Does the investment opportunities bias affect the investment-cash flow sensitivities of unlisted SMEs?

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Abstract

Using a panel of 5,999 small and medium-sized Belgian enterprises (SMEs) over the period 2002-2008, we identify three measures of investment opportunities suitable for unlisted firms. We then estimate firm-varying investment-cash flow sensitivities (ICFS) from reduced-form investment equations that include these measures, and compare them with those derived from a model that does not control for investment opportunities. We find that all our models yield similar ICFS estimates, which are significantly related to a wide set of proxies for financing constraints. These findings suggest that the ICFS of SMEs do not simply reflect investment opportunities. The investment opportunities bias may therefore have been overstated in previous literature.

Key-words: Financing constraints, Firm-varying investment-cash flow sensitivities, Investment opportunities, Gross added value

JEL-classification codes: D92, E22, G30, G31

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1. INTRODUCTION

A number of researchers have argued that, within a reduced-form *Q* model of investment, a significant cash flow coefficient may simply reflect the effect of increased investment opportunities not properly accounted for by Tobin's *Q*, rather than signaling financial frictions (Gilchrist and Himmelberg, 1995; Erickson and Whited, 2000; Bond et al., 2004; and Cummins et al., 2006). This problem is usually referred to as the investment opportunities bias, and is central in the debate on whether investment-cash flow sensitivities (ICFS) can be considered as useful proxies for financing constraints.

To resolve this issue, alternative proxies for investment opportunities have been proposed in the literature. Examples of these are Fundamental *Q* (Gilchrist and Himmelberg, 1995), Tobin's *Q* corrected for measurement error (Erickson and Whited, 2000), financial analysts' earnings forecasts (Bond et al., 2004; Cummins et al., 2006), and contracted capital expenditures (Carpenter and Guariglia, 2008)[1]. However, opinions are still mixed as to whether the remaining cash flow effect after controlling for investment opportunities in various ways can be considered as an adequate proxy to capture financing constraints. For instance, while Carpenter and Guariglia (2008) find that ICFS remain statistically significant for small firms, which suggests that they are adequate proxies for liquidity constraints, Cummins et al. (2006) and Bond et al. (2004) argue the opposite. Most of the literature which addressed the investment opportunities bias has focused on large listed companies, which are less likely to suffer from financing constraints than their small unquoted counterparts (Carpenter and Petersen, 2002; Beck and Demirguc-Kunt, 2006; Guariglia, 2008; Becchetti et al., 2009). To the best of our knowledge, no paper has directly addressed the effects of the bias with focus on small unlisted companies. Our main contribution is to fill this gap in the literature.

The widely known investment opportunities proxies, such as Tobin's *Q*, Fundamental *Q*, or financial analysts' earnings forecasts cannot be computed for unlisted companies because market values are not commonly available for them, and

[1] Fundamental *Q* is defined as the expected value of Marginal *Q* estimated using VAR forecasting techniques. Contracted capital expenditures are defined as contracts entered into for the future purchase of capital items, expenditure on machinery, equipment, plant, vehicles, and buildings, for which nothing has been paid by balance sheet date. While authors such as Bond et al. (2004) and Cummins et al. (2006) use financial analysts' earnings forecasts to construct an alternative measure of investment opportunities, Almeida and Campello (2007) use them to instrument Tobin's *Q*.

because these firms are usually not followed by analysts. Consequently, we identify three different proxies for investment opportunities, which can be used in the analysis of unlisted firms' investment behavior. These proxies are an accounting proxy for Marginal *Q* developed by Honda and Suzuki (2000), a sales accelerator term (Guariglia, 2008; Bakucs et al., 2009), and a proxy based upon the industry-level growth in added value.

Our second contribution is methodological: for the first time, we make use of a Bayesian estimator to derive firm-level ICFS. The estimation of ICFS at the firm-level rather than at the sample level was initially proposed by D'Espallier et al. (2008) and Hovakimian & Hovakimian (2009). The main advantage of this methodology is that the adequacy of the ICFS estimates in capturing financing constraints can be studied in detail in an ex-post analysis. Specifically, the estimated firm-varying sensitivities can be regressed on a number of proxies for financing constraints, in order to observe how much of their variation can be explained by these observable variables[2]. We advance this literature by using a Bayesian estimator to derive our firm-level ICFS. This methodology allows for a full probabilistic inference of all parameters, without relying on any normality assumptions. We then provide an ex-post evaluation of the ICFS derived from three models that differ in their control for investment opportunities, and compare the results with those obtained from a model that does not control for them. This approach enables us to assess which of the models produces the ICFS that fits best with the proxies for financing constraints.

We focus on small and medium-sized unlisted firms operating in Belgium over the period 2002-2008. Our choice of Belgium is motivated by the fact that it is an established market economy, where few companies are listed on the stock exchange

[2] Papers in the financing constraints literature typically partition firms ex-ante into more and less likely to face financing constraints based on a number of criteria such as size, age, the dividend payout ratio and so on. They then estimate separate investment regressions for the different sub-groups of firms and interpret a higher estimated aggregated ICFS in the financially constrained group as evidence in favor of the presence of financing constraints (see Schiantarelli, 1995; Hubbard, 1998; and Bond and Van Reenen, 2007, for surveys of this literature). Instead of partitioning the sample into categories, other authors prefer to interact cash flow with dummies indicating whether firms are ex-ante more or less likely to face financing constrains (e.g. Kaplan and Zingales, 1997; Guariglia, 2008). Ex-ante classifications of firms are, however, likely to be inaccurate and/or endogenous. Moreover, an aggregate estimated ICFS in a certain sub-sample could contain information about unobservable economic phenomena completely independent of financing constraints (D'Espallier et al., 2008). Our ex-post analysis of the estimated firm-varying ICFS enables us to test for the presence of financing constraints without classifying firms ex-ante into more and less likely to face financing constraints.

(Deloof, 1998)[3]. As unlisted firms are more likely than listed ones to suffer from asymmetric information problems and, hence, from financing constraints, Belgium represents an ideal setting for a study of the effects of these constraints on firm behavior. Moreover, a comprehensive dataset containing rich accounting information for small and medium-sized enterprises (SMEs) is available.

Our results show that, whichever the way we control for investment opportunities, we obtain very similar firm-varying ICFS estimates. Moreover, the correlation between the firm-varying ICFS derived from all our models is particularly high, and our firm-varying ICFS estimates are significantly related to a wide set of proxies for financing constraints. These findings suggest that investment-cash flow sensitivities do not simply reflect increased investment opportunities. In fact, even for the benchmark model that does not take up any control for investment opportunities, a large proportion of cross-sectional variation in the estimated ICFS can still be attributed to the existence of financing constraints. This suggests that the investment opportunities bias may have been seriously overstated in previous literature.

The remainder of this paper is organized as follows. In the next section, we discuss the relevant literature on financing constraints, with specific emphasis on the investment opportunities bias, and the recent empirical advances that focus on firm-varying ICFS. Section 3 describes our dataset, illustrates our measures of investment opportunities, and presents some descriptive statistics. Section 4 introduces the investment equations with different controls for investment opportunities that we estimate, discusses our estimation methodology, and describes our ex-post analysis aimed at validating our estimated ICFS. Section 5 summarizes our empirical results. Section 6 concludes and identifies possible extensions to our work.

2. BACKGROUND

2.1 ICFS and the investment opportunities bias

ICFS have a long-standing tradition in the empirical literature on financing constraints. In their seminal paper, Fazzari et al. (1988) predict, for the first time, that the investment response to a change in cash flow might be a good proxy to assess the

[3] Deloof (1998) documents that in November 1995, the total stock market capitalization of Belgian firms was only 44% of GDP compared to 93% for the US and 130% for the UK.

degree of financing frictions a firm faces. The reason for this is that financially constrained firms find it impossible or too expensive to access external finance, and depend therefore mainly on their internal funds to finance investment. As a result, a positive ICFS is expected for firms more likely to face financing constraints, but not for financially healthy firms. Fazzari et al. (1988) and many subsequent studies provide empirical support for this assertion, by showing that ICFS are higher for groups of firms classified ex-ante as more likely to face financing constraints[4].

Most of these studies estimate reduced-form investment equations augmented with cash flow within the *Q* model framework, where Tobin's Marginal *Q* (usually proxied by the firm's market-to-book value) is included as a control for investment opportunities. As has been noted by authors such as Gilchrist and Himmelberg (1995), Kaplan and Zingales (1997), and Bond et al. (2004), this analysis is only valid if the firm's market-to-book value is an adequate proxy to capture the firm's investment opportunities. Otherwise, instead of signaling financing constraints, a significant cash flow coefficient could simply reflect increased investment opportunities not captured by the market-to-book value. As the ability of the market-to-book value to properly capture firms' investment opportunities has been frequently questioned in the literature (Gilchrist and Himmelberg, 1995; Erickson and Whited, 2000; Bond et al., 2004; Cummins et al., 2006), the so called investment opportunities bias has posed a serious impediment for empirical studies in the field, and has incited many researchers to look for alternative proxies for investment opportunities, in order to isolate the effects of cash flow due to financing constraints from those due to investment opportunities. For instance, Erickson and Whited (2000) construct measurement error-consistent GMM estimates of Marginal *Q*. Along similar lines, Gilchrist and Himmelberg (1995) suggest the use of Fundamental *Q*, which is defined as the expected value of Marginal *Q* estimated using VAR forecasting techniques. Bond et al. (2004) and Cummins et al. (2006) use financial analysts' earnings forecasts as a proxy for Marginal *Q*. Other studies use completely different proxies to capture the firm's investment opportunities. Among these, Kadapakkam et al. (1998) include the ratio of lagged sales to net fixed assets as an additional explanatory variable, and

[4] See for instance, Devereux and Schiantarelli (1990), Hoshi et al. (1991), Oliner and Rudebusch (1992), Deloof (1998), and, more recently, Carpenter and Petersen (2002), Bond et al. (2003), Alayannis and Mozumdar (2004), Bhagat et al. (2005), Islam and Mozumdar (2007), Lyandres (2007), and Ağca and Mozumdar (2008). Also see Schiantarelli (1995), Hubbard (1998), and Bond and Van Reenen (2007) for surveys.

Carpenter and Guariglia (2008) use the contracted capital expenditure as a direct proxy for the firm's investment opportunities.

These studies reach contrasting conclusions with respect to the link between ICFS and financing constraints. For instance, while some find that, once improved measures of investment opportunities are used, investment is still sensitive to cash flow especially for financially constrained firms (Gilchrist and Himmelberg, 1995; Carpenter and Guariglia, 2008), others remain highly skeptical on the ability of the ICFS to capture financing constraints (Cleary, 1999; Erickson, and Whited, 2000; Bond et al., 2004; Cummins et al., 2006). In summary, although most researchers are aware of the problem of a potential investment opportunities bias, opinions on the effects of the bias on ICFS differ significantly.

2.2 Proxies for investment opportunities for unlisted firms

Most of the financing constraints literature is based on panels of listed companies. Yet, a number of very recent studies focus on small businesses to study the effects of financing constraints (Becchetti et al., 2009; Guariglia, 2008). As these studies point out, SMEs constitute an interesting group to focus on because asymmetric information problems are likely to be particularly severe for these firms, which usually have limited access to external financial markets (Hughes, 1994; Lopez-Garcia and Aybar-Arias, 2000). Additionally, SMEs tend to have lower borrowing capacity because of limited track-records and more static asset bases, which lower their collateral value (Binks and Ennew, 1996; Voordeckers and Steijvers, 2006). Finally, small businesses are usually unquoted and, therefore, cannot draw upon the stock market to attract external funds (Petersen and Rajan, 1994). In sum, SMEs might face much tougher conditions than their larger counterparts to access external finance. They therefore represent an ideal group to focus on when studying financing constraints (Holod and Peek, 2007).

Focusing on small unlisted businesses, however, poses the challenge of finding suitable controls for firms' investment opportunities. Market-information is in fact not available for them, and they are typically not followed by analysts, which makes it impossible to compute traditional proxies such as the market-to-book value, Fundamental *Q*, or analyst's earnings forecasts. To the best of our knowledge, only a handful of studies have experimented with proxies for investment opportunities in the case of unlisted firms. Most of these studies use sales growth to control for these opportunities (Bakucs et al., 2009; Guariglia, 2008; Konings et al., 2003).

In this paper, we identify three different proxies for investment opportunities, suitable for unquoted firms. We then compare the ICFS derived from investment models that include these proxies with those obtained from a benchmark model where investment opportunities are not controlled for. This analysis enables us to indirectly assess the ability of these proxies to satisfactorily capture firms' future growth opportunities, and, consequently, the ability of ICFS to proxy for the degree of financing constraints faced by firms.

2.3 Firm-varying sensitivities and ex-post analysis

A number of recent papers (D'Espallier et al., 2008; Hovakimian, 2009; and Hovakimian and Hovakimian, 2009) analyze firm-specific sensitivities, rather than a single sample-level ICFS estimate[5]. These studies emphasize that this seemingly small methodological alteration allows us to deal with a number of problems related to the traditional framework that have been identified in previous literature. First, it avoids working with sample-level estimates that might be potentially biased due to endogeneity or aggregation bias (Bond et al., 2003). Second, it avoids having to partition the observations beforehand using a classification criterion that might be endogenous or even ambiguous with respect to financing constraints (Gilchrist and Himmelberg, 1995). Finally, the new methodology enables us to test the ability of our estimated ICFS to capture financing constraint explicitly, using an ex-post analysis. Specifically, the estimated firm-level sensitivities can be regressed on a set of proxies for financing constraints in order to assess how much of their variation can be explained by these observables.

[5] D'Espallier et al. (2008) use a Generalized Maximum Entropy (GME) estimator to estimate ICFS directly as firm-varying cash flow coefficients in a reduced-form investment regression. In contrast, Hovakimian and Hovakiminan (2009) and Hovakimian (2009) calculate the firm-varying ICFS indirectly. The former compute the difference between the cash flow weighted time-series average investment of a firm and its simple arithmetic time-series average investment, and claim that this difference should be higher for firms investing more in high-cash flow years. Hovakimian (2009) estimates a reduced-form investment regression which excludes cash flow, and measures the firm-specific ICFS as the difference between the average of the error term derived from this regression weighted by firms' cash flows and its unweighted average. She claims that if a firm's investment is not affected by its cash flow, then the average weighted error term should not be statistically different from the average unweighted error term, while the opposite would happen in case of a positive correlation between a firm's investment and its cash flow.

We believe that this novel set-up provides an interesting framework to study the investment opportunities bias more in depth than has been done in previous literature. As D'Espallier et al. (2008) point out, different models can be evaluated using the ex-post evaluation procedure, and the 'best' model, i.e. the one that produces the ICFS that fit best with the proxies for financing constraints, can be identified. We use this methodology to evaluate the performance of three models that contain three different controls for investment opportunities suitable for unlisted firms.

3. MODELS AND ESTIMATION METHODOLOGY

3.1 Investment models

We analyze three reduced-form investment models, which include different controls for investment opportunities suitable for unlisted firms, and compare the ICFS derived from these models with those obtained from a benchmark model, where investment opportunities are not controlled for.

3.1.1 Marginal Q model. The first model (Marginal *Q* model) uses an accounting proxy of Marginal *Q* suggested by Honda and Suzuki (2000). It can be expressed as follows:

$$(I/K)_{i,t} = \beta_0 + \beta_1 (I/K)_{i,(t-1)} + \beta_2 (CF/K)_{i,t} + \beta_3 q_{i,t} + \delta_i + \eta_t + u_{i,t} \qquad (1)$$

$K_{i,t}$ is the real capital stock of firm *i* at time *t*, calculated using a forward iteration[6]; $(I/K)_{i,t}$ and $(CF/K)_{i,t}$ are the investment rate and cash flow rate. δ_i and η_t are a firm-specific effect and a time-specific effect, and $u_{i,t}$ is the idiosyncratic component of the error. $q_{i,t}$ is the proxy for Marginal *Q* suggested by Honda and Suzuki (2000)[7]. Building on the work by Yoshikawa (1980), Honda and Suzuki (2000) show that,

[6] As in Honda and Suzuki (2000), we compute the capital stock using a forward iteration based on the firm's depreciation policy. Specifically, the book value of net fixed assets one year prior to the start of the sample period is taken as the starting value for capital stock. Then, in subsequent years, the capital stock is calculated as $K_{i,t+1} = (1 - \rho_{i,t})K_{i,t} + I_{i,t}$, where ρ_{it} is firm *i*'s depreciation rate in year *t*. Our results were robust to simply using the book value of tangible fixed assets as a proxy for the capital stock.

[7] It should be noted that Honda and Suzuki (2000) focus their paper on large Japanese firms. Their proxy for investment opportunities is therefore not directly aimed at unlisted firms. Yet, because this proxy is not based on the market value of the firm, it is also applicable to unlisted firms.

under the assumptions of constant returns to scale and static expectations, Marginal Q can be expressed as the ratio of profit per unit of capital to the cost of capital, i.e.:

$$q_{i,t} = \frac{(\pi_{i,t}/K_{i,t-1})}{p_t(r_t+d)} \qquad (2)$$

where $\pi_{i,t}$ is gross profit (defined as ordinary income plus depreciation and interest payments, minus taxes); p_t is the price deflator for investment goods; r_t is the average after-tax nominal cost of debt; and d is the overall depreciation rate[8]. By allowing for a lagged dependent variable in Equation (1), we account for the potential lumpiness of investment (Caballero and Engel, 1999; Bloom et al., 2006; Cooper and Haltiwanger, 2006)[9].

3.1.2 GGAV model. In our second model (GGAV model), we use the industry-level growth in gross added value (GGAV) as an alternative proxy for investment opportunities. Added value is considered as an overall measure of efficiency. It is plausible to assume that exogenous efficiency shocks within a disaggregated industry give rise to a number of investment opportunities for all firms operating in that industry[10]. We therefore estimate the following equation:

$$(I/K)_{i,t} = \beta_0 + \beta_1(I/K)_{i,(t-1)} + \beta_2(CF/K)_{i,t} + \beta_3 GGAV_{i,t} + \delta_i + \eta_t + u_{i,t} \qquad (3)$$

where, denoting with $X_{S,t}$, the value of production and subsidies in industry S in year t[11]; with $U_{S,t}$, the total amount of expenses on intermediary goods in industry S in year t; and with Δ, the difference-operator, GGAV can be expressed as follows:

$$GGAV_{i\epsilon S,t} = \Delta(X_{S,t} - U_{S,t}) \qquad (4)$$

[8] As in Honda and Suzuki (2000), we use an exogenous value of 7.5% for the overall depreciation rate.
[9] We experimented with different lags of both dependent and independent variables and found that the most appropriate lag structure was that of Equation (1).
[10] Using industry-level variables to control for investment opportunities closely follows the intuition of Whited and Wu (2006).
[11] S is the firm's disaggregated NACE industry code, measured at the two-digit level.

3.1.3 Accelerator model. In our third model (Accelerator model), we include the ratio of lagged sales to capital stock (S_{-1}/K) as an additional independent variable in the investment equation. This yields:

$$(I/K)_{i,t} = \beta_0 + \beta_1(I/K)_{i,(t-1)} + \beta_2(CF/K)_{i,t} + \beta_3(S_{-1}/K)_{i,t} + \delta_i + \eta_t + u_{i,t} \qquad (5)$$

The ratio of lagged sales to capital stock is designed to reflect the sales accelerator theory of investment and has been used as a determinant for investment in Kadapakkam et al. (1998), Hoshi et al. (1991) and Guariglia (2008)[12].

3.2 Estimation methodology

We initially estimate equations (1), (3), (5), and a dynamic investment equation augmented with cash flow, which does not control for investment opportunities, using OLS, a fixed-effects estimator, a first-difference GMM estimator (Arellano and Bond, 1991), and a system-GMM estimator (Blundell and Bond, 1998). We then compare the sample-level ICFS estimates derived from these models. The GMM first-difference estimator accounts for unobserved firm heterogeneity by estimating the equation in first-differences. We control for the possible endogeneity of the regressors by instrumenting them with values of themselves lagged twice or more[13]. The system-GMM estimator is similar, except for the fact that it estimates the relevant equation in first-differences and levels in a system. The instruments in the differenced equation are values of the regressors lagged twice or more, while in the levels equation, the first-difference of the regressors lagged once are used as instruments.

Following D'Espallier et al. (2008), we then move on to estimate firm-varying ICFS. To this end, we allow the cash flow coefficients in the reduced-form investment equations to vary across firms, by introducing slope heterogeneity into the investment equations (1), (3), and (5) as follows:

$$(I/K)_{i,t} = \beta_0 + \beta_1(I/K)_{i,(t-1)} + \beta_{2,i}(CF/K)_{i,t} + \beta_3 q_{i,t} + \delta_i + \eta_t + u_{i,t} \qquad (6)$$

[12] Our results were robust to using the sales growth to capital ratio instead of the ratio of lagged sales to capital.

[13] As has been noted by many authors, cash flow and our investment opportunities measures are likely to be endogenous in our investment equation (Bond et al., 2003; Erickson and Whited, 2000). The first-difference GMM and system-GMM estimators account for this potential endogeneity bias and have been regularly used in the financing constraints literature.

$$(I/K)_{i,t} = \beta_0 + \beta_1 (I/K)_{i,(t-1)} + \beta_{2,i}(CF/K)_{i,t} + \beta_3 GGAV_{i,t} + \delta_i + \eta_t + u_{i,t} \quad (7)$$

$$(I/K)_{i,t} = \beta_0 + \beta_1 (I/K)_{i,(t-1)} + \beta_{2,i}(CF/K)_{i,t} + \beta_3 (S_{-1}/K)_{i,t} + \delta_i + \eta_t + u_{i,t} \quad (8)$$

In all specifications, $\beta_{2,i}$ is the firm-varying ICFS, which measures the firm's sensitivity of investment to cash flow after controlling for investment opportunities using in turn Marginal *Q*, GGAV, and the Accelerator term.

From a technical point of view, the estimation of the parameters from equations (6) to (8) is not an easy task for three reasons. First, the equation does not comply with the functional form of a typical linear panel data model such as a fixed effects or random effects model. Second, the number of parameters to be estimated is large with respect to the number of data-points which makes parameter estimates unstable and unreliable due to the loss in degrees-of-freedom. This is often referred to as the problem of *ill-positioning* causing traditional regression techniques to fail (Fraser, 2000; Golan et al., 1996). Finally, estimating the equations using traditional OLS-based techniques would involve many normality assumptions. In addition to the usual exogeneity assumption that requires the error to be independent from the regressors, one also has to assume normality for the heterogeneous intercept as well as for the heterogeneous slopes. Yet, it is widely documented in the econometrics literature that such normality assumptions are never met in practice and especially not when working with non-experimental data. This problem of *ill-conditioning* which is especially severe in social science research causes parameter estimates to be inaccurate and specification tests to be unreliable (Fraser, 2000).

In conclusion, there are sufficient technical arguments to refrain from using traditional regression techniques when modelling heterogeneous slopes in the context of panel data. We therefore estimate Equations (6) to (8) using a Bayesian estimator. As has been noted by several authors, the Bayesian estimation method is a more appropriate method when modelling heterogeneous slopes because it allows for a full probabilistic inference of all parameters including the firm-varying ones, without relying on any normality assumption (Berry, 1996). Alternatively, as Hansen et al. (2004) put it, the Bayesian estimation method is a more congruent empirical approach if one is interested in isolating the effects for individual firms and providing a meaningful interpretation of firm-level results. Details about this estimation procedure can be found in the Appendix.

3.3 Ex-post analysis

In order to assess the extent to which our estimated firm-varying ICFS are adequate measures of financing constraints, we next regress them on a set of proxies for financing constraints, and analyze whether the signs of the coefficients associated with each of these proxies are consistent with our expectations. This will be referred to as our ex-post-analysis. We use a wide selection of variables as proxies for financing constraints, which are related to the firm's size, liquidity, profitability, and leverage positions, as well as the firm's dependence upon external finance. All the variables investigated have been used in previous literature on financing constraints. Several papers have noted that financially constrained firms usually pay fewer dividends (e.g. Fazzari et al., 1988), are smaller (e.g. Carpenter and Petersen, 2002), hold less cash (e.g. Kaplan and Zingales, 1997), are more leveraged (e.g. Moyen, 2004; Whited and Wu, 2006), and have lower profitability ratios (Kaplan and Zingales, 1997; Cleary, 1999) than their unconstrained counterparts. In our ex-post regression analysis, we therefore expect to observe a negative relationship between our estimated ICFS and the dividend payout ratio, total assets, the cash ratio, the interest coverage ratio, and *EBIT;* and a positive relationship between our estimated ICFS and leverage. In addition we investigate the link between ICFS and the firm's dependence on external finance measured as the share of investments in fixed assets that cannot be financed with internally generated funds. This variable has been used as an exogenous measure for financing constraints in a recent paper by Duchin et al., (2010). We therefore expect a positive relation between the estimated ICFS and the dependence on external funds.

In Table 1, we summarize the different proxies for financing constraints that we consider, the relationship we expect them to have with firms' financing constraints status, and the sign we expect them to display in our ex-post analysis.

< Insert 'Table 1. Proxies for financing constraints and hypotheses' around here >

4. DATA AND SUMMARY STATISTICS

4.1 Data

Balance sheets and income statements were extracted from the *Bel-first* dataset published by Bureau Van Dijk for a large sample of Belgian SMEs over the period 2002-2008. According to the standard OECD definition, a SME is defined as a firm with less than 250 full-time equivalent employees, total assets less than €45,000,000, and turnover less than €50,000,000. Based on a two-digit NACE classification, we excluded firms active in the agricultural sector (NACE 00-05), the financial sector (NACE 65-67), and the service sector (NACE 60-64). Firms with less than 5 employees were also removed from the dataset since these firms have usually a low asset base and low investment needs.

Our final dataset consists of 5,999 firms over 7 years, which is equivalent to 41,993 firm-year observations. Outliers were removed from the dataset by trimming the highest and lowest 1% of the distribution of the key variables. This is a standard procedure in the literature on financing constraints (Bhagat et al., 2005). Additionally, extreme values, defined according to a standard statistical check, were manually removed[14].

4.2 Summary statistics

Table 2 reports summary statistics for the main variables used in our analysis[15]. The median firm in our sample has total assets of € 1.3 million and annual sales of € 1.8 million. The median firm's sales growth is 5.63%; its investment rate, 18.07%; and its cash flow rate, 31.65%[16]. The dividend payout ratio has a mean of 0.91% and a median value of 0.00%, indicating that the majority of Belgian SMEs do not pay out any dividends. The debt ratio has a mean value of 65.71%, which indicates that on average, firms have exhausted much of their debt capacity. Looking at the cash ratio (median value 6.24%), we see that cash reserves are not particularly high. Similarly,

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[14] As in D'Espallier et al. (2008), the following criterion was used to identify extreme values: observation x is an extreme value if $Q_1 - (3 * IQR) > x > Q_3 + (3 * IQR)$, where Q_1 and Q_3 are its first and third quartile, respectively, and IQR is its inter-quartile range.

[15] As all our investment models include a lagged dependent variable, the year 2002 is used to construct the latter. Our estimates are therefore based on the years 2003-2008. For consistency, our descriptive statistics also refer to this same time period.

[16] Note that firms in Belgium are not required to report their sales. This explains the large number of missing variables characterizing this variable and its growth in Table 2.

the interest coverage (median value 1.86) and the EBIT to total assets ratio (median value 4.58%) suggest that profitability is also not particularly high during the sample period. Overall, the summary statistics seem to indicate that financing constraints may have been severe in our sample.

< Insert 'Table 2. Summary statistics' around here >

In Table 3 we analyze our proxies for investment opportunities (Marginal *Q*, GGAV, and the Accelerator term) in detail by providing a number of summary statistics for each of these proxies in each of the years making up our sample. As can be seen there is considerable variation over the sample period for all three proxies investigated. Moreover, all three proxies point towards increased investment opportunities in later years (2006-2008) in comparison with earlier years (2003-2005) of the sample period[17].

< Insert 'Table 3. Investment opportunities proxies' around here >

5. EMPIRICAL RESULTS

5.1 Reduced-form investment equations

Table 4 reports the estimates of our reduced-form investment equations, obtained using standard regression techniques. Besides the OLS estimator and the fixed-effects-estimator (FE), we also make use of the GMM first-difference estimator, and the system-GMM estimator to account for the potential endogeneity of the regressors[18].

Panel A of Table 4 reports the regression results for the model without any control for investment opportunities, and for the Marginal *Q* model. In Panel B, we report the regression results for the GGAV model and the Accelerator model. As can be seen from column (1), cash flow is highly significant at the 1% significance level with an estimated coefficient of 0.47, which suggests that a 1% increase in cash flow is associated with an increase in investment of 0.47%. Lagged investment is also

[17] GGAV, however, shows a drop in 2008, which was probably due to the effects of the financial crisis.

[18] Note that the estimates obtained using the first-difference GMM estimator are based on a smaller sample than those obtained using the other estimators, as one observation per firm is lost through the first-differencing process.

highly significant at the 1% significance level with an estimated coefficient of 0.17. As a result, the long-run investment response due to a change in cash flow is 0.56[19]. As can be seen comparing columns (1) and (2), the OLS and FE estimators produce very similar results. In columns (3) and (4), we report the first-difference and system-GMM estimates. Again, cash flow and lagged investment are highly significant with estimated values of 0.57-0.58 and 0.06-0.08, respectively, leading to a long-run ICFS of 0.61 in both cases. The validity of the instruments was tested using the Sargan test of overidentifying restrictions, as well as the *m2* test of serial correlation of the differenced residuals[20]. Both tests do not reject the null hypothesis, suggesting that the instruments are valid. The ICFS estimates obtained using GMM are higher than those obtained with OLS and the fixed-effects estimator. This may reflect the fact that the latter suffer from endogeneity bias.

Estimates of the Marginal *Q* model are reported in columns (5) to (8) of Panel A of Table 4. We can see that the proxy for Marginal *Q* is always highly significant at the 1% significance level, with an estimated coefficient of 0.02 and 0.05 respectively in the OLS and the fixed-effects cases, and a coefficient of 0.01-0.02 in the GMM cases. In line with the benchmark model with no control for investment opportunities, lagged investment and contemporaneous cash flow are always highly significant at the 1% level, leading to a long-run ICFS of 0.43 and 0.56 in columns (5) and (6), and 0.69 and 0.67 in columns (7) and (8). The long-run ICFS obtained when investment opportunities are controlled for using Marginal *Q* are very similar to to those obtained in the model with no control for investment opportunities. Once again, in columns (7) and (8), the Sargan and *m2* tests do not reject the validity of the instruments.

Panel B of Tables 4 presents the estimates obtained using the Accelerator and GGAV models. Estimates of the former are presented in columns (1) to (4), and estimates of the latter in columns (5) to (8). Columns (1)-(4) indicate that the Accelerator term is a positive and significant determinant for investment, regardless of the estimation method being used. In line with the other models, lagged investment

[19] This is given by the coefficient of cash flow divided by 1 minus the coefficient of lagged investment.

[20] The Sargan test is a test for overidentifying restrictions. Under the null of instrument validity, this test statistic is asymptotically distributed as a chi-square with degrees of freedom equal to the number of instruments less the number of parameters. The *m2* test is asymptotically distributed as a standard normal under the null of no second-order serial correlation of the differenced residuals, and provides a check on the legitimacy of variables dated *t*-2 as instruments in the differenced equations. Since the most recent instruments used in our first-difference and system-GMM estimations are of the order *t*-2 (2^{nd} lags), we only report the tests for 1^{st} and 2^{nd} order serial correlation of the differenced residuals.

and contemporaneous cash flow are always highly significant and the long-run ICFS are very similar to those obtained with the other models. GGAV is a significant determinant of investment with an estimated coefficient of 0.18 and 0.17 in the OLS and fixed-effects cases, and of 0.04 in the first-difference and system GMM cases. Again, lagged investment is always highly significant and the long-run ICFS is around 0.53 in columns (1) and (2), and around 0.63 in columns (3) and (4). The ICFS estimates are very similar to those obtained in the benchmark model with no control for investment opportunities, and in the Marginal *Q* model, and the diagnostic statistics indicate that our instruments are valid.

In summary, the analysis in Table 4 indicates that both Marginal *Q* and GGAV are highly significant in the cash flow-augmented reduced-form investment equations. The Accelerator term is also positive, although significance levels are generally lower. Cash flow always remains highly significant at the 1% level when the different proxies of investment opportunities are used, suggesting a significant sensitivity of investment to cash flow, which persists even after controlling for investment opportunities. Additionally, lagged investment always displays a highly significant and positive coefficient, indicating that the long-run investment response due to a change in cash flow is significantly higher than the short-run investment response.

As the ICFS estimates are very similar across the different models that we estimated, we can conclude that using different controls for investment opportunities has only a minimal impact on the sample-level ICFS estimates.

< Insert ‘Table 4. Reduced-form investment equations’ around here >

5.2 Firm-varying ICFS estimates

Panel A of Table 5 reports summary statistics for the firm-varying long-run ICFS estimated from the benchmark model (column 1), Marginal *Q* model (column 2), Accelerator model (column 3), and GGAV model (column 4), using the Bayesian estimation procedure. The table shows that the mean ICFS is 0.55 for the benchmark model which does not control for investment opportunities, the Accelerator model and the GGAV model, and 0.51 for the Marginal *Q* model. Although the differences are rather small, the median ICFS is also slightly lower for the Marginal Q model in comparison with the other models.

The vast majority of firms (68.5%, 52.7%, 68.3% and 68.6%, respectively for the benchmark, Marginal *Q*, GGAV, and Accelerator models) have a long-run ICFS in the range of 0.50 to 1. Yet, in a limited number of cases, the firm-varying ICFS values are negative (suggesting that firms may increase their investments despite drops in cash flow or vice versa), or larger than 1 (suggesting that the investment response may be larger than the original cash flow shock)[21]

Panel B of Table 5 analyzes the correlation between the firm-varying ICFS estimates obtained from the different models, making use of the Pearson correlation coefficient. We can see that the correlation coefficients are very high and always statistically significant: firms which display a high (low) ICFS in the benchmark model with no control for investment opportunities will also display a high (low) ICFS in the other models.

In summary, in line with the regression analysis presented in the previous sub-section, these findings confirm that including different proxies for investment opportunities in our models has a very limited impact on the ICFS estimates.

< Insert 'Table 5. Firm-varying ICFS-estimates and their correlations' around here >

5.3 Ex-post analysis of financing constraints

Table 6 reports the regression results from the ex-post analysis in which the firm-varying long-run ICFS estimates obtained using the Bayesian estimator for the benchmark model (column 1), the Marginal *Q* model (column 2), the Accelerator model (column 3), and the GGAV model (column 4) are regressed against several proxies of financing constraints. Overall, the regression outputs return the signs that were hypothesized in Table 1.

Column (1) shows that the firm-varying ICFS estimated from the benchmark model with no control for investment opportunities are negatively related to the dividend payout ratio, the cash ratio, the EBIT to assets ratio and the interest coverage ratio. The coefficients on the debt ratio and external finance dependence are positive and significant. These findings indicate that firms with a higher ICFS pay out fewer dividends, carry less cash and are significantly less profitable. Furthermore, they have higher debt levels and depend more on external finance. These results suggest a tight

[21] See Guariglia (2008) for a discussion of how negative cash flow coefficients can be interpreted in an investment regression.

link between the firm-varying ICFS and financing constraints. Contrary to the predictions reported in Table 1, in all models, firm size is positively related to the firm-varying ICFS, suggesting that large firm are more financially constraints than their smaller counterparts. This apparently counter-intuitive result can be explained considering that within our sample of SMEs, the larger firms may be less financially flexible and less able to make use of working capital to alleviate the effects of financing constraints on fixed investment. Similar results were obtained in the Chinese context by Chow and Fung (2000) and Ding et al. (2010).

Interestingly, as can be seen from columns (2), (3) and (4) of Table 6, the regression results are very similar when using the ICFS computed from the other reduced-form investment equations. In general, we observe similar signs, similar coefficient magnitudes, and similar confidence levels, regardless of the model under study[22]. This indicates that the ICFS derived from the Marginal *Q*, GGAV, and Accelerator models are all positively related to the existence of financing constraints.

< Insert 'Table 6. Ex-post regression analysis' around here >

5.4 Mean values in different ICFS classes

Following D'Espallier et al. (2008), Hovakimian and Hovakimian (2009), and Hovakimian (2009), in Table 7, we report mean values for the proxies for financing constraints in different classes defined on the basis of our estimated ICFS. Specifically, firms are assigned to the high ICFS class if they have an estimated ICFS above the 70th percentile of the ICFS distribution. Similarly, firms are assigned to the low ICFS class if they have an estimated ICFS below the 30th percentile[23].

The results, which are presented in Panels A, B, C, and D of Table 7, respectively for the benchmark model, the Marginal *Q* model, the GGAV model, and the Accelerator model, are in line with the ex-post regression analysis presented in Table 6. In particular, firms assigned to the high ICFS class are in general less liquid

[22] We also ran the analysis with sales and sales growth excluded from the ex-post regression. This increased the number of observations because sales are often not reported (see footnote 16). Similar results to those in Table 6 were obtained.

[23] A drawback of this analysis, which we report to ensure comparability of our findings with the literature, is that the results are dependent on the choice of cut-off points. We experimented with different cut-off points and the results remained similar. Performing the ex-post analysis in terms of a regression aimed at explaining the determinants of the firm-level ICFS (as discussed in Section 5.3) is a preferred strategy as it is not sensitive to cut-off points.

in terms of their cash ratio, and have lower profitability, and a lower coverage ratio than firms assigned to the low ICFS class. Furthermore, firms in the high ICFS class have higher debt levels and show a higher dependence on external funds. The independent *t*-tests indicate that the differences between the groups are generally highly significant. Once again, these results hold regardless of the way in which investment opportunities are controlled for.

In summary, all our models yield similar ICFS estimates, which are significantly related to a wide set of proxies for financing constraints. These findings suggest that the ICFS of SMEs are unlikely to simply reflect investment opportunities.

< Insert ‘Table 7. Mean values in different ICFS classes’ around here >

6. CONCLUSIONS

The empirical literature on financing constraints is characterized by a substantial debate surrounding the role of cash flow in reduced-form investment equations. Some studies argue that positive and statistically significant ICFS signal the presence of financing constraints (Gilchrist and Himmelberg, 1995; Gugler et al., 2004), while others conclude that cash flow is a significant determinant of investment simply because it captures investment opportunities (Erickson and Whited, 2000; Bond et al., 2004; Cummins et al., 2006). This so-called investment opportunities bias has hindered further advances in this literature.

In this paper, we study the effects of the investment opportunities bias in a large sample of unlisted Belgian SMEs. We first identify three different measures of investment opportunities, which are suitable for unlisted firms. We then use a Bayesian estimator to derive firm-varying ICFS for different reduced-form investment models that include these controls for investment opportunities, and regress these estimates on a wide variety of proxies for financing constraints. In line with recent studies in the field such as Hovakimian and Hovakimian (2008) and D’Espallier et al., (2008), this exercise gives us an indication of the extent to which the ICFS resulting from a particular model can be related to the existence of financing constraints.

Our results indicate that the ICFS derived from all models are significantly related to our set of proxies for financing constraints. Additionally, the different models yield very similar estimates of the firm-varying ICFS, and the correlation between the ICFS obtained from the different models is particularly high. Even the benchmark model with no control for investment opportunities has considerable explanatory power in terms of financing constraints. Overall, these findings suggest that the ICFS of unlisted SMEs do not simply reflect investment opportunities, but signal the existence of financing constraints. The investment opportunities bias may therefore have been overstated in previous literature.

Our research could be extended in several directions. First, it would be interesting to see whether our results hold for other investment models, such as the error-correction model (Bond et al., 2003; Guariglia, 2008) or the Euler-equation model (Whited, 1992). Second, other proxies for investment opportunities could be developed in the context of small unlisted businesses. Third, although our ex-post regression analysis is based on a wide variety of financial variables that have a long-standing tradition in the literature, other proxies for financing constraints could be analyzed. This could offer interesting opportunities to look for other determinants of the ICFS. Fourth, in this study, the Bayesian estimator has been used to estimate the firm-varying ICFS. Yet, this is not the only estimator suited to tackle slope heterogeneity in the context of panel data. It would be interesting to assess whether our results hold with alternative estimation techniques. Finally, it would be interesting to see whether similar results can be found for different countries, characterized by different degrees of financial development. These extensions are in the agenda for future research.

METHODOLOGICAL APPENDIX ON BAYESIAN ECONOMETRICS

According to the Bayesian philosophy, parameters are estimated by combining prior information on these parameters with data, using Bayes' theorem, i.e.

$$p(\theta|y) \approx p(y|\theta).p(\theta) \qquad \text{(A1)}$$

Equation (A1) represents the continuous version of Bayes' conditional probability theorem, stating that the distribution of a certain parameter θ, conditional on the data y, $p(\theta|y)$ can be calculated by combining the distribution of the data $p(y|\theta)$ with the prior distribution on the parameter $p(\theta)$. The term $p(y|\theta)$ is generally referred to as the *likelihood* and summarizes the probability of the data for each possible value of the parameter. The element $p(\theta)$ is referred to as the prior information: it summarizes all existing prior knowledge on the parameter. The outcome of combining these two elements is the posterior density $p(\theta|y)$, which summarizes the new and updated belief of the parameter θ based upon what was already known about the parameter (the prior) and new evidence brought on by the data (the likelihood). This whole process of combining likelihood and prior information into a posterior density is also referred to as 'Bayesian updating' or 'Bayesian learning'.

Although the mathematical foundation of the Bayesian method dates back to the work of reverend Thomas Bayes (1702-1761), it was only in the late 1980s that this mathematical formula was put into practice in the field of statistics. The reason for the late application of this method was that only at that time numerical sampling-techniques such as Markov chain Monte Carlo-methods (Gibbs-sampler, Metropolis-Hastings algorithm) became popular. Nowadays, with the sampling techniques available, one can sample directly from the posterior density which is the joint density of likelihood and prior, without having to spell out probability densities for the prior and the likelihood separately.

The described method of recovering information about a certain parameter can be extended to estimate the parameters of a regression model. Specifically, Lancaster (2004), Koop (2003), and Hansen et al. (2004), which made the foundation of Bayesian econometrics, suggest a 5-step algorithm to estimate the parameters of any regression model[24].

Suppose that we wish to estimate the parameters of a panel data regression model with two regressors of the following type:

$$y_{i,t} = \beta_0 + \beta_1 x1_{i,t} + \beta_2 x2_{i,t} + u_{i,t} \tag{A2}$$

In the first step, the econometric model is written as a probability model conditional upon different values for the set of parameters. For instance, we could have:

$$y_{i,t} \approx N(\mu_{i,t}, \sigma_t^2) \tag{A3}$$

[24] The Bayesian algorithm can be applied to any kind of regression model such as for instance, linear regressions, non-linear regressions, probit/logit regressions, instrumental variables regressions etc. in the context of time-series or panel data.

$$\mu_{i,t} = \beta_0 + \beta_1 x1_{i,t} + \beta_2 x2_{i,t} \tag{A4}$$

Equations (A3) and (A4) state that the dependent variable $y_{i,t}$ can be considered as the realization of a normal distribution with expected value given by the regression model itself. In the second step, for each parameter, prior information is written down in the form of a probability distribution. Usually vague or uninformative priors are taken so that priors encompass reasonable values for the parameters. For instance:

$$\beta_0 = N(0{,}100) \tag{A5}$$
$$\beta_1 = N(0{,}100) \tag{A6}$$
$$\beta_2 = N(0{,}100) \tag{A7}$$
$$\tau = 1/\sigma_t^2 = \Gamma(0.001\,, 0.001) \tag{A8}$$

Equations (A5)-(A8) describe vague information about the parameters of the regression model by expressing them as a realization of a normal distribution with expected value zero and a wide variation. In the third step, the data are collected and inserted in the probability model. To this end, given the availability of sampling-techniques, the data are simply inputted in a Bayesian software. Step 4 then calculates the updated belief about each parameter by sampling numerically from the joint posterior density which yields a full distribution for each parameter as follows:

$$\hat{\theta} = (\widehat{\beta_0}, \widehat{\beta_1}, \widehat{\beta_2}, \hat{\tau}) \tag{A9}$$

Step 5 consists of critically evaluating the results by changing the prior information. This is important to convince readers that the results are not driven by subjective choice of the prior values. Although usually vague priors are being used and although it can be shown that the data dominates the prior information when samples are large (likelihood dominance)[25], the use of prior information as a building

[25] It can be shown that the posterior mean is the weighted sum of the prior mean and the sample mean with weights given by the precision (1/variance) of the prior mean and sample mean as follows: $\bar{\mu} = \frac{w_0}{w_0+w_1}\mu_0 + \frac{w_0}{w_0+w_1}\bar{y}$ where $\bar{\mu}, \mu_0\,, \bar{y}$ are the posterior mean, prior mean and sample mean, respectively and the weights are given by $w_0 = 1/\sigma_0^2\,, w_1 = \sigma^2/N$. The larger N, the less will the posterior distribution depend on the prior, and the more on the likelihood.

block in addition to data is sometimes perceived problematic for non-Bayesian researchers.

A number of ready-made software packages are available for undertaking Bayesian inference. Among these are 1st Bayes and WINBUGS (Bayesian Inference Using Gibbs Sampler). We use WINBUGS for our calculations of the firm-varying ICFS estimates. This is a menu-driven program that performs the Bayesian calculations using the GIBBS-sampler and offers a number of tools for exploring the posterior densities of the parameters. In addition, the program offers all kinds of diagnostic statistics such as trace plots[26], histograms, density plots and so on. A typical WINBUGS-run involves syntax checking, data-loading, specifying initial values for the MCMC-chains, running the Bayesian calculations and exploring the posterior densities and diagnostic statistics.

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[26] MCMC-methods for sampling from the posterior density require initial values to start the sampling-procedure. Trace-plots indicate whether or not different chains that use different initial values converge to similar values sampling-values.

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TABLES AND FIGURES

Table 1. Proxies for financing constraints and hypotheses

This table lists a number of variables related to the firm's financial constraints status, which have been widely used in previous literature. *lnTA* stands for the natural logarithm of total assets. The penultimate column indicates the relationship between each variables and the firm's financial constraints status. The last column summarizes the expected relationship between our proxies for financing constraints and the firm's investment-cash flow sensitivity (ICFS), assuming that ICFS are a good proxy for financing constraints. For definitions of all variables, see Table 2.

Observables	Variables	Relation with financial constraints	Hypotheses with respect to the ICFS *If the ICFS is a good indicator for financing constraints, then:*
Dividend payout policy	*Payout ratio*	negative	the payout ratio is negatively related to the ICFS
Liquidity position	*Cash ratio*	negative	the cash ratio is negatively related to the ICFS
Size	*lnTA*	negative	*lnTA* is negatively related to the ICFS
Leverage position	*Debt ratio*	positive	the debt ratio is positively related to the ICFS
Profitability position	*EBIT/TA*	negative	*EBIT/TA* is negatively related to the ICFS
Interest coverage	*Interest coverage*	negative	the interest coverage is negatively related to the ICFS
External finance dependence	*EFD*	positive	*EFD* is positively related to the ICFS

Table 2. Summary statistics

This table presents a number of summary statistics for a selection of financial and general variables for our sample of 41,993 firm-year observations. *TA* (total assets) and *Sales* are measured in thousands of euros. *LnTA* and *lnSales* are the natural logarithm of total assets and total sales, respectively. *Sales growth* is the percentage change in total sales. *(I/K)* is the change in real net fixed assets (Plan, Property and Equipment) between year *t* and *t-1*, divided by beginning-of-year capital stock *K*. *(CF/K)* is net income after interests and taxes plus depreciation and amortization divided by beginning-of-year capital stock. *Payout ratio* is the sum of total dividends over total assets. *Debt ratio* is total debt divided by total assets. *Cash ratio* is liquid assets divided by total assets. *Interest coverage* is defined as net income divided by the sum of interest expenses and preferred dividends. *(EBIT/TA)* is earnings before interest and taxes divided by total assets. *EFD* is external finance dependence measured as the share of investments in fixed assets that cannot be funded through funds from operations (investments in PP&E minus funds from operations / investments in PP&E).

	n	*mean*	*median*	*st.dev.*	*min*	*max*
TA	41,239	1,805	1,278	1,997	0.187	88,000
lnTA	41,239	13.76	14.06	1.63	5.23	18.29
Sales	12,874	3,860	1,832	5,933	0.100	172,000
lnSales	12,874	13.63	14.42	2.59	1.94	18.96
Salesgrowth	11,447	17.42%	5.63%	37.77%	-100%	100%
I/K	32,505	31.20%	18.07%	34.76%	0.00%	131%
CF/K	33,725	39.21%	31.65%	32.24%	-20.00%	120.00%
Payout rate	41,239	0.91%	0.00%	2.79%	0.00%	17.00%
Debt rate	35,817	65.71%	68.41%	19.80%	1.74%	98.00%
Cash rate	41,239	10.95%	6.24%	13.16%	0.00%	100.00%
Interest coverage	41,072	2.63	1.86	4.14	-10.00	10.00
EBIT / TA	41,220	5.21%	4.58%	7.08%	-15.00%	27.00%
EFD	41,993	16.86%	22.87%	30.19%	-81.00%	77.00%

Table 3. Investment opportunities proxies

This table presents mean, median, minimum, maximum, and standard deviation for our measures of investment opportunities for our sample of 5,999 SMEs, over the observed sample period.

Marginal *Q*	**all years**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
mean	2.27	2.17	1.99	1.93	2.75	2.96	3.27
median	1.58	1.74	1.51	1.36	1.85	2.00	2.17
min	0.001	0.001	0.001	0.001	0.001	0.001	0.001
max	17.39	17.39	17.39	17.39	17.39	17.39	17.39
st.dev	2.59	1.96	2.08	2.31	3.00	3.21	3.45
Accelerator	**all years**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
mean	9.53	8.63	9.04	9.58	9.79	10.95	10.58
median	5.25	4.96	4.98	5.24	5.10	5.92	6.13
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	80.00	80.00	80.00	80.00	80.00	80.00	80.00
st.dev	13.52	12.19	12.90	13.49	14.21	15.41	14.25
GGAV	**all years**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
mean	0.022	0.008	0.029	0.001	0.062	0.032	0.002
median	0.034	0.016	0.041	0.018	0.062	0.047	0.018
min	-0.380	-0.381	-0.382	-0.383	-0.384	-0.385	-0.386
max	0.350	0.351	0.352	0.353	0.354	0.355	0.356
st.dev	0.174	0.154	0.156	0.172	0.190	0.178	0.186

Table 4. Reduced-form investment equations

This table reports the regression results for the Marginal *Q* model (equation 1), the GGAV model (equation 3), the Accelerator model (equation 5), and for a benchmark model that does not control for investment opportunities. In Panel A, we report the results for the benchmark model and the Marginal *Q* model. In Panel B, we report the results for the GGAV model and the Accelerator model. FE, GMM and SYS-GMM represent respectively the Fixed Effects estimator, the GMM estimator developed by Arellano and Bond (1991), and the system-GMM estimator developed by Blundell and Bond (1998). Robust standard errors are provided in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively. Time dummies are included in all specifications. ICFS denote the long-run investment-cash flow sensitivities. Sargan reports the *p*-value of the Sargan test of overidentifying restrictions, which tests the null that the instruments are uncorrelated with the error term. 1st order corr. reports the *p*-value for the test for 1st order autocorrelation of the differenced residuals. 2nd order corr. reports the *p-value* for the test for 2nd order autocorrelation of the differenced residuals.

Panel A. Benchmark model and Marginal *Q* model

Dep. var.: I/K	**Benchmark model**				**Marginal Q model**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(CF/K)	0.47	0.39	0.58	0.57	0.39	0.48	0.67	0.62
	(0.007)***	(0.009)***	(0.018)***	(0.014)***	(0.009)***	(0.016)***	(0.021)***	(0.002)***
$(I/K)_{-1}$	0.17	0.11	0.06	0.08	0.10	0.14	0.04	0.08
	(0.006)***	(0.006)***	(0.009)***	(0.008)***	(0.008)***	(0.008)***	(0.012)***	(0.012)***
Q					0.02	0.05	0.01	0.02
					(0.002)***	(0.002)***	(0.004)***	(0.003)***
ICFS	**0.56**	**0.43**	**0.61**	**0.61**	**0.43**	**0.56**	**0.69**	**0.67**
N	27,274	22,678	22,197	27,274	22,678	22,679	16,941	22,679
F-stat / Chi-2 stat	948***	913***	1,290***	1,719***	739***	287***	1,157***	1,410***
Sargan (p-value)			0.77	0.23			0.46	0.14
1st order autocorr. (p-value)			0.00	0.00			0.00	0.00
2nd order autocorr. (p-value)			0.64	0.19			0.62	0.36
method	OLS	FE	GMM	SYS-GMM	OLS	FE	GMM	SYS-GMM

Panel B. Accelerator model and GGAV model

Dep. var.: I/K	**Accelerator model**				**GGAV model**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(CF/K)	0.51	0.51	0.61	0.61	0.48	0.48	0.59	0.59
	(0.018)***	(0.018)***	(0.030)***	(0.029)***	(0.007)***	(0.008)***	(0.012)***	(0.012)***
$(I/K)_{-1}$	0.10	0.11	0.10	0.10	0.10	0.10	0.06	0.08
	(0.009)***	(0.009)***	(0.025)***	(0.016)***	(0.005)***	(0.005)***	(0.008)***	(0.006)***
(S_{-1} / K)	0.01	0.01	0.01	0.01				
	(0.003)**	(0.003)**	(0.002)*	(0.002)*				
GGAV					0.18	0.17	0.04	0.04
					(0.074)***	(0.073)***	(0.004)***	(0.005)***
ICFS	**0.56**	**0.57**	**0.67**	**0.67**	**0.53**	**0.53**	**0.63**	**0.64**
N	27,274	22,678	22,197	27,274	22,678	22,679	16,941	22,679
F-stat / Chi-2 stat	948***	913***	1,290***	1,719***	739***	287***	1,157***	1,410***
Sargan (p-value)			0.77	0.18			0.46	0.00
1st order autocorr. (p-value)			0.00	0.00			0.00	0.00
2nd order autocorr. (p-value)			0.64	0.19			0.62	0.36
method	OLS	FE	GMM	SYS-GMM	OLS	FE	GMM	SYS-GMM

Table 5. Firm-varying ICFS estimates and their correlations

ICFS-bench, ICFS-Q, ICFS-ACC, and ICFS-GGAV indicate the ICFS derived respectively from the benchmark model that does not control for investment opportunities, the Marginal *Q* model, the Accelerator model, and the GGAV model. Panel A presents a number of summary statistics for the firm-varying ICFS estimates obtained from the different reduced-form investment equations, estimated using the Bayesian estimator described in the Appendix. *P(x)* represents the x^{th} percentile. Panel B presents the Pearson correlation coefficient between the firm-varying sensitivities in the four models. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Panel A. Bayesian estimation

	ICFS_bench	ICFS_Q	ICFS_ACC	ICFS_GGAV
Mean	0.548	0.507	0.547	0.549
Median	0.545	0.503	0.544	0.544
Min	0.037	-0.151	0.039	-0.315
Max	1.134	1.139	1.135	1.143
st.dev	0.141	0.146	0.142	0.143
P(0.01)	0.182	0.119	0.177	0.178
P(0.05)	0.306	0.255	0.305	0.304
P(0.10)	0.374	0.328	0.373	0.373
P(0.30)	0.496	0.455	0.494	0.496
P(0.70)	0.588	0.549	0.589	0.588
P(0.90)	0.74	0.705	0.741	0.743
P(0.95)	0.798	0.766	0.799	0.8
P(0.99)	0.911	0.891	0.917	0.917
prop. < 0	0.00%	0.03%	0.00%	0.05%
prop. in (0, 0.5)	31.28%	47.04%	31.57%	31.23%
prop. in (0.50, 1)	68.54%	52.67%	68.26%	68.56%
prop. > 1	0.15%	0.10%	0.15%	0.17%

Panel B. Correlations

	ICFS_bench	ICFS_Q	ICFS_ACC	ICFS_GGAV
ICFS_bench	1			
ICFS_Q	0.989***	1		
ICFS_ACC	0.997***	0.989***	1	
ICFS_GGAV	0.997***	0.988***	0.996***	1

Table 6. Ex-post regression analysis

This table presents the estimates obtained from regressing the firm-varying ICFS estimates on the proxies for financing constraints using OLS. ICFS-bench, ICFS-Q, ICFS-ACC, and ICFS-GGAV indicate the ICFS derived respectively from the benchmark model that does not control for investment opportunities, the Marginal *Q* model, the Accelerator model, and the GGAV model. Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and clustered at the firm-level. RMSE is the root mean squared error. R^2_{adj} is the adjusted R^2. *, **, and *** denote statistical significance at the 10%, 5% and 1% significance level, respectively.

Dep. var.: ICFS(i)	**ICFS_bench**	**ICFS_Q**	**ICFS_acc**	**ICFS_GGAV**
payout ratio	-0.59	-0.63	-0.60	-0.61
	(0.054)***	(0.056)***	(0.044)***	(0.055)***
lnTA	0.002	0.002	0.002	0.002
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
cash ratio	-0.06	-0.07	-0.07	-0.06
	(0.015)***	(0.016)***	(0.015)***	(0.016)***
debt ratio	0.12	0.13	0.12	0.12
	(0.008)***	(0.009)***	(0.008)***	(0.008)***
EBIT / TA	-0.07	-0.10	-0.07	-0.07
	(0.031)**	(0.033)***	(0.031)***	(0.032)***
interest coverage	-0.01	-0.01	-0.01	-0.01
	(0.001)*	(0.001)*	(0.001)*	(0.001)*
external finance dependence	0.09	0.09	0.09	0.09
	(0.006)***	(0.006)***	(0.006)***	(0.006)***
N	35,725	35,726	35,727	35,728
F-stat	104.84***	115.01***	105.42***	104.90***
R^2 adj.	0.11	0.12	0.11	0.11
RMSE	0.13	0.14	0.13	0.13

Table 7. Mean values in different ICFS classes

This table present mean values for the proxies for financing constraints in two mutually exclusive ICFS classes for the benchmark model (panel A), the Marginal *Q* model (panel B), the Accelerator model (panel C) and the GGAV model (panel D). Firms are assigned to the high (low) ICFS class if they are characterized by an ICFS higher (lower) than the 70th percentile (30th percentile) of the ICFS distribution. The last column in each Panel presents *t*-values from an independent samples *t*-test. *, **, and *** denote statistical significance at the 10%, 5% and 1% level.

Panel A. Benchmark model

	Low ICFS	High ICFS	t-stat
payout ratio	1.43%	0.48%	26.26***
lnTA	14.02	14.07	-4.25***
cash ratio	14.00%	9.51%	26.60***
debt ratio	60.78%	69.84%	-34.92***
EBIT / TA	6.68%	4.62%	23.29***
interest coverage	3.64	2.26	27.18***
external finance dependence	9.03%	24.77%	-42.53***

Panel B. Marginal Q model

	Low ICFS	High ICFS	t-stat
payout ratio	1.44%	0.47%	26.83***
lnTA	14.02	14.07	-3.76***
cash ratio	14.16%	9.44%	27.87***
debt ratio	60.48%	69.91%	-36.43***
EBIT / TA	6.81%	4.52%	25.78***
interest coverage	3.71	2.21	29.49***
external finance dependence	9.31%	24.88%	-42.25***

Panel C. Accelerator model

	Low ICFS	High ICFS	t-stat
payout ratio	1.42%	0.49%	25.63***
lnTA	14.01	14.07	-5.31***
cash ratio	13.99%	9.48%	26.69***
debt ratio	60.71%	69.85%	-35.15***
EBIT / TA	6.68%	4.62%	23.12***
interest coverage	3.64	2.25	27.17***
external finance dependence	9.27%	24.58%	-41.22***

Panel D. GGAV model

	Low ICFS	High ICFS	t-stat
payout ratio	1.41%	0.48%	25.68***
lnTA	14.01	14.07	-4.87***
cash ratio	14.04%	9.53%	26.66***
debt ratio	60.59%	69.72%	-35.20***
EBIT / TA	6.66%	4.64%	22.68***
interest coverage	3.63	2.27	26.61***
external finance dependence	9.06%	24.67%	-42.18***

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