Corporate investments and financing constraints: unraveling investment-cash flow sensitivities

Corporate investments and financing constraints: unraveling investment-cash flow sensitivities *

Bert D'Espallier[1], Sigrid Vandemaele[2]

ABSTRACT

In the literature on financing constraints, recent studies estimate firm-varying investment-cash flow sensitivities (ICFS) to avoid methodological problems related to comparing sample-level estimates across groups. We go along with these advances and suggest two additional methodological improvements. First, we estimate firm-varying ICFS by modeling heterogeneous slopes in the investment equation, thereby taking into account the dynamics of the underlying investment model. Secondly, we study the drivers of ICFS in an ex-post regression thereby accounting for non-linear effects and 'ceteris-paribus'-conditions. The results show that the ICFS is negatively related to *size*, *dividend payout*, *profitability*, and positively related to *leverage* suggesting a tight link between the ICFS and the firm's constraints-status. Additionally, the ICFS is negatively related to the *level* and *volatility* of cash flow, suggesting that a significant ICFS occurs mainly in low cash flow-states and is lowered by the practice of cash-buffering when cash flows are volatile. Finally, we find evidence of a non-linear tangibility effect in line with the non-monotonic credit multiplier suggested in previous research.

Keywords: financing constraints, investment-cash flow sensitivities, firm-specific sensitivities, slope heterogeneity

JEL-classification codes: G30, G31

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1. INTRODUCTION

In the empirical literature on financing constraints, a number of recent studies such as Hovakimian and Hovakimian (2009), Hovakimian (forthcoming) and D'Espallier et al. (2008) estimate firm-specific investment-cash flow sensitivities rather than sample-level investment-cash flow sensitivities in discrete sub-samples. The main reasons for using firm-level sensitivities are a. to avoid relying on *a priori* classification schemes that might not reflect a different susceptibility to capital market imperfections b. to avoid relying on sample-level estimates that might be severely biased because of endogeneity problems in the underlying investment equation and c. to be more in line with the firm-level theory on financing constraints.

In this paper, we go along with these advances in the literature and propose two important improvements to recent studies adopting this new approach. First, we argue that the firm-level sensitivity computed in Hovakimian and Hovakimian (2009; HH09 from hereinafter) looks at *levels* of cash flow and investment instead of marginal effects, thereby ignoring the original theoretical definition of investment-cash flow sensitivity. Therefore, we suggest to estimate firm-level sensitivities by allowing for heterogeneous slopes in the underlying investment equation, thereby taking into account the original definition of investment-cash flow sensitivity and respecting the dynamics of the underlying investment model.

Secondly, we suggest that the determinants of the investment-cash flow sensitivity should be analyzed through an ex-post regression analysis, rather than by investigating differences in averages for different ad-hoc sensitivity-classes. Such a regression analysis allows studying the *continuous* impact of a certain observable, holding constant (or *controlling for*) a number of necessary controls such as the level of investment (see discussion in Pawlina and Renneboog, 2005) and the level of cash flow (see discussion in HH09). Additionally, the regression analysis allows us to study non-linear effects in line with recent research in the field (see for instance Almeida and Campello, 2007 who suggest a non-monotonic effect of tangibility).

The results based upon a large longitudinal dataset of 1,233 US-based listed firms over a 5 year time period from 2000-2004 support a number of recent findings reported in the literature while contradicting a few others. First, we find a positive relation between the investment-cash flow sensitivity and a number of observable proxies of financing constraints, which is in line with recent research by Islam and Mozumdar (2007), Ağca and Mozumdar (2008), Carpenter and Guariglia (2008), among others. Secondly, we find empirical support for a non-linear relation between tangibility and the ICFS, which reflects the non-monotonic credit multiplier effect described in Almeida and Campello (2007). Thirdly, we find a negative relation between cash flow volatility and the ICFS confirming the findings by Cleary (2006) that firms facing high cash flow volatility will be inclined to buffer cash, thereby reducing the sensitivity of investment to cash flow. Finally, we find a significant negative relation between cash flow and ICFS suggesting that the ICFS is largely driven by *under*-investment in low cash flow-states rather than by *over*-investment in high cash flow-states. This last result is at odds with Pawlina and Renneboog (2005) who find that ICFS is mainly driven by over-investment resulting from wasting free cash flow.

The remainder of this paper is organized as follows. In the next section we describe the relevant literature on financing constraints, with specific attention to the recent attempts to estimate firm-level investment-cash flow sensitivities. The third section discusses our methodological approach and highlights its improvements over the existing studies that compute a firm-varying ICFS. Section 4 presents the main empirical finding and section 5 presents a number of additional analyses. Finally, in section 6 we present the main conclusions and limitations of this study.

2. LITERATURE

2.1 FINANCING CONSTRAINTS AND INVESTMENT-CASH FLOW SENSITIVITIES

In their seminal paper, Fazzari, Hubbard and Petersen (1988; FHP88 from hereinafter) project that the investment response due to a change in cash flow or the investment-cash flow sensitivity (ICFS) might be an interesting proxy to assess the degree of financing constraints a firm faces. This metric is intuitively appealing because a firm that has only limited access to external funds depends mainly on its internal funds and therefore grows or invests at the pace of its retained earnings (Carpenter and Petersen, 2002). FHP88 provide empirical evidence for this assertion by showing that the ICFS is higher for firms that pay out fewer dividends (and therefore are more likely to be financially constrained).

A large body of literature follows the argument of FHP88 and compares sample-level ICFS estimates for sub-samples of firms that have a different likelihood of financing constraints. For instance, Hoshi et al. (1991) and Deloof (1998) find that the ICFS is higher for firms with a looser banking relation. Kashyap et al. (1994) and Calomiris et al. (1995) find that the ICFS is higher for younger firms, confirming the assertion that the ICFS is higher for firms more likely to face financing constraints. Similarly, Bond et al. (2003) and Islam and Mozumdar (2007) find that the ICFS is higher in market-based Anglo-Saxon economies in comparison to bank-based European economies.

However, a number of recent empirical studies present counter-evidence and suggest that the ICFS is actually lower for firms more likely to face financing constraints. For instance, Kaplan and Zingales (1997, KZ97 from hereinafter) investigate the subset of most financially constrained firms of FHP88, i.e. the firms with the lowest dividend payout ratio, and find that the ICFS is lower for the most financially constrained firms. Cleary (1999) extends this research to a larger scale and finds a lower ICFS for firms more subject to capital market imperfections according to a constructed *Z-score index* based upon discriminant-analysis that predicts whether or not a firm has cut its dividends. Finally, Kadapakkam et al. (1998) find the ICFS is lower for smaller firms using a large international dataset covering 6 OECD countries.

This contradicting empirical evidence has inspired many researchers to revisit the theoretical evidence and identify several theoretical and methodological problems that affect the ICFS-approach such as potential endogeneity in the investment equation (Bond et al., 2003), a spurious cash flow effect originating from inadequacy to control for investment opportunities (Erickson and Whited, 2000; Bond and Cummins, 2001; Cummins et al. 2006) and problems related to the ex-ante sample classification approach (Gilchrist and Himmelberg, 1995; Almeida and Campello, 2007). Despite many efforts to resolve these methodological issues, there seems to be growing disagreement on the usefulness of the ICFS-metric even in the most recent literature on financing constraints. For instance, while Carpenter and Guariglia (2008), Guariglia (2008), Islam and Mozumdar (2007) and Ağca and Mozumdar (2008) present recent evidence in favor of the ICFS-approach, Lyandres (2007) and Cummins et al. (2006) present recent contradicting empirical evidence.

2.2 BENEFITS OF FIRM-SPECIFIC ESTIMATION METHODS

A recent stream of literature initiated by D'Espallier et al. (2008) and followed by Hovakimian (forthcoming) and HH09 estimates the ICFS on the firm-level rather than on the sample-level in order to avoid some of the methodological issues raised in the literature. These studies emphasize that there are a number of important benefits in analyzing firm-specific sensitivities compared to studying sample-level estimates across groups.

First, it is widely acknowledged that *cash flow* might be an endogenous variable in the investment equation and therefore the *sample-level* ICFS estimate (which is the coefficient of cash flow) might be severely biased. This potential endogeneity stems from the possibility of an omitted variables bias in the underlying investment equation or reversed causality between cash flow and investments (for a detailed discussion on potential estimation-bias, see for instance Bond et al., 2003). Note that not only the cash flow variable is potentially affected by this bias, but also cash flow interaction terms that are often added to investigate the direct impact of some observables on the estimated ICFS (see for instance Rauh, 2006 or Ascioglu et al., 2008; among others).

Endogeneity-proof estimation techniques such as GMM can be used to account for endogeneity of cash flow when estimating the parameters of the investment equation. However, these estimation techniques are critically dependent upon the ability to find good instruments that are both relevant i.e. highly correlated with the endogenous variables and exogenous i.e. low or uncorrelated with the error term. It remains an open issue whether GMM estimation techniques do away fully with the endogeneity problem and return consistent or unbiased sample-level estimates. Consequently, the first main benefit of using *firm-level* sensitivities is to avoid working with sample-level estimates that are potentially biased because of endogeneity in the underlying investment equation.

Secondly, a main benefit of using firm-level sensitivities is to avoid the practice of *ex-ante* sample classification where observations are being classified beforehand using a classification variable that reflects a different 'susceptibility' to capital market imperfections. As many authors point out, the results are critically dependent upon the classification scheme under consideration, and most classification schemes are in fact theoretically ambiguous with respect to financing constraints (KZ97, Almeida and Campello, 2007). As Gilchrist and Himmelberg (1995) point out: *"neither of the classification variables directly measure credit quality and are likely to produce a noisy signal of the severity of financing constraints"*.

A number of studies make the classification less rigid by using switching regression models (see for instance Almeida and Campello, 2007) or constructing indices that incorporate multiple variables (see for instance Cleary, 1999 or more recently Whited and Wu, 2006). Although these methods are considerable improvements over studies using a single classification scheme, it remains unclear whether resulting sub-samples are in fact to a different degree affected by financing constraints.

Finally, using firm-level sensitivities seems to be more in line with the firm-level theory on financing constraints. Essentially, financing constraints happen at the firm-level and not at the sample-level. As such, a methodological framework that empirically tests for financing constraints should account for firm-level heterogeneity instead of statistically neutralizing all firm-specific heterogeneity into a single sample-level estimate (see for instance, Cleary and D'Espallier, 2007 for a detailed discussion).

The previous discussion shows that there are a number of important methodological benefits in using firm-level sensitivities as opposed to the traditional empirical framework in which sample-level estimates are compared across groups. These benefits relate to (a) avoiding working with sample-level estimates that are potentially biased (b) avoiding classifying observations beforehand and (c) allowing for firm-specific heterogeneity instead of neutralizing all this information in an aggregate sample-level ICFS-coefficient.

2.3 HH09 REVISITED

HH09 estimate firm-level sensitivities by calculating the difference between the cash flow weighted time-series average investment of a firm and its simple arithmetic time-series average investment. Next, they compare averages of a selection of financial variables across different sensitivity-groups. We believe that there are two important limitations to this approach which we want to address in this paper.

First, the mathematical proxy for ICFS advanced in HH09 seems to be ad odds with the original definition of investment-cash flow sensitivity which has little to do with the correlation between the *level* of investment and the *level* of cash flow. HH09 compute the firm-level investment cash flow sensitivity as follows:

$$ICFS_i = \sum_{t=1}^{n}\left(I_{i,t} \times \frac{CF_{i,t}}{\sum_{t=1}^{n} CF_{i,t}}\right) - \frac{1}{n}\sum_{t=1}^{n} I_{i,t} \qquad (1)$$

where $I_{i,t}$ represents investment, $CF_{i,t}$ is cash flow and n is the number of observations for firm i and t represents the time-period. This can also be written as:

$$ICFS_i = \frac{\rho\sigma_I\sigma_{CF}}{\overline{CF}} = \rho\frac{\sigma_I\sigma_{CF}}{\overline{CF}} \qquad (2)$$

Equation (2) shows that the HH09-proxy for a firm-specific ICFS is merely the firm's correlation between the level of cash flow and the level of investment corrected with a factor that represents the coefficient of variation of cash flow times the standard deviation of investment.

We believe that this is a rather crude definition of the firm's ICFS that looks only at the correlation between the firm's investments and cash flow, without any control for investment opportunities. In fact, this definition seems to ignore totally any underlying model specification and seems to be at odds with the original definition of ICFS which is the investment *response* due to a *change* in cash flow, *holding constant* investment opportunities. Put differently, whereas the original theoretical proxy developed in FHP88 suggests studying the *marginal* impact of cash flow on investments controlling for the firm's future investment opportunities, HH09 looks only at the levels of cash flow and investment. We believe that this is an important limitation of the HH09-proxy.

We argue that the firm-specific ICFS can be estimated by introducing slope heterogeneity into the underlying investment equation. A firm-varying sensitivity estimated from the underlying investment model is much more in line with the original definition of the ICFS i.e. looks at the marginal investment effect and controls for the firm's future investment opportunities. In the next section we show how a panel data equation with varying slopes can be estimated using the Generalized Maximum Entropy (GME)-estimator, which is a semi-parametric estimation technique. Such an approach takes into account the dynamics of the underlying investment mode and therefore should return much better estimates for the firm's ICFS than the mathematical proxy calculated in HH09.

A second important limitation of the HH09-approach is the *ex-post* analysis on the basis of the estimated sensitivities. In HH09 the drivers of the ICFS are determined by analyzing differences in average values for a number of variables in arbitrarily determined ex-post ICFS-classes. Obviously, results are critically dependent upon the ICFS cut-off points used to classify the observations into the different ICFS-classes. In fact, it is unclear why certain cut-offs were used in this study. Moreover, no sensitivity-analysis was carried out to study the robustness of the results to the use of different cut-off points. Additionally, the approach does not isolate the impact of a single observable holding constant everything else.

We believe that firm-specific sensitivities provide an excellent opportunity to determine the drivers of the ICFS by means of a regression analysis. This analysis is able to investigate the continuous and *marginal* impact of one observable, controlling for other observables that are likely to have an important impact on ICFS. For instance, Pawlina and Renneboog (2005) argue that a significant ICFS might reflect both *under*-investment due to limited borrowing capacity as well as *over*-investment resulting from managers wasting free cash flow. In our specification, we add the level of investment as an additional explanatory variable so as to control for the differential investment effect. As a result, the marginal impact of certain variables is investigated *holding constant* the level of investment.

Similarly, there is recent evidence that the severity of financing constraints varies over the *cash flow*-cycle (see for instance Ağca and Mozumdar, 2008 or HH09). Therefore, we add *cash flow* as an additional control in the ex-post regression equation in order to study the marginal impact of a number of observables, controlling for the level of cash flow that captures the impact of the firm's cash flow-cycle.

Next to the benefit of studying marginal impacts of the explanatory variables under *ceteris-paribus*-assumptions, the ex-post regression offers the opportunity to study non-linear effects by adding higher order coefficients of certain observables in the regression equation. Recent research suggests that some observables show a non-linear relation to the estimated sensitivity (see for instance the non-monotonic credit multiplier effect described in Almeida and Campello, 2007).

In conclusion, we believe that the firm-specific sensitivities provide an excellent opportunity to study their relation to certain observables in detail using a regression analysis. Thereby we want to look at marginal effects 'ceteris paribus' and account for potential non-linear effects. We believe that the methodology presented below is a considerable improvement over the existing approach that compares averages across discrete and arbitrarily defined sensitivity-classes.

3. METHODOLOGY

In this section we describe a two-step estimation procedure for estimating the firm-varying sensitivities by modeling heterogeneous slopes in the investment equation (step 1) and unraveling the determinants of the ICFS through an ex-post regression analysis (step 2).

3.1. FIRM-VARYING SENSITIVITIES USING GME

The model under consideration is the static Q model of investment augmented with cash flow and time- and firm-fixed effects. This specification is frequently used in the literature and has been investigated in KZ97, Cleary (1999), Alayannis and Mozumdar (2004), Cleary (2006), Islam and Mozumdar (2007), among others. This specification relates corporate investments to Tobin's Q, cash flow and firm- and time-dummies and can be written as follows:

$$\left(\frac{I}{K}\right)_{i,t} = \beta_0 + \beta_1 \left(\frac{CF}{K}\right)_{i,t} + \beta_2 Q_{i,t} + \delta_i + \eta_t + u_{i,t} \tag{3}$$

where $I/K_{i,t}$ is investments scaled by beginning-of year capital stock; $CF/K_{i,t}$is cash flow scaled by capital stock; $Q_{i,t}$ is Tobin's Q added to capture the firm's investment opportunities; δ_i are firm-fixed effects added to capture all unobserved firm-specific changes in investment rate; η_t are time-fixed effects added to capture all unobserved time-specific changes in investment; β_1 is the ICFS defined as the investment response due to a change in cash flow holding constant the level of investment opportunities.

In order to calculate a firm-varying sensitivity we make the cash flow coefficient varying over firms by introducing slope heterogeneity in the specification as follows:

$$\left(\frac{I}{K}\right)_{i,t} = \beta_0 + \beta_{1,i}\left(\frac{CF}{K}\right)_{i,t} + \beta_2 Q_{i,t} + \delta_i + \eta_t + u_{i,t} \tag{4}$$

Equation (4) shows that the cash flow coefficient will be estimated for each individual firm in the sample. Firm-varying slopes in a panel data context cannot be estimated using traditional methods such as Fixed Effects (FE) or the Random Coefficients Model (RCM). The parameters of equation (4) will therefore be estimated using the Generalized Maximum Entropy- estimator (GME) developed in Golan et al. (1996). This is a semi-parametrical estimation method particularly suited to tackle models with heterogeneous slopes in a panel data setting. The GME-approach is attractive because it has a number of advantages over classical methods such as OLS or GMM. First, GME requires minimal distributional assumptions whereas classical methods rely on asymptotic distributions for the error term to make statistical inferences. Secondly, GME is well-suited to tackle problems where the number of parameters to be estimated is large, whereas the traditional dummy-variable panel data estimation typical for a fixed or random effects model quickly runs into a degrees-of-freedom problem. Finally, Golan et al. (1996) have shown that the GME estimator tends to outperform traditional estimators under various general conditions and that the GME-estimates are less sensitive to potential outliers or influential observation. Details about this estimation method can be found in a short appendix to this paper.

3.2 DETERMINANTS OF THE INVESTMENT-CASH FLOW SENSITIVITY

In a second step we determine the drivers of the ICFS by regressing the estimated firm-varying sensitivities $\widehat{ICFS}_i^{GME}$on a number of explanatory variables. The model incorporates a set of traditional financial ratios that have a long-standing tradition in the literature on financing constraints and assess the firm's financial status in terms of the firm's *debt, liquidity* and *profitability* position (see Cleary, 2006, p.1567). We also control for the level of *investment,* the level of *cash flow* and the *volatility of cash flows* and account for a potential non-linear *tangibility-effect*.

The baseline model can be written as follows:

$$\widehat{ICFS}_i^{GME} = f_1(\text{financial ratios}) + f_2\left(\frac{I}{K}\right) + f_3\left(\frac{CF}{K}\right) + f_4(CFvol_i) + f_5(\frac{1}{TANG}) + u_i$$

$$= \beta_0 + \beta_1(div) + \beta_2(lnTA) + \beta_3\left(\frac{cash}{K}\right) + \beta_4(debt) + \beta_5(coverage) + \beta_6\left(\frac{CF}{K}\right) + \beta_7\left(\frac{I}{K}\right) + \beta_8(CFvol) + \beta_9(\frac{1}{TANG}) + u_i \quad (5)$$

where *div* is the dividend payout rate, *lnTA* is the natural logarithm of total assets, *cash/K* is the ratio of cash over capital stock, *debt* is the debt ratio, *coverage* is earnings over interests, *(CF/K)* is the cash flow rate, *(I/K)* is the investment rate, *CFvol* is volatility of cash flow, *TANG* is tangibility rate. All right-hand side variables are averages over the observed-sample period and for robustness we also use the values in the most recent year of the sample-period. For the definition of the variables see Table 1.

Hypotheses with respect to the firm's financial status

A large literature projects a negative relation between the firm's dividend payout ratio and the existence of financing constraints (see for instance FHP88 and many subsequent studies). Therefore, if the ICFS is a meaningful indicator of the firm's financing constraints we expect a negative relation between div and the ICFS so that $\beta_1 < 0$.

Similarly, many studies project that smaller firms face tougher credit conditions and therefore are more likely to be financially constrained (see for instance Carpenter and Petersen, 2002 or Bond et al., 2003). Therefore we expect a negative relation between $lnTA$ and ICFS so that $\beta_2 < 0$.

Whited and Wu (2006) project a negative relation between the firm's cash ratio and the existence of financing constraints. This finding follows the belief that constrained firms fully exhaust their internal funds and therefore have a lower overall liquidity position. Therefore we expect a negative relation between $\left(\frac{cash}{K}\right)$ and ICFS so that $\beta_3 < 0$.

A number of studies such as KZ97 and Moyen (2004) investigate the relation between the firm's debt ratio and the existence of financing constraints on the basis of the wide-spread belief that external finance providers take into account the firm's existing debt position in their decision whether or not to extend credit. We expect that a high debt position negatively affects the firm's ability to obtain additional borrowings. Therefore, we expect a positive relation between the firm's $debt$ and the ICFS so that $\beta_4 > 0$.

Finally, KZ97 investigate the relation between the firm's interest coverage and the existence of financing constraints. Following these studies we expect that the firm's profitability position alleviates the firm's financing constraints, leading to a negative relation between $coverage$ and the ICFS so that $\beta_5 < 0$.

Necessary controls

As argued before, we add a number of controls in the ex-post regression to account for variables that have been shown to have a direct impact on the ICFS. As a first control we consider the level of cash flow. A number of authors (e.g. Ağca and Mozumdar, 2008 and HH09) argue that the severity of financing constraints varies over the cash flow-cycle. Specifically, financing constraints might play a more important role in low cash flow-states compared to high cash flow-states. Therefore, we control for the level of cash flow in the ex-post regression equation. By doing so we study the marginal effects of different constraints-proxies, controlling for the firm's cash flow-cycle.

Secondly, we add the level of investment in the ex-post regression equation. It seems logical that firms that hardly invest have a lower ICFS, ceteris paribus. Additionally, Pawlina and Renneboog (2005) argue that a significant ICFS might occur because of *under*-investment due to the existence of financing constraints as well as *over*-investments resulting from managers wasting free cash flow. By adding the level of investment we control for the differences in investment-rate described in Pawlina and Renneboog (2005).

Finally, in a recent study, Cleary (2006) argues that firms with more volatile cash flows will hold more cash in order to buffer against future cash flow-fluctuations. As a result, they will display a lower ICFS. Following this argument we add cash flow volatility as an additional regressor into the regression equation and expect a negative relation between $CFvol$ and the ICFS.

The non-linear tangibility-effect

Almeida and Campello (2007) describe a non-linear relation between asset tangibility and the ICFS. Specifically, they show that at low levels of tangibility, the sensitivity should be increasing in tangibility, whereas at high levels of tangibility, the sensitivity is independent of tangibility. The economic rationale behind this reasoning is the differential impact of the credit multiplier effect at high versus low levels of tangibility. This multiplier effect, which indicates that more tangible assets support more borrowing and therefore more investments, should only play at modest levels of tangibility whereas at higher levels, an extra unit of tangibility should not have a large effect. Following this reasoning a non-linear tangibility effect that can easily be studied by adding $\left(\frac{1}{TANG}\right)$ in the regression equation. The partial derivative of ICFS with respect to tangibility can be written as:

$$\frac{\partial ICFS_i}{\partial TANG} = \frac{-\beta_{(1/TANG)}}{TANG^2}$$

When the coefficient $\beta_{(1/TANG)}$ is negative, the ICFS is increasing in asset tangibility at a decreasing rate. At high levels of tangibility, the marginal impact of tangibility on the ICFS decreases towards 0. Following Almeida and Campello (2007), we therefore expect β_9 to be negative.

4. RESULTS

4.1 DATA AND SAMPLE DESCRIPTIVES

Annual financial data for US-based manufacturing firms were extracted from COMPUSTAT over a five year time-period from 2000-2004. Firms belonging to regulated and financial industries according to their two-digit SIC codes were excluded from the sample (43XX, 48XX, 49XX, 6XXX, 9XXX). An additional requirement for firms to enter our sample is that they do not report negative values for market-to-book, total assets or capital stock during the entire sample-period. Negative cash flow observations were also excluded from the sample so as to focus on firms facing financing constraints rather than on firms who are in a situation of financial distress (see for instance Alayannis and Mozumdar, 2004). In order to remove influential outliers, the upper and lower 1% of observations was deleted for all variables in the dataset. This leaves us with a large panel of 6,165 observations (1,233 firms over 5 years). In Table 1 we present a number of summary statistics for the sample under study.

< Insert Table 1 around here >

4.2 THE TRADITIONAL FRAMEWORK

In this section we follow the traditional framework and compare sample-level ICFS estimates across ex-ante classified groups according to five different classification schemes frequently used in the literature (*payout ratio*, *size*, *tangibility*, *debt rating* and *KZ-index*). Table 2 analyzes the association between the different schemes in terms of 'overlapping' observations (Panel A) and the Spearman's rank correlation coefficient (Panel B). From this table, it can be seen that the association between the different schemes is surprisingly low. For instance, column (1) of Panel A indicates that 3,391 observations were classified in the low-payout group, which represent 'constrained' observations following the traditional view. Only 29% of these observations were also classified as being 'constrained' observations according to the classification scheme *size*. This means that less than one third of the observations actually obtain the same constraints-status when using two different schemes. In fact an equal share of 30% of the 3,391 observations receives the classification 'unconstrained' according to the criterion *size*. The table shows that overlaps are rather low, indicating that different observations are being captured in the constrained and unconstrained group, depending upon the classification scheme that is being used. Panel B confirms this general finding by reporting relatively low and sometimes negative associations between classification schemes in terms of the Spearman's rank correlation coefficient.

< Insert Table 2 around here >

Table 3 presents the sample-level ICFS estimates in the different sub-groups computed by regressing equation (3) in the different sub-groups. In addition to the OLS-estimator, we report the GMM-estimator developed in Arellano and Bond (1991) that accounts for endogeneity of cash flow. As can be seen from the table, the ICFS-estimates are highly significant for all sub-groups, but differ largely across classification schemes. In general, the dividend payout scheme seems to reflect the finding of FHP88 in the sense that the ICFS is *higher* for firms more likely to face financing constraints (i.e. the ones that pay out less dividends). On the other hand, the other schemes seem to reflect the finding by KZ97 in the sense that the ICFS is *lower* for firms more likely to suffer from financing constraints.

< Insert Table 3 around here>

These results indicate that, even in a single sample, different conclusions can be reached depending on the classification scheme under consideration. As argued before, this is not very surprising given the low association between the different schemes and the use of sample-level estimates that are potentially biased because of endogeneity-issues. These findings seriously question the traditional approach of comparing sample-level ICFS estimates across groups and give further support to the novel approach of using firm-specific sensitivities as in HH09, Hovakimian (forthcoming) and D'Espallier et al. (2008).

4.3 THE TWO-STEP ESTIMATION PROCEDURE

Table 4 reports the estimation results from estimating the varying coefficients model of equation (4) using the GME-estimator. The mean firm-specific ICFS is 0.41 which is close to what is usually found in previous studies. As can be seen, this mean value originates from a wide dispersion of firm-specific sensitivities with a minimum value of 0 and a maximum of 1.41. A value greater than 1 means that a 1% increase in cash flow leads to an investment response greater than 1%. Although such a disproportionately large effect is perfectly possible from a theoretical viewpoint, only 0.6% of the firms show an investment response higher than the cash flow shock. Additionally, the table shows that the vast majority of firms (91.8%) have an ICFS between 0 and 0.5. This is very much in line with previous literature where similar values for the ICFS have been found.

< Insert Table 4 around here>

Table 5 presents the regression results from the ex-post regression analysis described in equation (5). Column (1) shows the results when the only regressors are the financial ratios proxying for the firm's constraints-status. In columns (2) to (5) the different controls are added one by one. As can be seen, the adjusted R^2 increases substantially from 7% to 36% when the different controls are added, indicating a substantial gain in explanatory power of the model. Moreover, all control variables are highly significant (1% significance level) indicating that controlling for the level of investment, the level of cash flow, cash flow volatility and the non-linear tangibility effect seriously improves the model fit.

< Insert Table 5 around here >

The coefficients on the financial ratios all have the expected signs. The coefficient on the dividend payout ratio is negative indicating that firms paying out lower dividends have a higher ICFS, which is in line with our expectations. However, when all controls are added, the coefficient is only marginally significant at the 10% significance level.

The coefficient on *lnTA* is, in line with expectations, negative in all model specifications. This means that the ICFS is higher for smaller firms and vice versa, the effect becoming statistically significant at the 5% significance level when the different controls are added. Interest coverage is also always significantly negative (10% level) in all model specifications, indicating that a higher ICFS is associated with lower profitability. The effect, however, is not particularly strong. The debt ratio is always positive and highly significant (1% significance level), indicating that a higher ICFS is associated with a higher leverage. Finally, the coefficient on cash/K is always negative, which is in line with expectations. However, the coefficient looses its significance when the level of cash flow enters the regression equation as can be seen in column (3). Likely, this result is caused by the high correlation between cash flow and the level of cash.

Turning towards the control variables added in the different columns, it can be seen that the coefficient on investment is always positive and highly significant at the 1% significance level. This finding suggests that a high ICFS is associated with higher levels of investment, ceteris paribus which is likely to reflect the obvious fact that the ICFS is low when the firm is not investing or investing at a very low pace.

The coefficient on cash flow is significantly negative in all model specifications, indicating that high ICFS is associated with low cash flows. This finding confirms recent research by HH09 and Ağca and Mozumdar (2008) who show that the ICFS depends upon the cash flow-cycle. However, our findings seem to contradict the findings by Pawlina and Renneboog (2005) who argue that ICFS is mainly driven by managers wasting free-cash flows reflecting an agency conflict between the managers and the shareholders of the firm. We find that ICFS is mainly observed when cash flows are low, suggesting that ICFS is given in by the existence of financing constraints when cash flows are low, and not by excessive cash flow spending in high cash flow-states.

The coefficient on the volatility of cash flow is always negative and highly significant (1% level). This finding is in line with the recent research by Cleary (2006) who finds that firms with volatile cash flows buffer cash in order to anticipate future fluctuations in cash flow. This buffering practice by firms facing high uncertainty about future cash flows, lowers the sensitivity of investment to cash flow.

Finally the coefficient on (1/TANG) is significantly negative supporting the non-linear tangibility effect described in Almeida and Campello (2007). In line with the non-linear effect, we find that at low levels of tangibility, ICFS is increasing with tangibility, whereas for high levels of tangibility, the ICFS becomes independent of asset tangibility. In Figure 1, we plot the partial derivative of ICFS with respect to tangibility against the level of tangibility derived from the estimated coefficient on (1/TANG) in the ex-post regression. From this figure, the non-linear relation between asset tangibility and the ICFS is clear.

< Insert Figure 1 around here>

Overall, the results from the ex-post regression indicate that a higher ICFS is associated with *smaller* firms, *less profitable* firms, *lower dividends* and *higher debt ratios* indicating a positive relation between the firm's ICFS and the existence of financing constraints. These findings seem to support recent studies that highlight the link between the ICFS and financing constraints such as Islam and Mozumdar (2007), Ağca and Mozumdar (2008), Carpenter and Guariglia (2008), among others.

Additionally, a high ICFS is associated with *lower* levels of cash flow, *higher* levels of investment, and *lower* cash flow volatility. These findings are in line with recent research by

HH09 and Cleary (2006). Finally, there is substantial empirical evidence of a non-linear relation between ICFS and the level of asset tangibility. All observed effects are *marginal* or *isolated* effects, holding constant everything else or 'ceteris paribus'.

5. ADDITIONAL ANALYSES

5.1. COMPARISON WITH THE HH09-RESULTS

For comparison with the HH09-results we present the firm-specific sensitivities according to the mathematical proxy suggested in HH09 in Table 6. From this table, it appears that the mean and median ICFS are very close to zero with negative ICFS-values for a substantial part of the sample (40.3%). The values seem to be centered around zero with a minimum of -0.81 and 0.84. These values seem to be in contrast with ICFS-values usually found in previous studies, where the values usually vary between 0.20 and 0.50.

Additionally, the large number of negative values seems to be difficult to reconcile with economic rationale. A negative ICFS can only occur when the firm has persistently invested over the observed sample-period despite negative cash flows, or when a firm has persistently de-vested over the observed sample-period despite positive cash flows. While such behavior is perfectly possible from a theoretical viewpoint in a certain given year, it is highly unlikely that such firm-behavior occurs over longer sample-periods. Therefore, it is hard to maintain that around 40% of the firms have consistently invested despite negative cash flows or vice versa, over the observed sample period of 20-years studied in HH09.

< Insert Table 6 around here >

In Table 7 we report the regression results from regressing the HH09-proxy on the variables suggested in section 3. In the columns (2) to (5) the different controls are added one by one. It can be seen that neither the financial variables nor the different controls show any statistically significant relation with the HH09-proxy. Moreover, the F-statistics denote that the regression models are jointly insignificant (the only exception being the full-model in column (5) where the F-stat denotes joint significance at the 10% significance level). This means that none of the observables suggested to have an impact on the ICFS according to a number of previous studies show any significance.

This finding together with the previous finding that the HH09-proxy returns values for the firm-specific ICFS that are not in line with economic theory, nor with previous research, seriously questions whether the mathematical HH09-proxy provides a good firm-varying equivalent for the investment-cash flow sensitivity.

< Insert Table 7 around here >

5.2. MEAN VALUES IN DISCRETE ICFS-CLASSES

For comparison with previous studies, we report mean values for the different observables in discrete ICFS-classes going from 'low sensitivity' (first quartile) to 'high sensitivity' (4^{th} quartile) in Table 8. This is essentially the same analysis as presented in previous studies focusing on firm-varying sensitivities such as D'Espallier et al. (2008) and HH09. In general, the same relations emerge for the different financial ratios and control variables that were tested in the ex-post analysis. In that respect, this analysis provides a further robustness check for the analysis presented in the previous section. Again the ICFS seems to be negatively related with the *dividend payout ratio*, firm *size*, *cash*, *cash flow*, *interest coverage* and *cash flow volatility* and positively related with *debt ratio* and the *investment rate*.

However, for most of the variables (such as *lnTA*, *cash/K*, *debt ratio, coverage* and *I/K*) the average value first increases and then decreases with the sensitivity-classes or vice versa. Such evidence has been identified in previous literature as evidence of a non-monotonic relation between the ICFS and a certain observable. However, it should be noted that this analysis does not satisfy 'ceteris paribus'-assumptions i.e. it does not control for other firm-observables. Secondly, this analysis looks only at *mean*-values i.e. provides an aggregation of the observable in the various sensitivity-classes. Therefore, we believe that the ex-post regression analysis provides considerable improvements over the conventional analysis of investigating differences in mean-values between different ICFS-classes.

< Insert Table 8 around here >

6. CONCLUSIONS, DISCUSSION AND LIMITATIONS

A new stream of literature estimates firm-specific investment-cash flow sensitivities rather than sample-level sensitivities when studying empirically the concept of financing constraints. These studies emphasize three main benefits of using firm-varying sensitivities. First, sample-level estimates might be seriously biased because of endogeneity of cash flow in the underlying investment equation. Secondly, using firm-varying sensitivities offers the possibility to study the drivers of the ICFS without having to rely on ex-ante classification into discrete sub-groups. Finally, estimating firm-varying sensitivities accounts for firm-heterogeneity instead of statistically neutralizing all firm-level variation into a single sample-level estimate.

The aim of this paper is to go along with these new advances and to propose a number of important improvements to the existing studies that deploy this new approach. First, we argue that the mathematical proxy developed in HH09 looks only at the *levels* of cash flow and investment, thereby ignoring the original definition of investment-cash flow sensitivity. We suggest estimating the firm-specific ICFS by allowing for slope-heterogeneity in the underlying investment equation. This approach yields a firm-level sensitivity that takes into account the underlying model dynamics and is in line with the original definition i.e. the investment *response* due to a change in cash flow holding constant the level of investment opportunities.

Secondly, we argue that the use of firm-specific sensitivities provides a unique opportunity to study the drivers of the ICFS using regression analysis. The regression analysis allows us to study marginal effects while controlling for other observables that have been shown to have an impact on the ICFS. Additionally, we can study non-linear effects by incorporating higher order coefficients into the regression equation. We believe that this analysis provides important benefits over the traditional approach in which averages are compared across ex-post defined sensitivity-classes.

This new estimation framework is put to the test using a large longitudinal sample of 1,233 US-based listed firms in a Q –investment model augmented with cash flow, time and firm-fixed effects. The main results can be summarized as follows: First, when analyzing a number of financial ratios that proxy for the firm's constraint-status, we find that the ICFS is negatively related with the firm's *dividend payout*, *size*, *profitability* and *liquidity* and positively related with the firm's *debt ratio*, ceteris paribus, indicating a tight link between the ICFS and the existence of financing constraints. These results are in line with recent findings by Islam and Mozumdar (2007), Carpenter and Guariglia (2008), Guariglia (2008), Ağca and Mozumdar (2008), among others.

Secondly, the ICFS is significantly negatively related to *cash flow,* ceteris paribus, suggesting that a positive ICFS emerges mainly when cash flows are low. This finding reflects the view of recent studies such as HH09 and Pawlina and Renneboog (2005) that the cash flow-cycle is an important determinant of the firm's ICFS. However, our findings are contrary to the findings of Pawlina and Renneboog (2005) who find that ICFS is mainly caused by over-investment due to managers wasting free cash flow in high-cash flow years. Rather, our results indicate that a high ICFS is mainly observed when cash flows are low, suggesting that mainly under-investment in the presence of low cash flows is driving the ICFS.

Thirdly, we find that the ICFS is negatively related to the firm's cash flow volatility, ceteris paribus. This finding confirms the results by Cleary (2006) who finds that firms with more volatile cash flows have the tendency to buffer cash in order to cope with future uncertain cash flow fluctuations. This cash buffering practice has a negative impact on the ICFS.

Finally, we find empirical support for the non-linear tangibility effect described in Almeida and Campello (2007). Specifically, at low levels of tangibility the ICFS increases with the level of tangibility because of the credit multiplier effect. At high levels of tangibility the marginal impact of tangibility on the ICFS decreases towards zero.

We believe that this study entails a number of implications that might be important for the empirical literature on financing constraints. First, we show that estimating firm-level sensitivities offers a number of important benefits over the traditional framework of comparing sample-level estimates across groups. As such, we highly support this new approach that might be an important element in the debate on the usefulness of estimating investment-cash flow sensitivities to capture financing constraints. Secondly, we show that investment models with firm-varying slopes can be estimated using modern econometrical techniques. As such, we can compute firm-level sensitivities that take into account the underlying model dynamics and stay close to the original definition, instead of computing mathematical proxies that look mainly at *levels* of investments and cash flows. Finally, we show that firm-specific sensitivities provide a unique opportunity to investigate the drivers of the sensitivity, thereby opening up the black-box of investment-cash flow sensitivities. Using an ex-post regression offers the possibility to look at marginal effects and to study non-linear effects.

Of course, this study also comes with a number of important caveats that should be kept in mind and that offer a number of interesting routes for future research. First, the augmented Q model of investment, although widely studied, is not the only investment paradigm that could be used, and, like any theoretical model, comes with a number of limitations. For instance, Gomes (2001) and Cummins et al. (2006) question whether Tobin's Q is an adequate proxy to capture investment opportunities, and whether the ICFS is not merely an artifact of cash flow capturing investment opportunities rather than signaling financing frictions. Our analysis shows that the ICFS, originating from this Q model, is related to the firm's constraints-status and therefore is not just merely an artifact of cash flow capturing investment opportunities. However, it would be interesting to see whether the results hold for other investment paradigms that have been suggested in the literature such as the neoclassical investment model (see for instance Guariglia, 2008) or the sales accelerator model (see for instance Kadapakkam et al., 1998).

Secondly, although the ex-post regression includes a wide variety of financial ratios as well as control variables that have a longstanding tradition in the literature, there might be other observables associated with the ICFS. In fact, the *R^2 adjusted* in the ex-post regression indicates that around 36% of cross-sectional is consistently explained by our observables. Therefore, a substantial part of residual cross-sectional variation remains unexplained by the observables used in the current study. Future research could aim at further unpacking the black-box of investment-cash flow sensitivities by analyzing the impact of other firm-characteristics such as managerial decision making (see for instance Bloom and Van Reenen, 2007) or reluctance to borrow (see for instance Howorth, 2001) on the ICFS.

Finally, in this study, the GME-estimator has been used to estimate the parameters of the varying-coefficients model. It should be noted, though, that this is not the only estimator suited to tackle slope heterogeneity in the context of panel data. For instance, full Bayesian econometrics (see for instance Lancaster, 2004) or mixed models for longitudinal data (see for instance Verbeke and Molenberghs, 1999) could also be used to estimate the model parameters. In that respect, it would be interesting to see whether the results would hold for these alternative estimation techniques.

APPENDIX ON ENTROPY ECONOMETRICS

The GME-estimator is a Quasi-Bayesian estimation technique based upon the principles of Information Theory. The estimator is developed and thoroughly discussed in the book by Golan et al. (1996). Applications of the GME-estimator to various fields in economics can be found in Judge and Golan (1992); Léon et al. (1999); Fraser (2000), Peeters (2004), among others. In this appendix we discuss the GME model formulation for the varying-coefficients model were Q is omitted for expository reasons. Following Golan et al. (1996) the GME formulation of the classical linear regression model can be written as:

$$\max_{p} \; H(\boldsymbol{p}) = -\sum_{k=1}^{K} p_k ln p_k \tag{A1}$$

Subject to:

$$\boldsymbol{y} = X\boldsymbol{\beta} + \boldsymbol{e} = X\boldsymbol{Z}\boldsymbol{p} + \boldsymbol{V}\boldsymbol{w} \tag{A2}$$

$$\sum_{k=1}^{K} p_{k,m} = 1 \qquad \forall m = 1, \dots M \tag{A3}$$

$$\sum_{t=1}^{T} w_{t,j} = 1 \qquad \forall j = 1, \dots J \tag{A4}$$

were $\boldsymbol{p}$ is a $(K \times M)$ matrix of unknown probabilities that need to be estimated; $\boldsymbol{Z}$ is a $(K \times KM)$ matrix of discrete support values for $\boldsymbol{\beta}$ with M the number of support points. Similarly, $\boldsymbol{V}$ is a $(T \times TJ)$ matrix of know support values for the error term $\boldsymbol{e}$ with J the number of support points and $\boldsymbol{w}$ the vector of unknown probabilities to be estimated. Equation (A1) represents the joint entropy of the parameters and the error term that need to be maximized with respect to $\boldsymbol{p}$. Equation (A2) represents the data-consistency constraint which is the parametrical version of the regression model that needs to be estimated. In this equation, each parameter is written as a linear combination of discrete support values and unknown parameters. Equations (A3) and (A4) represent additivity-constraints or normalization constraints that ensure that for each parameter the estimated probabilities add up to one. According to Golan et al. (1996) working through this maximization problem yields parameter estimates that are *least-informative* or expressing *maximum uncertainty* (i.e. closest to the discrete support values), while still consistent with the underlying model and the data. Applying this model formulation to the cash flow-augmented investment model yields:

$$\max_{\boldsymbol{p}_\beta, \boldsymbol{p}_{v_{i,t}}, \boldsymbol{p}_{u_{i,t}}} H(\boldsymbol{p}) = -\boldsymbol{p}_\beta' ln \boldsymbol{p}_\beta - \sum_{i=1}^{n}\sum_{t=1}^{T} \boldsymbol{p}_{v_{i,t}}' ln \boldsymbol{p}_{v_{i,t}} - \sum_{i=1}^{n}\sum_{t=1}^{T} \boldsymbol{p}_{u_{i,t}}' ln \boldsymbol{p}_{u_{i,t}} \tag{A5}$$

Subject to:

$$(I/K)_{i,t} = \left(\boldsymbol{p}_\beta' \boldsymbol{z}_\beta + \boldsymbol{p}_{v_{i,t}}' \boldsymbol{z}_{v_{i,t}}\right)(CF/K)_{i,t} + \boldsymbol{p}_{u_{i,t}}' \boldsymbol{z}_{u_{i,t}} \qquad \forall i, t \tag{A6}$$

$$\sum_{i=1}^{n}\sum_{t=1}^{T} \boldsymbol{p}_{v_{i,t}}' \boldsymbol{z}_{v_{i,t}} = 0 \tag{A7}$$

$$\sum_{i=1}^{n} \boldsymbol{p}_{u_{i,t}}' \boldsymbol{z}_{u_{i,t}} = 0 \quad \forall t \tag{A8}$$

$$\sum_{m=1}^{M} \boldsymbol{p}_{\beta,m} = 1; \; \sum_{g=1}^{G} \boldsymbol{p}_{v_{i,t},g} = 1; \; \sum_{h=1}^{H} \boldsymbol{p}_{u_{i,t},h} = 1 \qquad \forall i, t \tag{A9}$$

In this constrained maximization problem (A5) is again the joint entropy of the parameters and the error term that needs to be maximized in order to obtain ‘least-informative’ parameter estimates closest to the support values. (A6) represents the data-consistency constraint which is the parametrical version of cash flow –augmented investment model where the unknown parameters are written as linear combinations of the unknown probabilities and discrete support values. Equation (A7) is a mean preservation constraint that ensures a consistent mean cash flow coefficient so that ‘shrinkage’ is avoided (Golan et al., 1996, pg. 163). Equation (A8) imposes a mean zero error in each year so that covariates and errors are determined exogenously. Equation (A9) represents the additivity-constraints that ensure that for each parameter to be estimated, the estimated probabilities add up to one.

The posterior parameter estimates can be recovered by recombining the optimal probabilities and the discrete support values in a linear way as follows:

$$\widehat{\boldsymbol{\beta}} = \widehat{\boldsymbol{p}}_{\beta}^{'}\boldsymbol{z}_{\beta} \tag{A10}$$

$$\widehat{\boldsymbol{v}}_{i,t} = \widehat{\boldsymbol{p}}_{v_{i,t}}^{'}\boldsymbol{z}_{v_{i,t}} \tag{A11}$$

$$\widehat{\boldsymbol{u}}_{i,t} = \widehat{\boldsymbol{p}}_{u_{i,t}}^{'}\boldsymbol{z}_{u_{i,t}} \tag{A12}$$

In line with the Bayesian research paradigm, the GME estimator combines both prior information and data in order to form a posterior parameter estimate. Following prior information sets were used:

$$\boldsymbol{z}_{\beta} = [0,1]^{'} \tag{A13}$$

$$\boldsymbol{z}_{v_{i,t}} = [-10,10]' \tag{A14}$$

$$\boldsymbol{z}_{u_{i,t}} = \left[-3\hat{\sigma}_{I/K_{i,t}}, 3\hat{\sigma}_{I/K_{i,t}}\right] \tag{A15}$$

Equation (A13) expresses that the supports for the mean cash flow coefficient were chosen to be distributed symmetrically around 0.50. Equation (A14) expresses a wide support value for the shrinkage-parameter $v_{i,t}$ and (A15) expresses that the priors for the error term are bounded by three times the empirical standard deviation of the dependent variable, consistent with the ‘three-sigma’ rule suggested in Pukelsheim (1994).

For the Bayesian researcher, combining prior information with data is a natural way to enhance parameter estimates. However, for researchers not adhering to the Bayesian

paradigm, an objection often raised is the sensitivity of the results to using different information sets. While it is true that the prior information plays a role in the estimation process, its effect should not be overstated. First, when samples are sufficiently large, the information contained in the data often overshadows the information content provided by the non-sample information (Lancaster, 2004). Secondly, with the prior information sets wide enough and containing the true value of the parameter, the researcher imposes a minimal restriction and maximizes the influence of the data on posterior estimates (Koop, 2003). Therefore, we do not expect the support values to have a large impact on the GME-estimates.
However, in order to investigate the sensitivity of the estimates to the use of alternative prior information sets, we have conducted a sensitivity-analysis using the dual cross-entropy formulation in Golan et al. (1996). This procedure calculates the parameter estimates for 100 different prior values drawn randomly out of a distribution of choice. Specifically, 100 spike priors for $\boldsymbol{\beta}$ were drawn from a uniform distribution U(-1,1), a uniform distribution (-10,10) and a normal distribution N(0.5,0.3). This exercise reveals that the results are extremely insensitive to the use of different prior sets, which was to be expected given the large number of data points and the wide intervals that were used. Results from this exercise are available upon request.

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LIST OF TABLES AND FIGURES

Table 1. Summary statistics

This table summarizes the number of observations, mean, standard deviation, minimum and maximum for a selection of financial variables from the sample of 6,165 firm-year observations. *(I/K)* is defined as investments in PP&E divided by beginning-of-year capital stock. *(CF/K)* is defined as net income before extraordinary items plus depreciation and amortization divided by beginning-of-year capital stock. *Q* is the beginning-of-year market value of common equity divided by beginning-of-year book value of common equity. *Size* is total assets in millions US$. *Payout ratio* is the sum of total dividends and stock repurchases divided by net income. *Tangibility* is PP&E divided by net-fixed assets. *Debt ratio* is total debt divided by total assets. *Cash/K* is cash and equivalents divided by capital stock. *Slack/K* is (cash plus short term investments + 0.5 inventories+ 0.7 accounts receivables- short term loans) divided by capital stock. *Sales* is total net sales in millions US$. *Sales growth* is percentage growth in total net sales. *Coverage* is the interest coverage defined as EBIT divided by interest expenses and preferred dividends. *Current ratio* is current assets divided by current liabilities. *ROE* is return on equity defined as net income divided by beginning-of-year total common equity.

Variable	# obs	mean	median	st. dev	min	max
(I/K)	6,165	0.14	0.10	0.15	0.00	2.00
(CF/K)	6,165	0.37	0.21	0.57	0.00	5.00
Q	6,165	2.51	1.94	1.95	0.02	10
Size	6,165	1.66	0.48	3.25	1.61	42.26
Payout ratio	6,090	0.02	0.00	0.07	0.00	0.97
Tangibility	6,164	0.59	0.56	0.21	0.02	1.00
Cash/K	6,085	0.38	0.11	0.71	0.00	3.83
Slack/K	6,024	0.96	0.51	1.17	-1.69	4.50
Debt ratio	6,150	0.20	0.19	0.17	0.00	0.82
Sales	6,165	1.81	0.51	3.99	0.01	65.05
Sales growth	6,165	0.12	0.09	0.09	-0.81	1.00
Coverage	5,357	25.32	4.62	61.93	-7.00	300.00
Current ratio	6,006	2.69	2.03	2.63	0.22	47.56
ROE	6,158	0.11	0.10	0.09	-.15	0.40

Table 2. Association between 'popular' ex-ante classification schemes

PANEL A. Association in terms of percentage 'overlapping' observations

This table presents the number of observations within each sub-group on the diagonal elements as well as the percentage overlaps between the sub-groups on the off-diagonal element. Groups were formed as follows: first, observations were ranked annually according to their *payout ratio*, *size*, *tangibility*, and *KZ-index*. Then observations in the upper 30% tail were designated *high payout, large*, *high tangibility*, *high KZ*. Observations in the lower 30% tail were designated *low payout*, *small*, *low tangibility* and *low KZ*. For the debt-rating scheme, the observation is classified in the *unrated* subgroup if the firm had no debt rating in that particular year, and *rated* if the firm did have a debt-rating in that particular year.

	Payout ratio		Firm size		Tangibility		Debt rating		KZ index	
	low	*high*	*small*	*large*	*low*	*high*	*unrated*	*rated*	*high*	*low*
payout ratio										
low	**3,391**									
high		**2,754**								
Firm size										
small	29.13%	31.05%	**1,845**							
large	30.61%	29.48%		**1,860**						
Tangibility										
low	29.69%	29.95%	35.50%	28.98%	**1,835**					
high	30.49%	29.74%	25.42%	29.35%		**1,860**				
Debt rating										
unrated	67.97%	67.25%	72.25%	66.77%	81.14%	56.45%	**4,164**			
rated	32.03%	32.75%	27.75%	33.23%	18.86%	43.55%		**2,001**		
KZ-index										
high	21.35%	40.56%	33.71%	28.39%	34.82%	27.47%	31.63%	26.39%	**1,783**	
low	36.53%	19.61%	28.62%	29.46%	24.90%	32.47%	27.23%	32.43%		**1,845**

Table 2. Continued

PANEL B. Association in terms of the Spearman's rank correlation coefficient between the classification schemes

This table presents the Spearman's rank correlation coefficient between the rankings of firm-years according to the various classification schemes. * and ** denote statistical significance at the 5% and 1% significance level, respectively.

	Payout ratio	Firm size	Tangibility	Debt rating	KZ index
payout ratio *[low/high]*	1.000				
Firm size *[small/ large]*	-0.025	1.000			
Tangibility *[low/high]*	-0.008	0.086**	1.000		
Debt rating *[unrated/rated]*	0.008	0.059**	0.226**	1.000	
KZ-index *[high/low]*	-0.304**	0.050*	0.125**	0.083**	1.000

Table 3. OLS and GMM estimation results for the ICFS in different sub-samples

This table reports OLS and GMM estimates from regression equation (3) for the different sub-samples. Robust standard errors are provided in parentheses and *,** and *** denote statistical significance at the 10%, 5% and 1% significance level. The χ^2 statistic for the GMM estimation denotes the joint significance of the model.

Dep. var. (I/K)		OLS			GMM		
		CF/K	Q	R^2adj	CF/K	Q	χ^2-stat
All firms		0.18**	0.008***	0.19	0.16***	0.006**	39.82***
		(0.006)	(0.002)		(0.009)	(0.002)	
Payout ratio	Low	0.20***	0.010***	0.26	0.22***	0.003	46.43***
		(0.008)	(0.002)		(0.012)	(0.003)	
	High	0.15***	0.003	0.16	0.08**	0.008	36.76***
		(0.009	(0.002)		(0.012)	(0.003)	
Firm size	Small	0.13***	0.002	0.18	0.17***	-0.0006	45.16***
		(0.009)	(0.003)		(0.014)	(0.004)	
	Large	0.28***	0.009***	0.45	0.27***	0.01***	54.48***
		(0.009)	(0.002)		(0.014)	(0.003)	
Tangibility	Low	0.10***	0.009***	0.10	0.08**	0.006	13.58***
		(0.011)	(0.003)		(0.018)	(0.004)	
	High	0.13***	0.01***	0.27	0.20***	0.007	20.88***
		(0.012)	(0.003)		(0.013)	(0.004)	
Debt rating	Unrated	0.12***	0.003*	0.12	0.17***	0.0005	21.48***
		(0.007)***	(0.002)		(0.011)	(0.003)	
	Rated	0.20***	0.02***	0.35	0.15***	0.01**	54.53***
		(0.010)	(0.003)		(0.014)	(0.004)	
KZ-index	High	0.12***	0.008**	0.16	0.08**	0.008	12.67***
		(0.011)	(0.003)		(0.013)	(0.004)	
	Low	0.23***	-0.0003	0.28	0.26***	-0.006	16.23***
		(0.013)	(0.003)		(0.029)	(0.004)	

Table 4. GME estimation results of the varying coefficients model

This table presents a number of statistics for the GME estimates of the firm-varying ICFS estimated from equation (4). P(x) represents the x^{th} percentile. The pseudo-R² is defined as the squared correlation between actual and predicted (fitted) values of the dependent variable.

	firm-specific ICFS
mean	0.41
st.dev.	0.11
minimum	0.00
maximum	1.41
P(0.05)	0.28
P(0.10)	0.32
P(0.30)	0.39
median	0.41
P(0.60)	0.42
P(0.70)	0.43
P(0.90)	0.48
P(0.95)	0.56
Proportion in [0, 0.50[	91.8%
Proportion in [0.50, 1]	7.60%
Proportion > 1	0.60%
Mean lower 30% tail	0.32
Mean middle 40% area	0.41
Mean upper 30% tail	0.48
Other model parameters:	
β (fixed)	0.417
β_0 (constant)	0.008
β_2 (Tobin's Q)	0.001
Pseudo-R²:	
no fixed effects	0.63
time-fixed effects incl.	0.65
firm-fixed effects incl. (full model)	0.71

Table 5. Estimation results from the ex-post analysis

This table report the OLS estimation results from the ex-post regression. CFVOL is the cash flow volatility defined as the coefficient of variation of the cash flow rate over the observed sample period. All other variables are defined as in Table 1. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance level, respectively.

Dep var $\widehat{ICFS}_i^{GME}$	OLS estimates (robust standard errors)				
	(1)	(2)	(3)	(4)	(5)
Financial ratios					
Constant	0.44	0.44	0.38	0.38	0.41
	(0.012)***	(0.011)***	(0.013)***	(0.012)***	(0.019)***
Payout ratio	-0.17	-0.11	-0.07	-0.05	-0.05
	(0.038)***	(0.038)***	(0.033)***	(0.034)*	(0.036)*
LnTA	-0.002	-0.002	-0.002	-0.003	-0.004
	(0.002)	(0.002)	(0.002)	(0.001)**	(0.002)**
Cash/K	-0.02	-0.006	-0.001	-0.001	-0.001
	(0.004)***	(0.004)	(0.004)	(0.005)	(0.005)
Debt ratio	0.06	0.05	0.08	0.08	0.08
	(0.026)**	(0.025)**	(0.023)***	(0.024)***	(0.024)***
Coverage	0.03	0.04	-0.04	-0.05	-0.05
	(0.018)*	(0.017)**	(0.027)*	(0.028)*	(0.027)*
Control variables					
(CF/K)		-0.05	-0.13	-0.10	-0.10
		(0.006)***	(0.015)***	(0.015)***	(0.015)***
(I/K)			0.60	0.60	0.57
			(0.066)***	(0.065)***	(0.069)***
CFVOL				-0.02	-0.02
				(0.007)***	(0.007)***
(1/TANG)					-0.007
					(0.004)**
R^2 adj.	0.07	0.09	0.34	0.36	0.36
F-stat	14.00***	38.68***	23.65***	21.81***	22.09***
RMSN	0.11	0.10	0.09	0.09	0.09
n	1109	1109	1109	1109	1109

Table 6. Firm-specific ICFS according to HH09

This table presents a number of statistics for the firm-varying ICFS computed according to the definition suggested in HH09. The ICFS is defined as the difference between the cash flow weighted time-series average investment and its simple arithmetic time-series average investment. P(x) represents the x^{th} percentile.

	firm-specific ICFS
mean	0.006
st.dev.	0.057
minimum	-0.81
maximum	0.84
P(0.05)	-0.027
P(0.10)	-0.012
P(0.30)	-0.001
median	0.0008
P(0.60)	0.002
P(0.70)	0.005
P(0.90)	0.023
P(0.95)	0.046
Proportion < 0	40.3%
Proportion in [0, 0.50[	58.8%
Proportion in [0.50, 1]	0.90%
Mean lower 30% tail	-0.02
Mean middle 40% area	0.001
Mean upper 30% tail	0.035

Table 7. Regressing the HH09-proxy on the firm-observables

This table report the OLS estimation results from regressing the firm-varying ICFS computed as in HH09 on the observable measures suggested to have an impact on the ICFS in section 3.2. Robust standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance level, respectively.

Dep var $\widehat{ICFS}_i^{HH08}$	OLS estimates (robust standard errors)				
	(1)	(2)	(3)	(4)	(5)
Financial ratios					
Constant	-0.003	-0.002	-0.014	-0.015	-0.017
	(0.005)	(0.006)	(0.011)	(0.012)	(0.025)
Payout ratio	-0.03	-0.04	-0.06	-0.02	-0.02
	(0.011)**	(0.04)	(0.023)	(0.023)	(0.023)
LnTA	0.0008	0.0009	0.0008	0.0006	-0.0007
	(0.0008)	(0.0009)	(0.007)	(0.0009)	(0.0011)
Cash/K	0.013	0.007	0.008	0.01	0.01
	(0.0051	(0.007)	(0.007)	(0.008)	(0.008)
Debt ratio	-0.003	-0.003	0.002	0.004	0.005
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
Coverage	0.02	0.019	0.004	0.001	0.002
	(0.021)	(0.021)	(0.027)	(0.025)	(0.024)
Control variables					
(CF/K)		0.004	-0.013	-0.003	-0.003
		(0.018)	(0.013)	(0.013)	(0.013)
(I/K)			0.11	0.11	0.11
			(0.071)	(0.071)	(0.085)
CFVOL				-0.007	-0.007
				(0.012)	(0.008)
(1/TANG)					0.0007
					(0.005)
R^2 adj.	0.02	0.02	0.05	0.06	0.06
F-stat	1.33	1.11	1.34	2.42	3.01*
RMSN	0.05	0.05	0.05	0.05	0.05
n	1104	1104	1104	1104	1104

Table 8. Mean values in ex-post sensitivity classes

This table presents mean values for a number of financial observables in different ex-post ICFS-classes. The classes have been defined by sorting the firm-varying sensitivities according to GME-estimation of the varying coefficients model into quartiles. Non-monotonic relations are written in italics.

$ICFS_i^{GME}$	*Low* Q1	*Mod.-low* Q2	*Mod.-high* Q3	*High* Q4
Payout ratio	0.053	0.031	0.022	0.013
lnTA	*5.73*	*6.75*	*6.33*	*5.94*
Cash/K	*0.997*	*0.344*	*0.193*	*0.260*
Debt ratio	*0.168*	*0.195*	*0.220*	*0.216*
Coverage	*0.761*	*0.515*	*0.606*	*0.853*
CF/K	0.683	0.335	0.249	0.245
I/K	*0.138*	*0.116*	*0.117*	*0.204*
CFVOL	1.173	0.267	0.253	0.123

Figure 1. The non-linear tangibility effect

This figure plots the non-linear relation between the tangibility ratio and the partial derivative of ICFS with respect to tangibility estimated from the ex-post regression equation presented in equation (5).