Article:

Bhaumik, S.K., kumbhakar, S. and Sun, K. (2014) A note on a semiparametric approach to estimating financing constraints in firms. European Journal of Finance. Published online: 15 May 2014. ISSN 1466-4364

https://doi.org/10.1080/1351847X.2014.906068

A note on a semiparametric approach to estimating financing constraints in firms*

Sumon Kumar Bhaumik
Sheffield University Management School, University of Sheffield, UK,
IZA - Institute for the Study of Labor, Germany, &
William Davidson Institute, University of Michigan, Ann Arbor, USA

Subal C. Kumbhakar†
Binghamton University, New York, USA

Kai Sun
Aston Business School, Aston University, UK

March 14, 2014

*Bhaumik would like to acknowledge British Academy's small grant no. SG-54061 which was used to obtain the *Prowess* data set. The authors would like to than two anonymous referees for helpful comments, and they remain responsible for all remaining errors.

† *Corresponding author.* Department of Economics, Binghamton University, Binghamton, New York, USA. *Email*: kkar@binghamton.edu

A note on a semiparametric approach to estimating financing constraints in firms

Abstract

In this paper, we present a novel approach to modeling financing constraints of firms. Specifically, we adopt an approach in which firm level investment is a nonparametric function of some relevant firm characteristics, cash flow in particular. This enables us to generate firm-year specific measures of cash flow sensitivity of investment. We are therefore able to draw conclusions about financing constraints of individual firms as well cohorts of firms without having to split our sample on an *ad hoc* basis. This is a significant improvement over the stylised approach that is based on comparison of point estimates of cash flow sensitivity of investment of the average firm of *ad hoc* sub-samples of firms. We use firm-level data from India to highlight the advantages of our approach. Our results suggest that the estimates generated by this approach are meaningful from an economic point of view and are consistent with the literature.

Keywords: Financial constraint; Semiparametric approach; Robinson model

1 Introduction

Following the research of Fazzari, Hubbard and Petersen [FHP] (1988), the stylized literature has argued that if a firm's investment is significantly dependent on (and positively correlated with) its cash flow, then the firm can be deemed financially constrained. Specifically, it is argued that if a value maximizing firm is not financially constrained, its investment decisions depend only on its future prospect, which is captured by Tobin's q, and perhaps also by its current and past sales. However, if the firm is financially constrained, its investment is also affected by cash flow that is a proxy for internal resources.[1] Although brought into question (Kaplan and Zingales, 1997), this interpretation of the cash flow sensitivity of firm-level investment remains the stylized approach to examining financing constraints in firms.

The FHP-led literature has two important shortcomings. First, in this literature, the sample of firms is classified into groups, and inferences about the extent of financing constraints experienced by these groups is drawn from the differences in the cash flow sensitivity of investment of the firms (estimated at the mean) belonging to these groups. The basis for the creation of these groups is *ad hoc*,[2] that can lead to erroneous conclusions (Kaplan and Zingales, 1997; Laeven, 2003). Second, irrespective of whether or not the *average* firm in a group of firms experiences financing constraints, it is likely that within the group there is significant heterogeneity in the marginal impact of cash flow (and indeed other relevant firm characteristics such as leverage) on investment. From the perspectives of the firms' management and policymakers, it is important to identify the firms that are financially constrained and estimating firm-specific marginal effect of cash flow and other variables that affect financing constraint and the distribution of these marginal effects, respectively. However, the stylized FHP-led approach does not enable us to estimate these firm-specific effects.

In this paper, we propose the use of an alternative approach to modeling financial constraint. Specifically, leveraging the modeling approach of Robinson (1988), we propose the use of a partially

[1] This base specification is extended, as required, to examine the impact of factors over and above cash flow that can capture frictions in the capital market on investment levels. For example, Aivazian et al. (2005) demonstrate the leverage adversely affects firm investment in Canada. Furthermore, where panel data are used, firm and time-effects are added to control for possible firm- and time-heterogeneity in the intercept.

[2] The Fazzari *et al.* (1988) paper classified firms on the basis of their dividend payouts, while other studies have used firm characteristics such as size and age.

linear model that is linear in the variables that determine firm-level investment in a frictionless world, namely, Tobin's q and current and past sales, and non-linear, indeed non-parametric, in the key indicator variable, namely, cash flow.[3] This approach has several advantages over the stylised methodology. First, it enables us to estimate firm-specific value of the marginal impact of cash flow on investment. We, therefore, are able to draw conclusions about the extent of financing constraints of individual firms, not just the effect at the mean (*average* firm).[4] Second, firm-level estimates of cash flow sensitivity of investment (or the degree of financial constraints) also enable us to to compare financing constraint experienced by different firm cohorts without splitting of the sample into groups based on *ad hoc* criteria such as dividend payout. Finally, as we discuss later, the approach is also scalable, and we can extend it to model financial constraint as a joint outcome of multiple firm characteristics such as cash flow and ownership.

We use this partially linear semiparametric approach to estimate firm-specific cash flow sensitivity of investment of a panel of Indian manufacturing firms, for the 1997-2006 period. We report the results of the base model that is semiparametric only in cash flow, and then extend the model to highlight its scalability. Our results indicate that cash-flow sensitivity indeed varies significantly across firms, and our estimates are robust across model specifications. In the course of our analysis, we also draw comparisons with the stylised methodology, and demonstrate that the semiparametric approach provides additional insights without loss of information generated by the former methodology.

The rest of the paper is structured as follows: In Section 2, we discuss the conceptual basis for the model specification, and the semiparametric approach in particular. The data are described briefly in Section 3, and the model estimates are reported in Section 4. Finally, Section 5 concludes.

[3]We thank an anonymous referee for suggesting that we focus only on the cash flow variables. In additional specifications, we also control for firm characteristics such as fixed assets, leverage and business group affiliation.

[4]In the context of panel data, we are able to estimate firm-year specific estimates of cash flow sensitivity, thereby facilitating comparisons across time.

2 Modeling financing constraint

2.1 Introducing the semiparametric approach

The literature on investment decisions of firms builds on the work of Fazzari *et al.* (1988). They argue that if a value maximising firm is not financially constrained then its investment decisions depend only on its Tobin's q, which captures future prospects, and on current and past sales. If, however, the firm is financially constrained then its investment is also affected by its cash flow that is a proxy for internal resources. Following this, in the stylized literature, firm-level investment is modeled as follows:

$$\frac{I_{it}}{K_{i,t-1}} = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_2 \ln\left(\frac{S_{i,t}}{K_{i,t-1}}\right) + \beta_3 \ln\left(\frac{S_{i,t-1}}{K_{i,t-2}}\right) + \beta_4\left(\frac{CF_{it}}{K_{i,t-1}}\right) + u_{it} \tag{1}$$

where I is investment, K is capital, Q is Tobin's q, S is sales, CF is cash flow, and u is the error term that is uncorrelated with all the right-hand-side variables. The focus is on the β_4, the coefficient of the cash flow variable. If $\beta_4 > 0$ and statistically significant, the (average) firm is considered to be financially constrained.

This basic equation ((1)) has been extended to accommodate firm characteristics such as size, leverage and ownership structures. The expanded specification is given by

$$\frac{I_{it}}{K_{i,t-1}} = \beta_0 + \beta_1 \ln Q_{i,t-1} + \beta_2 \ln\left(\frac{S_{i,t}}{K_{i,t-1}}\right) + \beta_3 \ln\left(\frac{S_{i,t-1}}{K_{i,t-2}}\right) + \beta_4\left(\frac{CF_{it}}{K_{i,t-1}}\right) + \sum_k \phi_k FC_{k,it} + u_{it} \tag{2}$$

where the variables in FC_k include the aforementioned firm characteristics. Variants of this linear model have been estimated using both pooled(ordinary least squares) regression (Lang, Ofek and Stulz, 1996) and fixed effects panel regression models (Aivazian et al., 2005).

Wang (2003) and Bhaumik, Das and Kumbhakar [BDK] (2012) argue that when capital markets are perfect, firm-level investment is sufficiently characterized by Tobin's q and current and past sales. But when capital markets are imperfect, resulting in financing constraints of firms, investment is affected by factors such as cash flow and leverage. They develop a stochastic frontier approach to modeling financial constraints, that enables them to estimate measures of investment efficiency, namely, the efficiency with which a firm's Tobin's q and sales performance is converted into investment. It is easy to see that financial constraint is an inverse function of investment efficiency, and to that extent we have firm-level measures of financial constraints. BDK demonstrates that this enables us to estimate the conditional relationships between the degree of financial constraint and firm characteristics such as cash flow, fixed assets and leverage. This advantage notwithstanding, the Wang-BDK approach generates a point estimate of the cash flow sensitivity of investment efficiency, rather than firm-specific estimates of cash-flow sensitivity of investment.

We draw on the distinction that Wang (2003) and BDK (2012) make between the factors that explain investment decisions in the context of perfect capital markets and contexts where frictions that exist on account of capital market imperfections. Specifically, we argue that in the context of perfect capital markets investment decisions are adequately captured by

$$\frac{I_{it}}{K_{i,t-1}} = \gamma_1 \ln Q_{i,t-1} + \gamma_2 \ln\left(\frac{S_{i,t}}{K_{i,t-1}}\right) + \gamma_3 \ln\left(\frac{S_{i,t-1}}{K_{i,t-2}}\right) + u_{it}$$

while other firm characteristics such as cash flow play a role in determining investment when capital markets are imperfect. If the set of these firm characteristics are given by $\{CF,\ FC\}$,[5] therefore, our model specification is given by

$$\frac{I_{it}}{K_{i,t-1}} = \gamma_1 \ln Q_{i,t-1} + \gamma_2 \ln\left(\frac{S_{i,t}}{K_{i,t-1}}\right) + \gamma_3 \ln\left(\frac{S_{i,t-1}}{K_{i,t-2}}\right) + \gamma_0\left(\frac{CF_{it}}{K_{i,t-1}}, FC_{it}\right) + u_{it} \tag{3}$$

This specification, which is linear in the variables that determine investment decisions under the condition of a perfect capital market, and is nonparametric in the other firm level characteristics that affect investment when the capital market is imperfect, enables us to estimate firm-specific values of the impact of these other firm characteristics on the investment decision.[6]

In this paper, we first estimate a parsimonious version of (3), in which investment is a nonparametric function of cash flow alone, generating firm-year specific estimates of cash flow sensitivity

[5]In our case, the vector FC includes includes (log) assets, a dummy variable that takes the value 1 for high levels of debt, and a dummy variable that takes the value 1 for firms that are affiliated with business groups. The choice of these variables are consistent with BDK (2012).

[6]We thank an anonymous referee for pointing out that it is possible to argue that investment decision can be a nonparametric function of *all* the variables in (3). However, for the sake of parsimony, and in keeping with the suggestions made the referee, we shall retain the semiparametric specification for (3).

of investment. Later, to demonstrate the full capability of this approach, we estimate (3) itself, whereby investment is a nonparametric function of all firm characteristics that can affect investment under the condition of capital market imperfection. As we shall see later in the paper, even when γ_0 is estimated as a function of $\{CF,\ FC\}$, we able to isolate the marginal impact of cash flow and other firm characteristics on γ_0.

2.2 The econometrics of the semiparametric approach

Recapitulate that, based on Wang (2003) and BDK (2012), we can model firm level investment as a function of firm-level characteristics (X) such as Tobin's q that determine investment in the absence of friction in the credit or capital market, and firm characteristics such as cash flow and fixed assets (Z) that affect investment when credit and capital markets are imperfect. In light of this we rewrite the investment function as

$$E(Y_{it}|X_{it}, Z_{it}) = \gamma_0(Z_{it}) + X_{it}'\Gamma,\ i = 1, \ldots, N; t = 1, \ldots, T \tag{4}$$

where N and T denotes the number of firms and time periods, respectively. $Y_{it} = \frac{I_{it}}{K_{i,t-1}}$, X_{it} is a vector that includes Tobin's q and current and past sales, Z_{it} is a vector that includes cash flow (CF) and other firm characteristics (FC) such as fixed assets, leverage and ownership characteristics, $\gamma_0(\cdot)$ denotes an unknown smooth (i.e., nonparametric) function, and Γ denotes a k-vector of parameters. Note that we deliberately start with the most general formulation of the nonparametric specification. All other specifications, e.g., one in which firm-level investment decision is a nonparametric function of cash flow alone can then be a special case of this general specification. This specification implies that

$$Y_{it} = \gamma_0(Z_{it}) + X_{it}'\Gamma + u_{it}. \tag{5}$$

To estimate the parameters in Γ and the functional coefficient $\gamma_0(\cdot)$, we follow Robinson's (1988) two-step approach. In the first step, we transform (5) by taking the conditional expectation $E(\cdot|Z_{it})$ for both sides of the equation. We then subtract this transformed equation from (5) to obtain a linear parametric model, $Y_{it}^* = X_{it}^{*'}\Gamma + u_{it}$, under the assumption that $E(u_{it}|Z_{it}) = 0$, where $Y^*_{it} = Y_{it} - E(Y_{it}|Z_{it})$, and $X^{*'}_{it} = (X_{it} - E(X_{it}|Z_{it}))'$. This enables us to estimate Γ using the condition $E(X^*_{it}u_{it}) = 0$.[7] In the second step, we compute $\hat{\gamma}_0(\cdot)$ from $\hat{\gamma}_0 = \tilde{Y}_{it} - \tilde{X}'_{it}\hat{\Gamma}$ where $\hat{\Gamma}$ is the estimate of Γ; $\tilde{Y}_{it}$ is the estimate of $E(Y_{it}|Z_{it})$, and $\tilde{X}_{it}$ is the estimate of $E(X_{it}|Z_{it})$. Most importantly, we estimate the marginal impact of z on γ_0 from $\partial\hat{\gamma}_0/\partial z = \partial\tilde{Y}_{it}/\partial z - (\partial\tilde{X}'_{it}/\partial z)\hat{\Gamma}$. This marginal effect is observation-specific because $\hat{\gamma}_0$ is a nonparametric function of z.

Once observation-specific estimates of the marginal impact of the Z variables on γ_0, i.e., $\partial\hat{\gamma}_0/\partial z_1$ are obtained, we calculate their standard errors via wild bootstrap method (Mammen, 1993). The wild bootstrap works well when the error term is heteroskedastic (Horowitz 1997), and therefore it can be applied to obtain heteroskedasticity-robust standard errors. To do this first we estimate the original model, obtain $\hat{Y}_{it} = \hat{\gamma}_0 + X'_{it}\hat{\Gamma}$ (i.e., the estimated $E(Y_{it}|X_{it}, Z_{it})$), $\hat{u}_{it} = Y_{it} - \hat{Y}_{it}$, and $\partial\hat{\gamma}_0/\partial z_1$. The wild bootstrap error u^*_{it} is generated by replacing $\hat{u}_{it}$ by $[(1-\sqrt{5})/2]\hat{u}_{it}$ with probability $(1+\sqrt{5})/(2\sqrt{5})$; and by $[(1+\sqrt{5})/2]\hat{u}_{it}$ with probability $(\sqrt{5}-1)/(2\sqrt{5})$. Then we generate $Y^*_{it} = \hat{Y}_{it} + u^*_{it}$, and use the bootstrap sample $\{X_{it}, Y^*_{it}, Z_{it}\}^{NT}_{it=1}$ to estimate $\partial\gamma_0/\partial z_1$. We call these the bootstrap estimates of $\partial\gamma_0/\partial z_1$. We repeat the preceding steps 99 times. The standard error of $\partial\hat{\gamma}_0/\partial z_1$ for each observation is then calculated using the original estimates, $\partial\hat{\gamma}_0/\partial z_1$ and the bootstrapped estimates. The same procedure is applied to calculate the standard errors for the marginal impact of the other Z variables.

Finally, following Zhang *et al.* (2012) and Henderson *et al.* (2012), we can generate confidence intervals for the firm-year specific estimates of cash flow sensitivity. In the case of equation 3, we can generate the confidence intervals for the firm-year specific estimates of the marginal effects $\partial\gamma_0/\partial CF$. We discuss this further later in the paper.

3 Data

Our sample includes a set of 598 Indian private manufacturing firms incorporated prior to 1991, and the sample period is 1997-2006. The choice of manufacturing firms is consistent with the stylised practice of separately analysing financial decisions (and performance) of manufacturing

[7] We estimate $E(Y_{it}|Z_{it})$ and $E(X_{it}|Z_{it})$ using Nadaraya-Watson kernel estimator, $\sum_i\sum_t K(Z_{it}, z)W_{it}/\sum_i\sum_t K(Z_{it}, z)$, where $W_{it} \in \{X_{it}, Y_{it}\}$, $K(\cdot)$ denotes a product kernel function, and z denotes the datum at which the kernel function is evaluated.

and service sector firms, and the choice of private firms ensure that, unlike their public sector counterparts, they do not benefit from soft budget constraints. Further, while some of the firms in the sample have foreign equity participation, they are by and large dependent on the Indian credit and capital markets for financing their investments. This is representative of private sector firms in emerging markets, in general, and Indian firms, in particular. Finally, the choice of firms that were incorporated before 1991, a benchmark year in terms of liberalisation of the Indian economy, ensures that our results are not influenced by the inclusion of relatively new firms that may have weak relationships with banks and other financial institutions.

The data are obtained from the *Prowess* database that is marketed by the Centre for Monitoring the Indian Economy (CMIE). *Prowess* provides balance sheet and profit and loss accounts of firms in a standardised, and hence comparable, format. Data on variables such as sales, assets, investments and cash flows are either directly available, or can be easily computed. The database also provides information on key financial ratios such as the debt-to-equity ratio that is our measure of leverage,[8] and it has a clear identifier for firms that are affiliated to business groups.

Table 1: Summary statistics

Variable	Mean	Std Dev
(Log) Tobin's q	-1.06	1.43
(Log) current sales	0.31	0.90
(Log) past sales	0.36	0.82
Cash flow	2.25	2.21
(Log) assets	4.14	1.58
Proportion of firms with high leverage	0.16	0.36
Proportion of firms with business group membership	0.31	0.46

The summary statistics are reported in Table 1[9] and they are self explanatory.

[8]Following BDK (2012), we assume that a firm is highly leveraged if its debt-to-equity ratio exceeds 1.8.
[9]Source: Bhaumik, Das and Kumbhakar (2012); Table 1.

4 Results and discussion

In columns (1) and (2) of Table 2 we report the estimates of the parametric models (1) and (2). Since the purpose of these estimates is to set a benchmark against which we can discuss the estimates of the semiparametric model, we estimate the models using ordinary least squares (OLS). In columns (3) and (4), we report the estimates of the semiparametric specifications in which investment is a nonparametric function of cash flows alone and is a linear parametric function of all other relevant firm characteristics. The semiparametric models generate firm-year specific estimates of the coefficient of the cash flow variable. In Table 2, for the sake of comparison with the OLS estimates, we report only the means of the distribution of these firm-year estimates of cash flow sensitivity.[10]

Table 2: Regression estimates

	OLS		Semiparametric	
Variable	(1)	(2)	(3)	(4)
(Log) Tobin's q	0.0460 ***	0.0465 ***	0.0529 ***	0.0456 ***
	(0.0143)	(0.0146)	(0.0146)	(0.0148)
(Log) current sales	0.7660 ***	0.7514 ***	0.3492 ***	0.2193 ***
	(0.0403)	(0.0377)	(0.0695)	(0.0677)
(Log) past sales	-0.3015 ***	-0.2180 ***	-0.1941 ***	-0.1561 ***
	(0.0400)	(0.0385)	(0.0413)	(0.0405)
Cash flow	0.0033 ***	0.0033 ***	0.3834	0.4749
	(0.0010)	(0.0009)	(0.0171)	(0.0181)
(Log) assets		0.1854 ***		0.1753 ***
		(0.0117)		(0.0117)
High debt level		-0.2982 ***		-0.2711 ***
		(0.0567)		(0.0513)
Business group affiliation		0.0886 *		0.0949 ***
		(0.0402)		(0.0390)
Time		Yes ***		Yes ***

The estimates of both the OLS and semiparametric regression models are consistent with those reported in the literature (see BDK, 2012): investment is positively associated with (log) Tobin's q and current sales, (log) assets and business group affiliation, and negatively associated with past sales and high debt level. Importantly, given the context of our analysis, we can draw similar

[10]Correspondingly, we report the standard deviation of this distribution, not the standard error.

conclusions about financial constraints of the firms in our sample during the same period. The coefficients for the cash flow variable are positive and significant for the OLS regressions, indicating that the average firm experienced financial constraint during the sampling period. The means of the distributions of the firm-year specific coefficient of the cash flow variable generated by the semiparametric regression models indicate that, on average, firms in our sample were likely to have experienced financing constraints during the sample period.

Table 3: Cash flow sensitivity of investment by cash flow quartile

	(3)	(4)	(5)
Quartile 1	0.8828	1.0248	0.2801
	(0.0535)	(0.0553)	(0.0241)
Quartile 2	0.4276	0.5145	0.2526
	(0.0148)	(0.0162)	(0.0112)
Quartile 3	0.2118	0.2982	0.1494
	(0.0124)	(0.0140)	(0.0101)
Quartile 4	0.0110	0.01618	-0.0032
	(0.0348)	(0.0618)	(0.0154)

In Table 3, we report the cash flow sensitivity of firms by quartile of the distribution of cash flow. In column (3), we report the means and standard deviations of the firm-year specific values of cash flow sensitivity generated by model (3) in Table 2. Similarly, column (4) of Table 3 corresponds to model 4 of Table 2. In addition, in column (5), we report the means and standard deviations of the marginal effects $\partial\gamma_0/\partial CF$ based on the estimates of equation (3). While we are aware of the potential problem with these marginal effects on account of the curse of dimensionality,[11] we report it just to verify the extent to which the regression results remain robust to this additional layer of complexity.[12]

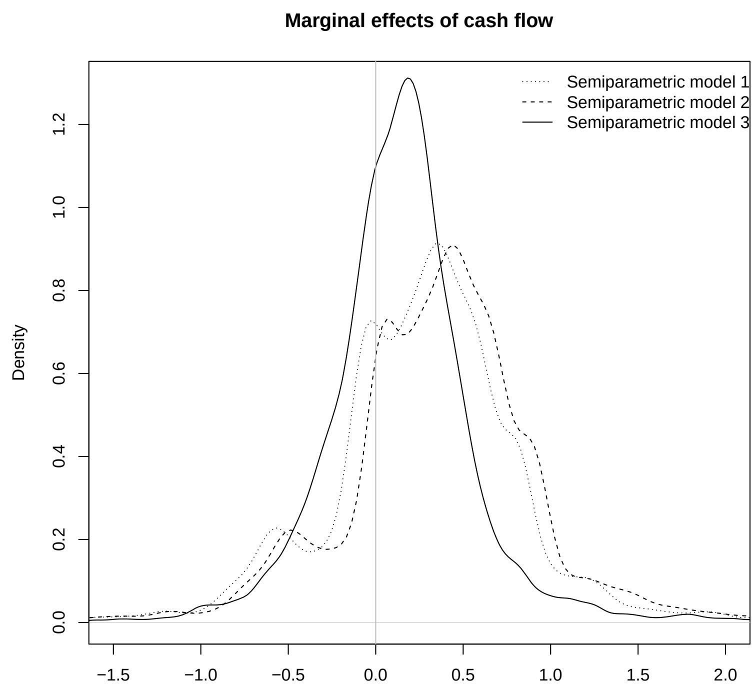
To begin with, we note that there is a significant variation of the cash flow sensitivity of investment over the firm-year distribution. This is also borne out by the plot of the distributions of cash flow sensitivity (or, in the case of column (5), the marginal impact $\partial\gamma_0/\partial CF$) reported in

[11]We thank an anonymous referee for highlighting this problem.

[12]The estimates of this third semiparametric specification too are consistent with the results reported in the stylised literature. For example, both Tobin's q and current sales are positively associated with investment. Further, the averages of the marginal effects $\frac{\partial\gamma_0}{\partial FC}$ are positive for $FC \in \{$(log) assets, business group membership$\}$ and negative for $FC \in \{$leverage$\}$.

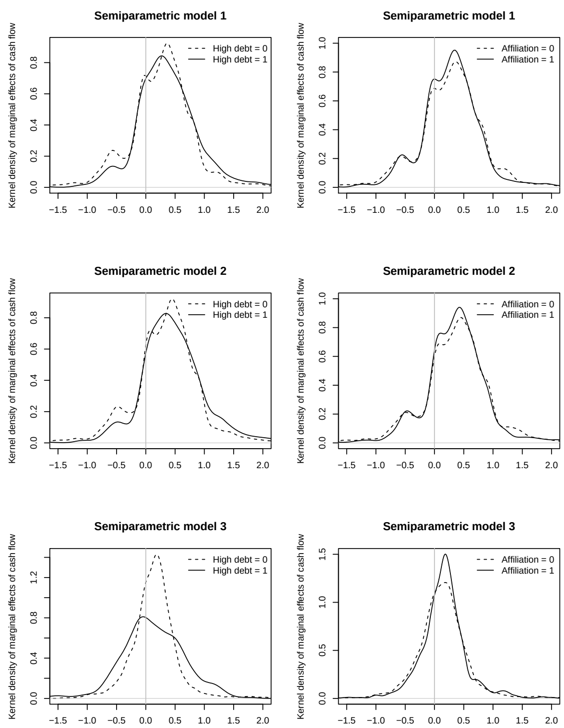
Figure 1. For all three semipramatric specifications, the firm-year specific estimates of cash flow sensitivity of capital varies over a wide range. This is what we had set out to demonstrate, and therein lies the advantage of the semiparametric approach to modeling financial constraints. The distributions of the estimates reported in columns (3) and (4) of Table 3 (semiparametric models 1 and 2 in Figure 1) are right-skewed which explains the positive average value of cash flow sensitivity of investment in all quartiles of the cash flow distribution. The distribution of the estimates of the marginal effect $\partial\gamma_0/\partial CF$ reported in column (5) (semiparametric model 3) is less skewed but as we have already seen positive values of this marginal effect dominate.

Figure 1: Distributions of firm-year specific estimates of cash flow sensitivity of investment



Further, we note that the firm-year specific estimates of cash flow sensitivity are meaningful from an economic point of view. Specifically, cash flow sensitivity is highest for firms in the lowest quartile of the cash flow distribution, and this sensitivity declines as the magnitude of cash flow increases. By contrast, the estimates of the piecewise linear component of a fully parametric specification in which investment is a piecewise linear function of cash flow and linear function of all other firm characteristics are less meaningful. In the piecewise linear model, whose estimates are available from the authors upon request, the coefficient of the cash flow variable is negative and insignificant for the two lowest quartiles of the cash flow distribution, positive but insignificant for the third quartile, and positive and statistically significant for the highest quartile.

Figure 2: Comparing distributions of cash flow sensitivity by firm cohorts



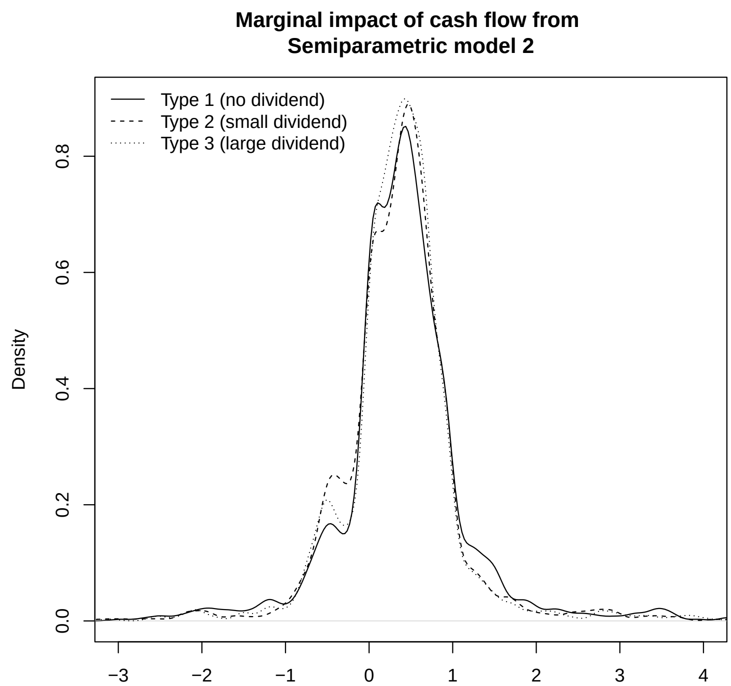
Next, in Figure 2, we plot together the distributions of firm-year specific cash flow sensitivities of different types of firms. Specifically, we compare the distributions of cash flow sensitivity of highly leveraged firms with those of firms that are not highly leveraged, and the distributions of firms that are members of business groups with those that are not business group members. We compare the distributions of cash flow sensitivity of these pairs of firm cohorts generated by all three semiparametric specifications mentioned above. Since the semiparametric approach generates firm-year specific estimates of cash flow sensitivity of investment, we are able to make these comparisons without splitting the sample on an *ad hoc* basis. Further, since the semiparametric approach enables us to compare distributions as opposed to point estimates of cash flow sensitivity, it facilitates a richer analysis by way of, for example, exploring stochastic dominance of one distribution by another.

We undertake another exercise to further highlight the advantage of estimating (and comparing) cash flow sensitivity of firms (or groups of firms) without splitting the sample on an *ad hoc* basis. We consider two stylized ways of separating firms *ex ante* into groups that are expected to experience different degrees of financial constraints. First, we consider dividend payout; firms that pay dividend are believed to be less constrained financially than those that do not. Second, following Hadlock and Pierce (2010), we consider firm characteristics that are arguably better than the KZ index.[13] Since the Indian market for corporate bonds remains underdeveloped, a very small proportion of the firms in the sample issue corporate bonds and thereby have credit ratings assigned to them by credit rating agencies. We were, therefore, unable to divide the firms into groups on the basis of their credit ratings.

Consider, to begin with, dividend payout which is a stylized *ex ante* indicator of financial constraint. However, the literature on both corporate finance and corporate governance suggest that dividend payment is a corporate governance mechanism rather than an indicator of a firm's financial constraint. For example, Acharya, Myers and Rajan (2011) demonstrate that firms that attempt to balance the interests of the internal stakeholders such as managers and external investors pay less dividend when a firm is young and with significant growth potential and more dividend when the firm is mature. External investors accept lower dividend when growth can lead to capital gains but require dividend payout as returns to investment decline. The link between dividend payout and financial constraints is likely to be weaker still in contexts where manager-owners are entrenched such that firms are characterized by the so-called *Type II* (or principal-principal) agency problem whereby majority shareholders can expropriate a firm's resources, to the detriment of the minority shareholders (Bhaumik and Selarka, 2012). In our sample, therefore, dividend payout should not indicate the extent of a firm's financial constraint. We separate the firms in our sample

[13] Hadlock and Pierce (2010) argue that the KZ measure "is unlikely to be a useful measure of financial constraints" (pp. 1911), on account of the fact that "the same information is mechanically built into both the dependent and the independent variables" (pp. 1911). They recommend that researchers rely entirely on firm age and firm size instead, a view that is consistent with the view taken in the wider corporate finance literature in which age and size are believed to be correlated with the extent of information asymmetry between firms and their creditors and investors that acts as a friction in the credit and capital markets (Berger and Udell, 1998).

Figure 3: Comparing distributions of cash flow sensitivity by extent of dividend payment



into three groups, namely, those that do not pay dividends (Type 1), those that pay dividends and in the lower half of the distribution of non-zero dividend payout ratios (Type 2), and those that are in the upper half of the same distribution (Type 3). The distributions of firm-specific cash flow sensitivity of these three types of firms are reported in Figure 3, and distributions are very similar, confirming that *ad hoc* separation of firms on the basis of an attribute such as dividend payout would not be always be appropriate, especially in the context of emerging market economies such as India.[14]

Thereafter, following Hadlock and Pierce (2010), we divide the firms in our sample by age and size. In the case of our sample, where business group affiliation (and hence access to internal capital markets), informal network of family firms and long-standing relationship based banking within trading communities are rampant (see, for example, Berger et al., 2008), the relationship between

[14]The means of the distributions are 0.41 (Type 1), 0.37 (Type 2) and 0.38 (Type 3). The distributions and their means were regenerated using the semiparametric model 2, and the results are similar to those of semiparametric model 1.

Table 4: Cash flow sensitivity of investment by firm size and firm age deciles

decile	size	age
1	0.4644	0.4687
2	0.3769	0.3433
3	0.3405	0.4571
4	0.3148	0.3127
5	0.4949	0.4656
6	0.3925	0.3876
7	0.4030	0.2533
8	0.3375	0.4636
9	0.3506	0.3050
10	0.3759	0.3848

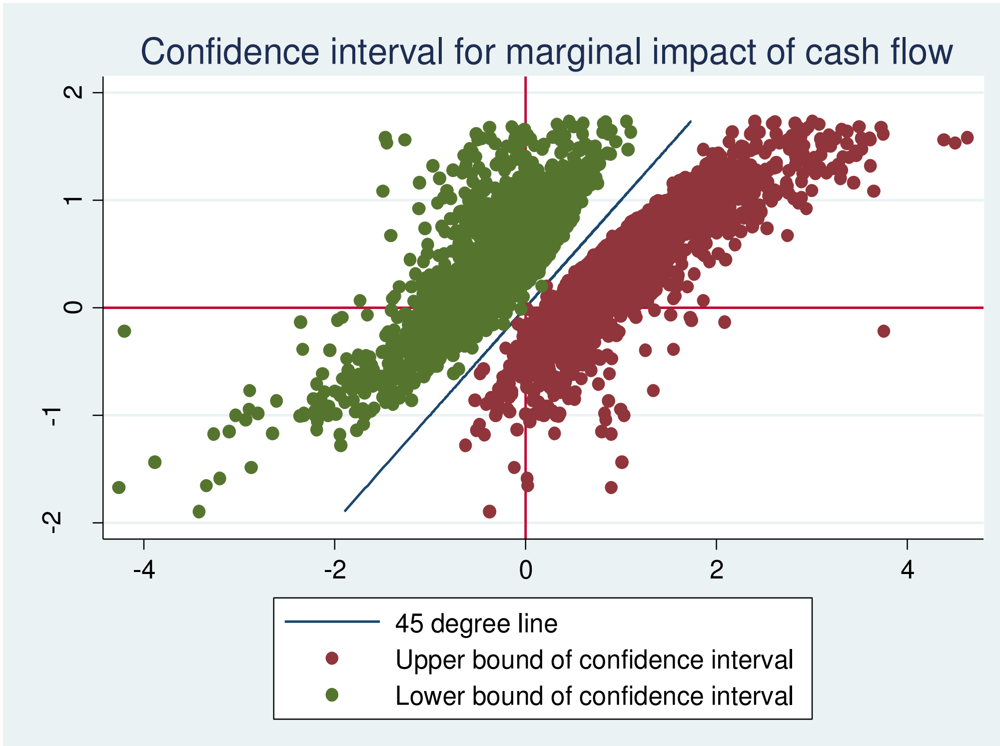
Table 5: Cash flow sensitivity of investment by size-age combinations

	Size: Q1	Size: Q2	Size: Q3	Size: Q4	Size: Q5
Age: Q1	0.4645	0.2697	0.4643	0.4198	0.4564
Age: Q2	0.3662	0.4864	0.4789	0.3061	0.3090
Age: Q3	0.2996	0.2485	0.6014	0.5019	0.4006
Age: Q4	0.4780	0.4068	0.3299	0.2724	0.2897
Age: Q5	0.5002	0.1908	0.2961	0.3300	0.3630

firm characteristics such as age and size and the extent of financial constraints is unlikely to be monotonic. In order to examine this, in Table 4 we report the mean values of firm-specific cash flow sensitivity by age and size deciles, and in Table 5 we report the mean values of cash flow sensitivity by combinations of age and size quintiles. The mean values confirm the absence of a monotonic relationship between age and size and cash flow sensitivity (and hence financial constraints) of firms, and once again highlight the advantage of estimating (and, thereafter, comparing) firm-level estimates of cash flow sensitivity over estimating the cash flow sensitivities of the average firm belonging to groups that are created on an *ad hoc* basis using rules of thumb that may work reasonably well in developed countries, in particular, in the USA, but those that are not necessarily applicable to other contexts such as emerging market economies.

Finally, we demonstrate the scope for a discussion about statistical significance of the firm-year specific estimates of cash flow sensitivity. We deliberately choose the most complex semiparametric

Figure 4: Statistical significance of firm-year specific estimates of cash flow sensitivity



specification that generates marginal effects of cash flow on investment, namely, $\partial\gamma_0/\partial CF$. Next, following Zhang *et al.* (2012) and Henderson *et al.* (2012), we generate confidence intervals for the firm-specific marginal effects of cash flow which is reported in Figure 4. We first plot $\partial\hat{\gamma}_0/\partial CF$ against $\partial\hat{\gamma}_0/\partial CF$, which plots $\partial\hat{\gamma}_0/\partial CF$ along the 45 degree line. Thereafter, we generate the upper and lower confidence bounds by adding and subtracting, respectively, twice the standard error from $\partial\hat{\gamma}_0/\partial CF$. This gives us an observation-specific confidence interval for each marginal effect on the 45 degree line. The graph, therefore, highlights both the sign and the statistical significance of these observation-specific marginal effects. If a marginal effect is to the right of the vertical line at zero, it is positive, and vice versa. If, on the other hand, the horizontal line at zero is outside the confidence interval for any marginal effect, then this marginal effect is statistically significant.

5 Conclusion

In this paper we use a partially linear semiparametric model to generate firm-year specific estimates of cash flow sensitivity of firms' investment. This enables us to distinguish between firms that are constrained and those that are not, rather that discussing whether or not the average firm is financially constrained. In addition, these firm-year specific estimates give us an idea about the range of the degrees of financial constraints experienced by a sample of firms. We are therefore able to compare the extent of financial constraints of different cohorts of firms, differentiated by ownership, location and other characteristics, without splitting the sample in an *ad hoc* manner. We also demonstrate how to obtain and report confidence interval of these firm-year specific cash flow sensitivities.

Since our approach enables us to estimate the impact of firm characteristics (specifically, cash flow) on investment for each firm-year, we are able to trace the cash flow sensitivity of individual firms over time, and hence facilitates linking both macro-regional events and firm-specific events to episodes of financing constraints. This is extremely valuable from the point of view of policymakers because it can enable them to be targeted in their approach to formulating policies that aim at alleviating financing constraints among firms. The relevance of this advantage of our approach to modeling financing constraints, over the stylized approaches, cannot be overstated in the on-going environment of post-crisis credit crunch.

A possible limitation of our research is that we use a sample of firms from a single market that has very specific macro-institutional characteristics, including the maturity of its credit-capital market, and the firms therein have characteristics that may not be shared by firms in other, especially developed, countries. Note, however, that despite possible idiosyncratic nature of the context of analysis, the estimates of both the linear component of the semiparametric models and the firm-year specific estimates of cash flow sensitivity are largely consistent with the stylised literature on financial constraints. Further, the purpose of this paper is to highlight the advantages of adopting a new approach to empirically modeling financial constraints, one that provides more policy-relevant information without sacrificing the basic insights of the stylised approaches. Comparable estimates using data from the USA and other developed countries, while outside the scope of this paper, can easily be generated to examine the extent to which the estimated distributions of firm-year specific cash flow sensitivity of investment are generalizable.

References

[1] Acharya, V.V., Myers, S.C., Rajan, R.G. (2011). The internal governance of firms, *Journal of Finance*, **66**, 689-720.

[2] Allayannis, G., Mozumdar, A. (2004). The impact of negative cash flow and influential observations on investment-cash flow sensitivity estimates, *Journal of Banking and Finance*, **28**, 901-930.

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

[4] Berger, A.N. *et al.* (2008). Bank ownership types and banking relationships, *Journal of Financial Intermediation*, **17**, 37-62.

[5] Berger, A.N., Udell, G.F. (1998). The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle, *Journal of Banking and Finance*, **22**, 613-673.

[6] Bhaumik, S.K., Das, P., Kumbhakar, S.C. (2012). A stochastic frontier approach to modelling financial constraints in firms: An application to India, *Journal of Banking and Finance*, **36**, 1311-1319.

[7] Bhaumik, S.K., Selarka, E. (2012). Does ownership concentration improve M&A outcomes in emerging markets? *Journal of Corporate Finance*, **18**, 717-726.

[8] Fazzari, S.M., Hubbard, R.G., Petersen, B.C. (1988). Financing constraints and corporate investments, In: Brainard, W.C., Perry, G.L. (Eds.) *Brookings Papers on Economic Activity*, vol. 1, Brookings Institutions Press, Washington, DC.

[9] Hadlock, C.J., Pierce, J.R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index, *Review of Financial Studies*, **23**, 1909-1940.

[10] Horowitz, J.L. (1997). Bootstrap methods in econometrics: Theory and numerical performance, In: D.M. Kreps and K.F. Wallis (Eds.), *Advances in Economics and Econometrics: Theory and Applications*, vol. 3, Cambridge, UK: Cambridge University Press, p. 188-222.

[11] Henderson, D.J., Kumbhakar S.C., Parmeter C.F. (2012). A simple method to visualize results in nonlinear regression models, *Economics Letters*, **117**, 578-581.

[12] Kaplan, S.N., Zingales, L. (1997). Do financial constraints explain why investment is correlated with cash flow? *Quarterly Journal of Economics*, **112**, 169-215.

[13] Laeven, L. (2003). Does financial liberalization reduce financial constraints? *Financial Management*, **32**, 5-34.

[14] Lang, L.E., Ofek, E., Stulz, R. (1996). Leverage, investment and firm growth. *Journal of Financial Economics*, **40**, 3-29.

[15] Mammen, E. (1993). Bootstrap and wild bootstrap for high dimensional linear models. *The Annals of Statistics*, **21**, 255-285.

[16] Robinson, P. (1988). Root-n-consistent semiparametric regression. *Econometrica*, **56**, 931-954.

[17] Wang, H.J. (2003). A stochastic frontier analysis of financing constraints on investment: The case of financial liberalization in Taiwan. *Journal of Business and Economic Statistics*, **21**, 406-419.

[18] Zhang, R., Sun, K., Delgado, M.S., Kumbhakar, S.C. (2012). Productivity in China's high technology industry: Regional heterogeneity and R&D. *Technological Forecasting and Social Change*, **79**, 127-141.