Product market performance and capital structure: A Hierarchical Bayesian semi-parametric panel regression model

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Abstract

The relationship between product market performance of a firm and its capital structure has drawn considerable amount of attention recently amongst corporate finance researchers. The same was established to be non-monotonic in the context of a developed market. The non-monotonicity in the functional form could be expressed by pieces of straight lines joined at different values of debt (or knots). In this paper we address the issue of estimating the slopes of different line segments along with the positions of the knots from a panel of firms using an adaptive hierarchical Bayesian semi-parametric regression model. Further,keeping in mind that such a relationship is less investigated in emerging economies where the debt market dynamics may be different we investigate the same for an emerging economy. In the process we provide the economic rationale for varying sign and magnitude of the slopes of the line segments discussed above.

1 Introduction

The fact that financing decisions are not just affected by the conflict within agents inside the firm but may also be influenced by the dynamic interaction of the firm with outsiders like competitors and consumers was theoretically established by [2]. With infusion of debt in a firm's capital structure there is incentive for the shareholders to take more risk and pursue aggressive investment policies. Brander and Lewis showed that in an oligopoly this behavior translates into aggressive policy in the output market. Consequently, the leveraged firm would produce more than the equity-financed firm resulting in a non-decreasing monotonic relationship between leverage and output. [1],however, used a Stackelberg like oligopoly framework and introduced a profit function of lenders to show that the relationship between capital structure and output market performance of firms is non-monotonic in nature. Empirical analysis of Campello considers sales growth as a measure of firm's output market performance and ratio of debt to total assets of the firm as a measure of its leverage. The relationship between these two variables is modeled using a piecewise linear function or spline with fixed and known knot points through a panel regression after controlling for other economic factors or co-variates. The influence of debt on output growth of firms are determined from the slopes of the line segments. Similar relationship between output market performance and leverage has also been reported by [3]. Recent studies having shown the importance of country specific factors in determining capital structures of firms [4], [5], it may reasonably be expected that output growth-debt relationships will be different in different economies reflected through different knots and slopes for the piecewise line segments. The challenge is therefore, to estimate the positions of knots which partition the range of debt and the functional relationship therein.

In this paper we adopt a hierarchical Bayesian semi-parametric regression with adaptive splines to model the output growth in terms of normalized leverage variable . The adaptive spline function assumes the positions of knots to be unknown and estimates of the same are obtained using Monte Carlo Markov Chain (MCMC) simulations. Recently, Bayesian framework has been effectively used to address address some important financial issues [6]. The hierarchical Bayesian framework helps to address two additional important issues, viz. endogeniety caused by lack of comprehensive list of co-variates (see [7] and references therein) and firm specific error variance or heteroscedasticity [1]. While existing literature suggests the use of instrument variable to tackle endogeneity, it is very difficult to find an instrument of leverage that is orthogonal to the error (*e.g* see [1], [8], [9]. An alternative approach to correct the endogeneity bias is through penalized Ridge regression [10]. In Ridge regression set up, a quadratic penalty function of the parameters of endogenous co-variates (to be called endogenous parameters henceforth) is added to the squared error loss which is subsequently minimized to obtain estimators of the regression parameters. Here we adopt a hierarchical Bayesian framework where squared error loss minimization is posited as maximum likelihood estimation problem for a normal random sample and the quadratic penalty function for endogeneity bias is included through Gaussian priors on the endogeneous parameters. The weights of the penalty function are assumed to be prior variances of the endogenous parameters. The non-negativity of penalty parameters ensures that the penalized Ridge estimators could be obtained from posterior means of the corresponding parameters. A similar prior specification for other regression parameters would address the issue of multi-colinearity among the covariates as Ridge regression is a standard technique to tackle the same. The other important issue is heteroscedasticity which induces a large number of parameters. To address the estimation problem in a high-dimensional parameter space we assume identical prior distributions for the error variances with a common hyper-parameter [11].

Empirical investigation of the interaction between capital structure and product market performance has mainly focused on developed markets (*e.g.* see [11], [12]. Starting with [13], recently there has been a few efforts to understand the systemic issues specific to emerging markets in capital structure product market intervention ([14], [3]. Although as a part of BRIC[1], India represents a unique opportunity for global investors, there has been only couple of studies conducted on Indian market to the best of the knowledge of the present authors [15], [16]. However,that work focused on only one sector, viz., the manufacturing sector. In this paper we consider a panel of 208 Indian firms without any restriction on the industry sector over 25 years to understand the interaction between their corporate financial strategies and product market through the lens of the hierarchical Bayesian model described above.

2 Hiearchical Bayesian panel regression model

Let $y_{i,t}$ be the measurement on output market performance of the i^{th} firm in the t^{th} year and $\mathbf{X}_{i,t}$ be the corresponding vector (row) of observations on p co-variates including control variables and leverage, $i = 1, 2 \ldots n,\ t = 1, 2 \ldots T$. Pooled panel regression model could be then represented as:

$$y_{i,t} = \mathbf{X}_{i,t}\boldsymbol{\beta} + \epsilon_{i,t} \tag{1}$$

Denoting the $T-$vector of errors corresponding to the i^{th} firm by $\boldsymbol{\epsilon}_i$, we assume $E[\boldsymbol{\epsilon}_i] = \mathbf{0}$, $V(\boldsymbol{\epsilon}_i) = \sigma_i^2 I_T$, and $E[\boldsymbol{\epsilon}_i\boldsymbol{\epsilon}_j'] = \mathbf{0}^{T\times T}\ \forall(i,j)$ such that $i \neq j$, where I_T is the identity matrix of order T. Least square estimator of $\boldsymbol{\beta}$ is obtained from the squared

[1]BRIC is an acronym for the nations Brazil, Russia, India and China used by the investment bank J P Morgan and is an internationally accepted acronym to describe the four fastest growing economies

error loss function as follows

$$\underset{\boldsymbol{\beta}}{argmin} \quad (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \tag{2}$$

where $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2 \ldots \mathbf{y}_N)'$ is the TN vector of observations on the dependent variable with $\mathbf{y}_i^T$ being the observations on the same corresponding to i^{th} firm. $X^{TN \times p}$ is the design matrix containing data on co-variates including the leverage variable. In the following subsection we describe how hierarchical Bayesian set up can be efficiently used to tackle the issues of endogeneity, heteroscedasticity and multicollinearity simultaneously .

2.1 Hierarchical Bayesian model for Endogneity, Heteroscedasticity and Multi-collinearity

We partition $\boldsymbol{\beta} = (\boldsymbol{\beta}_1, \boldsymbol{\beta}_2)$ where $\boldsymbol{\beta}_1^{p-k \times 1}$ and $\boldsymbol{\beta}_2^{k \times 1}$ corresponds to the set of exogenous and endogenous co-variates respectively. Corresponding partition of the design matrix is denoted by $\mathbf{X}_{[1]}$ and $\mathbf{X}_{[2]}$. The problem of estimating $\boldsymbol{\beta}$ consistently in presence of endogeneity bias could then be reformulated as minimization of the following squared error loss function [9]

$$\psi(\boldsymbol{\beta}, \boldsymbol{\Lambda}) = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) + (\mathbf{X}_{[2]}' M_1 \mathbf{X}_{[2]})\boldsymbol{\beta}_2' \boldsymbol{\Lambda} \boldsymbol{\beta}_2 \tag{3}$$

$\boldsymbol{\Lambda} = diag(\lambda_1, \lambda_2, \ldots \lambda_k)$ being the matrix of non-negative penalty parameters. The non-negativity constraint on the penalty parameters ensures that $\psi(\boldsymbol{\beta}, \boldsymbol{\Lambda})$ satisfies the standard properties of loss function. Notice that the expression in 3 is equivalent to the squared error loss related to penalized Ridge estimation upto a scaling factor. The loss minimization problem can be restated as maximization of the following function

$$\underset{\boldsymbol{\beta}}{argmax} \quad e^{-\frac{(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})'(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})}{2}} e^{-\frac{\boldsymbol{\beta}_2' \boldsymbol{\Lambda} \boldsymbol{\beta}_2}{2}} \tag{4}$$

where $\boldsymbol{\beta} \mid \boldsymbol{\Lambda}$ is assumed to follow the natural conjugate prior distribution, viz. $N_k(\mathbf{0}, \boldsymbol{\Lambda}^{-1})$. This formulation leads to Bayesian framework for regression. The non-negativity of the penalty parameters is ensured through the assumption of independent and identical Gamma priors on the penalty parameters with common hyper-parameter which leads to a hierarchical Bayesian model. To complete the Bayesian set up, we assume similar natural conjugate priors for $\boldsymbol{\beta}_1$ and iid inverse Gamma priors for firm specific variances ($\sigma_i^2,\ i = 1, 2 \ldots N$). Such a choice of priors for the variances as well as the penalty parameters reduces the complexity in estimation arising out of high-dimensionality of the parameter space caused by both heteroscedasticity and inclusion of penalty in the squared error loss. Thus in this hierarchical Bayesian formulation $\boldsymbol{\psi}(\boldsymbol{\beta}, \boldsymbol{\Lambda})$ is minimized at the posterior mean of $\boldsymbol{\beta}$ conditional to $(\mathbf{y}, \mathbf{X}, \boldsymbol{\Lambda})$ (see pp-117, [17]. Further, Ridge regression being devised to estimate regression parameters in presence of multi-collinearity [18], the Gaussian prior on $\boldsymbol{\beta}$ suffices to tackle the same.

In what follows, we describe the hierarchical Bayesian semi-parametric model to explain non-monotonicity of output-debt relation.

2.2 Hierarchial Bayesian semi-parametric model with adaptive splines

The non-linearity exhibited through the non-monotonic relation between output performance and debt of a firm is difficult to model parametrically. A flexible technique of doing so is to express the output performance as piecewise polynomial function (or polynomial splines) over low, moderate and high ranges of debt variable (say X_p in model (1)). In particular, we illustrate the same with linear splines over the partition of X_p defined by two knots, say $\xi_1 < \xi_2$. Thus the basis of the linear spline is $X_{[2]} = [1, X_p, (X_p - \xi_1)_+, (X_p - \xi_2)_+]$, where u_+ denotes $max(u, o)$. The non-linear relation of debt with output performance can then be expressed as a linear function of the basis which is also known as linear B-spline in the literature [19]. The complete semi-parametric panel regression model is given as follows

$$\begin{aligned} y_{i,t} &= \mathbf{X}_{[1]_{i,t}}^{p-1\times 1}\boldsymbol{\beta}_1 + f(X_{p_{i,t}}) + \epsilon_{i,t} \\ f(X_{p_{i,t}}) &= \beta_{p,I} + \beta_{p,II}X_{p_{i,t}} + \beta_{p,III}(X_{p_{i,t}} - \xi_1)_+ + \beta_{p,IV}(X_{p_{i,t}} - \xi_2)_+ \end{aligned} \quad (5)$$

where all the assumptions of model (1) are assumed to hold. Notice that in the above semi parametric model the slope of the line segment below ξ_1 is $\beta_{p,II}$, between ξ_1 and ξ_2 is $\beta_{p,II} + \beta_{p,III}$ and beyond ξ_2 the same is $\beta_{p,II} + \beta_{p,III} + \beta_{p,IV}$. Similarly the intercepts also change but the amount of change depends on the position of the knots.

Typically values of the knots are unknown in reality and more likely to depend on how developed the debt market is in a particular country along with other country specific influences. A robust way to determine the positions of the knots is to estimate them from data. In the current hierarchical Bayesian set up we put a non-informative prior on ξ_1 and ξ_2 with the range of the debt variable as support. Such a spline model is also known as Bayesian adaptive spline (see [20]. The condition $\xi_1 < \xi_2$ is ensured by assuming that ξ_1 is drawn from the distribution of the smallest order statistic of a sample of size two drawn from the parent distribution and similarly distribution of largest order statistic is assumed for ξ_2.

2.3 Markov Chain Monte Carlo (MCMC) estimation

The hierarchical Bayesian model proposed above requires calculation of mean and other summary statistics of the posterior distribution of the model parameters. We use MCMC technique to simulate from the posterior distribution of the parameters and compute the sample mean which converges to the posterior mean asymptotically. However, if the posterior distribution is non-standard then generating iid samples from it becomes difficult. In such a case, we use the well known Metropolis-Hastings algorithm to generate an ergodic Markov chain which asymptotically converge to the target posterior distribution. We refer to [21] and [22] for a comprehensive review of Bayesian computational techniques.

Let us denote the set of firm specific variances $\{\sigma_1, \sigma_2 \ldots \sigma_N\}$ by ϑ. The prior distribution of σ_i^2 is assumed to be $Inverse - Gamma(\frac{\nu}{2}, \frac{\nu}{2})$, $\forall i = 1, 2 \ldots N$. Further we assume $\lambda_1 = \lambda_2 = \ldots = \lambda_k = \lambda$ and the prior for λ is $Gamma(\frac{\nu_\lambda}{2}, \frac{\nu_\lambda}{2})$, $\forall i = 1, 2 \ldots k$. Denoting $(\beta_{pI}, \ldots \beta_{pIV})$ by $\boldsymbol{\beta}_2$, we assume the prior of the spline parameters as $N_4(\mathbf{0}, \lambda I_4)$. The non-informative prior of the knot points could be elicited from the fact that ξ_1 and ξ_2 are the smallest and largest order statistics from a sample of size two drawn from uniform distribution over (0,1). The prior density of ξ_i is $f_i(\xi_i) = i\binom{n}{i} F^{i-1}(\xi_i) f(\xi_i)(1 - F(\xi_i))^{n-i}$ where $F(\cdot)$ is the cumulative distribution function of $U(0,1)$ distribution, $i = 1, 2$. Priors of $\boldsymbol{\beta}$ is same as stated in **section (2.1)**.

The posterior distribution of the model parameters are given as follows:

- $f(\boldsymbol{\beta} \mid \mathbf{y}, \mathbf{X}, \lambda, \vartheta, \boldsymbol{\xi}) \propto e^{-\sum_i \frac{\sum_t (y_{i,t} - \mathbf{X}_{[1]_{i,t}} \boldsymbol{\beta}_1 - f(X_{p_{i,t}}))^2}{2\sigma_i^2}} \times e^{-\frac{\boldsymbol{\beta}_1' \boldsymbol{\beta}_1}{2\sigma_\beta^2}} e^{-\frac{\lambda \boldsymbol{\beta}_2' \boldsymbol{\beta}_2}{2}}$, where $\boldsymbol{\xi} = (\xi_1, \xi_2)'$
- $f(\lambda \mid \mathbf{y}, \mathbf{X}, \boldsymbol{\beta}, \vartheta, \boldsymbol{\xi}) \propto e^{-\frac{\lambda}{2}(\boldsymbol{\beta}_2' \boldsymbol{\beta}_2 + \nu_\lambda)} \lambda^{\frac{\nu_\lambda}{2} - 1}$
- $f(\sigma_i \mid \mathbf{y}, \mathbf{X}, \lambda, \boldsymbol{\beta}, \boldsymbol{\xi}) \propto e^{-\frac{\sum_t (y_{i,t} - \mathbf{X}_{[1]_{i,t}} \boldsymbol{\beta}_1 - f(X_{p_{i,t}}))^2 + \nu}{2\sigma_i^2}} \times \left(\frac{1}{\sigma_i^2}\right)^{\frac{\nu}{2}}$
- $f(\xi_i \mid \mathbf{y}, \mathbf{X}, \lambda, \boldsymbol{\beta}, \vartheta) \propto e^{-\sum_i \frac{\sum_t (y_{i,t} - \mathbf{X}_{[1]_{i,t}} \boldsymbol{\beta}_1 - f(X_{p_{i,t}}))^2}{2\sigma_i^2}} \times (\xi_i)^{i-1}(1 - \xi_i)^{2-i}$, i=1,2

To generate from the posterior distribution we use Metropolis-Hastings algorithm and the sampling scheme to generate M iid samples is as follows.

`Step I: Initialize the parameters` $\boldsymbol{\xi}, \lambda, \boldsymbol{\beta}, \vartheta$ `at` $\boldsymbol{\xi}^0, \lambda^0, \boldsymbol{\beta}^0, \vartheta^0$; `Set iteration =i`

`Step II: Generate` $\boldsymbol{\beta}^i$ `from` $f(\boldsymbol{\beta} \mid \mathbf{y}, \mathbf{X}, \lambda^{i-1}, \vartheta^{i-1}, \boldsymbol{\xi}^{i-1})$

`Step III: Generate` ϑ^i `from` $f(\lambda \mid \mathbf{y}, \mathbf{X}, \boldsymbol{\beta}^i, \lambda^i, \boldsymbol{\xi}^{i-1})$

`Step IV: Generate` λ^i `from` $f(\lambda \mid \mathbf{y}, \mathbf{X}, \boldsymbol{\beta}^i, \vartheta^i, \boldsymbol{\xi}^{i-1})$

`Step V: Generate` $\boldsymbol{\xi}^i$ `from` $f(\boldsymbol{\xi} \mid \mathbf{y}, \mathbf{X}, \boldsymbol{\beta}^i, \vartheta^i, \lambda^i)$; `Set iteration = i+1;`

`Step VI: Repeat from Step II until iteration=M.`

First few observations are dropped to ensure no auto-correlation (also called burn-in sample) and from the rest sample statistics are computed. In the following section we present the data analysis results and their interpretations based on the model and posterior sample generation scheme given in this section.

3 Data and results

This study uses a panel data of 208 Indian firms listed on the Bombay Stock Exchange Ltd from 1988 to 2013, available in the CMIE database Prowess. The sample selection was based on data availability . Only firms with complete set of observations for the entire period were considered.

3.1 Variables and Model

Product market performance has been represented by various proxies like pricing policies [23], Profitability [3], or Growth in annual sales [1]. As explained in section 1, the infusion of debt in capital structure is likely to influence a firm's policy towards increased level of output. The variable which best proxies the change in level of output of a firm is its annual growth in sales. Hence as a proxy for output market performance of firms we chose Sales growth , which is given by,

$$Sales_Growth_{i,t} = \ln \frac{Sales_{i,t}}{Sales_{i,t-1}} \tag{6}$$

where $Sales_Growth_{i,t}$ is the growth in annual sales and$Sales_{i,t}$ is the annual sales of firm 'i'for the year't'. The reason for taking log difference as a measure of change in sales is to ensure that the dependent variable can assume any value between $-\infty$ and ∞.

The proxy for capital structure is*Leverage*, given by *Borrowings* divided by *Total Assets*.Since borrowings represent the total debt of the firm, the relationship between debt and output market is suitably captured through this variable.

The sales growth of a firm can be affected by the investment decisions of the firm. Other factors which may impact the growth in annual sales of a firm are firm size, profitability and a firm's expenditure towards promotion and advertisement. Keeping this mind, and taking cue from previous literature we have considered the usual control variables which include *Size*, *Investment*, *Sales Expenditure* and *Profitability* variables. As a proxy of *Size* we have taken natural log of *Total Assets*. For *Investment* we considered *Capital Work in Progress* as a proportion of *Total Assets*. *Profitability* is represented by the sum of *Profit After taxes* and *Depreciation* divided by *Total Assets*.

To facilitate estimation of knots we transform the Leverage variable within the interval [0,1] by

$$Leverage_i = \frac{Leverage_i - Leverage_{min}}{Leverage_{max} - Leverage_{min}} \tag{7}$$

3.2 Model Description

The hierarchical Bayesian semi-parametric model with adaptive splines as given by equation(5) may be stated in terms of the panel data described in previous section as:

$$\begin{aligned} SalesGrowth_{i,t} &= \beta_0 + \beta_1 \log(Size_{i,t-1}) + \beta_2 Investment_{i,t-1} + \beta_3 SalesExpenditure_{i,t-1} \\ &+ \beta_4 Profitability_{i,t-1} + f(Leverage_{i,t-1}) + \epsilon_{i,t} \end{aligned} \tag{8}$$

3.3 Results and interpretations

Table(1) reports the results from estimation of the parameters in Eq(9). The parameters of importance are the knot points and the slopes of the piecewise line segments of the spline. The distribution of the location of the knot points are given by the values of ξ_1 and ξ_2. From that we find that the expected value of ξ_1 is 0.3669 which means that the first break point occurs at a point where the standardised *Leverage* value is about 0.37. The posterior density plot of the first knot point(Figure) reveals that the values are heavily skewed towards left of mean value, indicating a very low probability of having a value higher than the mean value. Similarly from the expected value of ξ_2, we can estimate that the second break point is at the standardised *Leverage* value of about 0.70. The posterior density plot here shows that the distribution is heavily right skewed, which effectively means that the probability of having values lower than mean is very low. This shows that the degree of responsiveness of the sales growth of Indian firms to the respective leverage of the firms changes at these two points. That means product market performance of Indian firms with leverage below the standardized value of 0.37 react to the capital structure decision of firms in a different manner than that of the firms with leverage above the break point. There is a further shift in behaviour for firms with levels of leverage above the standardised value of 0.70. The findings confirm that the relationship between the two variables for firms with moderate levels of debt is different from that of firms with low and high levels of debt. The exact nature of the relationship is given by the posterior distribution of the intercept and slopes $\beta_{p,I}$, $\beta_{p,II}$,$\beta_{p,III}$ and $\beta_{p,IV}$. While $\beta_{p,I}$ (Table 1)represents the intercept and $\beta_{p,II}$ the slope of the regression curve of $SalesGrowth$ on *Leverage* with the usual control variables till the first break point, the sum of $\beta_{p,II}$ and $\beta_{p,III}$ gives the slope of the curve from the first break point to the second one. The sum of $\beta_{p,II}$, $\beta_{p,III}$ and $\beta_{p,IV}$ is the estimate of the slope of the curve beyond the

Parameter	Mean	SD	95% Credible Interval
$\beta_{p,I}$	0.0041773	0.38798	(-0.75856,0.76678)
$\beta_{p,II}$	0.0080681	0.53473	(-1.0654,1.1079)
$\beta_{p,III}$	-0.00070032	0.78008	(-1.5633,1.542)
$\beta_{p,IV}$	-0.00085372	0.91059	(-1.8178,1.8182)
β_1	0.010362	0.038581	(-0.06571,0.085644)
β_2	0.013788	0.70669	(-1.3775,1.4148)
β_3	0.15731	0.82382	(-1.4801,1.7897)
β_4	-0.052532	0.80869	(-1.6522,1.5546)
deviance	344.18	7.1483	(330.27,358.31)
ξ_1	0.3669	0.2495	(7.4992e-06,0.81108)
ξ_1	0.69773	0.22894	(0.24226,1)

Table 1: Table displaying the posterior distribution estimates for all the regression parameters

second break point. The expected values of $\beta_{p,II}$,$\beta_{p,III}$ and $\beta_{p,IV}$ from Table 1 shows that the slope of the regression curve is 0.008 up to the first break point, .007 between first and second break point and 0.006 beyond the second break point. The density plots for the parameters $\beta_{p,I}$, $\beta_{p,II}$,$\beta_{p,III}$ and $\beta_{p,IV}$ show that the values are symmetric across mean. The intercepts may be computed from the values of knot points and slope. The non-monotonic relationship between $SalesGrowth$ and $Leverage$ may be represented by the graph depicted in Figure 8. This effectively means that the capital structure decision of firms have a low degree of increasing effect on the product market performance of the Indian firms.

The close to zero slope suggests a much weaker influence of capital structure decision of firms on their product market performance in Indian market as compared to

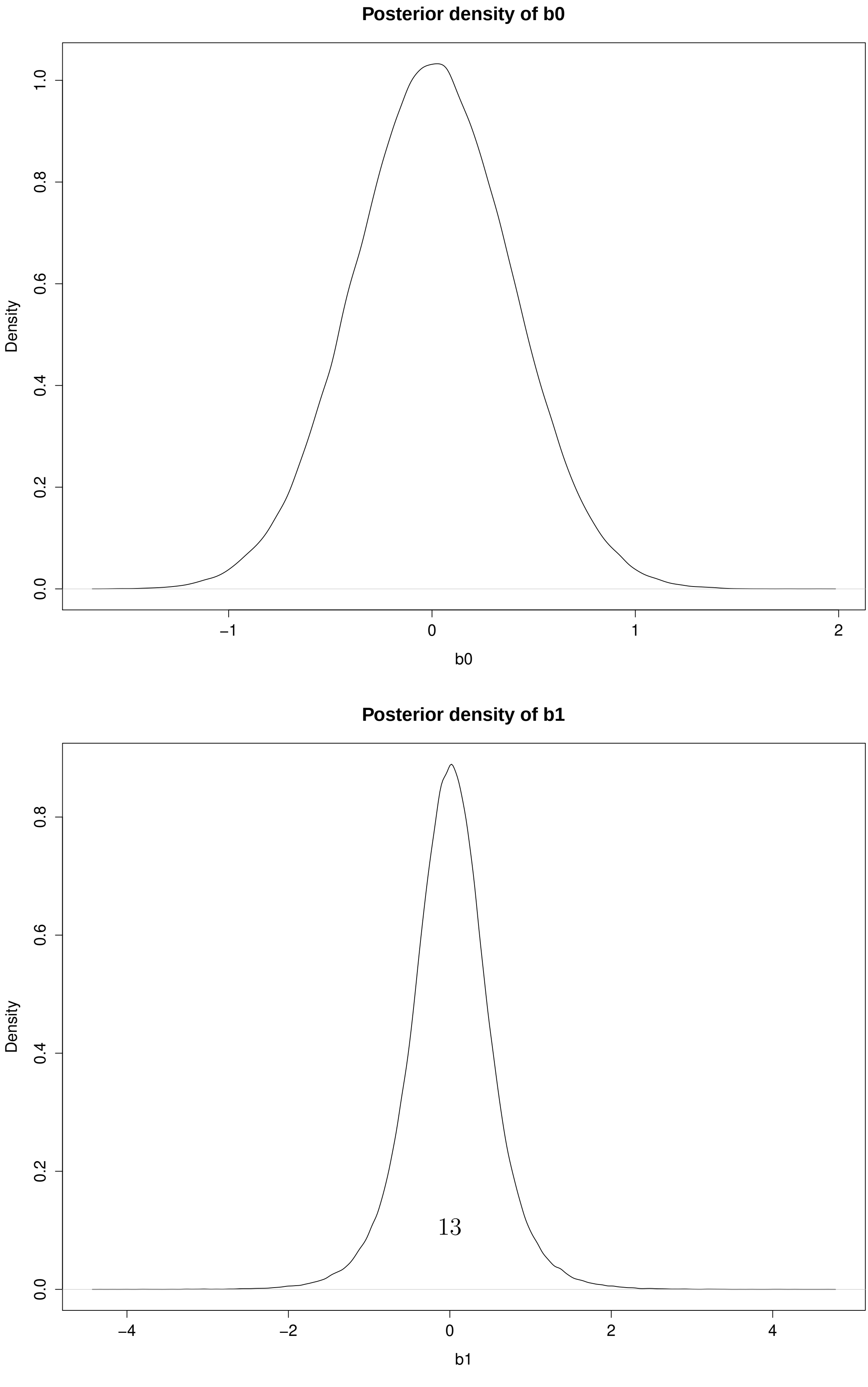

Figure 1: Posterior density plot for $\beta_{p,I}$ (top),$\beta_{p,II}$(bottom)

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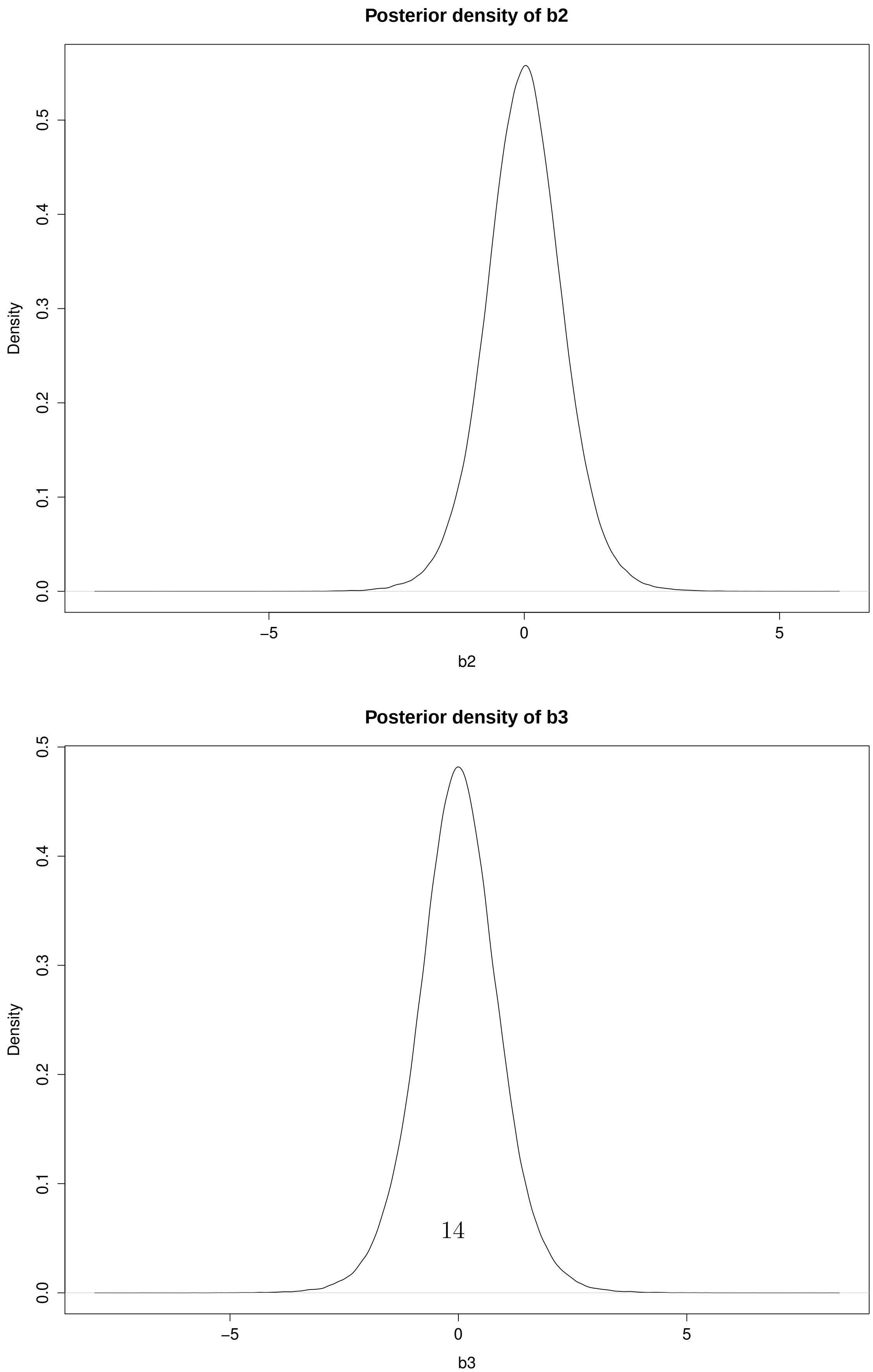


Figure 2: Posterior density plot for $\beta_{p,III}$ (top),$\beta_{p,IV}$(bottom)

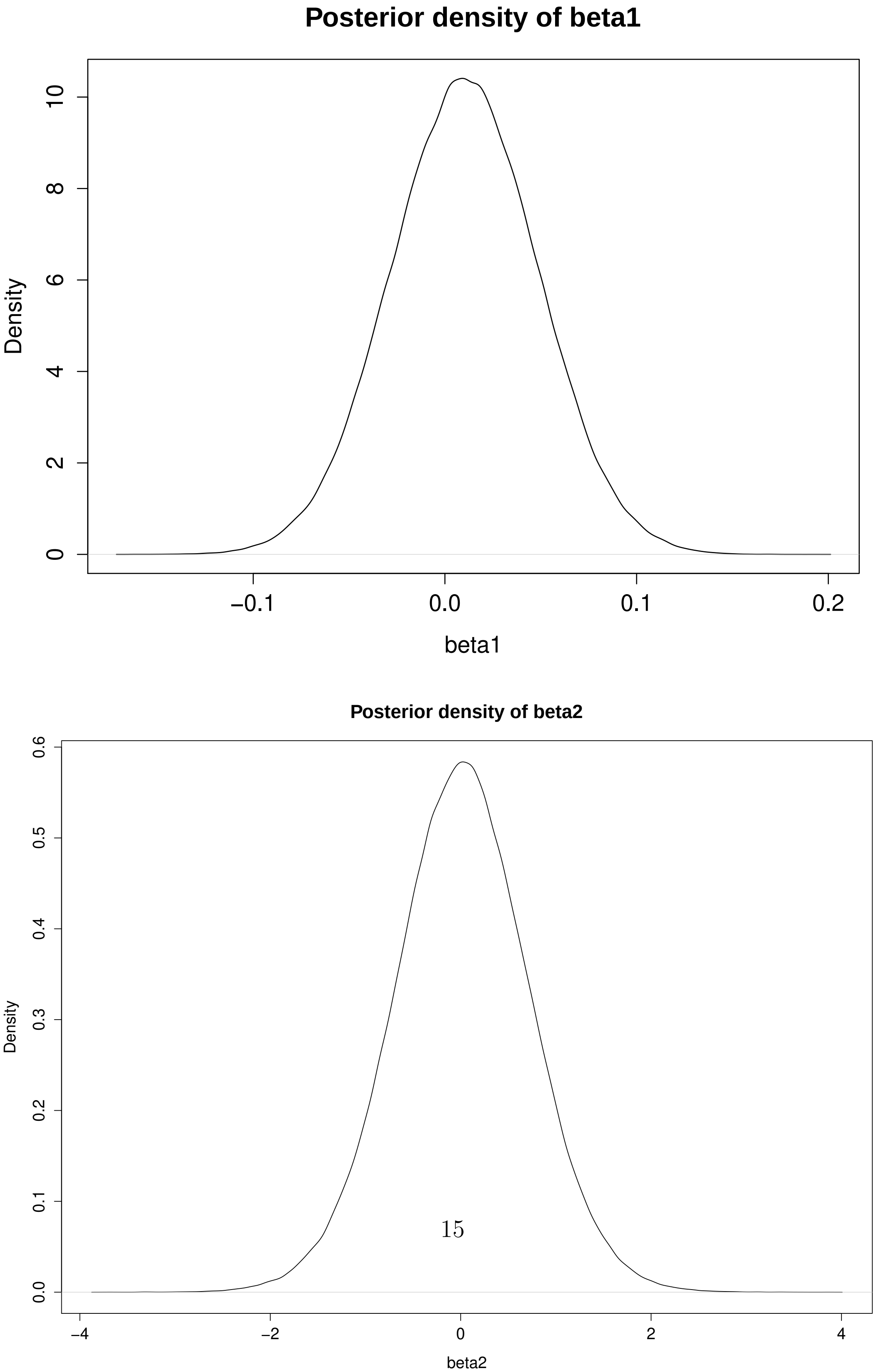


Figure 3: Posterior density plot forβ_1(top), β_2(bottom)

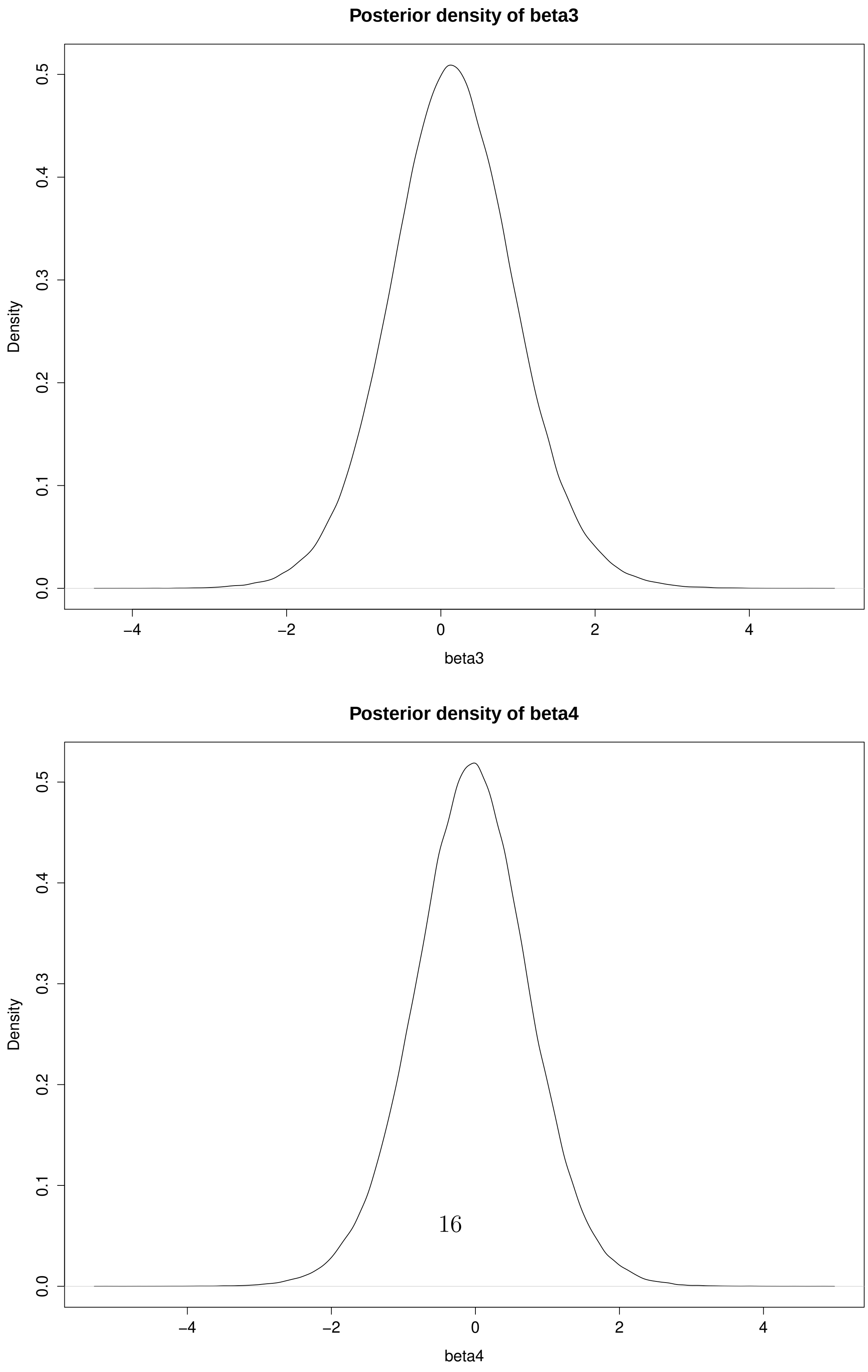
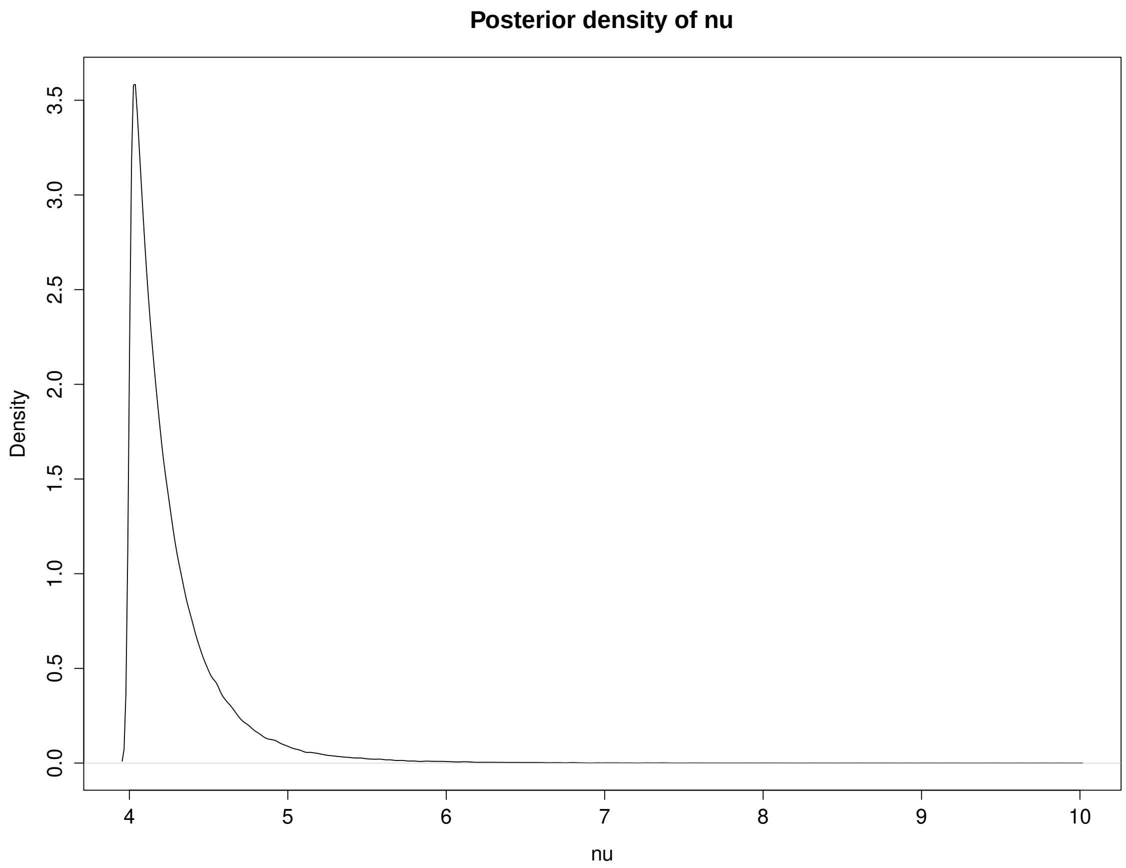


Figure 4: Posterior density plot forβ_3(top), β_4(bottom)



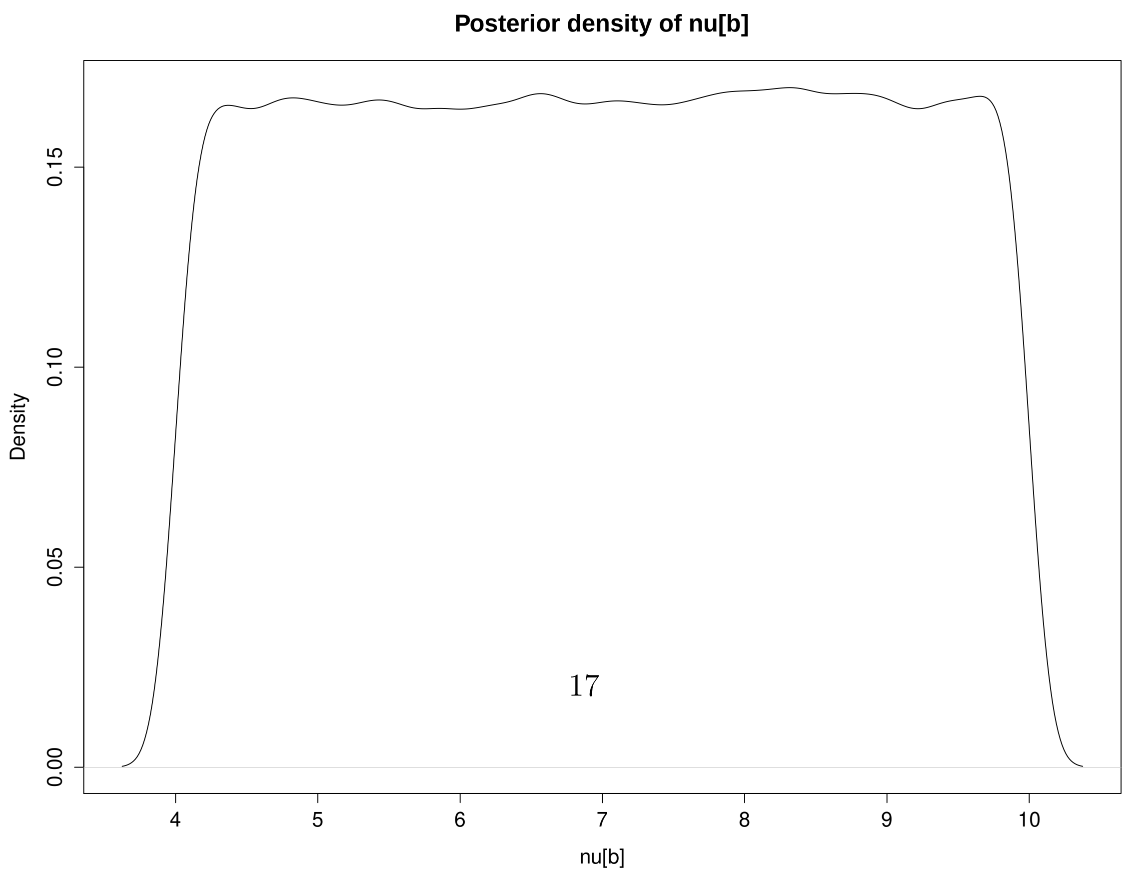


Figure 5: Posterior density plot forν(top),ν_b(bottom)

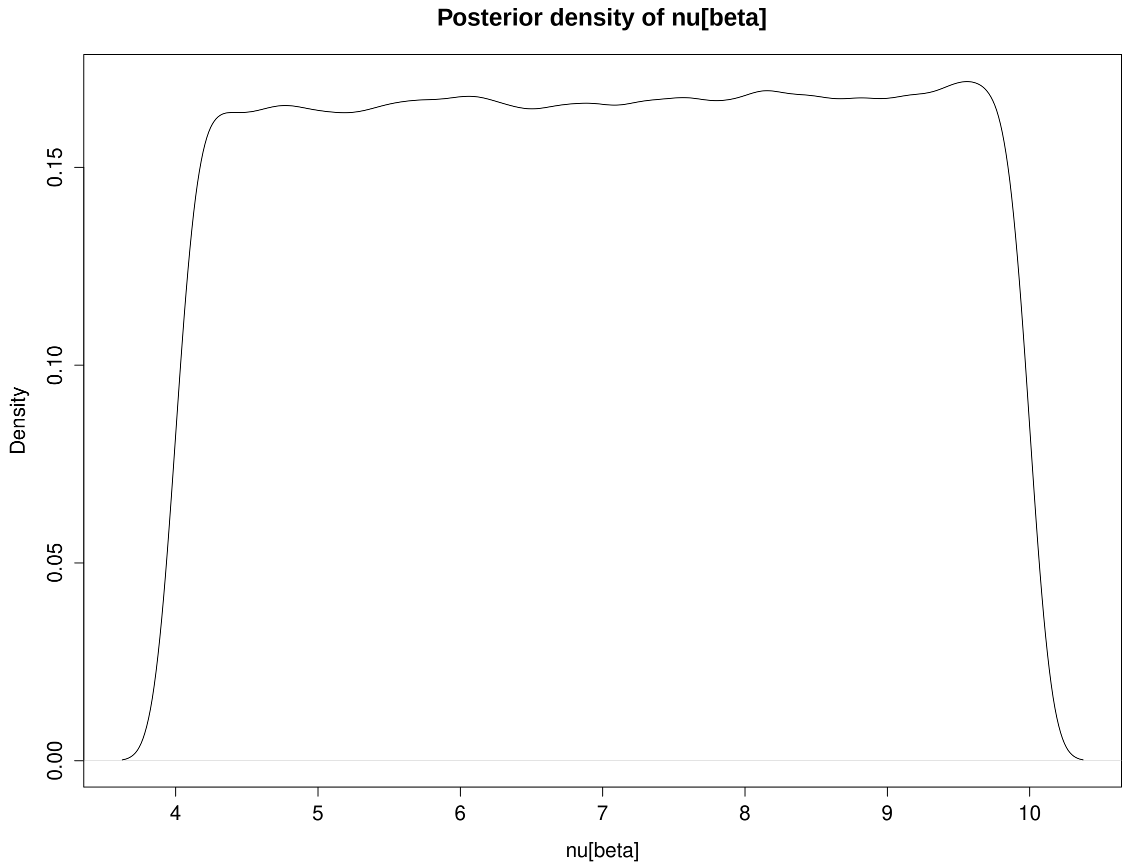
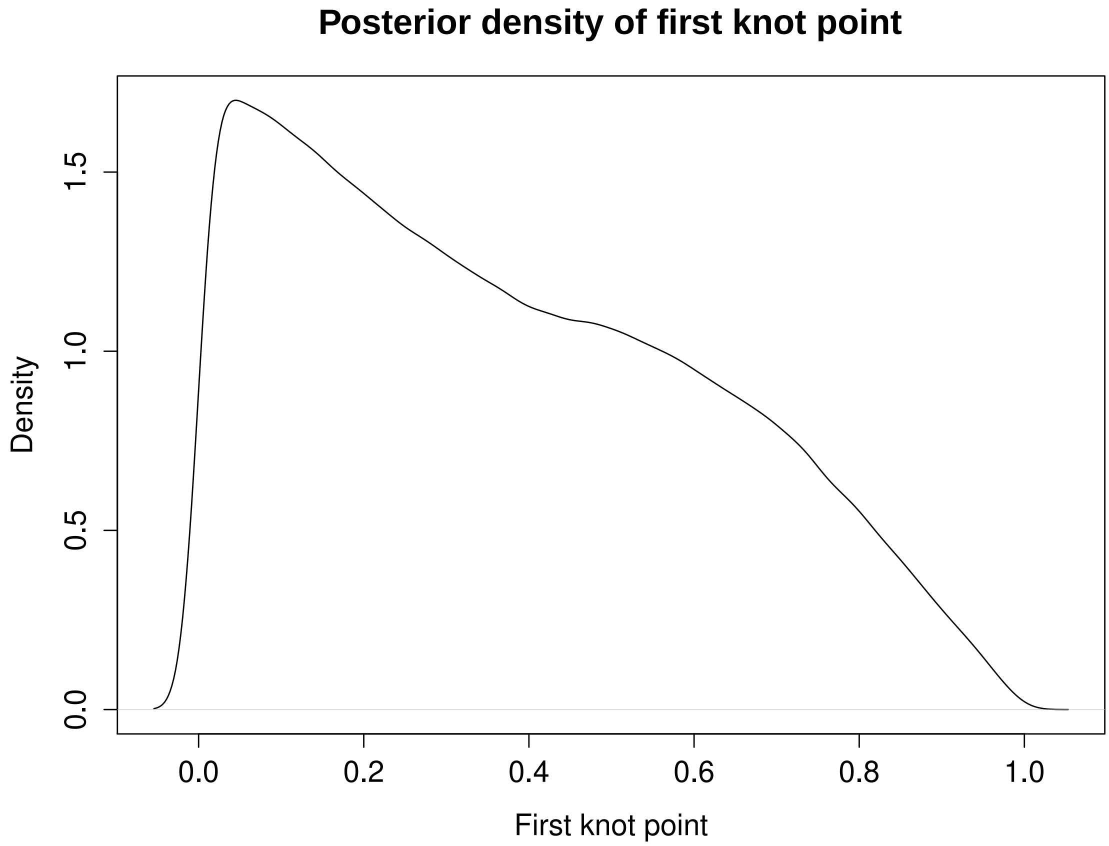


Figure 6: Posterior density plot forν_β



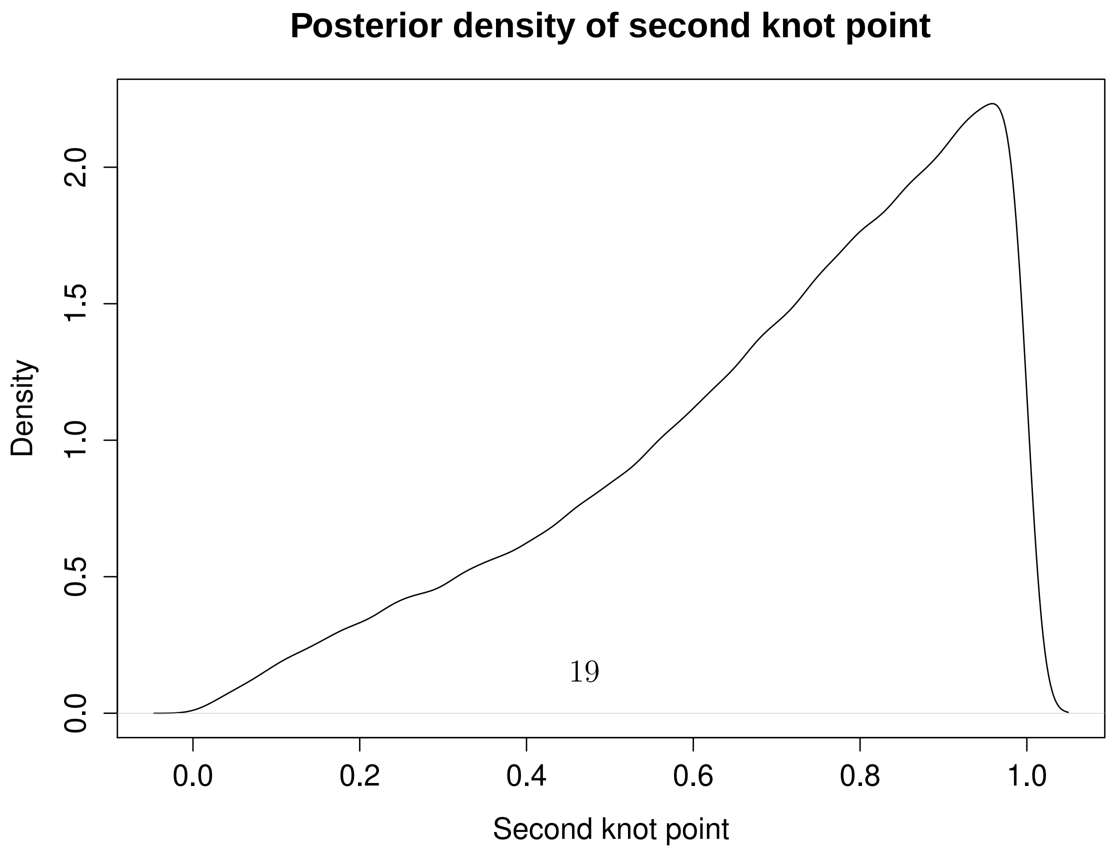


Figure 7: Posterior density plot forξ_1(top), ξ_2(bottom)

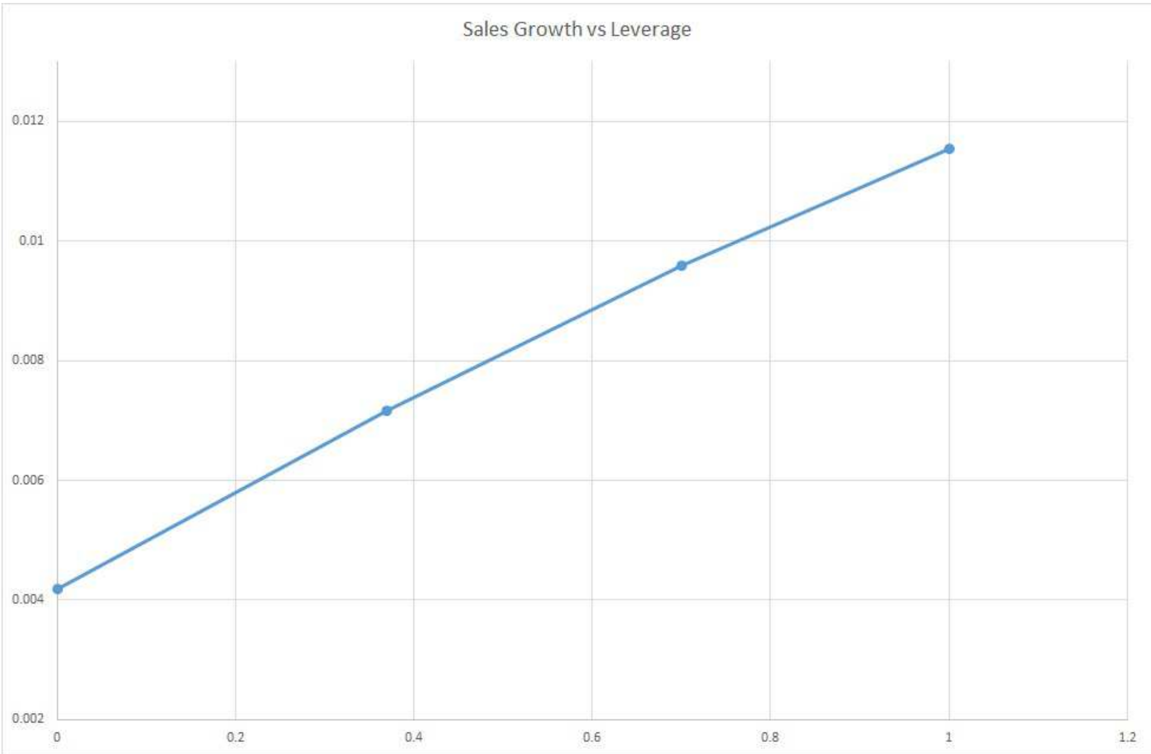


Figure 8: Spline showing the functional relationship between Sales Growth and Leverage

the United States of America market [1]and some other markets like South Africa [3]. The economic intuition could be the presence of a more conservative debt market and stricter regulatory intervention in the Indian market. The limited liability effect which induces firms with higher external borrowings to adopt more aggressive product market policies resulting in enhanced product market performance will not be very pronounced in a conservative debt market and banking environment. The stronger covenants associated with debt finance in such a market will discourage firms to adopt aggressive product market policies. In absence of any comparative study of Indian and other debt market policies, one can only conjecture at this point. However, our findings open up a new area of research in this direction.

4 Conclusions

Looking at previous literature on empirical relationship between firms'capital structure and product market it was observed that there exists a non-monotonic relationship between output market performance of firms and their leverage in that the output market performance had different responsiveness to leverage at different levels of leverage.The different levels of leverage at which the relationship changed, or the knot points, were estimated using heuristics. All these empirical studies had issues of endogeneity and heteroscedasticity biases. It had also been established that capital structure decisions were influenced by country specific factors which indicated that the exact nature of the relationship including the location of the break points must be data specific . Thus it was necessary to evolve a statistically robust data driven method which will address all these issues. In this study we have constructed a hierarchical semi-parametric Bayesian regression model with adaptive splines to address all these issues. We thus addressed all the issues associated with the empirical investigation of capital structure and product market performance of firms with innovative use of Bayesian framework using a single regression model.

Our contribution to the empirical literature was important from two perspectives. To the best of our knowledge this is the first time a study on the non-monotonic relationship between debt and output of firms has been conducted on Indian data. India being of utmost strategic importance to the global investors, our study brings some fresh perspectives on the corporate finance dynamics of Indian market. Our studies establish that the relationship between product market performance of firms and their capital structure in India is distinctly different from that in some other countries. This has great significance for policy makers as well as global investors. On the research front this also opens up a need for further investigation into comparative studies of debt market environments of different countries. The country specific findings further establishes the utility of our methodology which may now be employed to study and compare the capital structure dynamics of several countries.

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