ENTREPRENEURIAL FIRMS AND SIGNALING FOR CREDITWORTHINESS: A BAYESIAN MODELING APPROACH

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ABSTRACT

To fulfill their growth aspirations, entrepreneurial ventures depend on short-term, liquid sources of debt financing such as bank loans. However, because of the twin problems of information asymmetry and moral hazard, banks make their lending decisions by considering the venture's creditworthiness score provided by private information exchanges. Using theoretical arguments grounded in venture financing literature and signaling theory, we develop two new concepts, the venture's emergent volatility of size and deliberate diversity of the financing portfolio, and test the signaling impact of these two attributes on venture creditworthiness. Further, we incorporate in the model multilevel features, by considering at both firm and industry levels. In doing so, we make use of hierarchical Bayesian models with beta distributed likelihoods and use Markov chain Monte Carlo methods to obtain model parameters. This research is likely the first empirical study to examine the financial health of entrepreneurial firms based on emergent volatilities as well as deliberate diversities, and contrasted for entrepreneurial ventures in manufacturing versus services. Our paper offers guidance on how variability in firm-level attributes (intended or otherwise) sends signals that affect the firm's creditworthiness, and therefore, its ability to secure debt-financing.

INTRODUCTION

Growth-oriented entrepreneurial ventures demonstrate unique financial needs not served by optimal capital structure rules. They also face hurdles with regard to funding their operations, which makes it difficult for these ventures to sustain their growth aspirations (Beck and Demirguc-Kunt, 2006; Thornhill, Gellatly and Riding, 2004). By viewing the venture's growth aspirations through a financial growth cycle paradigm, Berger and Udell (1998) suggest that different capital structures become optimal at different stages during the life-cycle of the firm. For a venture embarking on a high growth trajectory, its capital structure must incorporate both equity-based (e.g. angel finance, venture capital and private and public equity) and debt-based (e.g. trade credit, short-term bank credit, and intermediate-term financial institution credit) financing (Denis, 2004; Markova and Petkovska-Mircevska, 2009), with debt financing forming a significant proportion of the venture's funds, especially in the early stages (Berger and Udell, 1998; Chavis, Klapper and Love, 2010; Le and Nguyen, 2009).

Even though the entrepreneurial venture needs assured debt financing, banks face two problems in making such funds available: asymmetric information and moral hazard, arising because of the principal-agent nature of the relationship (Bougheas, Mizen and Yalcin, 2006; Dell'Ariccia, 2001). To alleviate these concerns, banks take recourse to credit information about the entrepreneurial venture, made available by third-party private information exchanges. A popular form of credit information used by banks happens to be the venture's Paydex score, supplied by the Business Credit Services Division of Dun & Bradstreet (D&B), the world's largest private information broker (Kallberg and Udell, 2003). The Paydex score is "D&B's unique dollar-weighted numerical indicator of how a firm paid its bills over the past year, based on trade experiences reported to D&B by various vendors".[1]

Even as the Paydex score is utilized by banks, it serves as a powerful tool in the venture's hands to signal its creditworthiness to the external world. In this paper, our aim is to examine the ways in which the entrepreneurial venture's attributes may influence its creditworthiness reflected in its Paydex score, coming from the perspective of signaling theory. We are especially interested in assessing the likely signaling impact of the entrepreneurial venture's: (i) *emergent volatilities* of size or unintended changes in the firm's revenues as well as employees (termed volatility, hereafter), and (ii) *deliberate diversities* of financing or intended diversification in the firm's financing portfolio (termed diversity, hereafter) on its creditworthiness as reflected in its Paydex score. This is important because the operating context is especially dynamic for a growing entrepreneurial firm. Not everything can be planned out in advance and both intended changes in its financing portfolio and unintended shifts in its revenues and employees may occur. Using an extensive dataset of US based high-growth entrepreneurial firms available through the Edward Lowe Foundation's Institute for Exceptional Growth Companies we empirically develop and test the model using a Bayesian perspective. The Bayesian approach allows inferences to be expressed probabilistically. It can also incorporate information coming from other sources in addition to data via the so called prior distributions. Further, we incorporate in the model multi-level features, by considering co-variates operating at firm and industry levels.

Based on our paper, we make several contributions. First, ours is probably one of the earliest studies to examine how signaling by the entrepreneurial venture based on its emergent volatilities and deliberate diversities affect its creditworthiness, thus influencing the firm's ability to access debt financing. Second, post-hoc analysis after categorizing the entrepreneurial ventures in our sample under manufacturing versus service revealed very interesting results. While our findings were robust for service ventures (with signaling impact of emergent volatilities and deliberate diversities occurring in directions as theoretically predicted), the results were mixed for manufacturing ventures. This makes us believe that manufacturing versus service entrepreneurial ventures perform their signaling initiatives to the external world based on firm attributes in fundamentally different ways. Finally, given the skewness in our sample of growth-oriented entrepreneurial ventures (likely true for entrepreneurial firms, in general) our study incorporated the Bayesian approach in modeling and analysis, which too is one of the earliest attempts to

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[1] https://www.dandb.com/glossary/paydex/#1

incorporate Bayesian methods in an empirical context in the entrepreneurship domain.

THEORY AND HYPOTHESES

Using Signaling to Influence Creditworthiness

Short-term bank credit is a special form of financing because "…the financial intermediary [i.e. the bank] is permanently in a position between the borrower and the ultimate lender" (Scholtens, 1999: 141). Contrary to popular perception, Robb and Robinson (2010) find entrepreneurial ventures rely on external debt sources such as bank credit far more than informal sources such as contribution from friends and family to fulfill their growth aspirations. However, banks face two problems in their efforts to lend to entrepreneurial ventures - asymmetric information and moral hazard - arising because of the principal-agent nature of their relationship (Dell'Ariccia, 2001). On the one hand, as creditors banks face uncertainty with regard to the creditworthiness and paying capacity of potential entrepreneurial ventures they could lend to, resulting in the problem of asymmetric information. On the other hand, the moral hazard problem arises if the entrepreneur behaves in an opportunistic manner after receiving credit and defaults on repayment.

To alleviate these concerns, banks offer credit to entrepreneurial ventures through what authors have called the 'balance sheet channel', by closely monitoring parameters such as profitability, previous loan payments history and outstanding debt (Bernanke and Gertler, 1995; Bougheas *et al,* 2006). One other critical information banks also use is credit information about the entrepreneurial venture provided by third-party private information exchanges. A popular form of such credit information is the firm's Paydex score supplied by the Business Credit Services Division of Dun & Bradstreet (D&B), the world's largest private information broker (Kallberg and Udell, 2003). "PAYDEX is a number between 0 and 100, which translates (approximately) into the average number of days past due for the given firm's last year of trade experiences. The PAYDEX score thus characterizes the turnover behavior of debt payment information furnished to D&B by suppliers of trade credit and other forms of business debt" (Kalberg and Udell, 2003: 457). The Paydex score is qualitatively interpreted as follows: 90-100 (excellent), 71-80 (good), and 70 and below (bad).

Signaling to the external environment (Spence, 1973) arises as a legitimacy-seeking strategy by firms, mainly to overcome the problem of adverse selection (Akerlof, 1970; Janney and Folta, 2006). While the Paydex score informs the bank's lending decision, it is also a variable of interest that the entrepreneurial venture can manipulate through signaling efforts, in order to improve its overall creditworthiness. Generally defined, a signal constitutes "[any] manipulable attributes or activities that convey information about the characteristics of economic agents" (Erdem and Swait, 1998: 134). Prior research investigating signaling efforts by entrepreneurial ventures suggests such firms rely on a range of attributes to convey a positive status about themselves: patents (Gopalakrishnan, Scillitoe and Santoro, 2008), private equity placements (Janney and Folta, 2003), entrepreneur's direct involvement in projects (Levy and Lazarovich-Porat, 1995), venture backing and reputation of underwriter (Ragozzino and Reuer, 2007), venture capitalist (VC) control rights (Cumming, 2008), customer reputation (Reuber and Fischer, 2005), top

management team background (Cohen and Dean, 2005), and board composition (Certo, 2002). These characteristics can be usefully summarized as falling along two major dimensions for the entrepreneurial venture: (i) emergent volatilities (or unplanned outcomes) associated with the firm's sales and employees, and (ii) deliberate diversities (or planned outcomes) associated with the firm's external financing portfolio. We are interested to explore the signaling impact of the emergent volatilities and deliberate diversities on the entrepreneurial venture's creditworthiness as measured by its Paydex score.

Signaling Impact of Emergent Volatility

Firm size has a beneficial impact on the venture's overall capital structure (Winker, 1999). According to Cassar (2004), smaller firms face higher difficulties with regard to resolving informational asymmetries with banks and other lenders. Moreover, because of their lower asset base it becomes difficult for them to convince lenders that they will be able to honor their prior commitments in the case of liquidation. As such, lenders are more reluctant to extend credit to smaller firms (Kotey, 1999). In contrast, large firms not only find it easier to access bank loans (Beck and Demirguc-Kunt, 2006) but they are also in a position to manipulate bank loan contract terms to favor themselves (Dennis and Sharpe, 2005). Similarly, growth-oriented entrepreneurial ventures with a higher employee base are placed in an advantageous position. Increased employee strength suggests to the external world about the firm's continued stability of operations and also its future growth potential based on human capital (Kim, Aldrich and Keister, 2006) which, in turn, would positively influence its creditworthiness and its attempts to secure additional financing.

While firm size has benefits, the focus of this paper is to examine the likely influence that the emergent volatility associated with the entrepreneurial venture's revenues and employees will have on its efforts to signal its creditworthiness. According to the Mirriam-Webster dictionary, volatility arises when a parameter "…is characterized by or [is] subject to rapid or unexpected change". In the case of entrepreneurial ventures with high growth aspirations and associated difficulties in organizing required external financing, some level of fluctuation in year-to-year revenue streams is only to be expected. To a lesser extent, the firm may also be able to explain a temporary fluctuation in its employees. However, if the venture depicts major fluctuations in either revenues or employees or both over a long time-period, it will be viewed by external entities as being unstable. Lending agencies such as banks will infer the fluctuations arising as not just an outcome of the venture's ambitious growth plans but also because of inherent inadequacies associated with the venture itself and its stability. In effect, an entrepreneurial venture beset with the emergent volatility of size will find it very difficult to signal to the external world and influence its creditworthiness. This makes us suggest:

Hypothesis 1a: Emergent volatility of revenues is negatively associated with Paydex score.

Hypothesis 1b: Emergent volatility of employees is negatively associated with Paydex score.

Signaling Impact of Deliberate Diversity

Prior external financing received has a positive effect on the entrepreneurial venture's ability to secure additional funds as well as on its creditworthiness. To support their growth plans, firms scout for venture financing from several possible sources: angel-based, venture capital, and private equity. These are three alternate sources that lend funds to entrepreneurial ventures, and with somewhat different motives (Elitzur and Gavious, 2003; Heukamp, Liechtenstein and Wakeling, 2007). Angels are high net-worth individuals. They invest in the venture at an early stage by providing seed capital, either by themselves or in association with others who together form an angel association. Along with financing, angels offer perform four complementary value-added roles, which serve to immensely benefit the growing venture: sounding board for strategic planning and choices, supervision and monitoring, resource acquisition, and mentoring (Politis, 2008). In contrast, venture capitalists (VC) are financial intermediaries between the entrepreneur and investors, who come in at a somewhat later stage in the venture's life-cycle. Chahine, Filatotchev and Wright (2007) note that the business angels financing has more informal expectations while venture capitalist financing brings more formal expectations from the entrepreneurial firm. An essential difference between angel investors and VCs is that the latter expect to wield some form of management control in the entrepreneurial venture, in return for providing the financing. Private equity is the third form of external financing received by the entrepreneurial venture. It can come at different stages in the venture's life-cycle and is provided by the entrepreneur's friends, acquaintances and relatives, who are looking for a good return on the investment made.

An entrepreneurial venture that has received external financing from more than one source, its financing portfolio necessarily exhibits the characteristics of deliberate diversity. In effect, this means the venture has satisfied the stringent but somewhat conflicting demands of each group of lenders and has been able to convince each party of its latent potential, in order for them to simultaneously contribute to the venture. In contrast, for an entrepreneurial venture with lesser deliberate diversity, the firm has been required to fulfill the requirements of and convince fewer lender groups. Further, for the entrepreneurial venture having a financing portfolio with high levels of deliberate diversity, the organization also receives the complementary benefits of entrepreneurial mentoring, management guidance, and friendly support from each of the three lending agencies: angels, venture capitalists, and private equity partners, respectively. In effect, it is quite likely that such an entrepreneurial venture is able to deal more effectively with business risks and environmental uncertainty and achieve its growth plans. Thus, having been the recipient of angel financing or private equity in the early stages creates subsequent additional investment opportunities as well as financing needs for the firm. These can be met by a venture capitalist, stepping in the next stages of growth by providing to the firm additional funding (Harrison and Mason, 2000). Further, this also has a positive impact on mitigating the information asymmetry problem associated with the venture in the eyes of short-term lending agencies. "An extensive body of theoretical literature suggests that the combination of intensive monitoring, provision of value-added services, and powerful control rights in these types of deals should alleviate agency problems between entrepreneurs and institutional investors." (Kerr, Lerner and Schoar, 2011: 1-2). In view of these arguments, a growth-oriented entrepreneurial venture that has developed deliberate diversity in its financing portfolio, this will have a positive impact on its creditworthiness. In other words:

Hypothesis 2: Deliberate diversity of the financing portfolio is positively associated with Paydex score.

DATA AND METHODS

Paydex Score and its Distribution: Rationale for Adopting the Bayesian Approach

In analyzing the financial health of entrepreneurial ventures, we make use of an extensive data set which consists of a total number of 12,033 firms that were still active as of the end of 2010. The common characteristic for all these ventures is that they are entrepreneurial in nature due to the fact that they have received some form of funding between the years of 1995-2010. To assess the creditworthiness of the entrepreneurial ventures, we use their D&B Paydex score (at the end of year 2010, the last year of our data). As of 2010, the Paydex score was being used in 212 countries, as a measure of creditworthiness of firms, with the U.S. being the dominant player. In our analysis, more specifically, we use the maximum Paydex score in the last 12 months in 2010 (scaled by 100 units so that it is a number between 0-1) and refer to this measure as Paydex in the narrative.

Because the distribution of Paydex score in our sample depicts left-skewness in its density estimate, we propose using the beta distribution, which is flexible enough to cover several types of density behavior including left-skewness and consider its Bayesian inference. In addition, we adopt a hierarchical (multi- level) Bayesian approach in our modeling, which can account for both firm and industry level effects simultaneously on the firm's Paydex score (see Gelman, Carlin, Stern, and Rubin, 2003 for a thorough summary of Bayesian methods). To estimate the model parameters, we make use of Markov chain Monte Carlo (MCMC) estimation methods.

Use of Bayesian methods in management and associated fields has been increasingly gaining popularity (Hahn and Doh, 2006; Hansen, Perry and Reese, 2004; Rossi and Allenby, 2003). This is due to the modern computational advances in estimation, previously only available in closed form for a limited number of applications.) An attractive feature of the Bayesian approach is that all inference is free from asymptotic approximations and can be implemented in the face of paucity of data, unlike traditional regression models. Further, because all uncertainty in the Bayesian paradigm is quantified via probability distributions, all inference can be represented probabilistically due to the existence of so called posterior distributions of model parameters (Hahn and Doh (2006; Hansen, Perry, and Reese, 2004). Instead of obtaining solely point estimates of model parameters (e.g. an estimate of a regression coefficient in classical regression), the Bayesian approach provides full probability distributions, based on which inference can be drawn using any standard measures of interest such as the mean, mode, median, standard deviations and probability intervals that are not necessarily symmetric. For instance, by adopting the Bayesian approach in our study we are able to compute the probability that the effect of any one co-variate of interest (e.g. employee volatility) being negative (or positive) on the Paydex score. The summary of the features of the proposed approach would be threefold: The model can account for non-standard density behavior due to the use of the beta distribution and for multi-level effects such as the firm and the industry due to the hierarchical structure imposed. In addition, probabilistic arguments about the effects of co-variates due to

the adopted Bayesian point of view of inference can easily be obtained as an inherent outcome of the approach.

Co-variates of Interest

For this study, the co-variates of interest include volatility in employees, volatility in revenues, and diversity in the venture's financing portfolio. Other variables that we considered as control variables include firm size (measured by sales), firm age, and financing received in the last three years. Employee volatility is calculated as the standard deviation of the number of employees a venture has had yearwise, since its inception. A high value indicates the venture's employee strength has been fluctuating rapidly from year to year. Similarly, revenue volatility is measured as the standard deviation of the firm's sales. It accounts for unstable/stable revenue behavior.

For any firm in the sample, types of funding received in the past could be one or more of the following: angel funds, venture capital, or private equity. Each of these financing types was coded as a binary variable (value 1 if the venture received this funding type in the last three years, 0 otherwise). Thereafter, diversity in the venture's financing portfolio was calculated using Blau's index of diversity (Blau, 1997), widely used in management research to measure diversities in different firm-level attributes (see, for example, Carpenter and Fredrickson, 2001). The diversity measure for venture j is calculated via

$$\text{Diversity}_j = 1_i - \sum_{i=1}^{N} P_i^2 \, , \forall j \tag{1}$$

where P_i is calculated as the proportion of the ith type of funding to the total number of rounds of funding received by venture j and $N = 3$ since there are only three types of funding a venture can get. Thus, a high diversity measure indicates a more heterogeneous type of funding behavior, whereas a low value indicates a more homogeneous behavior. For instance, if a venture got all three types of funding multiple times in the past (angel, venture capital and private) then their diversity measure will be high as opposed to a venture who only received angel type funding. In all of our analysis, we scale the co-variates (except the funding received variable which is binary) such that they are defined between 0-1 (by dividing each value by its maximum) to facilitate MCMC generation and interpretation.

Finally, as control variables we use the sales in 2009 (proxy for firm size), firm age in 2010, and total funding received in 2007-2010.

Modeling the Paydex Score

The histogram and the smoothed empirical density estimates in Figure 1 for the Paydex scores of all entrepreneurial ventures (scaled by 10 units) show that the sample values are defined in the positive real line and are realizations from a skewed to the left distribution. Such heavy skewness to the left makes classical least squares regression methods infeasible to adopt. Thus, we consider a beta density for the likelihood function that is capable of handling several density shapes some of which are shown in Figure 2.

Let y_{ij} represent the Paydex score of the ith firm in the jth industry where $i = 1, \ldots, 12, 033$ and $j = 1, \ldots, 3$ in our model. Even though the beta

density has been used in many applications in several fields, its use with the effects of co-variate information has been quite scarce with the exception of a few. Our approach is loosely based on the model proposed by Branscum, Johnson, and Thurmand (2007) which we summarize below. We assume a hierarchical structure using a beta likelihood using the following form

$$p(y_{ij}|a_{ij}, b_{ij}) = \frac{\Gamma(a_{ij}+b_{ij})}{\Gamma(a_{ij})\Gamma b_{ij})} y_{ij}^{a_{ij}-1} (1 - y_{ij})^{b_{ij}-1}, \qquad (2)$$

where a_{ij}, $b_{ij} > 0$ and Γ represents the gamma function. The parameters a_{ij} and b_{ij} are assumed to have the following form

$$a_{ij} = \mu_{ij}\gamma, \qquad (3)$$

and

$$b_{ij} = \gamma(1 - \mu_{ij}) \qquad (4)$$

where μ_{ij} represents the mean of y_{ij}, namely the average Paydex score of the ith firm in the jth industry and γ acts as a precision parameter for which fixed values of the mean, larger values of γ implies smaller variance (i.e. less heterogeneity in data). In order to account for the firm and industry specific effects on the Paydex we link the mean parameter using a logit function as

$$logit(\mu_{ij}) = \theta_j + \sum_{i=1}^{K} \beta_i X_i, \qquad (5)$$

where $logit(x) = \frac{e^x}{1+e^x}$, θ_j is a term which captures the jth industry specific effects on the Paydex score, β_is are regression type coefficients which account for firm specific effects such as the employee volatility, firm size, firm age, recent funding and funding volatility with K representing the total number of firm specific co-variates effecting the Paydex score (in our example $K = 6$). We note here that the above model is similar to that of Branscum et al. (2007) except for the inclusion of the random effects of θ_js. It is possible to think about (5) as if it is composed of two parts, a random effects part via θ_js and a deterministic part via X_is, the co-variates. Being able to obtain the posterior joint distribution of θ_js can provide several managerial insights in terms of the effects of the industry on the financial condition of a venture. For instance, it would be straightforward to compute the probability that the effect of the manufacturing industry being greater (or less) than that of the service industry on the Paydex score for firms with the same level of characteristics. Another attractive feature of the beta regression models is their ability to allow non-constant variance which is rarely justified using standard regression model. In addition, the Bayesian hierarchical approach requires that we quantify our prior uncertainty about the unknown parameters via probabilities in the form of prior distributions which we discuss next.

Bayesian Inference from the Model

The implementation of Bayesian analysis adopts the likelihood principle which simply implies that the likelihood function has all the information needed for statistical inference. As presented in (2), we use a beta distribution in the likelihood. For notational convenience, let D represent the set of all the data at hand, which includes the Paydex scores of all 12,033 firms from 3 distinct industries with characteristics. The main difference between Bayesian and classical estimation procedures is the specification of the prior distributions for all unknown model parameters. Bayesian inference always consists of the prior distributions and

the likelihood function. We assume the following priors and hyper-priors on the model parameters

$$\theta_j \sim N(a_{\theta j}, b_{\theta j}), \text{ for } j = 1, \ldots, 3, \qquad (6)$$

where N represents the normal distribution, $a_{\theta j}$ and $b_{\theta j}$ are the location (mean) and shape (precision=1/variance) parameters of the normal distribution, respectively. We also note here that θ_js are independent a priori, however this does not necessary imply that they will stay independent when combined with the information from the likelihood. In addition,

$$\beta_i \sim N(a_{\beta i}, b_{\beta i}), \text{ for } i = 1, \ldots, 6, \qquad (7)$$

where β_is are independent a priori. The variance parameter of the model, γ, is assumed to be

$$\gamma \sim G(a_\gamma, b_\gamma), \qquad (8)$$

where G represents the gamma distribution, a_γ and b_γ are the location and shape parameters, respectively. In general, the values of a.s and b.s are either elicited from expert knowledge or are chosen such that our uncertainty about the model parameters is at best vague. Since we do not have any expert knowledge that we can incorporate to the analysis, we assign values of a.s and b.s such that our prior uncertainty is uninformative. More specifically, we assign $\theta_j \sim N(0, 0.001)$, for $j = 1, \ldots, 3$, $\beta_i \sim N(0, 0.001)$, for $i = 1, \ldots, 6$ and $\gamma \sim G(0.001, 0.001)$. Such priors are referred to as flat but proper priors in Bayesian inference.

The next and the final step in Bayesian inference is to obtain the distributions of all the unknown model parameters. Such distributions are referred to as the posterior distributions and contain all the information needed for inference about a given parameter of interest. For instance, it is possible to obtain statistics of interest such as the mean, mode, median, standard deviation and probability intervals as a consequence of the process. This is a major area where classical and Bayesian methods differ. Using classical methods, one only gets point estimates such as the mean of a parameter. It is very rare to find closed form posterior results for modern applications. However, thanks to recent advances in computational methods called Markov chain Monte Carlo (MCMC) methods, obtaining posterior distributions for several scenarios is now possible, including the one considered here. In estimating the posterior distributions of model parameters, we make use of MCMC methods such as the Metropolis-Hastings algorithm within the Gibbs sampler; see Smith and Gelman (1992) and Chib and Greenberg (1995) for common practice in MCMC.

One of the key requirements of the Gibbs sampler is the full conditional distributions of all model parameters (either in closed form or as a function up to a certain proportionality). We use the notation $p(./ \ldots, D)$ to represent the full conditional distribution for a given parameter given all the other parameters. The full conditional distributions can be obtained as the product of the likelihood function and the prior distributions up to a constant. The idea is to generate samples from the joint posterior distribution of all model parameters, $p(\theta, \beta, \gamma|D)$. To do so, we need to sequentially generate samples from the distributions of $p(\theta|\beta, \gamma, D)$, $p(\beta|\theta, \gamma, D)$ and $p(\gamma|\theta, \beta, D)$. This method is referred to as the Gibbs sampler in Bayesian analysis and is straightforward to implement in most cases. Since some of these full conditional distributions will not be well known probability distributions, we can use a method called Metropolis-Hastings algorithm to generate the necessary samples.

In summary, to model and to estimate the financial condition of entrepreneurial ventures using the Paydex scores, we make use of hierarchical Bayesian regression type models with beta distributed likelihoods. To estimate the model parameters, we use MCMC techniques whose implementation requires the calculation of common measures of convergence such as the shrink factors to assess the adequacy of the proposed estimation techniques. We present and discuss the results of posterior inference and convergence checks in the next section.

ANALYSIS

Bayesian Implementation and MCMC

In what follows, we discuss the implications of taking the Bayesian point of view in inferring both the firm and industry level effects on the financial condition of entrepreneurial firms. To obtain the posterior distributions of model parameters, MCMC methods were used as discussed previously. To do so, the WinBUGS software was used and the code is available via email upon request from the authors. We assumed flat but proper priors for model parameters when required. We also note that the inference of model parameters was not sensitive to the choices of priors as long as they were flat but proper. Anytime, an MCMC type method is used, one needs to assess the convergence of the algorithms. We ran three parallel chains with different initial points. The chains were run for 20,000 iterations as the burn-in period and 10,000 samples were collected. To preserve space we will omit a detailed summary of convergence for all model parameters and note that similar results were obtained for the rest. In summary, we did not encounter a problem of convergence. This can informally be observed from the trace plots in Figure 3 which freely oscillate within the sample space without getting stuck at a particular range or value. In addition, the autocorrelation functions showed quick decays and the shrink factor estimates were around 1 for all parameters; see Brooks and Gelman (1998) for a detailed discussion on MCMC convergence measures.

Effects of Emergent Volatility and Deliberate Diversity

An attractive feature of Bayesian inference is the graphical representation of inference using the posterior distributions from which initial managerial insights can be gained as opposed to just point estimates of classical methods. Such posterior distributions inherently contain information regarding the mode, mean, median, probability intervals and shape of the distribution. The posterior density estimates of the firm level effects are shown in Figure 4. For instance, the first distribution on the top left panel represents the effects of employee volatility on the Paydex score of an entrepreneurial firm which implies that the effect is negative with a very high probability. In addition, the mode of the distribution is roughly around -0.5 which is the mostly likely estimate of the employee volatility effect.

Another co-variate of interest is if the firm received any type of financing in the last three years whose posterior density is given by the distribution at the bottom middle panel. In this case, the effect is defined between a magnitude of 0.01 and 0.06 that are all positive which simply implies that an entrepreneurial venture will be in better financial status if they have received any kind of finding (angel, venture capital or private) in the last three years with probability one. On the other hand, the effects of the Diversity in financing measured by the diversity calculation from (1) are shown at the bottom right density. Based on the distribution, it is possible to

deduce that the most likely effect will be positive based on where the mode will be (somewhere between 0 and 0.1).

Diversity measures the amount of heterogeneity in a given variable. In this case, a higher diversity implies more diverse type of funding from all sources such as angel, venture capital and private. The findings imply that getting financed from diverse sources as opposed to just one type will have a positive effect on the financial health of the firm. However, the distribution also implies that for a certain percentage of firms (roughly estimate it to be 20%) it will have a negative effect when we consider firms from all industry types.

In Bayesian analysis, it is also possible to summarize statistics of interest based on the posterior distributions as in Table 1 where measures such as the mean, standard deviation, median and 95% inter-quartile (credibility) intervals are shown. Most of the inference that was drawn from the graphical representations can also be observed from the summary statistics. Unlike confidence intervals whose interpretations are not as straightforward as one would hope, credibility intervals are simply probabilities. We can easily say, for instance, there is a 95% probability that the effect of employee volatility will have a negative effect on the Paydex score due to its credibility interval of $(-0.899; -0.035)$. Similarly, the credibility interval for the financing volatility can be obtained as $(-0.055; 0.130)$ which shows support in both negative and positive regions with more on the positive side. This is in line with our previous discussion on the financing volatility.

As also pointed out by Hansen et al. (2004), all inference is probabilistic in Bayesian analysis, it is possible to compute the probabilities of the firm level variables having positive or negative effects on the Paydex score which we show in Table 2 where $P(\beta_i < 0/D)$ represents the probability of a negative effect and $P(\beta_i > 0/D)$ a positive effect. For instance, we can use Table 2 to strongly argue that employee volatility has a negative effect on the Paydex score of a firm with a probability of 0.98, which shows strong support in its favor. This, at the same time, implies that the employee volatility has a negative effect on the Paydex score for 98% of all entrepreneurial ventures considered in the study. Such an analysis will not have been possible using traditional least squares estimates from regression. In a similar manner, we can now compute exactly the effect of financing volatility having a positive effect on Paydex as 0.77, which leads us to wonder for which kind of ventures it has a positive (or negative) effect.

Post-hoc Analysis of the Industry Effect

The hierarchical structure introduced in (2) makes it possible to assess the industry specific effects on Paydex score whose posterior estimates are given in Table 3. Based on these estimates, it is possible to infer that entrepreneurial ventures in the service and other categories have, on the average, better financial status as opposed to those in manufacturing given all the previously discussed co-variate effects. In addition, the standard deviation estimate for the random effect of the firms in the manufacturing industry is slightly higher, implying the existence of more uncertainty in the financial health of entrepreneurial firms in manufacturing as opposed to that of the service and the others.

Figure 5 shows a boxplot of the industry specific effects on the Paydex score given all the other co-variates. Given some of the inference discussed previously and the behavior of the industry specific effects led us to explore potential differences of the effects of some of the firm level measures across industries. Thus,

we decided to split the dataset into two major industries, manufacturing and service. We ended up with 3,567 ventures for the manufacturing and 4,303 for the service whose implications we discuss in the sequel.

To preserve space, we only included the probability estimates of the posterior distributions for comparison purposes that are given in Tables 4 and 5 for ventures in manufacturing and service industries respectively. The probability estimates confirm our suspicions about the existence of different effects across industries for some of the variables of interest. For ventures in the service industry, the probability that the financing volatility has a positive effect on the financial health is estimated to be one, as opposed to its estimate 0.45 for the manufacturing firms. This shows evidence in favor of having a diverse portfolio of funding types (a combination of angel, venture capital and private) to be extremely important for ventures in the service industry. Another finding is about the sales volatility for the service industry ventures, which indicates a negative effect with probability 0.79 on the Paydex score. In other words, exhibiting a sales behavior which constantly changes over time negatively affects the financial health of the entrepreneurial firms in the service industry that are looking for funding.

Several other differences exist between the entrepreneurial firms that are in manufacturing and service industries. For manufacturing most variables such as sales, financing in the last three years and financing volatility have posterior probabilities close to 0.50. This is not exactly equivalent to having non significant effects using traditional methods, but it can be interpreted in a similar manner. It simply indicates that the effects can sometimes (about 50% of the time) negatively effect the financial health of a given venture and sometimes positively. Another interesting findings for firms in the manufacturing industry is that getting funded in the last three years only affects their financial status 50% of the time as opposed to that of the service industry firms which was computed to be 100%. In short, it is possible to argue that developing a diverse portfolio of funding, in addition to securing funding, is more important for entrepreneurial ventures in the service industry. On the other hand, the direct impact of the employee volatility for ventures that are in the service industry is less than those in manufacturing due to its posterior probability estimate of 0.50. In summary, we found that several differences exist between the service and manufacturing industries in terms of the firm specific characteristics effects on the financial status of a given venture. We believe that these can provide guidelines in the form of signals for entrepreneurial firms that are looking for funding. Such signals can then be perceived by the investors or acquirers to make decisions in the face of information asymmetry regarding the financial health of a venture.

DISCUSSION

Contribution

For growth-oriented entrepreneurial ventures, firm size and prior financing significantly impact the venture's efforts to secure additional future funding, including short-term credit. However, due to growth pressures as well as variations in external and internal conditions, not all plans work out exactly as intended for entrepreneurial firms. So, from one year to the next fluctuations could arise with regard to sales achieved or employees on the payroll. At the same time, these firms also have available the ability to source and stick with just one form of external financing (in the form of angel funds, venture capital,

or private equity) or incorporate different types of financing in their portfolio. The focus of the present study was to go beyond what we already know from prior literature with regard to factors that have a positive impact on the venture's creditworthiness in the eyes of private information exchanges.

First, ours is one of the earliest studies to examine the methods a growth-oriented entrepreneurial venture can signal to an external private information exchange, in order to improve the venture's creditworthiness rating as assessed by the latter. Specifically, we examined the signaling impact of two sets of venture characteristics: (i) unintended changes (or emergent volatility) associated with firm revenues and employees, and (ii) intended changes (or deliberate diversity) associated with the firm's financing portfolio and obtained very interesting results. As predicted, emergent volatility associated with employment has a negative effect on the firm's Paydex score. However, contrary to expectations we found that emergent volatility associated with revenues had a positive impact on Paydex score. This result is counter-intuitive. Because we had a multilevel model of the Paydex score, we were able to parse out the effects of these co-variates for firms in different industries. Thus, we found that the relationship between emergent volatility of revenues on Paydex score is positive for manufacturing but negative for service ventures (the latter being in line with our theoretical prediction). There likely exist other unaccounted for factors that stabilize the impact of revenue volatility on creditworthiness for firms in the manufacturing sector. Since the Paydex score is a measure of the firm's ability to pay its bills in the short-term, it is likely that a growth-oriented entrepreneurial venture in manufacturing is able to compellingly demonstrate this ability because it has a tangible product, an asset base incorporating technology and manufacturing capabilities, traditional supplier and distributor relationships, and asset-based collateral for debt, all of which may not be the case for a corresponding venture in the service industry. In effect, the negative relationship between emergent volatility of revenues and the Paydex score exists for the service venture but is mitigated for the manufacturing venture.

Second, in line with our prediction we found deliberate diversity associated with an entrepreneurial venture's financing portfolio has a positive impact on its creditworthiness as reflected in its Paydex score. Previous research has demonstrated that access to external financing is beneficial for the entrepreneurial venture, improving its growth prospects as well as its performance. Different types of external financing (angel-based funds, venture capital, and private equity capital) play complementary roles. Not only does access to any one form improves the venture's chances of obtaining another but also they help improve the firm's ability to secure debt financing such as bank credit. Our paper goes one step further. We are able to show that any planned attempt at incorporating deliberate diversity in the venture's financing portfolio is beneficial. In other words, we suggest deliberate diversity in the firm's financing portfolio performs the role of an organizational ambidexterity: While it is certainly difficult to successfully secure multiple types of external financing and meet the due diligence requirements of multiple providers, entrepreneurial ventures that are able to do so definitely improve their creditworthiness, more than would have been otherwise possible if the firm had received only one form of external financing, be it angel-based funds, venture capital or private equity. This result becomes especially salient when it is probed further for entrepreneurial ventures in the service industry, discussed below.

Third, post-hoc analysis revealed very interesting results with regard to the association between deliberate diversity in the financing portfolio and Paydex score, contrasted between firms in manufacturing versus service. For manufacturing, firms were almost equally balanced with regard to whether there was an influence of deliberate diversity of financing on Paydex score or not. However, for service ventures, 100% of the firms depicted a strong positive association between deliberate diversity of financing and Paydex score. Service firms may be by their very nature a more diverse set of firms since service firms could span various sectors from software developers to social media applications to medical research, and a plethora of other types. Service firms also traditionally lack hard assets for any collateral based lending and thus rely more on equity financing from a variety of sources. Manufacturing may be a more "close-knit" sector in terms of what they do. As such, from an investor viewpoint service firms may likely have the ability to draw a more diverse set of investors while manufacturing firms (with the presence of hard assets) may draw a more limited set of financial sources. When interpreted in association with the previous results on emergent volatility of revenues, our study indicates very robust findings for service firms: Any signaling effort by such firms must carefully consider the likely impact of emergent volatility of size (reflected in revenues) and deliberate diversity of the financing portfolio on the firm's creditworthiness (reflected in its Paydex score). The effect is strongly negative for the former and strongly positive for the latter. It appears that service firms make up for the adverse impact of the volatility of their size by signaling based on the deliberate diversity associated with their financing portfolio.

Implications for Practitioners

Our study findings have several important implications for growth-oriented entrepreneurial ventures and the entrepreneurs leading them. First, we show that in terms of attempting to influence the venture's creditworthiness as assessed by external information exchanges (such as the D&B), entrepreneurs need to be cognizant of the signaling effects of firm-level attributes such as the emergent volatility of revenues, emergent volatility of employees, and deliberate diversity of the firm's financing portfolio. In general, these forces act in opposing ways: with (unplanned) volatilities in employment having a negative impact on creditworthiness and (planned) diversities in financing sources having a positive impact. However, the relationships are not that straightforward for the impact of revenue volatility versus that of employee volatility. Similarly, the results are different for manufacturing ventures versus service ventures. Employment volatility has a negative effect on creditworthiness as depicted in the Paydex score, which measures the firm's ability to pay its bills on time, and this effect is not sector dependent. Unstable levels of employment can be costly to the firm both in the direct costs of hiring and training and in the indirect costs of perceived instability in the firm. For revenue (sales) volatility the effect is sector dependent with revenue volatility having a negative effect on creditworthiness for service firms but this is mitigated for manufacturing firms. In effect, these findings serve to provide an important insight to entrepreneurs: the need to go beyond considering signaling to the external world based on baseline attributes (such as sales, employees, and financing) and also be mindful of associated volatilities and diversities.

Second, because our research is anchored in the Bayesian approach using a very large sample of high-growth entrepreneurial ventures, we provide insights for

entrepreneurs that are very meaningful and easily interpreted, expressed as they are in probabilistic terms. For instance, we are able to state that "employee volatility depicted a negative relationship with creditworthiness for 98% of the firms in the sample" or that "financing portfolio diversity had a positive impact on creditworthiness for 100% of the ventures in the service industry sample". As the entrepreneur develops strategies for sustainable growth these probabilistic relationships provide the entrepreneur the framing for making decisions in the larger context of strategic development.

Directions for Future Research

So far, research in the entrepreneurship domain has only considered signaling impact of certain firm-level attributes such as patents, private equity placements, venture backing and reputation of underwriter, and venture capitalist control rights, amongst others. Planned or unplanned shifts in these attributes over time (expressed as emergent volatilities and deliberate diversities, respectively) and their signaling impact have not been considered. While our study attempted to do so, we obtained rather different results for manufacturing entrepreneurial ventures versus service entrepreneurial ventures. In fact, our findings were not as strongly supported for manufacturing firms as they were for service firms. This implies that manufacturing firms utilize attributes such as emergent volatility and deliberate diversity in ways that are different from how service firms do so, which can be a promising avenue for future research. Even within manufacturing firms, it is possible that R&D intensive ventures in industries such as biotech or nanotech utilize volatility and diversity in signaling in ways that are different from ventures in other sub-sectors within manufacturing. This can be a direction for future research. Additionally, further sector delineation may lead to interesting findings, especially utilizing a tech/non-tech rubric to tease out differences in emergent volatility and deliberate diversity across sectors.

Second, our study assessed the impact of emergent volatility and deliberate diversity on the venture's creditworthiness. Future research can examine the impact of these attributes on other variables of interest for the growth-oriented entrepreneurial venture such as acquisition likelihood, prospects for IPO, and alliance partnerships.

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TABLE ONE

Posterior Statistics for Firm Level Effects

	mean	st.dev	2.5Q	median	97.5Q
Employee Volatility	-0.470	0.21	-0.899	-0.4679	-0.035
Sales	-0.239	0.227	-0.690	-0.232	0.195
Sales Volatility	0.291	0.269	-0.216	0.278	0.831
Age	-0.183	0.035	-0.254	-0.183	-0.115
Financing Received	0.031	0.006	0.018	0.031	0.044
Diversity	0.036	0.048	-0.055	0.036	0.130

TABLE TWO

Probability Estimates for Firm Level Effects

	$P(\beta_i < 0|D)$	$P(\beta_i > 0|D)$
Employee Volatility	0.98	0.02
Sales	0.84	0.16
Sales Volatility	0.13	0.87
Age	1.00	0.00
Financing Received	0.00	1.00
Diversity	0.23	0.77

TABLE THREE

Posterior Statistics for Industry Level Effects

	mean	st.dev	2.5Q	median	97.5Q
Service(θ_1)	1.084	0.007	1.075	1.089	1.100
Manufacturing (θ_2)	1.034	0.008	1.019	1.034	1.050
Other (θ_3)	1.089	0.007	1.075	1.089	1.100

TABLE FOUR

Probability Estimates for Firm Level Effects (Manufacturing)

	$P(\beta_i < 0|D)$	$P(\beta_i > 0|D)$
Employee Volatility	1.00	0.00
Sales	0.53	0.47
Sales Volatility	0.005	0.995
Age	1.00	0.00
Financing Received	0.50	0.50
Diversity	0.55	0.45

TABLE FIVE

Probability Estimates for Firm Level Effects (Service)

	$P(\beta_i < 0|D)$	$P(\beta_i > 0|D)$
Employee Volatility	0.50	0.50
Sales	0.80	0.20
Sales Volatility	0.79	0.21
Age	0.99	0.01
Financing Received	0.00	1.00
Diversity	0.00	1.00

FIGURE ONE

Histogram Plot (left) and Smoothed Empirical Density Plot (right) for the Paydex Scores
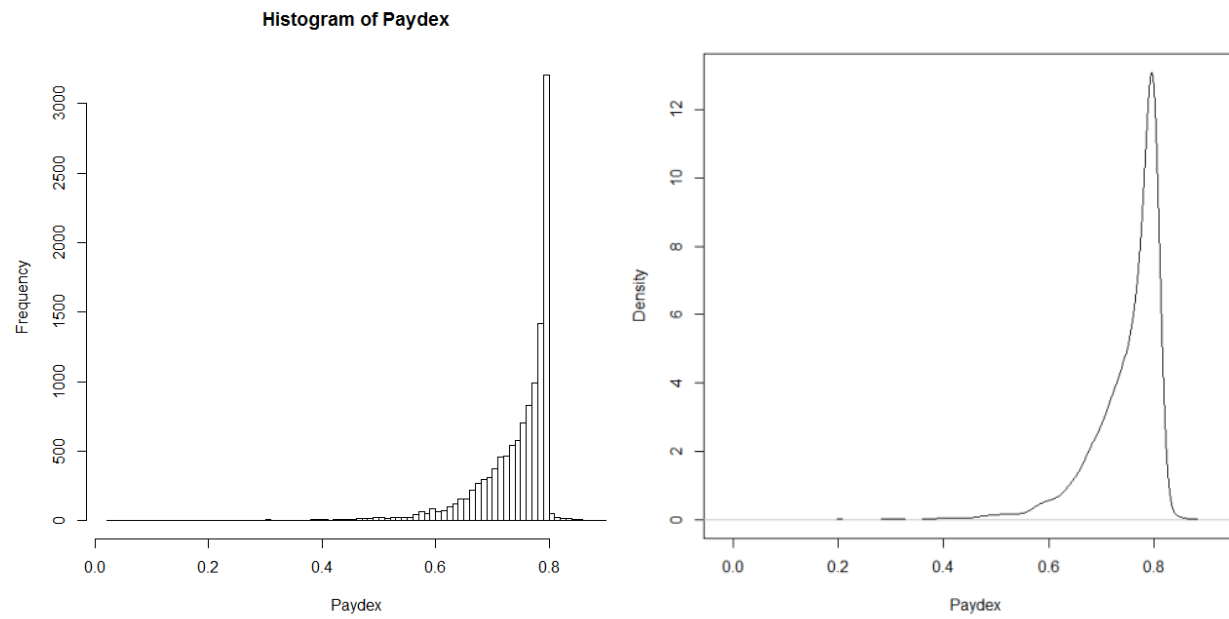

Histogram of Paydex

FIGURE TWO

Different Shapes of the Beta Density

FIGURE THREE

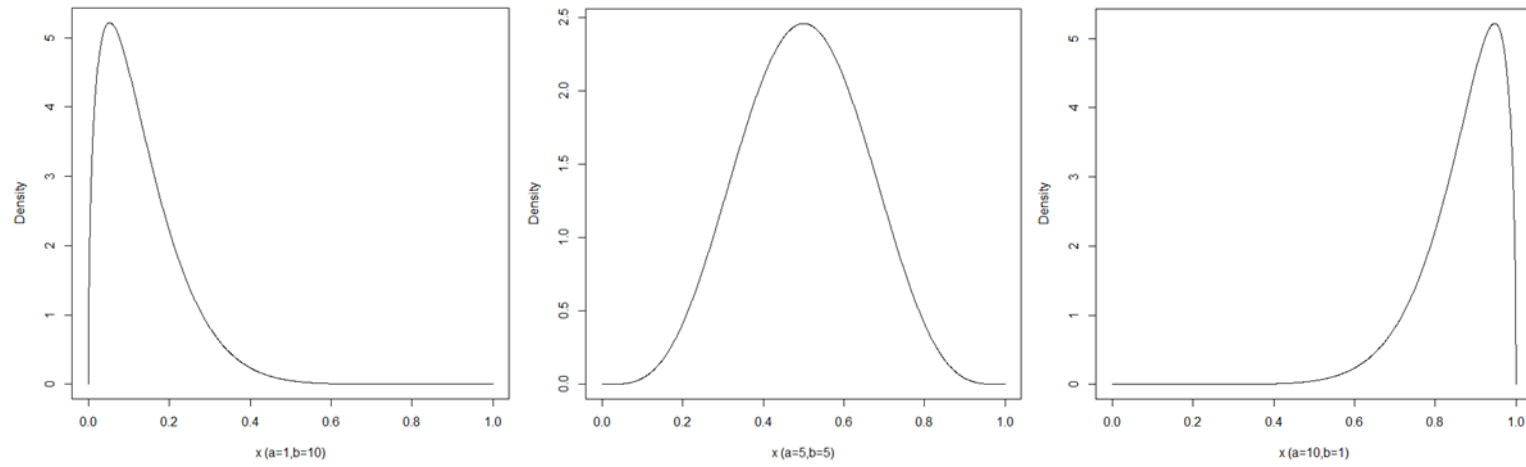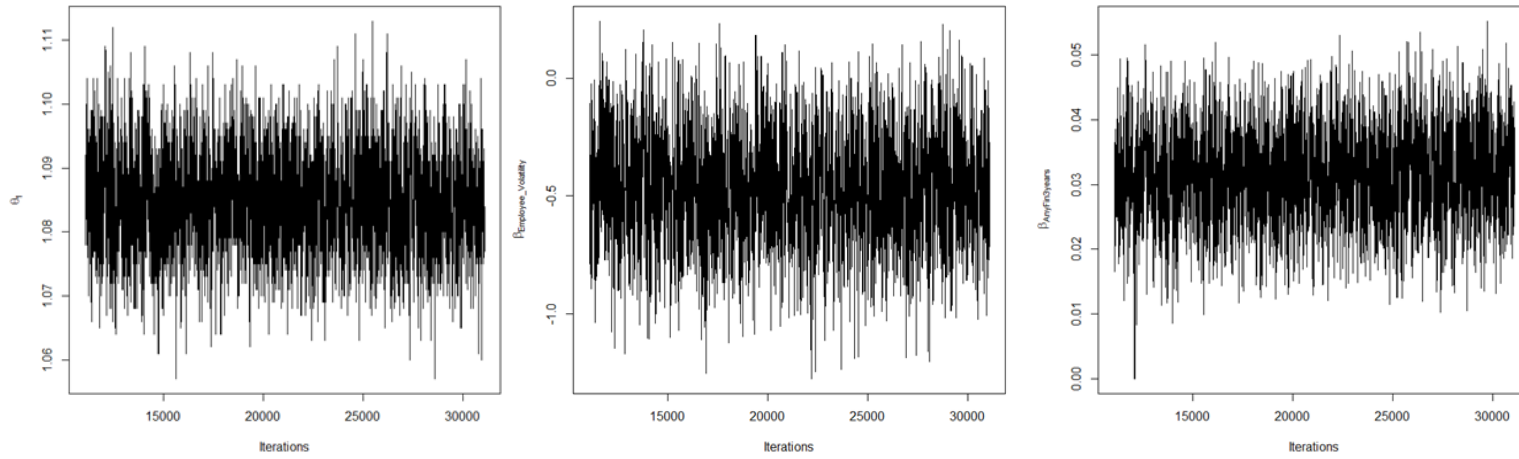**Analysis of the Firm Level Effects on the Financial Condition of Entrepreneurial Ventures in All Industries**

FIGURE FOUR
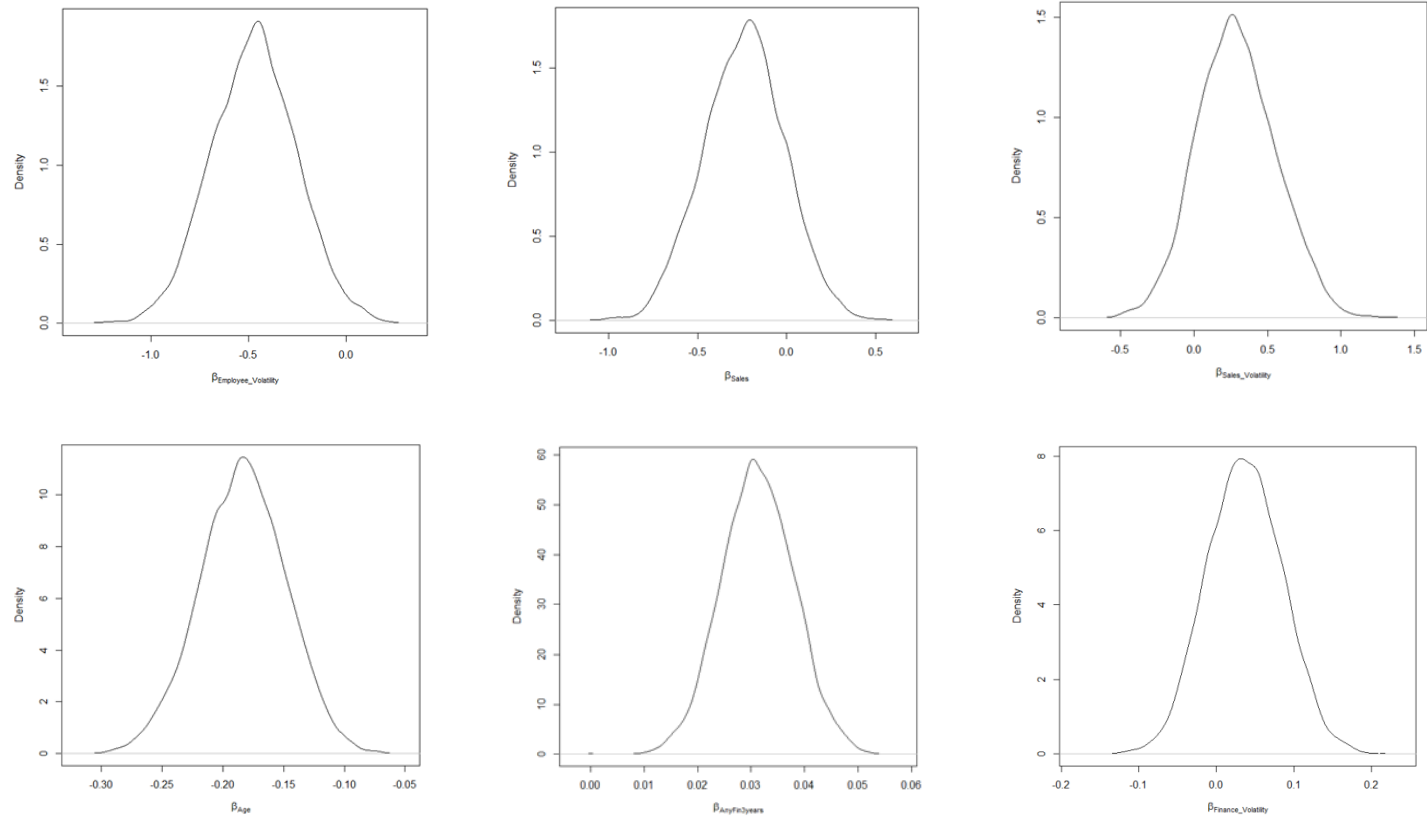
Posterior Density Plots for Firm Level Effects

FIGURE 5

Boxplots for Industry Level Effects

Industry Type (Service, Manufacturing, Other)