from the data records that did not add up (By record we mean a company-year). We have also deleted from the raw data firms that failed to report major items such as after-tax income, depreciation, equity finance or debt finance. At this stage we lost about four-hundred companies, leaving us with 10,667 companies. It is noteworthy that the sample has a high turnover rate caused by firms' births and deaths. Only 6,293 of these companies were 'still alive' at 1998; only 4,253 of them were 'yet born' in 1988. Only 5,568 had five consecutive records; the rest were effectively discarded as our filter was programmed to detect an investment spike relative to the two years before and two years after it.

The next step was to aggregate the data into the following categories:

(2) $I_{ti} = OPR_{ti} + EQUITY_{ti} + LTDEBT_{ti} + OHTER_{ti}$

where,

OPR: cash flow from operations (after tax),
I: fixed investment,
EQUITY: Equity Finance (net),
LTDEBT: long-term debt finance (net),
OTHER: sum of all other variables,
t: a time index and
i : a company index.

Appendix A provides more information about the exact items included in each aggregate (with their COMPUSTAT labels). A positive (negative) sign on the right hand side means 'source of funds' ('use of funds'). For example: LTDEBT is positive (negative) when the firm borrows (repays debt).

The problem of missing variables is endemic in COMPUSTAT. Remember that at this stage all records add-up, so the word 'missing' does not mean 'unaccounted for' but rather 'aggregated to some other item in a non-systematic way'. COMPUSTAT does not guarantee that if item x is missing, it is certainly aggregated into item y; it might as well be aggregated into item z. Hence, we have replaced missing values with zeroes *within* the variables I, OPR, EQUITY and LTDEBT. For example: EQUITY=SSTK+ PRSTKC (sale of equity and purchase of equity, respectively, see Appendix A). If both SSTK and PRSTKC are missing, we delete the whole record (already in the previous step). If, however, only one is missing, we replaced it by zero and carried on, assuming that EQUITY is already reported on a net basis. Examining 'manually' a certain sub-sample of original accounts we believe that the measurement error introduced by this procedure is tolerable.

All the rest is aggregated into OTHER. That means that OTHER includes both 'changes in liquid assets', 'measurement errors' genuine 'other'. In spite of a great deal of effort and experimentation, we could not separate the first of these items, which is of great economic interest, from the two others. We shall have to live with the that ambiguity in the interpretation of the result, taking comfort that the other variables are reasonably accurate.

4. The Filter

We search the raw data for investment patterns with a clear spike in the middle. Essentially, we look for five-year strings of company investment with a good fit to the pattern

(3) $\left(1,\ 1,\ (2\ \textit{or more}),\ 1,\ 1\right)$,

where 1 normalises the off-spike *base level* of investment. The number 2 is arbitrary.

The filer is programmed to search the raw data record by record, trying to fit each year with the pattern (3). First, it computes a base-level of investment,

(4) $$b_{i,t} = \frac{I_{i,t-2} + I_{i,t+1} + I_{i,t+1} + I_{i,t+2}}{4}.$$

Given the base-level of investment, a $p_{i,t+j}$ receives the base level off spike, and double the base level on spike:

(5) $$p_{i,t+j} = \begin{cases} 2b_{i,t} & if \quad j=0 \\ b_{i,t} & otherwise \end{cases}, \quad j = -2,...,+2 \ .$$

The next step is to calculate the sum of squared errors from the pattern (adjusted to the level of base-investment):

(6) $$ER_{i,t} = \frac{\sqrt{\sum_{j=-2}^{2} u_{i,t+j}^2} \Big/ 5}{b_{i,t}} \ .$$

However, since we define the spike as double *or more* the base level, we treat positive spike deviations as perfect fit.

(7) $$u_{i,t+j} = \begin{cases} \min\left(0, I_{i,t+j} - p_{i,t+j}\right) & if \quad j=0 \\ I_{i,t+j} - p_{i,t+j} & otherwise \end{cases}, \quad j = -2,\mathrm{K}\ ,+2$$

The result is a mapping from each record of the panel[2] to a measure of the quality of the five-year time series to the pattern defined in equation (1), (where the quality of fit is measured in terms of the (relative) sum of squared errors from the pattern.

We have no statistical procedure to infer a point that would cut-off a bad fit away from a good one. We use an 'intuitive criterion' instead. Intuition is derived from Figure 1, which shows a sample of strings by decreasing order of our measure of fit (best fit is at upper-left corner). Each string contains five yearly observations along the time index t = -2,...,2 with the spike at t=0. The point 0.25 seems (to us) a sensible cut-off point.

insert Figure 1 here

[2] Less first two and last two years of each company.

- The filtered sample has a problem of extreme values. We delete 17 such record and obtain our working sample with 535 companies, all with 5 complete records with a spike in the middle.

insert Table 3A here

- Before we proceed, a word about selectivity: maybe, by filtering out spikes we have biased the sample towards firms of certain size, performance capital structure or sector. In Table 4 we report both raw sample and filtered sample statistics. We also run probit regressions where the dependent variable is 1 if the firm is sampled and zero otherwise. The purpose of this regression is to detect systematic patterns in the sampling process.
- It seems that the filtered sample is somewhat biased towards mature companies as both size larger and gearing is lower; also, the filtered sample has a much larger share of NYSE companies that the raw sample does. This make sense: we would not expect to find this pattern of investment in young and fast-growing companies.
- It is important to note, however, that the sample has enough smaller companies so that by means of a regression analysis we should be able to analyse their behaviour as well.

insert Table 4 here

Table 1:
Investment finance: the 'common wisdom'

Sources of finance, as a proportion of gross investment: an aggregation across time and firms. Source: the 'raw sample' (see Table 3).

sources of finance	%
operations	0.77
debt	0.15
equity	0.01
other	0.07
investment	1

Table 2:
Aggregation – a numerical example

Here are the flow-of-funds accounts of two fictitious firms (+ is a source, **-** is a use of funds). Both firms have to finance a lumpy project. Firm A is internally financed while Firm B is (largely) externally financed. Yet, after aggregation (fourth column), the two firms look exactly the same: wholly finance by retentions.

	firm A				firm B			
time	1	2	3	aggr.	1	2	3	aggr.
investment	0	0	-150	-150	-150	0	0	-150
operations	+50	+50	+50	+150	+50	+50	+50	+150
liquid assets	-50	-50	+100	0	0	0	0	0
external fin.	0	0	0	0	-100	-50	-50	0

Figure 1:
A sample of investment strings and the quality of fit

The figure provides an idea about the relationship between the *ER* measure of the quality of fit and possible investment strings. For the definition of *ER* see equation (5). We have sampled strings with *ER*s between 0.1 and 0.4. at ticks of (approximately) 0.02. Note that the quality of fit is decreasing across strings (i.e. *ER* is increasing from upper-left to down-right). Investment, *I*, is deflated by the base-level of investment, *b*. τ is time index for 'project year' with the spike at τ=0.

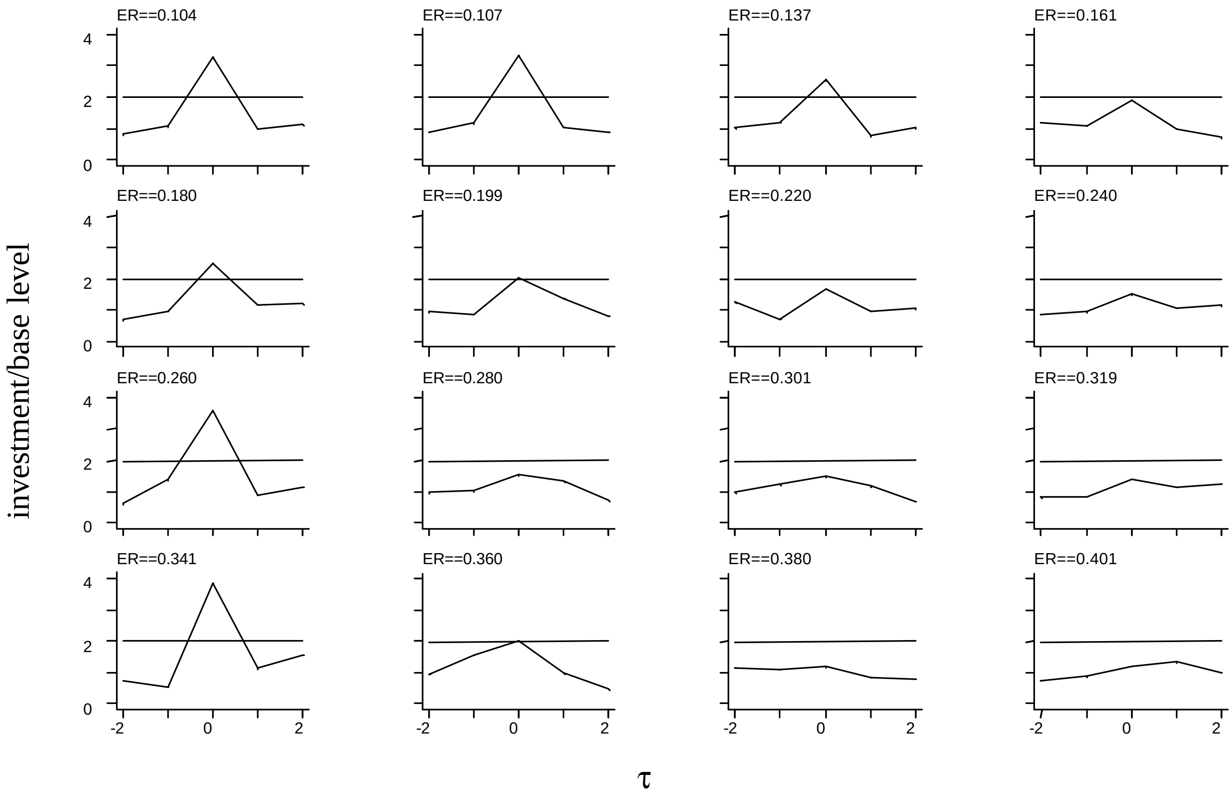

Table 3:
Testing for sampling a bias

In this table we look for systematic differences across the raw panel and the filtered sample, where the spikes are. Numbers reported are means across company means. We also run a probit regression where we try to predict the event that a certain company is filtered out (z stats).

	mean		probit
	raw panel	filtered sample	
total assets ($k)	468	1,173	0.00 (1.08)
earning/ assets*	0.03	0.05	0.13 (3.92)
investment/assets	0.10	0.08	-1.46 (-3.87)
acquisition/investment	0.12	0.11	-0.00 (-0.02)
debt/asset	0.35	0.26	-0.25 (-2.18)
	incidence		
manufacturing	45.7%	57.6%	0.06 (0.59)
commerce	47.6%	36.1%	-0.10 (-0.93)
NYSE	19.0%	45.9%	0.59 (7.30)
NASDAQ	62.6%	42.7%	0.03 (0.08)
N	10667	316	
R^2			0.06

Table 4:
Firm characteristics across size groups, means and (SD)

This Table reports means and SD of cross-firm characteristics, the characteristics themselves being means or SD's of intra-firm variables.
The definition of firm's characteristics:
Total assets: at by COMPUSTAT definitions (see data appendix).
Growth: total assets, t=-2 to t=2, annualised.
Growth to spike: total assets, t=-2 to t=0, annualised over *five* years (comparable with row above).
Market/book: total liabilities + market value of equity/ book value of assets (at t=-2).
Profit: ibc/base level of investment; see Data Appendix for 'ibc'.
Leverage (static): total debt/ total assets.
volatility: intra-firm standard deviation of 'operations' as in Table 5.

size-group	big	medium	small
total assets ($ million), (τ=-2)	3,061 (6,188)	144 (114)	25 (29)
growth (%)	4.7 (8.4)	5.9 (10.6)	5.2 (12.7)
growth to spike (%)	4.8 (6.4)	5.9 (8.4)	6.4 (11.4)
market/book (τ=-2)	1.92 (1.34)	1.83 (1.28)	1.94 (1.53)
market/book (τ=2)	1.93 (1.26)	1.57 (0.80)	1.75 (1.43)
profit	0.67 (1.24)	0.60 (1.66)	-0.75 (4.45)
EBITDA/total assets			
leverage (static) (τ=-2)	0.26 (0.17)	0.25 (0.21)	0.24 (0.24)
cash-flow volatility	0.57 (0.76)	1.04 (1.55)	3.10 (3.48)

Table 5:
Flow of funds for filtered sample, means and (SD)

Flow of funds, for the filtered sample (545 firms), aligned against project year t. All variables are deflated by the base-level of investment; namely OPR, EQUITY LTDEBT and OTHER by b as defined in equations (1) and (3). A + indicates a source of funds, a - indicates a use of funds, so that all rows add-up, horizontally, to zero. Size is measured according to the base-level of investment, and the sample is split into three groups with, roughly, the same number of observations in each size-groups. Arithmetic means and standard deviations are calculated for each size group.

τ	investment	operations	equity	debt	other
			big firms (N=179)		
-2	-0.96 (0.18)	1.00 (0.92)	0.18 (1.00)	-0.18 (1.00)	-0.03 (1.52)
-1	-1.00 (0.17)	1.20 (0.86)	-0.01 (090)	-0.03 (1.97)	-0.16 (1.91)
0	-2.71 (1.80)	1.04 (1.16)	0.01 (0.90)	1.03 (1.60)	0.63 (1.40)
1	-1.04 (0.17)	1.13 (1.63)	0.04 (1.06)	-0.04 (1.30)	-0.09 (1.92)
2	-0.99 (0.17	1.33 (1.23)	-0.32 (1.08)	-0.07 (0.81)	0.05 (1.16)
			medium-size firms (N=178)		
-2	-0.94 (0.18)	1.02 (2.82)	0.52 (2.29)	-0.06 (1.77)	-0.54 (3.55)
-1	-1.03 (0.20)	1.39 (1.51)	0.41 (1.86)	-0.16 (1.76)	-0.61 (2.07)
0	-2.85 (2.45)	1.36 (2.25)	0.20 (1.10)	1.17 (2.52)	0.12 (2.97)
1	-1.05 (0.20)	1.25 (2.01)	0.07 (1.54)	-0.04 (2.29)	-0.23 (2.82)
2	-0.98 (0.20)	1.27 (2.72)	0.01 (2.30)	-0.08 (3.18)	-0.22 (4.02)
			small firms (N=178)		
-2	-0.96 (0.21)	0.85 (4.68)	2.06 (6.13)	-0.54 (3.60)	-1.41 (6.71)
-1	-1.03 (0.21)	1.20 (5.45)	2.57 (6.66)	-0.75 (3.69)	-1.98 (7.23)
0	-3.81 (4.69)	0.78 (5.90)	2.56 (7.53)	0.64 (4.84)	-0.17 (7.85)
1	-1.01 (0.20)	-0.07 (6.59)	0.59 (3.98)	-0.30 (3.78)	0.79 (7.17)
2	-0.99 (0.21)	0.13 (7.31)	1.12 (5.72)	-0.65 (3.58)	0.39 (7.57)

Table 5A:
Derived project leverage, spike years (%)

Assuming that the project is the extra investment, beyond the base-level of investment, which equals 1 by definition. For example we calculate debt finance for big firms as 1.03/(2.71-1)=0.602.

	debt	equity
big	60.2	0.6
medium-size	63.2	10.8
small	22.8	91.1

Table 6:
Flow of funds for 'significant equity issues, and buy-backs, means and (SD)

Flow of funds, for firms that have engaged in 'significant' equity operations, namely if 'equity' falls out of the segment [-1,1]. All definitions are identical to those used in Table 5.

τ	N	investment	operations	equity	debt	other
			big firms (N=179)			
equity issues						
-1,-2	24	-0.92 (0.21)	0.70 (0.67)	2.41 (2.08)	-0.97 (2.15)	-1.22 (2.10)
0	8	-3.06 (2.25)	-1.11 (3.00)	2.45 (1.64)	-0.24 (1.84)	1.95 (2.84)
1,2	14	-1.07 (0.15)	0.85 (1.05)	2.41 (1.31)	-1.16 (1.91)	-1.04 (1.32)
buy-backs						
-1,-2	15	-1.00 (0.15)	2.12 (1.53)	-1.82 (0.99)	0.24 (0.98)	0.46 (1.08)
0	7	-2.54 (1.23)	2.44 (1.79)	-2.62 (1.75)	1.63 (2.42)	1.08 (1.51)
1,2	29	-1.02 (0.16)	2.90 (1.76)	-2.62 (1.88)	0.51 (1.46)	0.24 (1.71)
			medium-size firms (N=178)			
equity issues						
-1,-2	29	-1.07 (0.20)	1.14 (1.51)	4.52 (4.54)	-1.86 (3.05)	-2.73 (3.50)
0	17	-4.90 (6.20)	1.06 (1.27)	2.73 (1.65)	1.34 (4.36)	-0.23 (1.68)
1,2	18	-1.02 (0.23)	1.57 (6.74)	4.81 (3.22)	-2.26 (4.77)	-3.10 (8.71)
buy-backs						
-1,-2	8	-1.06 (0.18)	1.72 (0.77)	-1.72 (40.5)	0.82 (1.24)	0.25 (1.25)
0	5	-2.71 (1.13)	2.18 (0.65)	-2.16 (1.89)	0.08 (0.21)	2.61 (1.81)
1,2	24	-1.05 (0.18)	2.39 (2.07)	-3.44 (4.52)	1.03 (4.87)	1.06 (2.28)
			small firms (N=178)			
equity issues						
-1,-2	91	-1.03 (0.23)	-0.20 (6.10)	9.63 (9.23)	-1.35 (4.35)	-7.04 (8.02)
0	42	-5.58 (7.07)	-3.50 (9.06)	10.89 (12.3)	2.20 (7.13)	-4.01 (11.7)
1,2	54	-1.01 (0.23)	-2.83 (9.11)	6.97 (9.51)	-0.89 (4.13)	-2.24 (11.0)
buy-backs						
-1,-2	14	-1.04 (0.18)	1.61 (4.65)	-3.91 (2.99)	1.10 (3.46)	2.24 (6.62)
0	6	-3.07 (2.08)	1.63 (6.32)	-1.95 (0.54)	0.30 (3.15)	3.09 (6.53)
1,2	17	-1.01 (0.22)	3.70 (9.56)	-5.20 (7.75)	-1.93 (5.42)	4.44 (8.40)

Table 7:

Testing the pecking-order theory: debt finance in spike year (t-stats)

Dependant variable: debt finance. D-EQ is a dummy variable that receives a value of one if 'equity' >1 at t=-2,-1 (and zero otherwise). D-BK is a dummy variable that receives a value of one if 'equity' <-1 at t=-2,-1 (and zero otherwise). To facilitate the interpretation of the regression, 'investment' was multiplied by (-1).

	big firms (N=179)				
operations	-0.08	-0.05	-0.11	-0.18	-0.08
	(-1.00)	(-0.52)	(-1.32)	(-1.85)	(-0.99)
investment	0.61	0.61	0.61	0.61	0.40
	(11.66)	(11.36)	(11.75)	(11.74)	(2.26)
D-EQ*investment	0.16	0.32	0.15	0.16	0.17
	(1.4)	(1.79)	(1.38)	(1.47)	(1.54)
D-BK*investment	-0.11	-0.09	-0.10	-0.11	-0.11
	(-1.22)	(-0.76)	(-1.09)	(-1.26)	(-1.25)
D-EQ*operations		-0.40			
		(-1.15)			
D-BK*operations		-0.05			
		(-0.27)			
other (τ-1)			-0.08		
			(-1.62)		
operations (τ-1)				0.23	
				(1.84)	
$(\text{investment})^2$					0.02
					(1.27)
R^2	0.45	0.45	0.46	0.46	0.45
	medium-size firms (N=178)				
operations	-0.02	-0.01	-0.02	-0.02	-0.02
	(-0.23)	(-0.01)	(-0.25)	(-0.34)	(-0.24)
investment	0.65	0.65	0.66	0.66	0.68
	(10.93)	(10.72)	(10.86)	(10.84)	(4.54)
D-EQ*investment	-0.25	-0.25	-0.25	-0.25	-0.25
	(-2.08)	(-1.79)	(2.08)	(-2.05)	(-2.01)
D-BK*investment	0.21	0.49	0.21	0.21	0.20
	(1.12)	(2.12)	(-1.12)	(-1.13)	(1.05)
D-EQ*operations		-0.01			
		(-0.05)			
D-BK*operations		-1.14			
		(-2.02)			
other (τ-1)			-0.01		
			(-0.10)		
operations (τ-1)				0.04	
				(0.35)	
$(\text{investment})^2$					-0.00
					(-0.19)
R^2	0.43	0.44	0.43	0.43	0.43

Table 7 (cont.)

	small firms (N=178)				
operations	-0.01	-0.24	0.01	-0.08	-0.03
	(-0.10)	(-2.46)	(0.11)	(-1.37)	(-0.64)
investment	0.33	0.31	0.33	0.31	-0.29
	(4.00)	(3.82)	(4.04)	(3.77)	(-1.49)
D-EQ*investment	0.48	0.45	0.42	0.48	0.44
	(4.83)	(4.60)	(4.15)	(4.9)	(4.56)
D-BK*investment	0.27	2.45	0.29	0.26	0.44
	(1.53)	(1.43)	(1.66)	(1.53)	(2.52)
D-EQ*operations		0.33			
		(2.79)			
D-BK*operations		0.15			
		(0.57)			
other (τ-1)			-0.08		
			(-1.78)		
operations (τ-1)				0.14	
				(2.20)	
$(\text{investment})^2$					0.23
					(3.51)
R^2	0.41	0.43	0.42	0.42	0.45

Figure 2:
Static leverage, dynamic leverage, big firms, spike year

Dynamic leverage is defined as debt/(investment –1) at t=0.
Static leverage is defined as total debt/total assets at t=–2.
Observations are split to three groups:
'issue' firms are those with equity>1 either at t=–2 or at t=–1;
'buy-back' firms are those with equity<–1 at t=–2 or at t=–1;
'none' are those that neither issued nor bought back t=–2,–1.
'equity' is deflated by the base level of investment.

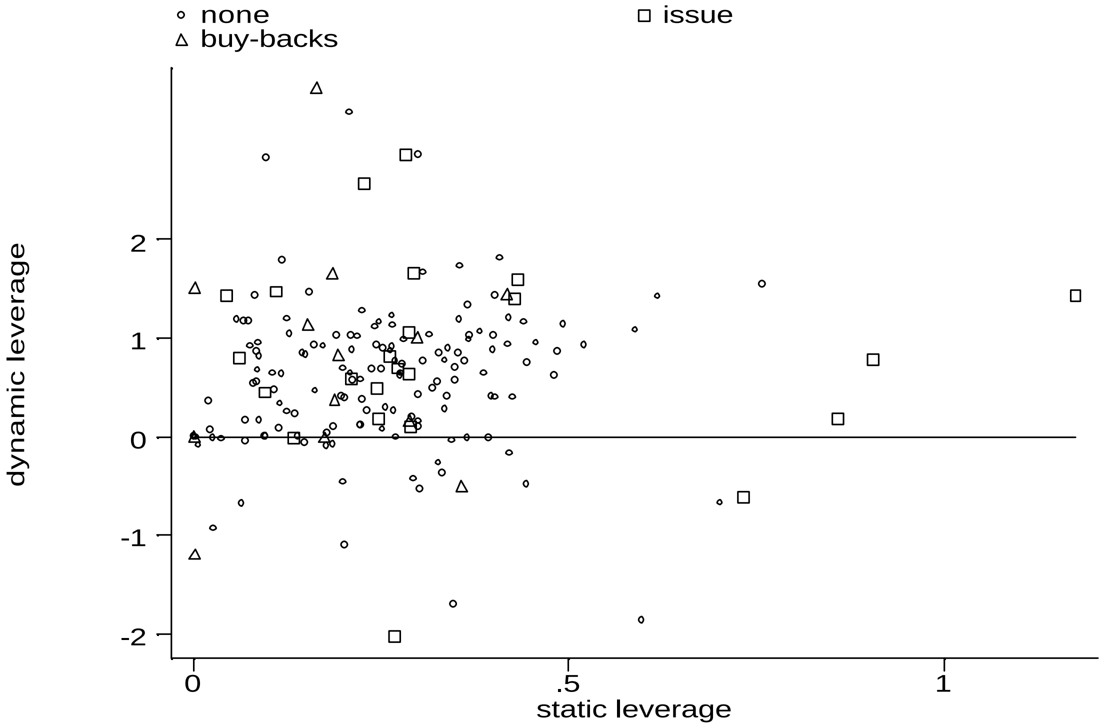

Table 9:
Aggregating over t = -1,0,1
Panel A: flow of funds, means and (SD)

This panel is identical to Table 5, only that each item is aggregated over τ=-1,0,1.

investment	operations	equity	debt	other
big firms (N=179)				
-4.76 (1.79)	3.36 (2.91)	0.05 (2.12)	0.97 (2.70)	0.38 (3.42)
medium-size firms (N=178)				
-4.92 (2.47)	4.00 (4.61)	0.67 (2.81)	0.98 (3.64)	-0.73 (4.96)
Small firms (N=178)				
-5.86 (4.67)	1.91 (14.66)	5.72 (14.12)	-0.41 (7.12)	-1.36 (13.37)

Panel B: debt regressions (t-stat)

Dependant variable: debt. Debt, investment and operations are aggregated t =-1,0,1. Operations are separated to positive and negative cash flows (profit and loss respectively). Leverage is defined total debt/total assets at t =-2.

	big firms	medium size fims	small firms
investment	0.59 (5.05)	0.85 (7.48)	0.65 (4.91)
operations +	-0.19 (-2.06)	-0.20 (-3.04)	-0.24 (-3.31)
operations -	0.26 (2.04)	-0.49 (-4.57)	0.05 (0.98)
leverage*investment	-0.79 (-3.44)	-0.49 (-2.33)	-1.28 (-4.34)
R^2	0.16	0.35	0.17

Panel C: equity regressions (t-stat)

Dependant: equity. Equity, investment and operations are aggregated t =-1,0,1. Operations are separated to positive and negative cash flows (profit and loss respectively). Leverage is defined total debt/total assets at t =-2.

	big firms	medium size firms	small firms
investment	0.10 (1.21)	0.03 (0.32)	-0.53 (-0.28)
operations +	-0.53 (-8.17)	0.18 (3.01)	0.11 (1.08)
operations -	0.03 (0.37)	-0.06 (-0.66)	-1.00 (-14.12)
leverage*investment	4.41 (2.60)	0.59 (3.12)	1.21 (2.87)
R^2	0.33	0.12	0.57

Data Appendix
Definitions of cash-flow accounts

The basic accounting identity is:

I=OPR+EQUITY+LTDEBT+OHTER,

(time and company indexes were omitted for brevity). Typically, all items (except OTHER) have a positive sign.

OPR: cash flow from operations (after tax)
- **ibc: after tax income before extraordinary items**
- **dpc: depreciation and amortization**
- **dv: cash dividends**

I: fixed investment
- **capx: capital expenditure**
- **aqc: acquisition**

EQUITY: Equity Finance (net)
- **sstk: sale of equity**
- **prstkc: purchase of equity**

LTDEBT: long-term debt finance (net):
- **dltis: issuance of long-term debt**
- **dltr: reduction in long-term debt**

OTHER: sum of all other variables
- **sppe: sale of property, plant and equipment**
- **apalch: change in account payables and accrued liabilities**
- **txach: change in accrued income taxes**
- **dlcch: change in current debt**
- **esubc: equity in net loss (earnings)**
- **xidoc: extraordinary items**
- **fopo: other funds from operations**
- **exre: exchange rate effect**
- **recch: change in receivables**
- **txdc: deferred tax**
- **aoloch: change in other assets and liabilities**
- **fiao: other financing**
- **ivaco: other investment**
- **sppiv: Loss(Gain) in sale of investment &PPE**
- **ivch: : increase in investment**
- **siv: sale of investment**
- **ivstch: increase in short-term investment**
- **chech: change in cash and equivalent**
- **invch: change in inventory**

Definitions of balance-sheet items

at=dt+seq
- **at: total assets**
- **dt: total debt**
- **seq: total equity**

Table A1:
Extreme values

In this table we report a procedure to eliminate 17 firms with extreme values. Criterion for ‘extreme’: if ‘operations’ or ‘other’ fall outside the [-40,40] segment. All variables are deflated by the base-level of investment, b as defined in equations (1) and (3).

	mean	SD	min	max
552 firms filtered out				
investment	-1.45	1.85	-35.75	-0.53
operations	1.34	16.24	-172.71	454.75
equity	1.17	7.65	-31.14	178.96
debt	0.09	5.85	-59.81	137.85
other	-1.16	20.69	-585.76	122.26
535 firms (after the elimination of extreme values)				
investment	-1,42	1.69	-35.75	-0.53
operations	0.99	3.81	-33.42	25.48
equity	0.67	3.84	-31.14	45.94
debt	0.00	2.89	-36.95	37.33
other	-2.23	4.73	-39.97	38.60

Table A2:
Leverage and industries, mean (SD)

Dynamic leverage is defined as debt/investment at $\tau=0$.
Static leverage is defined as total debt/total assets at $\tau=-1$.
See Appendix for industry definitions

Industry name	SIC codes	N	dynamic leverage	static leverage
agriculture	1-999	3	-0.09 (1.47)	0.14 (0.09)
mining	1000-1299	7	0.84 (0.89)	0.26 (0.14)
Oil and gas extraction	1300-1399	24	0.49 (0.65)	0.26 (0.23)
Construction related	1400-1799	10	0.33 (0.50)	0.17 (0.14)
food	2000-2099	25	0.58 (0.60)	0.25 (0.12)
tobacco	2100-2199	2	0.51 (1.43)	0.18 (0.25)
Textile	2200-2299	7	0.88 (0.90)	0.39 (0.20)
Apparel	2300-2399	11	0.25 (0.42)	0.16 (0.17)
Lumber and wood	2400-2499	5	0.65 (0.44)	0.21 (0.12)
Furniture and fixture	2500-2599	5	0.36 (1.13)	0.41 (0.34)
Paper	2600-2699	11	0.40 (0.73)	0.33 (0.21)
Printing and publishing	2700-2799	13	0.55 (1.12)	0.17 (0.15)
Chemicals	2800-2899	46	0.64 (0.89)	0.19 (0.16)
Petrol refining	2900-2999	6	0.82 (0.71)	0.32 (0.23)
Rubber and plastic	3000-3099	17	0.11 (1.01)	0.26 (0.16)
Leather	3100-3199	3	-0.94 (4.39)	0.32 (0.06)
Stone an concrete	3200-3299	4	1.11 (0.65)	0.29 (0.14)
Primary metal	3300-3399	12	1.01 (1.75)	0.34 (0.18)
Other metal	3400-3499	9	0.33 (1.07)	0.30 (0.14)
Machinery	3500-3599	42	0.63 (1.14)	0.18 (0.14)
Electrical products	3600-3699	49	0.69 (2.03)	0.24 (0.22)
Transportation equipment	3700-3799	8	0.83 (1.84)	0.25 (0.14)
Other: watches, photos	3800-3899	32	0.07 (0.72)	0.16 (0.18)
Miscellaneous products	3900-3999	7	0.05 (1.06)	0.41 (0.15)
Transportation services	4000-4799	12	0.03 (1.30)	0.22 (0.20)
Communication	4800-4899	18	0.70 (1.77)	0.36 (0.35)
Wholesale	5000-5199	35	-1.26 (7.14)	0.34 (0.21)
Retail	5200-5999	36	0.47 (1.18)	0.31 (0.21)
Other services	7000-9099	56	0.21 (1.96)	0.22 (0.29)
other	other	20	0.79 (1.19)	0.31 (0.14)
the whole population		535	0.37 (2.26)	0.24 (0.21)