REVISTA ESPAÑOLA DE FINANCIACIÓN Y CONTABILIDAD
Vol. XL, n.º 151 · julio-septiembre 2011 · pp. 439-467

Analyzing firm-varying investment-cash flow sensitivities and cash-cash flow sensitivities: A Bayesian approach *

Medición de restricciones financieras con estimaciones individuales de la sensibilidad de la inversión a la liquidez: un enfoque bayesiano

Bert D'Espallier **. Hogeschool-Universiteit Brussel and Lessius University College
Jolien Huybrechts. Hasselt University
Félix Javier López Iturriaga. Universidad de Valladolid

ABSTRACT We employ a Bayesian estimator to construct firm-varying investment-cash flow sensitivities (ICFS) for a sample of 90 Spanish listed firms over a 10-year period (1999-2008). We then analyze which variables are associated with the firm-level ICFS estimates. The results indicate that firms with high ICFS are capital-intensive firms with high growth rates that have exhausted much of their debt capacity. Furthermore, high-ICFS firms have lower liquidity, lower profitability and lower stock market valuation than their counterparts. These results provide evidence that high-ICFS firms have higher external financing needs while faced with fewer available external financing sources. Our analysis suggests that, at least for Spanish listed firms over the observed sample period, the ICFS is an adequate proxy for gauging a firm's exposure to financing constraints. A similar exercise on firm-varying cash-cash flow sensitivities (CCFS) suggests no relation between the firm's CCFS and exposure to financing constraints.

KEYWORDS Financing constraints; Investment-cash flow sensitivities; Cash-cash flow sensitivities; Firm-level estimation; Bayesian estimation.

RESUMEN Partiendo del empleo de técnicas bayesianas de estimación, en el presente trabajo obtenemos indicadores para cada empresa de la sensibilidad de su inversión a la liquidez. Este procedimiento permite superar las limitaciones de los métodos tradicionalmente utilizados para estudiar las restricciones financieras a la inversión corporativa. Hemos aplicado este procedimiento a una muestra de 90 empresas cotizadas en el Mercado Continuo español entre 1999 y 2008 para analizar qué características influyen en dicha sensibilidad, tanto mediante un análisis univariante o descriptivo como mediante un análisis multivariante o explicativo. Nuestros resultados ponen de manifiesto que las empresas cuya inversión está condicionada en mayor medida por la disponibilidad de liquidez son empresas más intensivas en capital, con altas tasas de crecimiento y que han agotado la mayor parte de su capacidad de endeudamiento. También se observa que esas empresas disponen de menor liquidez, son menos rentables y están peor valoradas en el mercado. De todo ello se infiere la conveniencia de utilizar la sensibilidad de la inversión a la liquidez como una medida del grado de incidencia de las restricciones financieras a la inversión.

PALABRAS CLAVE Restricciones financieras; Inversión; Liquidez; Estimación bayesiana.

* **Acknowledgments:** We are grateful to Esther del Brío (Editora Asociada), Josep Tribó and two anonymous referees for their comments on a previous version. All remaining errors are the authors' own responsibility.
** **Corresponding Author**: Bert D'Espallier. Hogeschool-Universiteit Brussel and Lessius University College. Stormstraat 2, 1000 Brussels, Belgium. Phone: + 32 496 07 81 79. E-mail: bert.despallier@hubrussel.be.

Recibido 06-04-10 · Aceptado 12-12-10 · · ISSN: 0210-2412

1. INTRODUCTION

Whether the investment-cash flow sensitivity (ICFS) or the cash-cash flow sensitivity (CCFS) is a good proxy to gauge a firm's exposure to financing constraints is a question that has puzzled researchers for some time (Fazzari *et al.*, 2000; Kaplan and Zingales, 1997 and 2000).

While a number of recent empirical studies support the performance of the ICFS metric in measuring financing constraints (Islam and Mozumdar, 2007; Carpenter and Guariglia, 2008; Ağca and Mozumdar, 2008), other studies remain skeptical on its usefulness (Erickson and Whited, 2000; Lyandres, 2007; Wei and Zhang, 2008). For the more recent CCFS metric, opinions also differ. Whereas most empirical studies find a higher CCFS for firms more likely to suffer from financing constraints (see for example Almeida *et al.*, 2004; Khurana *et al.*, 2006), other studies claim there is no relation (Riddick and Whited, 2009; D'Espallier *et al.*, 2008). The overall conclusion seems to be that the literature is still in doubt whether the firm's exposure to financing constraints should be assessed by studying the firm's investment behavior (ICFS) or the firm's cash behavior (CCFS) in response to a cash flow shock.

In order to help resolve this «yes or no»—debate that has dominated the empirical literature for years, a few papers have shifted the estimation method towards constructing ICFS or CCFS on the *firm-level*— (see for instance D'Espallier *et al.*, 2008; Hovakimian, 2009; Hovakimian and Hovakimian, 2009). This is in stark contrast with the bulk of research, in which *sample-level* ICFS estimates are compared across groups with a different likelihood of financing constraints. The main benefit of the former methodology is that, once the firm-varying ICFS estimates have been constructed, one can analyze in greater detail which variables are driving the firm's ICFS, enabling a more thorough judgment on the usefulness of the metric.

In this paper, we argue that firm-varying ICFS estimates can be conveniently recovered by means of a Bayesian analysis. This estimation method is well-suited to model heterogeneous slopes in the context of panel data (Hansen *et al.*, 2004). Therefore, firm-varying cash flow coefficients can be estimated directly from the reduced-form investment equation. As a result, the firm-varying ICFS estimates comply with the theoretical definition of ICFS and are constructed in accordance with the underlying investment model. Similarly, firm-varying CCFS estimates can be recovered by modeling firm-varying cash flow coefficients in the underlying cash model. The Bayesian estimation method has been widely used in a variety of academic fields, including social science research, and can be considered a robust estimation method. The first aim of this paper is thus to propose the Bayesian estimator as a flexible and easy-to-use method for recovering firm-varying ICFS (and CCFS estimates) in coherence with the underlying reduced-form investment model (and reduced-form cash model).

Once firm-varying ICFS and CCFS estimates have been constructed using the Bayesian method, we use univariate and regression analysis to analyze which variables are driving both metrics. Such an ex post analysis is very similar to other papers that have analyzed

ICFS and CCFS at the firm-level. The second aim of this paper is thus to shed new light on the debate regarding the usefulness of the ICFS and CCFS metrics in capturing financing constraints.

The results are based upon a sample of 90 Spanish listed firms over a 10-year period from 1999 to 2008. We find that firms with high ICFS values are significantly different from firms with low ICFS values in terms of exposure to financing constraints. High-ICFS firms are capital intensive and have high growth rates, suggesting that a high ICFS is associated with higher external financing needs. High-ICFS firms also have higher debt rates but lower liquidity levels and profitability levels, suggesting that they are less likely to access additional external funding in debt markets. Furthermore, high-ICFS firms are valued lower on the stock markets than their counterparts with lower ICFS values, suggesting that raising additional external equity will also prove more difficult. These results suggest that, at least for this sample over the observed sample period, the ICFS is a good indicator for assessing a firm's exposure to financing constraints. Interestingly, a similar analysis of the firm's CCFS yields very different results. We find that the CCFS metric is not related to increased financing needs nor to lower access to financing, suggesting the firm's CCFS is not a good measure for capturing the firm's susceptibility to financing constraints.

This paper proceeds as follows. Section 2 provides an overview of the most recent studies on ICFS and CCFS and contains an overview of the Spanish evidence on this matter. Section 3 introduces the Bayesian estimator as a flexible method for recovering firm-varying ICFS estimates from a reduced-form investment equation and firm-varying CCFS estimates from a reduced-form cash equation. Section 4 describes the data and discusses the main empirical results. Section 5 summarizes the results and discusses the implications of the research.

2. CONCEPTUAL FRAMEWORK

2.1. Financing constraints and the firm's ICFS and CCFS

The theoretical arguments on financing constraints and their impact on corporate finance policies are relatively well-established. Fazzari *et al.* (1988) and Carpenter and Petersen (2002) show that in the presence of costly external financing due to informational asymmetries between investors and the firm, the firm will depend mainly on internal funds, resulting in sub-optimal investment. In other words, agency problems translate into a cost wedge where the cost of external funds is higher than the cost of internal funds, causing some firms to have only limited access to outside funds (Bond *et al.*, 2003; Cleary *et al.*, 2007). We call these firms «financially constrained», since that they are not growing at an optimal level because of a lack of outside funding. The existence of financing constraints poses a barrier for growth not only for individual firms, but also for the entire macro-economic environment (Bernanke *et al.*, 1996).

Despite agreement on the theoretical issues, there is much controversy over how these financing constraints can be measured empirically. Thus far, two metrics have been suggested —the firm's ICFS and CCFS— but there is much disagreement on the usefulness of each of these metrics. The ICFS metric measures the firm's investment response due to a change in cash flow and is estimated by adding cash flow in a reduced-form investment equation. The cash flow coefficient in this equation is the ICFS. This metric is supposed to be higher when there is greater exposure to financing constraints because a firm that has only limited access to external funds must invest at the pace of its retained earnings. A large body of empirical research has verified this assertion by estimating a sample-level ICFS for different groups 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 looser banking relationships. Similarly, Kashyap *et al.* (1994) and Calomiris *et al.* (1995) find that the ICFS is higher for younger firms. Bond *et al.* (2003) and Islam and Mozumdar (2007) find that ICFS is higher in market-based economies than in bank-based countries.

However, many other studies have been skeptical of the usefulness of measuring financing constraints by means of ICFS. For instance, Kaplan and Zingales (1997), Cleary (1999) and Kadapakkam *et al.* (1998) provide counter-evidence that the ICFS is actually lower for firms that are more likely to suffer from capital market imperfections. Along the same lines, Erickson and Whited (2000) argue that a significant ICFS is driven by measurement error in the reduced-form investment equation in the sense that controls for investment opportunities (for instance, Tobin's Q) are insufficient and therefore the cash flow coefficient captures increased investment opportunities rather than financing constraints.

Despite many subsequent studies and significant progress in methodological issues, the disagreement among researchers persists even in the most recent literature. For instance, while some recent studies find that ICFS is higher for firms that seem more likely to suffer from financing constraints even after taking into account mis-measurement error and endogeneity of cash flow (Carpenter and Guariglia, 2008; Guariglia, 2008; Islam and Mozumdar, 2007), other studies remain highly skeptical regarding the usefulness of ICFS (Bond and Cummins, 2001; Cummins *et al.,* 2006).

The more recently proposed CCFS metric, measures a firm's *cash* response in the event of a cash flow shock, and is estimated by adding cash flow in a reduced-form cash equation. This metric was developed by Almeida *et al.* (2004), who show that in the presence of costly external finance, a value-maximizing firm will buffer cash to compensate for unexpected fluctuations in income. The cash flow coefficient measures the marginal cash effect of an extra dollar in cash flow, and is supposed to be higher for financially constrained firms since these firms tend to buffer cash, whereas unconstrained firms have no incentive to buffer cash [(1)].

Using an empirical approach similar to that of the ICFS metric, a number of studies have verified the usefulness of the CCFS metric by comparing sample-level CCFS estimates across groups that differ in their susceptibility to financing constraints. For instance, Khurana *et al.* (2006), Han and Qiu (2007) and Lin (2007) find that the CCFS is higher for

(1) As argued in Almeida *et al.* (2004), this metric analyzes a «financial» variable (cash) rather than a «real» variable (investment), so this approach is less driven by endogeneity or mis-measurement in the underlying reduced-form equation.

firms that are younger, have a looser banking relationship and pay out fewer dividends. However, as is the case with the ICFS metric, opinions on the CCFS metric differ among researchers. For instance, Riddick and Whited (2009) argue that the firm's cash policy is determined by income uncertainty and taxation issues and not by the cost of external funds.

The previous discussion indicates that despite a great deal of research and analysis, existing research is still divided on whether the firm's exposure to financing constraints should be evaluated by studying the firm's investment behavior (ICFS) or the firm's cash behavior (CCFS) in response to a cash flow shock. Nonetheless, this debate seems more relevant than ever in light of today's worldwide financial crisis where credit is scarce and access to outside financing has become increasingly difficult.

2.2. Spanish background

Research on the impact that financing constraints have on the investment function of manufacturing firms in Spain has run parallel to international studies. After a number of seminal tests of the interrelation between financial decisions and real investment decisions (Alonso and Bentolila, 1993; Hernando and Vallés, 1992; Mato, 1988), the literature has addressed a number of other corporate investment decisions potentially affected by financial factors. These investment decisions range from capital expenditures (Maestro *et al.*, 2007; Rodríguez Brito, 2001) to intangible assets (Lozano *et al.*, 2001), R&D expenditures (Correa *et al.*, 2002), inventories and employment (Hernando and Martínez-Carrascal, 2008).

Similar to the international evidence, most of this literature relies on a sharp division of the firms according to some ex ante criterion to proxy for financing constraints, such as the size of the firm (Álvarez, 1996 and 1998; Estrada and Vallés, 1998; Hernando and Vallés, 1992; Mato, 1990; Maroto, 1997), age of the firm (Hernando and Vallés, 1992), dividend policy (Álvarez, 1996; Hernando and Tiomo, 2002), assets specificity (García, 1998), interest rates (Mato, 1990; Estrada and Vallés, 1998) and bank affiliation (Álvarez, 1996; Hernando and Vallés, 1992; García and Ocaña, 1999; García and Vicente Lorente, 1999).

Most studies find the firm's financial position has a significant impact of on corporate investment decisions, which translates into a significant ICFS. Another common result is the strong influence of liquidity on business investment to the extent that the omission of financial variables leads to the rejection of the neoclassical model (Estrada and Vallés, 1998). In addition to the well documented impact of cash flow, financial leverage arises sometimes as another determinant of business investment (Maroto, 1997). However, it remains unresolved also in the Spanish literature whether the observed relation between financial decisions and real investments in the form of a significant ICFS is indeed a good proxy for assessing the degree of financing constraints.

Furthermore, the shift of the Spanish financial system toward dis-intermediation as well as the current financial crisis that has heavily touched the Spanish economy, suggests that testing whether frictions in capital markets still persist and to what extent financial intermediaries can help to relax financial constraints is more than ever relevant.

2.3. Benefits and challenges of firm-specific estimation

A recent set of papers have shifted the estimation method towards estimating ICFS or CCFS on the firm-level rather than on the sample-level (see for instance D'Espallier *et al.,* 2008; Hovakimian, 2009; Hovakimian and Hovakimian, 2009). As these papers point out, this approach allows for a more thorough analysis of the usefulness of the ICFS and CCFS metrics in capturing financing constraints.

First, when firm-level sensitivities are being analyzed, there is no need to classify the sample beforehand using a classification criterion that reflects a different susceptibility to financing constraints (for instance, size, payout rate, age, and commercial paper rating). Many authors point out that this ex ante classification approach is problematic because the results are critically dependent upon the classification scheme under consideration and neither classification scheme produces a clear distinction between different degrees in capital market imperfections (Gilchrist and Himmelberg, 1995; Cleary, 1999; Whited and Wu, 2006; Almeida and Campello, 2007).

Second, many authors point out that cash flow might be endogenous in the reduced-form investment equation and in the reduced-form cash equation. This potential endogeneity stems from a possible omitted variables bias problem in the reduced-form equations and might severely bias the sample-level cash flow coefficients (Bond *et al.*, 2003) [(2)]. The second benefit of analyzing firm-level sensitivities is therefore to avoid working with sample-level estimates that are potentially biased because of endogeneity in the underlying reduced-form equation.

Third, the use of firm-level ICFS and CCFS estimates seems to be more in line with the economic theory on financing constraints. Essentially, financing constraints are induced by the firm's agency costs and happen at the individual firm-level and not at the sample-level. Therefore, a methodological framework that empirically tests for financing constraints should account for firm-level heterogeneity rather than statistically neutralizing all firm-heterogeneity into a single sample-level estimate (Cleary and D'Espallier, 2007).

Finally, after the firm-varying ICFS and CCFS estimates have been computed, one can analyze in detail which variables are driving the sensitivity by means of an ex post analysis. Unraveling which variables affect the firm's ICFS or CCFS allows for a more thorough judgment of how useful the metrics are in capturing financing constraints.

Hovakimian and Hovakimian (2009) construct a mathematical proxy for the firm-level ICFS, defined as the difference between the cash flow weighted time-series average investment of the firm and its simple arithmetic time-series average investment. As the authors point out, this difference will be higher for firms that display higher investment in years with high cash flows and lower investment in years with low cash flows. Alternatively, the difference will be smaller when the level of investment is not severely affected by the level of cash flow. While this is an interesting approach, the suggested definition

(2) Not only the cash flow coefficient is potentially affected by this bias, but also any cash flow interaction terms that are often added to investigate the direct impact of a certain observable on the estimated ICFS or CCFS [see for instance Rauh (2006) or Ascioglu *et al.* (2008)].

only takes into account the actual levels of cash flow and investment. This is not in line with the original definition of ICFS, which is the *change* in investment induced by an exogenous cash flow shock, holding constant the level of investment opportunities. Their mathematical proxy does not take into account that the ICFS is by definition a *marginal* effect and not a *level* effect. As such, their mathematical proxy seems to be at odds with the theoretical definition of ICFS.

An alternative approach is to introduce heterogeneous slopes into the underlying investment equation, thereby estimating a cash flow coefficient for each individual firm. D'Espallier *et al.* (2008) adopt a Generalized Maximum Entropy estimator (GME) to estimate the parameters of the varying slopes model. The main benefit of this approach is that the underlying investment model is respected, thereby complying with the original definition of ICFS.

Overall, there seem to be a number of potential benefits in analyzing ICFS and CCFS on the firm-level rather than on the sample-level. However, it is unknown how these firm-level estimates should be constructed and existing studies disagree on this matter. The main challenge for this stream of literature is now to come up with a way to construct robust and reliable firm-varying ICFS and CCFS estimates. In this paper we suggest that firm-varying sensitivities can be conveniently recovered from the reduced-form investment and reduced-form cash equations by means of a Bayesian estimation procedure.

3. RECOVERING FIRM-VARYING ICFS AND CCFS BY MEANS OF BAYESIAN ESTIMATION

3.1. Reduced-form investment model and reduced-form cash model

To estimate ICFS we use a reduced-form Q model of investment augmented with cash flow which has been used extensively in the literature (Kaplan and Zingales, 1997; Cleary, 1999; Allayannis and Mozumdar, 2004; Cleary, 2006; Islam and Mozumdar, 2007). This model adds the firm's market-to-book value as a proxy for Tobin's Q to control for investment opportunities as follows:

$$(I_{i,t} / K_{i,t-1}) = \beta_0 + \beta_1 (CF_{i,t} / L_{i,t-1}) + \beta_2 MB_{i,t-1} + \mu_i + u_{i,t} \tag{1}$$

where $(I_{i,t} / K_{i,t-1})$ is the firm's investment rate defined as the change in total fixed assets net from depreciations and amortizations scaled by beginning-of-year capital stock; $(CF_{i,t} / K_{i,t-1})$ is the firm's cash flow rate defined as cash flow scaled by beginning-of-year capital stock; $MB_{i,t-1}$ is the market-to-book rate measured at the end of the previous accounting year; μ_i is a firm-specific effect that takes up unobserved firm-specific heterogeneity and $u_{i,t}$ is the idiosyncratic error. In addition to looking at this static model, we experiment with the inclusion of lagged investment to take into account that investment projects are typically «lumpy» meaning they carry over to multiple time-periods (Doms and Dunne, 1998; Cooper and Haltiwanger, 2006). We also experiment with the inclusion of sector-dummies and time-dummies to pick up differences in investment between sectors and over the years. In model (1) the ICFS is given by the cash flow coefficient $\beta_{1,}$ which measures the investment response due to a change in cash flow [3].

To estimate CCFS we use a reduced-form cash model augmented with cash flow. This model relates changes in the cash account to cash flow, firm size (in terms of the natural logarithm of total assets) and market-to-book as a proxy for Tobin's Q in line with Almeida *et al.* (2004) as follows:

$$(\Delta CH_{i,t} / K_{i,t-1}) = \beta_0 + \beta_1 (CF_{i,t} / K_{i,t-1}) + \beta_2 lnTA_{i,t} + \beta_3 MB_{i,t-1} + \mu_i + u_{i,t} \quad (2)$$

where $(\Delta CH_{i,t} / K_{i,t-1})$ is the firm's change in cash and equivalents divided by beginning-of-year capital stock; $(CF_{i,t} / K_{i,t-1})$ is the firm's cash flow rate defined as cash flow scaled by beginning-of-year capital stock. $lnTA_{i,t}$ is the firm's natural logarithm of total assets; $MB_{i,t-1}$ is the market-to-book rate measured at the end of the previous accounting year; μ_i is a firm-specific effect that takes up unobserved firm-specific heterogeneity and $u_{i,t}$ is the error. Again we experiment with the lagged dependent variable (to allow that the firm's cash policy might carry over into the next time period) and with the inclusion of sector-dummies and time-dummies (to pick up differences in cash policy between sectors and over the years). In model (2), CCFS is given by the cash flow coefficient $\beta_{1,}$ which measures the change in the cash account due to a change in cash flow [4].

3.2. Firm-varying ICFS and CCFS using Bayesian analysis

Estimating the parameters of regression equations (1) and (2) using traditional techniques results in a single ICFS and CCFS for the entire sample instead of the desired firm-varying estimates. In order to get firm-varying ICFS and CCFS estimates, we make the cash flow coefficient β_1 varying for each firm in (1) and (2), which amounts to introducing slope heterogeneity into the equations as follows:

$$(I_{i,t} / K_{i,t-1}) = \beta_0 + \beta_{1,i} (CF_{i,t} / K_{i,t-1}) + \beta_2 MB_{i,t-1} + \mu_i + u_{i,t} \quad (3)$$

$$(\Delta CH_{i,t} / K_{i,t-1}) = \beta_0 + \beta_{1,i} (CF_{i,t} / K_{i,t-1}) + \beta_2 lnTA_{i,t} + \beta_3 MB_{i,t-1} + \mu_i + u_{i,t} \quad (4)$$

Estimating the parameters of (3) will return firm-varying ICFS estimates $\beta_{1,i}$ and estimating the parameters of (4) will return firm-varying CCFS estimates $\beta_{1,i}$ where index *i* indicates that we obtain a parameter for each individual firm.

From a technical point of view, it is not an easy task to estimate the parameters of (3) and (4). First, equations (3) and (4) do not comply with the everyday functional form of a typical random coefficient panel data model. Indeed, the wellknown random coefficient

(3) In the dynamic model where lagged investment is taken up as an extra regressor, ICFS is the long-run investment response due to a change in cash flow given by the cash flow coefficient β_1 divided by 1 minus the coefficient of lagged investments.

(4) In the dynamic cash model where the lagged change in cash is used as an extra regressor, CCFS is given by the cash flow coefficient β_1 divided by 1 minus the coefficient of lagged change in cash.

model includes a heterogeneous intercept μ_i but does not take up heterogeneous slopes. Consequently, a model with firm-varying slopes in the context of panel data is usually not implemented in common statistical software packages.

Second, the number of parameters to be estimated is large with respect to the number of data points. In addition to the *i* parameters needed to estimate the firm-specific intercept μ_i, we need an additional *i* parameters to estimate the firm-specific slope $\beta_{1,i}$. Thus the number of parameters to be estimated increases to (2*i* + 2) for equation (3) and (2*i* + 3) for equation (4) for (*i* x *t*) observations. When the number of parameters is large in relation to the number of data points, parameter estimates will be unstable and unreliable due to loss in degrees of freedom. This is often referred to as the problem of *ill-positioning*, where traditional regression techniques such as OLS fail (Fraser, 2000).

Finally, estimating equations (3) and (4) 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 must assume normality for the heterogeneous intercept as well as for the heterogeneous slopes. It is widely documented in the econometrics literature that these normality assumptions are not met in practice, which means that parameter estimates are inaccurate and specification tests are unreliable. This is often referred to as the problem of *ill-conditioning,* which is especially severe when working with non-experimental data, as is usually the case in social science research (Fraser, 2000).

In conclusion, there are sufficient technical arguments to refrain from using traditional regression techniques when estimating the parameters of equations (3) and (4). As has been noted by several authors, the Bayesian method is more appropriate when modeling firm-varying slopes because it allows for a full probabilistic inference of all parameters, including the firm-varying ones, without relying on any normality-assumptions (Hansen *et al.*, 2004; Berry, 1996). Or as Hansen *et al.* (2004) argue, 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 individual firm-level results (5). Therefore we estimate the parameters of (3) and (4) using Bayesian estimation.

In the Bayesian methodology, parameters are estimated by combining a prior probability distribution together with a probability distribution that describes the data using Bayes' probability theorem (6). Specifically, for each parameter that must be estimated, a probability distribution is formed (called the *posterior* probability) using prior information on the parameter (described in the *prior* probability) and the data (described in the *likeli-*

(5) Hansen *et al.* (2004) argue that modeling heterogeneous slopes is especially useful if the theory is about extraordinary performers or outliers, and not about averages. They use a Bayesian operationalization to model heterogeneous slopes in a firm-performance regression to test the Resource-Based View in the management literature. While this management application is different from our finance application, there are many similarities with our application. For instance, the theory on financing constraints is also a theory about outliers or extraordinary performers in the sense that some firms, but definitely not all firms, might suffer from financing constraints.

(6) Bayes' conditional probability theorem can be written as meaning that the chance of event A conditional upon event B is the chance of A and B divided by the chance of event B.

hood function). This posterior probability function can be explored to make inferences about the parameter of interest.

Advocates of the Bayesian method have identified several benefits of estimating the parameters of a regression model with the above-mentioned method (Hansen *et al.*, 2004; Berry, 1996). First, Bayesian models provide complete distributional estimation for each parameter, rather than a point estimate. As such, there is more detailed information on each parameter and probabilistic statements can be made for each parameter.(7) Second, Bayesian methods are not subject to assumptions regarding the error-term (such as the exogeneity assumption). Therefore, Bayesian estimation provides arguably more accurate information on the parameters. Finally, the Bayesian method is not limited to certain pre-specified functional forms. In fact, within the Bayesian algorithm, the researcher specifies the functional form of the regression equation as he or she likes. It is this qualification that allows us to estimate heterogeneous slopes, whereas this type of model is usually not available in traditional software. Details about the Bayesian estimation can be found in the Appendix.

4. MAIN EMPIRICAL RESULTS

4.1. Summary statistics and sample-level ICFS

Data for 90 listed Spanish firms over a 10-year period (1999-2008) are extracted from the Thompson One Banker database. This database provides worldwide coverage of industry-level and firm-level financial data, including detailed balance sheets and income statements as well as market information. We exclude banks and other financial firms because their investment is not comparable to the investment of non-financial counterparts. We select all firms for which we have at least two consecutive years of data out of the 10 most recent years. Taking into account that the number of non-financial firms quoted in the *Mercado Continuo* (8) ranges from 121 firms in 1999 and 96 firms in 2005, one can assess how representative our sample is. On average, the firms in our sample account for 85.3% of the market capitalization.

Table 1 reports a number of summary statistics for the main variables used in this study. As can be seen, investments are on average 15% of capital stock and cash flows account for 19% of capital stock on average. The market-to-book rate is on average 2.42, indicating that firms are valued roughly 2.5 times higher on the stock-market than the firm's book value.

(7) Flexible probabilistic statements can be made for each parameter. For instance, one could assert that there is *x*% probability that the parameter takes on a value between a_1 and a_2, or one could assert that there is *y*% probability that the parameter is below or above a certain threshold value, and so forth.
(8) The Mercado Continuo includes the most frequently traded stocks in Spanish capital markets, and accounts for 99% of total daily trading.

Table 1
Summary statistics

This table presents the number of observations (n), mean, median, standard deviation (st. dev.), minimum (min.) and maximum (max.) for a number of key variables used in this study. The sample consists of 90 Spanish listed firms over a 10-year time-period from 1999 to 2008 (included). All variables have been winsorized at the 5th and 95th percentile. *TA* is total assets measured in thousands of Euros. *lnTA* is the natural logarithm of *TA*. *Sales* is total sales measured in thousands of Euros. *lnSales* is the natural logarithm of Sales. $(I_{i,t} / K_{i,t-1})$ is the investment rate defined as change in total fixed assets net from depreciations and amortizations scaled by beginning-of-year capital stock. $(CF_{i,t} / K_{i,t-1})$ is the cash flow rate defined as net income plus depreciations and amortizations scaled by beginning-of-year capital stock. $MB_{i,t}$ is the market-to-book rate. $(\Delta CH_{i,t} / K_{i,t-1})$ is the change in cash and equivalents defined as beginning-of-year capital stock. *Sales growth* is the annual percentage change of Sales. *Financial debt rate* is total financial debt divided by total liabilities. *ST financial debt rate* is bank and financial short-term liabilities divided by total liabilities. *NWC / TA* is net working capital divided by total current assets minus current liabilities as a percentage of total assets. *Current ratio* is total current assets divided by total current liabilities. *EBITDA* is earnings before interests, taxes, depreciation and amortizations as a percentage of total assets. *Net income* is income after interest and taxes. *Dividends / TA* is dividends as a percentage of total assets. *PP&Egross / TA* is property, plant and equipment before depreciations as a percentage of total assets. *PP&Enet* is property, plant and equipment after depreciations as a percentage of total assets.

Variable	*n*	*Mean*	*Median*	*St.Dev.*	*Min.*	*Max.*
TA	837	4,667	561	12,545	0.365	100,281
lnTA	837	6.49	6.33	1.99	-1.01	11.51
Sales	837	2,552	377.65	7,109	0.287	57,946
lnSales	837	5.89	5.93	2.08	-1.24	10.96
$I_{i,t} / K_{i,t-1}$	737	0.15	0.07	0.33	-0.42	1.20
$CF_{i,t} / K_{i,t-1}$	761	0.19	0.12	0.23	-0.06	0.98
MB	790	2.42	1.81	1.97	0.47	8.31
$\Delta CH_{i,t} / K_{i,t-1}$	761	0.027	0.002	0.149	-0.260	0.470
Sales growth	815	0.15	0.09	0.48	-0.99	2.00
Financial debt rate	837	0.288	0.285	0.176	0.00	1.00
ST financial debt rate	837	0.111	0.086	0.100	0.00	0.80
NWC / TA	811	0.105	0.089	0.176	-0.70	0.74
Current ratio	811	1.40	1.23	0.725	0.15	5.00
EBITDA / TA	836	0.108	0.104	0.111	-0.98	0.68
Net income / TA	837	0.036	0.037	0.094	-1.12	0.49
Dividends / TA	781	0.02	0.008	0.046	0.00	0.50
PP&Egross / TA	837	0.386	0.357	0.230	0.001	0.99
PP&Enet / TA	783	0.645	0.664	0.302	0.002	1.00

The reduced-form investment equation (1) is estimated using traditional regression techniques in Table 2. This analysis gives us an idea about the magnitude of ICFS for the entire sample. In the different columns, we experiment with including lagged investment as well as time and sector dummies. Besides the random effect estimator (RE), we also use different endogeneity-proof estimation techniques that have been used in prior literature to account for the fact that cash flow might be endogenous in the reduced-form investment equation (Erickson and Whited, 2000). HT is the Hausman-Taylor approach developed in Hausman and Taylor (1981), which accounts for potential endogeneity resulting from correlation between the error and the unobserved firm-specific effect. GMM and SYS-GMM are, respectively, the GMM estimator developed in Arellano and Bond (1991) and the system-GMM estimator developed in Blundell and Bond (1998) to account for endogeneity resulting from correlation between the regressors and the idiosyncratic component of the error.

As can be seen in column (1), cash flow is a significant determinant for investment. It has an estimated coefficient of 0.42 in the static case where no time and sector dummies are taken up. When lagged investment is added in columns (2), (3), and (4), its coefficient is significant and positive, indicating that investments carry over to other time periods. As a result, the long-run ICFS is higher, and ranges between 0.35 and 0.50 depending upon whether time and sector dummies are included. Columns (3) and (4) indicate that time and sector dummies add to the explanatory power of the model. The endogeneity-proof estimation techniques also return positive cash flow effects, suggesting that cash flow remains a significant determinant for investment even after endogeneity is taken into account.

Table 2

Investment-cash flow sensitivity based on reduced-form investment equations

This table reports estimates for the ICFS based on estimation of reduced-form investment equations using traditional regression techniques. *RE, HT, GMM* and *SYS-GMM* represent the Random Effects estimator, the Hausman-Taylor IV approach developed in Hausman and Taylor (1981), the *GMM* estimator developed in Arellano and Bond (1991) and the system-GMM estimator developed in Blundell and Bond (1998), respectively. Robust standard errors are provided in parentheses. ICFS denotes the investment response due to a change in cash flow, which is given by the coefficient of cash flow in the static case (column 1) and the coefficient of the cash flow rate divided by 1 minus the coefficient of lagged investment rate in the dynamic case (columns 2-7). *Sargan (p-value)* reports the *p-value* of the Sargan-test of overidentifying restrictions, which tests the null that the instruments used in the GMM estimation are uncorrelated with the error term. *1st order corr. (p-value)* reports the p-value for the test for first-order autocorrelation of the differenced residuals. *2nd order corr. (p-value)* reports the p-value for the test for second-order autocorrelation of the differenced residuals. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

Dep. var. $(I_{i,t-1}/K_{i,t-1})$	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
$(CF_{i,t}/K_{i,t-1})$	0.42	0.32	0.32	0.49	0.71	0.86	0.78
	(0.105)***	(0.080)***	(0.081)***	(0.108)***	(0.086)***	(0.236)***	(0.271)***
$MB_{i,t-1}$	-0.004	-0.01	-0.01	-0.01	-0.01	0.00	-0.006
	(0.008)	(0.005)	(0.006)	(0.009)	(0.009)	(0.014)	(0.015)
$(I_{i,t-1}/K_{i,t-2})$		0.10	0.10	0.03	0.01	0.04	0.05
		(0.033)***	(0.032)***	(0.035)	(0.032)	(0.030)*	(0.033)
Time dummies	excluded	excluded	included	included	included	included	included
Sector dummies	excluded	excluded	excluded	included	included	included	included
ICFS	***0.42***	***0.35***	***0.35***	***0.50***	***0.72***	***0.89***	***0.82***

(Continúa pág. sig.)

TABLE 2 (CONT.)
INVESTMENT-CASH FLOW SENSITIVITY BASED ON REDUCED-FORM INVESTMENT EQUATIONS

Dep. var. $(I_{i,t-1} / K_{i,t-1})$	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
n	643	612	612	612	612	524	612
F-stat / χ^2*-stat*	18.27***	24.43***	47.08***	198.78***	127.64***	41.44***	38.59***
Sargan (p-value)						0.89	0.87
1st order corr. (p-value)						0.00	0.00
2nd order corr. (p-value)						0.80	0.75
R^2	0.03	0.05	0.09	0.20			
Method	RE	RE	RE	RE	HT	GMM	SYS-GM

Notes: A Hausman-test was done to choose between Random Effects or Fixed Effects. This test does not reject the null that both estimators return consistent estimates. A robustness check has been carried out where outliers at the 5%-level have been removed rather than winsorized. This yields similar results.

4.2. BAYESIAN ESTIMATION OF FIRM-VARYING ICFS AND EX POST ANALYSIS

Table 3 summarizes the results from estimating the parameters of varying coefficients model (3) using the Bayesian procedure described above. In panel A the static model is analyzed while in panel B a dynamic model that uses lagged investment as an extra regressor is analyzed. In column (2) time dummies are included and in column (3) time and sector dummies are included. We report minimum, maximum, standard deviation, median and quartiles of the distribution of firm-varying ICFS values. We also report a fixed cash flow coefficient estimated with the Bayesian technique to compare the analysis with the sample-level estimation in Table 2.

As can be seen, the Bayesian analysis returns an overall sample-level ICFS estimate that is close to the analysis in Table 2. For instance, in the dynamic case with time and sector dummies, the Bayesian ICFS is 0.58; for the RE model, it is 0.50. The fact that the Bayesian analysis returns a fixed cash flow coefficient in the same order of magnitude as the traditional regressions offers further justification that the Bayesian method provides a robust estimation. In addition to the fixed coefficient, the Bayesian analysis also returns firm-varying ICFS estimates (9). As can be seen from Table 3, the firm-varying ICFS has a wide range (10), indicating that some firms have very low ICFS values whereas others have high ICFS values. For instance, in the dynamic case with time and sector dummies, the ICFS ranges between a minimum of -0.01 and a maximum of 1.28.

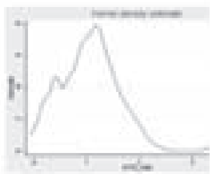
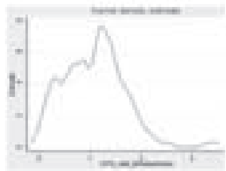
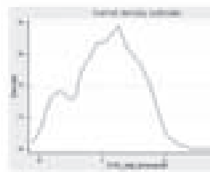
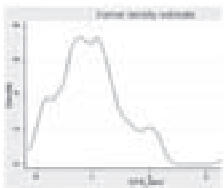
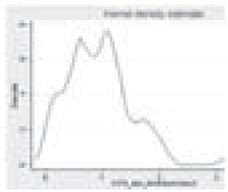
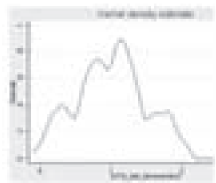
(9) A sensitivity analysis is conducted to test the robustness of the results for changes in the prior information imposed. For instance, we experiment with the following prior distributions for the cash flow parameter: $N(0,10^1)$, $N(0,10^2)$, $N(0, 10^4)$, $N(0, 10^6)$, and $U(-10^3, 10^3)$. The estimated cash flow parameters remain the same on a 3-digit level, which is to be expected given the fact that the data dominate the prior information in large enough samples, as indicated in the appendix on Bayesian estimation.

(10) Note that it is perfectly possible for a firm to have a negative ICFS value. This means that the firm has observed negative investments (divestitures) despite positive cash flow shock, or positive investments despite negative cash flows.

Table 3

Firm-varying investment-cash flow sensitivities using Bayesian estimation

This table reports the estimation results and a kernel-density graph for the firm-varying ICFS estimates obtained using Bayesian econometrics. Panel A summarizes the results from a static model that includes only market-to-book and a firm-varying cash flow coefficient as regressors. We experiment with the inclusion of time-dummies (column 2) and time and sector dummies (column 3). Panel B summarizes the results from a dynamic model in which lagged investment is included in addition to market-to-book and the firm-varying cash flow coefficient. Again we experiment with the inclusion of time-dummies (column 2) and time and sector-dummies (column 3).

Panel A. Static model							
Dep. var.: ($I_{i,t}$ / $K_{i,t-1}$)		*(1)*		*(2)*		*(3)*	
Fixed		0.76		0.75		0.75	
Varying	*Min*	0.03		-0.04		0.009	
	Max	3.43		3.41		3.12	
	St.Dev.	0.57		0.59		0.54	
	P(25)	0.71		0.68		0.75	
	Median	1.08		1.07		1.11	
	P(75)	1.35		1.40		1.48	
Time dummies		excluded		included		included	
Sector dummies		excluded		excluded		included	
Panel B. Dynamic model							
Dep. var.: ($I_{i,t}$ / $K_{i,t-1}$)		*(1)*		*(2)*		*(3)*	
Fixed		0.59		0.58		0.58	
Varying	*Min*	0.00		-0.07		-0.01	
	Max	3.39		3.17		3.00	
	St.Dev.	0.59		0.56		0.53	
	P(25)	0.58		0.55		0.71	
	Median	0.94		0.92		1.02	
	P(75)	1.27		1.21		1.28	
Time dummies		excluded		included		included	
Sector dummies		excluded		excluded		included	

Now that firm-varying ICFS estimates are computed, we can assess in detail which characteristics are associated with a low or a high ICFS value (11). This ex post analysis is done both univariately (analyzing different characteristics in firms with high ICFS values versus firms with low ICFS values) and multivariately (regressing the firm-varying ICFS estimates against the different firm characteristics).

In Table 4 we compare median values for different firm characteristics in firms with a value for ICFS higher than the median value (high-ICFS firms) and in firms with a ICFS lower than the median value (low-ICFS firms) (12). The characteristics analyzed relate to growth, debt capacity, liquidity, profitability, dividends and tangibility. The last column reports the Pearson's χ^2-test to analyze whether observed differences are statistically significant. As can be seen, high-ICFS firms have higher growth rates both in terms of investment rate and sales growth, the differences being highly significant. Furthermore, high-ICFS firms have significantly higher fixed assets to total assets, indicating they are more capital intensive than their counterparts. The higher growth and higher capital intensity suggest that high-ICFS firms face higher external financing needs than their counterparts with low ICFS values.

The variables measuring debt-capacity indicate that high-ICFS firms have higher existing debt rates than their counterparts, both in terms of total debt as well as financial debt. Again, the differences are highly significant. For instance, for high-ICFS firms, the ratio *common equity/TA* is 0.32, indicating that the firm's liabilities constitute 68% of its balance sheet total. This suggests that high-ICFS firms have exhausted much of their spare debt capacity, whereas firms with low ICFS estimates still have more room for increasing debt positions. This finding is in line with Azofra *et al.* (2007) and Such and Parte (2007).

Turning to the different liquidity measures (*current ratio*, *net working capital/TA*, and *cash flow rate*), we see that liquidity is much lower for high-ICFS firms, suggesting that they have a lower cash-buffer to protect them from future income shocks. Furthermore, investor valuation is significantly lower for high-ICFS firms. This suggests that they are less popular on the stock-market and will therefore face greater difficulty in attracting funds from the external financial markets. Profitability is also significantly lower for high-ICFS firms both in terms of *EBITDA/TA* as well as *net income*. This suggests that high-ICFS firms can rely less on their future revenue stream to continue financing their growth.

(11) For the ex post analyses we use the firm-varying ICFS estimates from the dynamic model that includes sector and time dummies. However, using the Bayesian estimates from the other models (static model, no time and sector dummies) yields very similar results. This is to be expected given the high correlation (always over 90%) that exists between firm-varying Bayesian ICFS estimates from the different models.

(12) As an extra robustness check (unreported), a similar exercise is conducted where we analyze the characteristics for five different classes of firms ranging from «very low ICFS» if the firm's ICFS is lower than the 20th percentile of the ICFS distribution to «very high ICFS» if the firm's ICFS is higher than the 80th percentile of the ICFS distribution. Similar results are obtained.

TABLE 4

DIFFERENCES BETWEEN HIGH-ICFS *VERSUS* LOW-ICFS FIRMS: UNIVARIATE ANALYSIS

This table reports median values of variables measuring capital intensity, firm growth, debt capacity, liquidity, investor valuation, profitability and dividends for «All firms,» «High-ICFS firms» and «Low-ICFS firms.» High-ICFS firms are firms for which ICFS is higher than the median value of ICFS. Low-ICFS firms are firms for which ICFS is lower than the median value. The third columns is the non-parametrical Pearson χ^2-test to determine whether the differences in median values are statistically significant. *, ** and *** denote statistical significance at the 10%, 5% and 1% significance levels, respectively.

		All firms	*High-ICFS firms*	*Low-ICFS firms*	*Pearson χ^2-test*
		n = 90	*n = 45*	*n = 45*	
Capital intensity	PP&Egross / TA	0.59	0.78	0.28	5.37^{**}
	PP&Enet / TA	0.33	0.45	0.23	12.84^{***}
Growth	Investment rate	0.14	0.18	0.06	42.71^{***}
	% Sales growth	0.14	0.21	0.05	23.51^{***}
Debt-capacity	Financial debt rate	0.28	0.32	0.23	7.51^{***}
	ST-financial debt rate	0.08	0.09	0.10	3.61
	Common equity / TA	0.36	0.32	0.43	10.00^{***}
Liquidity	Working capital / TA	0.10	0.03	0.17	23.29^{***}
	Current ratio	1.29	1.11	1.53	12.53^{***}
	Cash flow / K	0.15	0.14	0.16	0.40
Investor valuation	Market-to-book	1.98	1.83	1.98	2.04^{**}
Profitability	EBITDA / TA	0.10	0.09	0.11	2.17^{*}
	Net income / TA	0.04	0.03	0.05	2.18^{*}
Dividends	Dividends / TA	0.01	0.00	0.01	0.40

In Table 5 the relation between ICFS and the firm-characteristics is analyzed multivariately by means of a regression where the dependent variable is the firm-varying ICFS and the independent variables are the firm characteristics. In the different columns we use different proxies that measure the same variable to avoid collinearity problems. This analysis is similar to the univariate analysis, but is able to identify the isolated relation between the ICFS and a variable, while controlling for variations in the other variables (ceteris paribus).

The table confirms the findings from the univariate analysis. A higher ICFS is significantly associated with higher growth both in terms of investment rate and sales growth, holding the other characteristics constant. Furthermore, ICFS is positively related to fixed tangible assets, confirming that firms with a higher ICFS are more capital intensive. Similarly, a higher ICFS is associated with a higher debt rate and lower debt capacity as well as lower liquidity measures, lower profitability measures and a lower market valuation, ceteris paribus.

Table 5
The relation between ICFS and firm characteristics: Multivariate analysis

We regress the firm-varying ICFS estimates against the firm characteristics by means of OLS. The different columns correspond to different proxies that measure the same variable . We also experiment with the inclusion of sector dummies in columns (5) and (6). Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% significance levels, respectively.

Dep. var.: ICFS		*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Growth	*Investment rate*	0.34 (0.078)***	0.45 (0.085)***			0.18 (0.067)***	
	% Sales growth			0.19 (0.055)***	0.30 (0.059)***		0.14 (0.045)***
Debt-capacity	*Common equity / TA*	-0.40 (0.195)***		-0.47 (0.182)***		-0.02 (0.190)	-0.02 (0.171)
	Financial debt rate		0.62 (0.111)***		0.75 (0.106)***		
Liquidity	*Working capital /TA*	-0.33 (0.195)**		-0.22 (0.181)*		-0.60 (0.195)***	-0.58 (0.173)***
	Cash flow / K		-2.17 (0.482)***		-2.28 (0.442)***		
Profitability	*EBITDA / TA*	0.53 (0.339)	0.22 (0.337)	0.41 (0.324)	0.14 (0.302)	0.24 (0.273)	0.10 (0.258)
Dividends	*Dividends / TA*	-2.19 (0.611)***	-1.24 (0.494)**	-2.04 (0.509)***	-1.20 (0.358)***	-1.96 (0.576)***	-1.34 (0.462)***
Capital intensity	*PP&Enet / TA*	0.87 (0.115)***	0.88 (0.077)***	0.89 (0.113)***	0.89 (0.074)***	0.55 (0.135)***	0.55 (0.124)
Valuation	*Market-to-book*	-0.04 (0.008)***	-0.03 (0.008)***	-0.04 (0.008)***	-0.03 (0.008)***	-0.03 (0.010)***	-0.04 (0.009)***
Sector dummies		excluded	excluded	excluded	excluded	included	included
n		667	688	720	744	667	720
F-stat		56.95***	63.69***	54.76***	68.17***	94.67***	99.56***
RMSE		0.43	0.42	0.44	0.42	0.35	0.34
R^2		0.34	0.38	0.31	0.36	0.57	0.57

Notes: The same result holds if a dummy is used for dividends rather than the dividend rate.

In general, both the univariate and multivariate analyses reveal that high-ICFS firms are significantly different from low-ICFS firms. High-ICFS firms are more capital intensive and have higher growth rates, indicating that they face higher financing needs than low-ICFS firms. Furthermore, high-ICFS firms have exhausted much of their debt capacity and are valued lower on the stock market, suggesting they will face greater difficulty in attracting new external funds from the capital markets. Additionally, they face lower liquidity and profitability, suggesting a weaker internal position in terms of cash-buffer and internal revenues for servicing their future financing needs. On the whole, our analyses clearly suggest that high-ICFS firms are much more susceptible to financing constraints than low-ICFS firms.

4.3. The relation between the firm's CCFS and financing constraints

In this section we repeat the exercise for the CCFS metric. This metric has been recently suggested as an alternative proxy to capture financing constraints (Almeida *et al.*, 2004) but has been criticized in a recent paper by Riddick and Whited (2009). In Table 6 we report the sample-level CCFS estimates recovered from the reduced-form cash equation (2) using traditional techniques. In Table 7 we report the firm-varying estimates computed from the reduced-form cash equation with heterogeneous cash flow coefficients with the Bayesian estimation procedure [equation (4)].

As can be seen in Table 6, cash flow is a significant positive determinant for cash changes, indicating that a positive cash flow shock will lead to an increase in the cash account, suggesting that firms buffer cash from positive cash flow shocks. Lagged cash flow is also significant in the cash equation, indicating that the firm's cash policy spans multiple periods. The negative sign suggests a cyclical movement in the cash account where an increase in one year is followed by a decrease in the next year. The CCFS is around 0.12 in the static case and 0.11 in the dynamic case, although estimations differ somewhat depending upon the method used (0.15 for the HT approach, 0.08 for GMM and SYS-GMM). Table 7 shows that CCFS estimates are somewhat higher when the Bayesian estimation method is being used (0.20 in the static case and 0.17 in the dynamic case) and that the firm-varying CCFS estimates have a wide range. For instance, in the dynamic case with sector and time dummies, the lowest CCFS value is -0.05 while the highest CCFS value is 0.82.

Similar to the exercise on ICFS, we provide a univariate and multivariate ex post analysis to test whether the high-CCFS firms are related to the variables measuring financing needs and available financing sources. Table 8 reports univariate differences between high-CCFS firms (those with a CCFS value above the median) and low-CCFS firms (those with a CCFS value below the median). As can be seen, the high-CCFS firms do not differ from the low-CCFS firms in the characteristics regarding growth, debt capacity, capital intensity, liquidity, profitability or investor valuation. High-CCFS firms do not face higher growth figures, or have much lower debt capacity, nor are they valued lower on the stock market. This suggests that high-CCFS firms do not face higher financing needs and are not faced with lower financing alternatives. The only difference that is statistically significant is that high-CCFS firms have lower net working capital. This suggests that cash-buffering is higher for firms that need to catch up on short-term liquidities to finance their short-term liabilities.

Table 6

Cash–cash flow sensitivity based on reduced-form cash equations

This table reports estimates for the cash–cash flow sensitivity based on estimation of reduced-form cash equations using traditional regression techniques. *RE, GMM* and *SYS-GMM* represent the Random-Effects estimator, the GMM estimator developed in Arellano and Bond (1991) and the system-GMM estimator developed in Blundell and Bond (1998), respectively. Robust standard errors are provided in parentheses. *CCFS* denotes the investment response due to a change in cash flow and is given by the coefficient of the cash flow in the static case (column 1) and the coefficient of cash flow divided by 1 minus the coefficient of the lagged cash rate in the dynamic case (columns 2-7). *Sargan (p-value)* reports the *p-value* of the Sargan-test of overidentifying restrictions, which tests the null that the instruments used in the GMM estimation are uncorrelated with the error term. *1st order corr. (p-value)* reports the p-value for the test for first-order autocorrelation of the differenced residuals. *2nd order corr. (p-value)* reports the p-value for the test for second-order autocorrelation of the differenced residuals. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Dep. var.	$\Delta CH_{i,t} / K_{i,t-1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(CF_{i,t} / K_{i,t-1})$	0.12	0.12	0.11	0.13	0.16	0.09	0.09
	(0.046)***	(0.047)**	(0.047)**	(0.057)**	(0.044)***	(0.101)*	(0.101)*
$lnTA_{i,t}$	0.004	0.005	0.005	0.003	0.005	0.01	0.02
	(0.002)**	(0.002)**	(0.002)**	(0.005)	(0.005)	(0.009)	(0.015)*
$MB_{i,t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.01
	(0.004)	(0.004)	(0.004)	(0.002)	(0.004)	(0.008)	(0.008)
$(\Delta CH_{i,t-1} / K_{i,t-2})$	-0.01	-0.004	-0.04	-0.07	-0.07	-0.07	
		(0.006)*	(0.062)	(0.061)*	(0.038)**	(0.089)	(0.094)
Time dummies	excluded	excluded	included	included	included	included	included
Sector dummies	excluded	excluded	excluded	included	included	included	included
CCFS	0.12	0.11	0.11	0.12	0.15	0.08	0.08
n	653	621	621	621	621	526	621
F-stat / χ^2*-stat*	9.93**	11.21**	19.93***	70.89***	46.27***	12.91***	16.01***
Sargan (p-value)						0.00	0.78
1st order corr. p-value						0.00	0.00
2nd order corr. p-value						0.02	0.18
R^2	0.03	0.04	0.05	0.09			
Method	RE	RE	RE	RE	HT	GMM	SYS-GMM

We also conduct a multivariate analysis (unreported) in which the firm-varying CCFS estimates are regressed against the firm characteristics. This multivariate analysis confirms that there is no link between the firm's CCFS and the characteristics examined. Both the univariate and multivariate analyses confirm that the firm's cash policy is a poor indicator of the firm's constraints status in line with recent research by Riddick and Whited (2009).

TABLE 7

FIRM-VARYING CASH–CASH FLOW SENSITIVITIES USING BAYESIAN ESTIMATION

This table reports the estimation results and a kernel-density graph for the firm-varying CCFS estimates obtained using Bayesian econometrics. Panel A summarizes the results from a static model that includes (natural logarithm of) total assets and market-to-book as regressors, in addition to the firm-varying cash flow coefficient. We experiment with the inclusion of time-dummies (column 2) and time and sector dummies (column 3). Panel B summarizes the results from a dynamic model where lagged cash-changes is included in addition to (natural logarithm of) total assets and market-to-book and the firm-varying cash flow coefficient. Again we experiment with the inclusion of time-dummies (column 2) and time and sector-dummies (column 3).

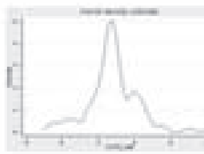
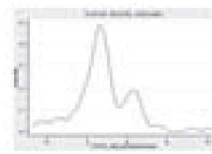
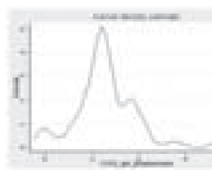
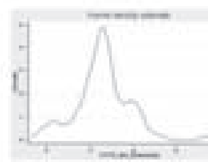
Panel A. Static model							
Dep. var.: ($I_{i,t}$ / $K_{i,t-1}$)		*(1)*		*(2)*		*(3)*	
Fixed		0.20		0.21		0.21	
Varying	*Min.*	-0.07		-0.05		-0.06	
	Max.	0.82		0.83		0.84	
	St.Dev.	0.14		0.14		0.15	
	P(25)	0.22		0.22		0.22	
	Median	0.28		0.28		0.29	
	P(75)	0.36		0.36		0.36	
Time dummies		excluded		included		included	
Sector dummies		excluded		excluded		included	
Panel B. Dynamic model							
Dep. var.: ($I_{i,t}$ / $K_{i,t-1}$)		*(1)*		*(2)*		*(3)*	
Fixed		0.17		0.18		0.18	
Varying	*Min*	-0.04		-0.02		-0.05	
	Max	0.84		0.81		0.82	
	St.Dev.	0.14		0.14		0.14	
	P(25)	0.20		0.20		0.20	
	Median	0.25		0.25		0.26	
	P(75)	0.34		0.34		0,33	
Time dummies		excluded		included		included	
Sector dummies		excluded		excluded		included	

TABLE 8
DIFFERENCES BETWEEN HIGH-CCFS AND LOW-CCFS FIRMS

This table reports median values of variables measuring capital intensity, firm growth, debt capacity, liquidity, investor valuation, profitability and dividends for «All firms,» «High-CCFS firms» and «Low-CCFS firms.» High-CCFS firms are firms for which CCFS is higher than the median value of CCFS. Low-CCFS firms are firms for which CCFS is lower than the median value. The third columns is the non-parametrical Pearson χ^2-test to see whether the differences in median values are statistically significant. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

		All firms	*High-CCFS firms*	*Low-CCFS firms*	*Pearson χ^2-test*
		n = 90	*n = 45*	*n = 45*	
Capital intensity	*PP&Egross / TA*	0.59	0.57	0.59	0.04
	PP&Enet / TA	0.33	0.36	0.30	0.40
Growth	*Investment rate*	0.14	0.17	0.12	1.06
	% Sales growth	0.14	0.19	0.12	2.03
Debt-capacity	*Financial debt rate*	0.28	0.29	0.27	1.11
	ST-financial debt rate	0.08	0.08	0.10	2.60
	Common equity / TA	0.36	0.31	0.40	3.51
Liquidity	*Working capital / TA*	0.10	0.04	0.15	11.04***
	Current ratio	1.29	1.14	1.48	6.07**
	Cash flow / K	0.15	0.15	0.14	0.05
Investor valuation	*Market-to-book*	1.98	2.28	1.92	0.40
Profitability	*EBITDA / TA*	0.10	0.09	0.11	2.52
	Net income / TA	0.04	0.03	0.04	3.45
Dividends	*Dividends / TA*	0.01	0.01	0.01	0.52

5. CONCLUSIONS, DISCUSSION AND LIMITATIONS

There is considerable debate in the empirical corporate finance literature on how a firm's exposure to financing constraints can be measured. Some studies suggest that the firm's investment response in the event of a cash flow shock (ICFS) is a good proxy, whereas other studies claim this metric is largely driven by measurement error and endogeneity. More recently, some studies advocate analyzing the firm's cash response in the event of a cash flow shock (CCFS) as a proxy for financing constraints. However, this metric has been also criticized as being driven by income uncertainty.

In order to help solve this debate, a number of studies have suggested analyzing firm-level sensitivities rather than comparing sample-level estimates across ex ante classified groups. Some of the benefits over the traditional empirical approach include: 1) avoiding ex ante classification, 2) avoiding endogeneity and aggregation bias and 3) allowing for a thorough judgment on the usefulness of ICFS and CCFS by identifying in detail which variables are driving the sensitivity.

In this paper we argue that firm-varying ICFS estimates can be conveniently computed from the underlying reduced-form investment model by means of Bayesian estimation. Similarly, firm-varying CCFS estimates can be computed from the underlying cash model.

The Bayesian estimation procedure is particularly well-suited to model heterogeneous slopes in the context of panel data because it allows for flexibility in the functional form, requires only minimal assumptions and is able to tackle a large number of parameters in relation to the data points. In this respect, the firm-varying estimates produced by the Bayesian estimation are in accordance with the underlying investment and cash models. This represents a considerable benefit over Hovakimian and Hovakimian (2009), who use a mathematical proxy based upon the levels of cash flow and investment. Furthermore, the Bayesian method has been widely used in different fields and can be considered a robust estimation method.

Our results, based upon a dataset of 90 listed Spanish firms over the 1999-2008 period show that high-ICFS firms are considerably different from low-ICFS firms, and these differences hold both univariately as well as multivariately. High-ICFS firms are more capital intensive and have higher growth rates both in terms of investments and sales growth. This suggests that high-ICFS firms face considerably higher financing needs than their counterparts. Additionally, high-ICFS firms have exhausted much of their debt capacity, are valued lower on the stock-markets and have considerably lower liquidity and profitability measures. This suggests that high-ICFS firms find fewer financing alternatives and face higher financing costs. On the whole, the analysis points towards a strong correlation between the firm's ICFS and the firm's exposure to financing constraints. This result finds support in recent insights by Carpenter and Guariglia (2008) and Islam and Mozumdar (2007).

When a similar analysis is conducted with the firm's CCFS, we find no relation between CCFS and the susceptibility to financing constraints. This result is in line with Riddick and Whited (2009), who claim that other factors influence the firm's CCFS to such a degree that it cannot be considered an adequate proxy for gauging the firm's exposure to financing constraints.

Overall, this study complements previous research on the relation between financing constraints and debt (Aivazian *et al.,* 2005; Galeotti *et al.,* 1994; Marra Domínguez, 2007), access to financial markets (Aivazian and Santor, 2008), liquidity (Calem and Rizzo, 1995) and growth opportunities (Alti, 2003). More specifically, we believe this paper complements the literature in a number of ways. First, to the best of our knowledge, this study is the first to use a Bayesian estimation procedure for recovering firm-varying ICFS and CCFS estimates. Our approach adds to previous studies on the benefits of firm-varying ICFS estimation by devising different methods for computing these estimates.

Second, this paper adds to the Spanish evidence on financing frictions and interrelations between financing decisions and investment decisions. Our results indicate that financing constraints are still causing under-investment and hampering firm growth. This means that there is still room for stimulating growth through increased credit availability, which is an important insight for policy-makers in light of the current economic crisis and the accompanying credit-crunch that has severely affected Spain.

Third, our research calls into question the recent shift towards using CCFS as a proxy for capturing the firm's exposure to financing constraints. Our results suggest that the firm's cash policy is not driven by increased financing needs or decreased credit availability, and thus that the CCFS is a poor indicator of the firm's constraints status. Our results indicate the ICFS better captures the firm's constraints status, even taking into account the problems of endogeneity and difficulty in controlling for investment opportunities.

There are evidently also a number of caveats that should be kept in mind. First, the empirical results are based upon a sample of 90 Spanish listed firms over a well-defined time period. Since only listed firms are studied, there is a bias in our sample towards medium and large firms. It would be interesting to test whether the results hold for smaller firms.

Second, our results are based upon the standard cash flow-augmented Q model of investment. This model has a long-standing tradition in the literature and Adam and Goyal (2008) argue that this proxy best captures the firm's investment opportunities. However, it should be noted that other proxies for Marginal Q have also been used such as the market value of capital over the replacement value of capital (Miguel and Pindado, 2001), a measurement-corrected version of Marginal Q (Erickson and Whited, 2000) and a forward-looking value based upon VAR-forecasting techniques (Gilchrist and Himmelberg, 1995). Our research could be extended to other model specifications that take up different controls for investment opportunities or use a different functional form, such as the neoclassical model (see, for instance, Bond *et al.,* 2003) or the sales-accelerator model (see, for instance, Kadapakkam *et al.,* 1998).

Finally, in the ex post analysis we identify a relation between the ICFS and a number of variables regarding firm growth, debt capacity, market valuation, liquidity and profitability. However, this analysis could be extended to identify other determinants of the ICFS. Similarly, given the fact that CCFS seems unrelated to the firm's constraints status, it would be interesting to identify in detail which variables drive the firm's CCFS.

REFERENCES

Adam, T., and Goyal, V. K. 2008. The investment opportunity set and its proxy variables. *Journal of Financial Research* 31(1): 41-63.

Ağca, S., and Mozumdar, A. 2008. The impact of capital market imperfections on investment-cash flow sensitivity. *Journal of Banking and Finance* 32: 207-216.

Aivazian, V. A.; Ge, Y., and Qiu, J. 2005. The impact of leverage on firm investment: Canadian evidence. *Journal of Corporate Finance* 11: 277-291.

Aivazian, V. A., and Santor, E. 2008. Financial constraints and investment: Assessing the impact of a World Bank credit program on small and medium enterprises in Sri Lanka. *Canadian Journal of Economics* 41: 475-500.

Allayannis, G., and Mozumdar, A. 2009. The impact of negative cash flow and influential observations on investment-cash flow sensitivity estimates. *Journal of Banking and Finance* 28: 901-930.

Almeida, H., and Campello, M. 2007. Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies* 20: 1.429-1.460.

Almeida, H.; Campello, M., and Weisbach, M. S. 2004. The cash flow sensitivity of cash. *Journal of Finance* 59: 1.777-1.804.

Alonso, C., and Bentolila, S. 1993. La relación entre la inversión y la q de Tobin en las empresas industriales españolas, en: Dolado, J. J.; Martín, C., and Romero, L. R. (eds.) *La industria y el comportamiento de las empresas españolas. Ensayos en homenaje a Gonzalo Mato*. 77116. Madrid: Alianza Editorial.

Alti, A. 2003. How sensitive is investment to cash flow when financing is frictionless? *Journal of Finance* 58: 707-722.

Álvarez Otero. S. 1996. Inversión de sostenimiento e inversión discrecional: Un modelo financiero del comportamiento inversor de la empresa industrial española. *Investigaciones Europeas de Dirección y Economía de la Empresa* 2: 81-105.

— 1998. Evidencia empírica de la relación entre la inversión de la empresa industrial española y las variables financieras. *Investigaciones Europeas de Dirección y Economía de la Empresa* 4: 45-56.

Arellano, M., and Bond, S. R. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* 58: 277-297.

Ascioglu, A.; Hedge, S. P., and McDermott, J. B. 2008. Information asymmetry and investment-cash flow sensitivity. *Journal of Banking and Finance* 32: 1.036-1.048.

Azofra, V.; Saona, P., and Vallelado, E. 2007. Oportunidades de crecimiento y estructura de propiedad como determinantes del apalancamiento de las empresas españolas. *Revista Española de Financiación y Contabilidad* 36(133): 11-30.

Bernanke, B.; Gertler, M., and Gilchrist, S. 1996. The financial accelerator and the flight to quality, *The Review of Economics and Statistics* 78: 1-15.

Berry, D. A. 1996. *Statistics: A Bayesian perspective*. New York: Wadsworth Publishing Company.

Blundell, R., and Bond, S. 1998. GMM estimation with persistent data: An application to production functions. *Econometric Reviews* 19: 321-340.

Bond, S., and Cummins, J. 2001. Noisy share prices and the Q model of investment. *Institute for Fiscal Studies* discussion paper 22.

Bond, S.; Elston, J. A.; Mairesse, J., and Mulkay, B. 2003. Financial factors and investment in Belgium, France, Germany, and the United Kingdom: A comparison using company panel data. *The Review of Economics and Statistics* 85: 153-165.

Calem, P. S., and Rizzo, J. A. 1995. Financing constraints and investment: New evidence from hospital industry data. *Journal of Money, Credit and Banking* 27: 1.002-1.014.

Calomiris, C.; Himmelberg, C., and Wachtel, P. 1995. Internal finance and firm-level investment: Evidence from the undistributed profits tax of 1936-1937. *Journal of Business* 68: 443-482.

Carpenter, R. E., and Guariglia, A. 2008. Cash flow, investment and investment opportunities: New tests using UK panel data. *Journal of Banking and Finance* 32: 1.894-1.906.

Carpenter, R. E., and Petersen, B. C. 2002. Is the growth of small firms constrained by internal finance? *The Review of Economics and Statistics* 84: 298-309.

Cleary, S. 1999. The relationship between firm investment and financial status. *Journal of Finance* 54: 673-691.

— 2006. International corporate investment and the relationships between financial constraints measures. *Journal of Banking and Finance* 30: 1.559-1.580.

Cleary, S., and D'Espallier, B. 2007. Financial constraints and investment: An alternative empirical framework. *Anales de Estudios Económicos y Empresariales* 17: 1-41.

Cleary, S.; Povel, P., and Raith, M. 2007. The U-shaped investment curve: Theory and evidence. *Journal of Financial and Quantitative Analysis* 42: 1-39.

Cooper, R., and Haltiwanger, J. 2006. On the nature of capital adjustment costs. *Review of Economic Studies* 73: 611-633.

Correa, R. A.; Molina, A. M., and Barrios del Pino, I. 2002. Fuentes de financiación e inversión en I+D: Análisis para la gran empresa manufacturera española. *Revista de Economía y Empresa* 47: 63-84.

Cummins, J.; Hasset, K., and Oliner, S. 2006. Investment behaviour, observable expectations and internal funds. *American Economic Review* 96: 796-810.

D'Espallier, B.; Vandemaele, S., and Peeters, L. 2008. Investment-cash flow sensitivities or cash-cash flow sensitivities? An evaluative framework for measures of financial constraints. *Journal of Business Finance and Accounting* 35: 943-968.

Deloof, M. 1998. Internal capital markets, bank borrowing, and financial constraints: Evidence from Belgian firms. *Journal of Business Finance and Accounting* 25: 945-968.

Doms, M., and Dunne, T. 1998. Capital adjustment patterns in manufacturing plants. *Review of Economic Dynamics* 1: 409-449.

Erickson, T., and Whited, T. 2000. Measurement error and the relationship between investments and Q. *Journal of Political Economy* 108: 1.027-1.057.

Estrada, A., and Vallés, J. 1998. Investment and financial structure in Spanish manufacturing firms. *Investigaciones Económicas* 22: 337-359.

Fazzari, S. M.; Hubbard, R.G., and Petersen, B.C. 1988, Financing constraints and corporate investment. *Brookings Papers on Economic Activity* 1: 141-195.

— 2000. Investment-cash flow sensitivities are useful: A comment on Kaplan and Zingales. *Quarterly Journal of Economics* 115: 695-705.

Fraser, I. 2000. An application of maximum entropy estimation: The demand for meat in the United Kingdom. *Applied Economics* 32: 45-59.

Galeotti, M.; Schiantarelli F., and Jaramillo, F. 1994. Investment decisions and the role of debt, liquid assets and cash flow: Evidence from Italian panel data. *Applied Financial Economics* 4: 121-132.

García, M. T. 1998. Liquidez, costes financieros e inversión de las empresas españolas: Un análisis empírico. *Revista Española de Economía* 15: 463-486.

García, M. T., and Ocaña, C. 1999. The effect of bank monitoring on the investment behavior of Spanish firms. *Journal of Banking & Finance* 23: 1.579-1.603.

García, M. T., and Vicente Lorente, J. D. 1999. Los efectos de la participación bancaria en la política de inversión de las empresas españolas: Una aplicación del modelo neoclásico de inversión. *Revista Española de Financiación y Contabilidad* 28: 325-348.

Gilchrist, S., and Himmelberg, C. P. 1995. Evidence on the role of cash flow for investment. *Journal of Monetary Economics* 36: 541-572.

Guariglia, A. 2008. Internal financial constraints, external financial constraints and investment choice: Evidence from a panel of UK firms. *Journal of Banking and Finance* 32: 1.795-1.809.

Han, S., and Qiu, J. 2007. Corporate precautionary cash holdings. *Journal of Corporate Finance* 13: 43-57.

Hansen, M.; Perry, L. T., and Reese, C. S. 2004. A Bayesian operationalization of the resource-based view. *Strategic Management Journal* 25: 1.279-1.295.

Hausman, J. A., and Taylor, W. E. 1981. Panel data and unobservable individual effects. *Econometrica* 49: 1.377-1.398.

Hernando, I. and Martínez-Carrascal, C. 2008. The impact of financial variables on firms' real decisions: Evidence from Spanish firm-level data. *Journal of Macroeconomics* 30: 543-561.

Hernando, I. and Tiomo, A. 2002. Financial constraints and investment in France and Spain: A comparison using firm level data. *Bank of Spain Working paper* 214.

Hernando, I. and Vallés, J. 1992, Inversión y restricciones financieras: Evidencia en las empresas manufactureras españolas. *Moneda y Crédito* 195: 185-222.

Hoshi, T.; Kashyap, A., and Scharfstein, D. 1991. Corporate structure, liquidity and investment: Evidence from Japanese industrial groups, *Quarterly Journal of Business and Finance* 106: 33-60.

Hovakimian, G. 2009. Determinants of investment cash flow sensitivity, *Financial Management* 38: 161-183.

Hovakimian, A., and Hovakimian, G. 2009. Cash flow sensitivity of investment, *European Financial Management* 15: 47-65.

Islam, S. S., and Mozumdar, A. 2007. Financial market development and the importance of internal cash: Evidence from international data. *Journal of Banking and Finance* 31: 641-658.

Kadapakkam, P. R.; Kumar, P. C., and Riddick, L. A. 1998. The impact of cash flows and firm size on investment: The international evidence. *Journal of Banking and Finance* 22: 293-320.

Kaplan, S. N., and Zingales, L. 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112: 169-215.

— 2000. Investment-cash flow sensitivities are not valid measures of financing constraints, *Quarterly Journal of Economics* 115: 707-712.

Kashyap, A.; Lamont, O., and Stein, J. 1994, Credit conditions and the cyclical behavior of inventories, *Quarterly Journal of Economics* 109: 565-592.

Khurana, I.; Martin, X., and Pereira, R. 2006. Financial development and the cash flow sensitivity of cash. *Journal of Financial & Quantitative Analysis* 41: 787-806.

Koop, G. 2003. Bayesian econometrics. New Jersey: Wiley Interscience.

Lancaster, T. 2004. An introduction to modern Bayesian econometrics. New Jersey: Blackwell Publishing.

Lin, Y. 2007. The cash flow sensitivity of cash: Evidence from Taiwan. *Applied Financial Economics* 17: 1.013-1.024.

Lyandres, E. 2007. Costly external financing, investment timing and investment-cash flow sensitivity. *Journal of Corporate Finance* 13: 959-980.

Lozano, B.; Miguel, A., and Pindado, J. 2001. Determinantes financieros de los activos inmateriales. *Revista de Economía Aplicada* 27: 63-81.

Maestro, M. H.; Miguel, A., and Pindado, J. 2007. Modelo de inversión basado en la ecuación de Euler con límite máximo de endeudamiento: Evidencia empírica internacional. *Cuadernos de Economía y Dirección de la Empresa* 30: 93-128.

Maroto Acín, J. A. 1997, Ahorro empresarial e inversión. *Papeles de Economía Española* 70: 84-99.

Marra Domínguez, M. A. 2007. Tamaño, restricciones financieras e inversión en I+D. Revista *de Economía Aplicada* 15: 99-123.

Mato, G. 1988. Investment demand at the firm level: The case of Spain. *Recherches Economiques de Louvain* 54: 325-336.

— 1990. Estructura financiera y actividad real de las empresas industriales, *Economía Industrial* 272: 107-114.

MIGUEL, A., and PINDADO, J. 2001. Determinants of capital structure: new evidence from Spanish panel data. *Journal of Corporate Finance* 7(1): 77-99.

RAUH, J. D. 2006. Investment and financing constraints: Evidence from the funding of corporate pension plans. *Journal of Finance* 61: 33-71.

RIDDICK, L., and WHITED T. 2009. The corporate propensity to save. *Journal of Finance* 64: 1.729-1.766.

RODRÍGUEZ BRITO, M. G. 2001. Restricciones financieras en un contexto de asimetrías informativas: Incidencia de la estructura financiera en las decisiones de inversión. *Estudios de Economía Aplicada* 18: 209-232.

SUCH, M. J. and PARTE, L. 2007. La financiación de la actividad productiva: Una aproximación empírica a los determinantes del endeudamiento de las empresas hoteleras españolas. *Revista Española de Financiación y Contabilidad* 36(133): 147-174.

WEI, J. and ZHANG, Y. 2008. Ownership structure, cash flow, and capital investment: Evidence from East Asian economies before the financial crisis. *Journal of Corporate Finance* 14: 118-132.

WHITED, T. and WU, G. 2006. Financial constraints risk, *The Review of Financial Studies* 19: 531-558.

APPENDIX ON BAYESIAN ECONOMETRICS

In the Bayesian philosophy, parameters are estimated by combining prior information on the parameter with data using Bayes' theorem:

$$p(\theta|y) \approx p(y|\theta)_i \cdot p(\theta) \tag{A1}$$

Equation (A1) is the continuous version of Bayes' conditional probability theorem, which states that the distribution of a certain parameter conditional on the data $p(\theta|y)$ can be calculated by combining the distribution of the data $p(y|\theta)$ with the prior distribution on the parameter $p(\theta)$. The element $p(y|\theta)$ is called the likelihood and summarizes the probability of the data for each possible value of the parameter. The element $p(\theta)$ is called the «prior information» and 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 parameter θ based upon what was already known about the parameter (the prior) and new evidence brought on by the data (likelihood).

This method for recovering information about a certain parameter can be extended to estimate the parameters of any regression model using a five-step algorithm (Lancaster, 2004; Koop, 2003; Hansen *et al.*, 2004). Suppose that we want to estimate the parameters of a panel data regression model with two regressors as follows:

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

In the first step, the econometric model is written as a probability model conditional upon different values for the set of parameters:

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

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

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

$$\beta_0 = N(0{,}100) \tag{A5}$$

$$\beta_1 = N(0{,}100) \tag{A6}$$

$$\beta_3 = N(0{,}100) \tag{A7}$$

$$\tau = 1 / \sigma_t^2 = \Gamma(0.001,\ 0.001) \tag{A8}$$

Equations (A5), (A6), (A7) and (A8) describe vague information about the parameters of the regression model by expressing them as a realization of a normal distribution with a wide variation and an expected value of zero. In the third step the data are collected and inserted into the probability model. Before the development of sampling techniques, this would require that the distribution of the data be written as a probability distribution. However, Bayesian software allows inputting the data directly into the software without specifying the probability distribution. Step 4 calculates the updated belief about each parameter by sampling numerically from the joint posterior density using Markov Chain Monte Carlo (MCMC) sampling methods. This yields a full distribution for each parameter as follows:

$$\hat{\theta}_3 = (\widehat{\beta_0},\ \widehat{\beta_1},\ \widehat{\beta_2}, \hat{\tau}) \quad \textbf{(A9)}$$

Step 5 consists of critically evaluating the results by changing the prior information. This is critical for ensuring that the results are not driven by subjectively choosing the prior values. Although usually vague priors are being used and it can be shown that the data dominate the prior information when samples are large (likelihood dominance) [(13)], the use of prior information as a building block in addition to data is sometimes perceived as problematic for non-Bayesian researchers.

(13) It can be shown that the posterior mean is the weighted sum of the prior mean and the sample mean with weights 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 $\bar{\mu}$, μ_0, $\bar{y}$ are the posterior mean, prior mean and sample mean, respectively, and the weights are given by $w_0 = 1/\sigma_0^2$, $w1 = \sigma^2/N$. This means that if N becomes larger, the posterior distribution will depend very little on the prior and more on the likelihood.