# Self-Selectivity in Firm's Decision to Withdraw IPO: Bayesian Inference for Hazard Models of Bankruptcy With Feedback

Rong CHEN, Re-Jin GUO, and Ming LIN

Examination on firm performance subsequent to a chosen event is widely used in finance studies to analyze the motivation behind managerial decisions. However, results are often subject to bias when the self-selectivity behind managerial decisions is ignored and unspecified. This study investigates a unique corporate event of initial public offering (IPO) withdrawal, where a firm's subsequent likelihood of bankruptcy is specified in a system of switching hazard models, and the expected difference in post-IPO and postwithdrawal survival probabilities serves as a "feedback" on a firm's decision to cancel its offering. Our Bayesian inference procedure generates strong evidence that incidence of withdrawal unfavorably affects the subsequent performance of a firm, and that the "feedback" is an important determinant in managerial decisions. The econometric and statistical model specification and the accompanying estimation procedure we used can be widely applicable to study self-selective corporate transactions.

KEY WORDS: Bayesian inference; Decision model; Hazard model; IPO withdrawal; Self-selectivity.

## 1. INTRODUCTION

Numerous empirical studies have been conducted to investigate the effect of an event, a treatment, a policy, or a regulation. For example, in clinical research the focus is to access the effect of certain medical treatments. In those studies, the effect can be quantified by the differential health status between patients randomly assigned to treatment and control groups. In many finance studies, the interest is to investigate the effect of a corporate event on postevent corporate performance. In such studies, however, direct inference drawn from standard analysis assuming random assignments could be susceptible to bias, as observed data are generated by managers making a deliberate choice of belonging to one group (conducting corporate transactions) or another (no action).

As unobservable factors may correlate with a firm's decision to engage in a corporate transaction, and with posttransaction performance, ignoring such correlation results in self-selection bias. It is documented that conclusions drawn only on sample firms associated with observed corporate transactions could be misleading. Empirical findings susceptible to selection bias have been documented in finance studies on underwriter compensation (Dunbar 1995), diversification discount (Campa and Kedia 2002; Chevalier 2004), and long-run performance after seasoned equity offerings (Cheng 2003). Different econometric approaches have been developed and applied in different experiment designs to address managerial self-selectivity. One commonly used methodology is the two-stage procedure developed by Heckman (1976), where the self-selection is accounted for in a reduced form analysis by adding an adjustment term of inverse Mills ratio to the analysis on the sample firms associated with the corporate transactions. In cases when outcomes are observed for both choices for a firm self-select (or not), switching regression is often employed instead of Heckman's single-outcome regression (Maddala and Nelson 1975; Griliches, Hall, and Hausman 1978; Lee and Trost 1978; Kenny et al. 1979; Willis and Rosen 1979). However, models in this latter strand of literature have mostly been limited to linear models and the model estimation is mostly conducted via reduced form analysis similar to the Heckman (1976) procedure (see, e.g., Dunbar 1995). The review paper by Li and Prabhala (2007) provides a good survey of the self-selection issues and the existing models used in corporate finance.

The effect of feedback is another layer of self-selectivity that is important and should not be ignored. Examples include the studies on stock trading (Khanna and Sonti 2004; Teo and Woo 2004), adaptive learning (Chen and White 1998), incomplete markets (Calvet 2001), and a firm's cash flows (Subrahmanyam and Titman 2001).

In this study, we extend the prior literature on models with self-selectivity to examine models with duration dependent variable and nonrandom selection. We formulate (nonlinear) switching hazard models, and incorporate the effect of "feedback" from the anticipated postevent outcome on the corresponding managerial decisions. Our model could be considered as an extension of the "structural self-selection models with simultaneity," as categorized in Li and Prabhala (2007). However, unlike the model by Roy (1951), our model allows for more flexibility in firm's self-selection mechanism. The nonlinearity of our bankruptcy duration model in formulating postevent firm performance adds challenges in model estimation using traditional non-Bayesian approach.

Under this general framework, we focus on one unique corporate decision, the withdrawal of IPO. Specifically, econometric specifications are formulated to examine the corporate

Rong Chen is Professor, Department of Statistics, Rutgers University, Piscataway, NJ 08854 and Department of Business Statistics and Econometrics, Peking University, Beijing, China (E-mail: *rongchen@stat.rutgers.edu*). Re-Jin Guo is Associate Professor, Department of Finance, University of Illinois at Chicago, Chicago, IL 60607. Ming Lin is Associate Professor, Wang Yanan Institute for Studies in Economics, Xiamen University, Xiamen, China. Chen's research is sponsored in part by NSF grants DMS 0800183, DMS 0905763 and Oxford-Man Institute of Quantitative Finance, Oxford University. The authors thank the two editors, an associate editor, and three anonymous referees for their helpful comments. The paper was previously circulated under the title "On the Cost of Withdrawn Initial Public Offerings." The authors would like to thank Brian Adams (discussant), Larry Benveniste, Walid Busaba, Chun Chang, Konan Chan, Hsuan-Chi Chen (discussant), Wei-Ling Song, Michael Stutzer, David Runkle, and participants at the 2005 NTU International Conference on Economics, Finance, and Accounting, and the 2005 Financial Management Association meeting for their helpful suggestions.


Journal of the American Statistical Association
December 2010, Vol. 105, No. 492, Applications and Case Studies
DOI: 10.1198/jasa.2010.ap08663

event of IPO withdrawal, analyzing jointly a firm's decision of whether to withdraw its IPO, and the effect of IPO withdrawal on subsequent performance. Our models can be easily extended and applied to studies which examine timing information of postevent performance and incorporates self-selectivity in the firm's decision making for a complete and unbiased analysis.

Many firms choose to terminate their primary issuances after initiating the process of going public. On one hand, it has been suggested that IPO issuers could benefit from this viable option to finalize their offerings based on the outcome of the premarket process. Busaba, Benveniste, and Guo (2001) examine this option-like feature of withdrawal, and propose that this option could strengthen a firm's bargaining position when marketing its IPO to potential investors. As a result, firms that are perceived to be more likely to withdraw their offerings ex ante could reduce the amount of underpricing as payment for investor information if they choose to finalize their offerings. On the other hand, various corporate theories suggest a substantial opportunity cost of IPO withdrawal. For example, Maksimovic and Pichler (2001) report that public firms enjoy insurmountable competitive advantage by establishing industry standards. Subrahmanyam and Titman (1999) document that aggregation of serendipitous and diverse information available in the public equity market could also be important for firms in future investment decisions. Hof (1999) states that: "Public firms command instant credibility, the ability to raise money for future offerings, and a lofty stock price that can be used for acquisition." Furthermore, IPO withdrawal can be associated with adverse consequences. Anecdotal evidences indicate a reduced opportunity for the withdrawing firms to reenter the public market, as well as reputation loss and potential unfavorable impact on firms' real business (Lerner 1994). If a manager is forward-looking and apprehensive of those postwithdrawal consequences, she would include the corresponding anticipated effect in her decision to withdraw an offering.

We examine the self-selection by managers to complete or withdraw the offerings, in anticipating the consequent benefits and costs of this going public decision. To quantify the anticipated effect of the decision, we use the difference in expected survival probability for a prespecified duration as a public and a private firm as a proxy. Such a loss function summaries various aspects of the anticipated effects. The difference in survival probability is estimated based on hazard models of bankruptcy for firms with completed and withdrawn IPOs respectively, with the use of a unique duration data of postwithdrawal bankruptcy information. The anticipated effect of withdrawal then serves as a "feedback" to the firm's decision on whether to cancel its offering, as the ultimate goal of the corporate management is to promote future firm prosperity. A complete analysis consists of a joint estimation of the switching hazard models and the firm's decision model to withdraw its IPO. In such an analysis, the firm's self-selectivity and the endogeneity between the consequence and decision of withdrawal are explicitly specified.

Our analysis makes use of a unique dataset rarely available in finance empirical studies. First, we hand-collect detailed firm information directly from the prospectuses for firms electing to withdraw their IPOs. Second, we gather duration data of bankruptcy for those firms subsequent to their withdrawn offerings. To our best knowledge, this is the first study to make use of the duration data of bankruptcy of withdrawn IPOs. Other ex post performance measure of firms might be used, except that, collection of such data remains a challenge in financial studies, as the majority of firms remain private after the abandonment of their IPOs.

We adopt a Bayesian estimation strategy, which has the following three distinct advantages. First, our Bayesian estimation procedure, with the incorporation of the recent development of Markov chain Monte Carlo (MCMC) method (Gelfand and Smith 1990; Robert and Casella 1999; Liu 2001), is powerful and flexible in dealing with complex nonlinear problems, where the classical maximum likelihood approach encounters severe computational difficulties. Second, the Bayesian strategy enables us to examine the entire posterior distribution landscape, and avoid the dependence on asymptotic properties to assess the sampling variability of the parameter estimates. This benefit could be significant, considering the limited sample size used in many corporate finance studies. Finally, our approach allows us to perform Bayesian model selection and cross-validation procedures, with much gain in computational efficiency over those used in the conventional classical estimation.

We report the following findings from our analysis. First, we find a strong self-selectivity in a firm's decision to withdraw its IPO. The anticipated effect of withdrawal (quantified as the differential survival probability) serves as an important feedback to a firm's decision of whether to complete its offering. Second, we document the evidence that the incidence of withdrawal unfavorably affects subsequent firm performance. Our results indicate a significant larger expected survival probability for firms that elect to complete their offerings. Third, our analysis on a firm's subsequent survival rates uncovers different sets of determinants (or covariates) for firms with completed and withdrawn IPOs, respectively. Our results indicate that withdrawn firms with offerings filed by a highly ranked underwriter are likely to survive longer. This finding is consistent with that the certification role of underwriter extends beyond what has been reported in the IPO process (Carter and Manaster 1990; Carter, Dark, and Singh 1998). We do not, however, find such correlation between underwriter rankings and survival rates in our subsample of firms with completed offerings. Fourth, we also report evidence of a significant positive time dependence of bankruptcy rate for firms with completed IPOs. For those firms, the likelihood of bankruptcy at time $t$, conditioned upon surviving up to time $t$, increases with $t$. This finding is consistent with the "immediate" benefit of going public for firms that elect to complete their offerings but the impact diminishes over time. On the other hand, we find no significant time dependence of bankruptcy rate for firms with withdrawn IPOs after controlling for other determinants.

Our study makes the following contributions. First, our study extends the prior econometric literature on models with self-selectivity in formulating a full structural model which examines postevent performance in nonlinear switching hazard models, and incorporates the effect of "feedback" from the anticipated postevent outcome on the corresponding managerial decisions. The proposed framework of switching hazard models with self-selectivity provides a widely applicable method of analyzing the behavior of managerial decisions jointly with the postevent consequences. Our methodology could be useful in event-type studies on numerous corporate transactions. Second, our Bayesian estimation procedure provides powerful tools for estimating highly nonlinear models, conducting model comparison and validation with substantial improvement in computation efficiency and accuracy. Finally, results of our study provide an in-depth understanding of the IPO withdrawal behavior. To our best knowledge, we report the first evidence that IPO withdrawal could be costly. This is important information for a firm in consideration of whether to walk away from its offering, when the suggested share price (from the book-building process) is undesirable.

The rest of the paper is organized as the following. Section 2 describes the data under study with simple descriptive statistics. Section 3 presents the model and the inference procedure used for analyzing the data. Section 4 presents detailed empirical results on estimation, model comparison, and validation. Section 5 concludes.

## 2. DATA

A sample of IPOs underwritten by firm-commitment contracts in the period 1990–1992 is obtained from the New Issue Database from Security Data Corporation (SDC). The final sample consists of 530 IPOs (420 completed offerings and 110 withdrawn offerings), after excluding unit offerings (offering with bundles of common stocks and warrants), American deposit receipts, offerings filed by foreign firms, real estate investment trusts, filings of mutual funds, financial institutions, and certain service companies. This portion of the data consists of information disclosed in the first registration documents of firms, including financial data, ownership structure, as well as tentative offerings terms.

Duration to bankruptcy is the time elapsed between the IPO filing decision (complete or withdraw) and the firm's bankruptcy, recorded as the largest integer (in years) smaller than the actual survival time. It is right censored if the firm survives longer than the measurement period.

Post-IPO bankruptcy duration data are extracted from the database maintained by the Center for Research in Security Prices (CRSP) and the electronic news retrieval service Nexis. Bankrupt firms are first identified from firms that are delisted from the exchanges. The major stock trading avenues (NYSE, AMEX, and Nasdaq) delist securities regularly: when firms bankrupt, when firms merge, when exchange offers make securities obsolete, when firms liquidate or move to another exchange, or when the performance of firms falls below the listing criteria of the exchange. We first screen the delisting records maintained by CRSP, which documents the specific reasons these firms are delisted with special code numbers assigned. Firms with CRSP delisting codes of 400, 572, and 574 are categorized as bankrupt (Shumway 1997). Among the rest of firms delisted for performance reasons, additional bankrupt firms are identified from Bankruptcy Data source and News files maintained by Nexis. Timing information of bankruptcies, mergers, and acquisitions is extracted from CRSP and Nexis databases. For simplicity we do not distinguish Chapters 7 and 11 bankruptcy filings.

Postwithdrawal bankruptcy duration data are obtained from multiple sources. Most firms stay private after abandoning their offerings. Except the confidential reports filed with the IRS for tax purposes, a private firm has no obligation to report any financial information to government or any other authority. We collect our data on private firms from several unique sources including the Dun and Bradstreet database, state records, and direct contacts with the firms. Dun and Bradstreet maintains a comprehensive database covering both public and private firms, which collectively account for more than 90% of the national GNP. In most cases, Dun and Bradstreet keeps information such as change of ownership, credit history, and public filings. Many state governments keep an annual corporate/partnership record, most of which indicates the firms' tax status. A firm that went bankrupt or out of business would fail to pay taxes and be identified as "out-of-existence" or "not-in-good-standing." Available state filings are obtained from Nexis and the state government of Delaware. For firms no longer in business, the year after their last filing with the state government is recorded as their last survival year.

In this analysis, if a firm is acquired or merged during the postdecision measurement period, we treat its bankruptcy duration as censored. Although it is possible that the censoring is not completely random, as underperforming firms are likely to put themselves on the sale block and be consequently acquired, its impact should be minimal, as studies in the finance literature also document numerous economic reasons (such as under-valuation, industry consolidation, and ownership structure), other than firm underperformance, behind firm acquisition.

We note that the data and the issue of interest in this study is distinctly different from those in Dunbar and Foerster (2008). While we analyze whether the anticipated consequence of withdrawing an IPO has an effect on their going public decision, Dunbar and Foerster (2008) are interested in the decision of firms coming back to IPO market after their prior withdrawn IPOs. Our data consists of subsequent performance of a full sample of firms filing IPOs in our sample period (with completed and withdrawn IPOs), while Dunbar and Foerster (2008) focus on firms with withdrawn IPOs which "elect" to come back to IPO market again.

Postwithdrawal and post-IPO performance data for firms that filed IPOs with the U.S. Securities and Exchange Commission (SEC) between 1990 and 1992 are presented in Table 1. Performance is categorized by the status of the firm in the year of 2003, namely, whether it was public, private, merged and acquired, or bankrupt. The numbers and percentages of both subsamples of withdrawn and completed IPOs are presented

Table 1. Subsequent performance of IPO firms filed with SEC in 1990–1992

| Outcome (year 2003) | Completed IPOs | Withdrawn IPOs | Full sample |
|---|---|---|---|
| Public | 135 | 20 | 155 |
| Private | 60 | 48 | 108 |
| Merged/acquired | 179 | 25 | 203 |
| Bankrupt | 46 | 17 | 63 |
| Total | 420 | 110 | 530 |

NOTE: The table summaries the status of the firms in year 2003, showing whether public, private, merged or acquired, or bankrupt (including firms that went bankrupt or out of business).

for each performance category in Table 1. The $\chi^2$ tests show that the proportions of each category in the two subsamples are significantly different at 1% level, except that the proportions of bankrupt firms of the completed IPO firms (10.95%) and the withdrawn IPO firms (15.45%) are not significantly different at 5% level. We examine the detailed temporal information for the bankruptcy data. Within the category of bankrupt firms, the average duration, namely, the difference between the years of IPO filing and of bankruptcy, is 3.41 years for firms with withdrawn IPOs. This is compared to an average of 6.93 years for firms with completed IPOs. However, the raw number of duration does not account for the censoring nature of the data, nor does it consider the possible effect of self-selectivity.

We have also obtained a set of determinants (covariates) for a firm's decision to complete or withdraw its IPO offering. It consists of the following firm and offering characteristics (Busaba, Benveniste, and Guo 2001). VENTURE is a dummy variable indicating whether one of the major shareholders (ownership of 5% or above) is a venture capitalist. REV is the firm's most recent 12-month revenue (in millions) prior to the offerings. Prior studies in the IPO literature report that shares sold by the original shareholders, shares retained by the original shareholders after the IPO, as well as ownership of venture capitalists have effects on pricing IPOs. However, Busaba, Benveniste, and Guo (2001) document that effects of shares sold by the original shareholders and shares retained by the original shareholders after the IPO are not significantly predictive of an IPO withdrawal decision. We therefore only include the ownership of venture capitalists in our model of IPO withdrawal. DUSEP is a dummy variable indicating debt payment as the primary use of proceeds. MKCAP is the expected market capitalization, which is the product of midpoint of the offer price range and the expected shares outstanding after the offerings. CMRank is the updated Carter and Manaster ranking by Carter, Dark, and Singh (1998). It measures the IPO underwriter's reputation and has been shown to be highly correlated with the underwriter's market share of the IPO underwriting business. RET30 is the NASDAQ average 30-day return over the filing period. NumIPOs is the number of IPOs filed in the month of issuance. DEBT is the book value of total debt over the book value of assets.

As financial weakness precedes mortality, an issuing firm is more likely to go bankrupt due to existing unfavorable financial conditions prior to its IPO filing (Altman 1968, 1993; Altman, Haldman, and Narayanan 1977; Ohlson 1980; Li 1999; Shumway 2001). We use the following determinants for a firm's hazard rate of bankruptcy. We include the firm's asset size (AST), profitability ratio (ROA), and debt ratio (DEBT) as proxies for the preexisting financial condition of the firms. The profitability ratio (ROA) is the earnings before interest and tax over the book value of assets. The variables of ASTaft, ROAaft, and DEBTaft are included for the hazard model of firms with completed offerings. The three variables are, respectively, the expected book value of asset, the expected ratios of the earnings before interest and tax over the expected asset size, and the book value of debt over the expected asset size after the offering, after inclusion of the immediate obtained cash inflows from the proceeds of the offerings. The values of these variables are obtained for both complete-IPO firms and withdrawn-IPO firms, using their IPO prospectuses.

Summary statistics for the aforementioned variables are presented in Table 2 for subsample of firms with completed and withdrawn offerings. We also include the annual market return (MKT) as the time-varying variable for some of the models we consider. It is calculated as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks, using data from CRSP. Since the financial variables for firms with withdrawn IPOs are only observed in the year prior to their IPO filings (as disclosed in the prospectuses), but not in any other subsequent year, we only include the generally available annual market return as a time-varying factor in our analysis. Other variables such as short-term interest rate and annual GDP growth were included in the analysis. However, since these variables are not significant in any of the models, we omitted them here for clarity. Nonetheless, our econometric specifications are general, and are designed to analyze any comprehensive sets of time-varying covariates in dynamic models.

Table 2. Summary statistics of ex ante firm and offering characteristics for firms filing IPOs with SEC in 1990–1992

| | Mean | | | Median | | |
|---|---|---|---|---|---|---|
| Variables | Completed IPOs | Withdrawn IPOs | $p$-value | Completed IPOs | Withdrawn IPOs | $p$-value |
| VENTURE | 0.51 | 0.27 | 6.829e−007 | 1.00 | 0.00 | 7.157e−005 |
| REV | 73.50MM | 103.84MM | 0.240 | 35.90MM | 34.13MM | 0.554 |
| DUSEP | 0.38 | 0.60 | 4.730e−005 | 0.00 | 1.00 | 4.838e−004 |
| MKCAP | 26.86MM | 36.30MM | 0.055 | 24.00MM | 24.70MM | 0.223 |
| CMRank | 7.10 | 7.13 | 0.918 | 8.75 | 8.75 | 0.760 |
| RET30 | 0.01 | −0.00 | 0.020 | 0.01 | 0.00 | 0.034 |
| NumIPOs | 3.21 | 3.30 | 0.211 | 3.18 | 3.33 | 0.118 |
| DEBT | 0.22 | 0.47 | 6.002e−010 | 0.15 | 0.42 | 1.267e−010 |
| AST | 50.89MM | 67.93MM | 0.205 | 24.50MM | 22.39MM | 0.960 |
| ROA | 0.06 | −0.08 | 0.020 | 0.13 | 0.05 | 4.491e−008 |
| DEBTaft | 0.13 | 0.24 | 5.337e−007 | 0.06 | 0.19 | 9.479e−007 |
| ASTaft | 77.75MM | 104.23MM | 0.139 | 49.90MM | 53.28MM | 0.620 |
| ROAaft | 0.06 | 0.01 | 4.612e−005 | 0.08 | 0.03 | 4.192e−010 |

NOTE: $p$-value is for 2-tailed $t$-test of mean value or Wilcoxon test of median value.

## 3. MODEL SPECIFICATION AND INFERENCE PROCEDURE

We investigate firm performance based on the metric of survival duration, which is measured as the time till bankruptcy dated from the event of completion or withdrawal of an IPO. The cross-sectional variation of our duration data is examined in hazard models of bankruptcy.

For the $i$th firm, we have the following record:

$$(I_i, T_i^*, c_i, \mathbf{X}_{0,i}, \mathbf{X}_{1,i}, \mathbf{Z}_i, \mathbf{W}_s, s_i),$$

where $I_i$ is the decision indicator reflecting a firm's decision on completion ($I_i = 1$) or withdrawal ($I_i = 0$) of an IPO. $T_i^*$ is the time elapsed between the IPO filing decision and bankruptcy for firm $i$, recorded as the largest integer (in years) smaller than the actual survival time. That is, $T_i^* = \lfloor T_i \rfloor$ where $T_i$ is the actual survival time of firm $i$. It is right censored if the firm survives longer than the measurement period. The indicator $c_i$ reflects such censoring status, with $c_i = 1$ if a firm is merged, is acquired, or continues as an independent business entity, and $c_i = 0$ if a company is bankrupt during the measurement period.

The covariates $\mathbf{Z}_i$ are financial records and other relevant information of the $i$th firm at the time just before the IPO filing decision. This set of covariates is only related to the decision-making process. The covariates $\mathbf{X}_{0,i}$ are financial records of the $i$th firm before the IPO filing decision. The covariates $\mathbf{X}_{1,i}$ are the *expected* financial status of the $i$th firm if the firm is to complete its IPO as planned. The values are calculated based on the firm's IPO prospectuses filed to SEC. Both $\mathbf{X}_{0,i}$ and $\mathbf{X}_{1,i}$ are obtained for every firm, regardless of whether they completed or withdrew their IPO. However, only $\mathbf{X}_{0,i}$ is used to model the survival time of the withdrawn-IPO firms, and only $\mathbf{X}_{1,i}$ is used for the complete-IPO firms. This is due to the fact that only firms that completed IPO will enjoy the financial benefit of IPO. $\mathbf{Z}_i$ and $\mathbf{X}_{0,i}$, $\mathbf{X}_{1,i}$ may have some common variables.

We also incorporate, in the survival model, certain time-varying covariates $\mathbf{W}_s$ that reflect the general market/economic conditions at year $s$. It is not firm specific and recorded every year. And $s_i$ is the year of the IPO filing decision for firm $i$. We assume that the time-varying covariates are constants $\mathbf{W}_{s_i+t}$ in the period $(t, t+1]$, as our survival models are based on continuous time.

In this section, we first describe our formulation of the hazard models of bankruptcy and the firm's decision model to withdraw its IPO. We then discuss various specifications of the switching hazard models with firm's self-selectivity.

### 3.1 Hazard Model of Bankruptcy

The hazard model of bankruptcy used in our analysis is specified as the following. The instantaneous probability of failure at any given time $t$ for firm $i$, the hazard function $h_{I_i,i}(t)$, is specified as

$$h_{I_i,i}(t) = p_{I_i} \lambda_{I_i,i}(t) \big(\lambda_{I_i,i}(t)t\big)^{p_{I_i}-1}. \tag{1}$$

The hazard function follows a time-varying Weibull distribution, commonly used in modeling survival time of firms (Kennan 1985; Greene 2003). The parameter $\lambda_{I_i,i}(t)$ is a function of firm-specific covariates predictive of firm's time till failure at time $t$. Specifically, we assume

$$\lambda_{I_i,i}(t) = \exp\{-\boldsymbol{\beta}'_{I_i}\mathbf{X}_{I_i,i} - \boldsymbol{\zeta}'_{I_i}\mathbf{W}_{s_i+t}\}, \tag{2}$$

where $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$, $\boldsymbol{\zeta}_0$, and $\boldsymbol{\zeta}_1$ are a set of parameters. The parameter $p_{I_i}$ in (1) captures the length dependent property that is often observed in firm survival data. When $p_{I_i}$ equals one, the hazard function reduces to $\lambda_{I_i,i}(t)$. When $p_{I_i} < 1$, the hazard rate exhibits "negative time dependence," which decreases as time increases. When $p_{I_i} > 1$, the hazard rate exhibits "positive" time dependence, which increases as time increases. In the case of "positive time dependent" hazard function, the longer a firm survives, the lower survival ability it would have in the future.

Due to the assumption that the time-varying covariates $\mathbf{W}_s$ remain constant in the intervals of $(j, j+1]$, $\lambda_{I_i,i}(t)$ is a constant for $t \in [j, j+1)$ for all $j = 0, 1, 2, \ldots$. The corresponding survival function is

$$\begin{aligned} S_{I_i,i}(t) &\triangleq P(T_i \ge t | I_i) = \exp\left\{-\int_0^t h_{I_i,i}(s)\, ds\right\} \\ &= \exp\left\{-\sum_{j=0}^{\lfloor t \rfloor -1} \big[\big((j+1)\lambda_{I_i,i}(j)\big)^{p_{I_i}} - \big(j\lambda_{I_i,i}(j)\big)^{p_{I_i}}\big] \right. \\ &\quad \left. - \big[\big(t\lambda_{I_i,i}(\lfloor t \rfloor)\big)^{p_{I_i}} - \big(\lfloor t \rfloor \lambda_{I_i,i}(\lfloor t \rfloor)\big)^{p_{I_i}}\big]\right\}. \end{aligned} \tag{3}$$

Considering the censoring information, we have, for firm $i$,

$$\begin{aligned} P(T_i^* = j | I_i, c_i = 0) &= P(j \le T_i \le j+1 | I_i, c_i = 0) \\ &= S_{I_i,i}(j) - S_{I_i,i}(j+1) \end{aligned}$$

and

$$P(T_i^* = j | I_i, c_i = 1) = P(T_i \ge j | I_i, c_i = 1) = S_{I_i,i}(j).$$

There are several possible extensions to the hazard model we have specified here. Unobserved heterogeneity models often used in studying mortality and other duration data (Vaupel, Manton, and Stallard 1979; Heckman and Singer 1984; Trussell and Richards 1985; Hougaard 1986; Vaupel 1990). It would be interesting to study the use of such models in our switching with feedback framework. It is also possible to extend our model to nonparametric and semiparametric hazard models such as those in Bearse, Canals, and Rilstone (1998), Horowitz (1999), and Lee (2008).

### 3.2 Decision Model of IPO Withdrawal

We model the decision behavior for a firm to withdraw its offering during the premarket process based on a set of ex ante observable firm and offering characteristics in a binary choice model. We examine the effect of covariates $\mathbf{Z}_i$ and the survival functions $S_{0,i}(t)$, $S_{1,i}(t)$ on firm $i$'s decision to complete ($I_i = 1$) or withdraw ($I_i = 0$) its offering. Specifically, the probability of firm $i$ completing its IPO offering is modeled as

$$P(I_i = 1) = \frac{\exp\{\alpha + \boldsymbol{\gamma}'\mathbf{Z}_i + \eta L_i\}}{1 + \exp\{\alpha + \boldsymbol{\gamma}'\mathbf{Z}_i + \eta L_i\}}, \tag{4}$$

where $\alpha$ is a constant term and $(\boldsymbol{\gamma}, \eta)$ are unknown coefficients. The covariates $\mathbf{Z}_i$ consist of the characteristics of the firm and its offering observed at the time of offering. The loss function $L_i$, defined as the (log) difference in the probabilities that the firm survives longer than $T_L$ (i.e., $T_{I_i,i} \ge T_L$), captures the potential (undesirable) consequence of IPO withdrawal. Specifically,

$$L_i = \log[S_{1,i}(T_L)] - \log[S_{0,i}(T_L)], \tag{5}$$

where $T_L$ is a prespecified constant that serves as a chosen benchmark of the survival duration. In this study, we use $T_L = 10$ which coincides with the measurement period of the data.

We include the term $L_i$ in the decision model (4) to reflect the "anticipated" effect of withdrawal in the decision making process. The "feedback" $L_i$, from the anticipated postevent outcome on the corresponding managerial decisions, captures self-selectivity often ignored and unspecified in the prior literature. Alternative specifications of the loss function, such as the difference in the mean/median of survival time, can be used. We did not find significant differences with several other loss functions experimented.

### 3.3 Switching Hazard Models of Bankruptcy With Feedback

We examine and compare the following four specifications of the switching hazard models:

*Model I* (Models with time-varying covariates and feedback). We conduct a joint estimation of two hazard models of bankruptcy for a firm with a withdrawn or completed IPO, as well as firm's decision model of IPO withdrawal. The corresponding posterior distribution of parameter

$$\boldsymbol{\Theta} = (\alpha, \eta, \boldsymbol{\gamma}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1, p_0, p_1)$$

is

$$\begin{aligned} &P(\alpha, \eta, \boldsymbol{\gamma}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1, p_0, p_1|\text{data}) \\ &\quad \propto P(\alpha, \eta, \boldsymbol{\gamma})P(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1)P(p_0, p_1) \\ &\qquad \times P(\text{data}|\alpha, \eta, \boldsymbol{\gamma}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1, p_0, p_1) \\ &\quad \propto P(\alpha, \eta, \boldsymbol{\gamma})P(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1)P(p_0, p_1) \\ &\qquad \times \prod_{i:c_i=0} \big(S_{I_i,i}(T_i^*) - S_{I_i,i}(T_i^*+1)\big) \prod_{i:c_i=1} S_{I_i,i}(T_i^*) \\ &\qquad \times \prod_{i=1}^{n} [1 + \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}]^{-1} \\ &\qquad \times \prod_{i:I_i=1} \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}, \end{aligned} \tag{6}$$

where $P(\alpha, \eta, \boldsymbol{\gamma})$, $P(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1)$, $P(p_0, p_1)$ are the prior distribution for parameters. The functions $S_{I_i,i}$ and $L_i$ follow (3) and (5), respectively.

*Model II* (Models with time-invariant covariates and feedback). Here we only use the time-invariant covariates, that is, $\boldsymbol{\zeta}_0 = \boldsymbol{\zeta}_1 = 0$ in (2).

*Model III* (Models with time-varying covariates and no feedback). Here we force $\eta = 0$ in Model I.

*Model IV* (Models with time-invariant covariates and no feedback). Here we force $\eta = 0$ and $\boldsymbol{\zeta}_0 = \boldsymbol{\zeta}_1 = 0$ in Model I.

### 3.4 Bayesian Inference

Implementation of our Bayesian estimation is described as the following:

(1) Nearly flat priors are used for the parameters in the model. Specifically, we assume $P(\alpha, \eta, \boldsymbol{\gamma}) \sim \mathrm{N}(0, \Sigma_1)$ and $P(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1) \sim \mathrm{N}(0, \Sigma_2)$ with $\Sigma_1 = 100E_p$, $\Sigma_2 = 100E_q$ where $E$ denotes the identity matrix. In addition, we use a uniform distribution between 0.4 to 3 as the prior distribution for parameters $p_0$ and $p_1$.

(2) A modified Markov chain Monte Carlo (MCMC) algorithm is used to draw random samples from the highly complex posterior distribution (6). A detailed description on the implementation is presented in the Appendix.

(3) The random samples drawn from the posterior distribution using MCMC are used to make inferences on the parameters. For each of the parameters (say, $\theta$), a complete set of four statistics is obtained, using the samples $\theta_1, \theta_2, \ldots, \theta_m$ drawn from the posterior distribution, including *posterior mean*, *posterior standard deviation*, *the* 95% *Bayesian interval* which is the minimum length interval $(a, b)$ that includes 95% of the samples $\{\theta_j, j = 1, \ldots, m\}$, and *the posterior odds of being* $\theta^*$

$$r_{\theta^*}(\theta) \triangleq \frac{P(\theta > \theta^*|\text{data})}{P(\theta < \theta^*|\text{data})} \approx \frac{\sum_{j=1}^m \mathbb{I}(\theta_j > \theta^*)}{\sum_{j=1}^m \mathbb{I}(\theta_j < \theta^*)}, \tag{7}$$

where $\mathbb{I}(\cdot)$ is the indicator function. A ratio with value greater than 19 or smaller than 0.05 can be interpreted as the parameter being significantly different from $\theta^*$, serving as the counterpart of a one-sided test at 5% level in the classical hypothesis testing framework.

### 3.5 Model Comparison

For the purpose of comparing and selecting among the four models specified, we obtain Bayesian posterior probabilities of each available model (Stewart and Davis 1986; Gelfand and Dey 1994; Kass and Raftery 1995; Berger and Pericchi 1996; Raftery, Madigan, and Hoeting 1997; Volinsky et al. 1997; George 1999). We also calculate a Bayesian equivalence of the leave-one-out cross-validation measure, widely used in statistics literature (Craven and Wahba 1979; Wahba and Wendelberger 1980; Picard and Cook 1984; Rust and Schmittlein 1985; Copas 1987; Azzalini, Bowman, and Hardle 1989; Zhang 1991; Cessie and Van Houwelingen 1992; Burman, Chow, and Nolan 1994; Xiang and Wahba 1996). In the calculation of our model comparison measures, we make repeated use of the importance sampling procedure. Such technique allows us to gain much computation efficiency.

For Models I to IV specified in Section 3.3, we calculate the following posterior probabilities:

$$P(M = u|\text{data}) = \frac{P(\text{data}|M = u)P(M = u)}{\sum_{v=1}^4 P(\text{data}|M = v)P(M = v)},$$

where $P(M = u)$ is the prior probability for model $u$. Here $u = 1, 2, 3, 4$ correspond to Model I, II, III, and IV, respectively.

Importance sampling method (Marshall 1956) is used to estimate the above posterior probability. Specifically, we draw samples $\widetilde{\boldsymbol{\Theta}}_u^{(k)}$, $k = 1, \ldots, K$, from a selected trial distribution $g(\boldsymbol{\Theta}_u)$, then $P(\text{data}|M = u)$ is estimated by

$$\widehat{d}_u = \frac{1}{K} \sum_{k=1}^{K} \frac{P(\text{data}|\widetilde{\boldsymbol{\Theta}}_u^{(k)}, M = u)P(\widetilde{\boldsymbol{\Theta}}_u^{(k)}|M = u)}{g(\widetilde{\boldsymbol{\Theta}}_u^{(k)})}.$$

A "good" sampling distribution $g(\boldsymbol{\Theta})$ would be the one that is approximately proportional to $P(\text{data}|\boldsymbol{\Theta}_u, M = u)P(\boldsymbol{\Theta}_u|M = u)$, based on importance sampling principle (Robert and Casella

1999; Liu 2001). Hence we use samples $\mathbf{\Theta}_u^{(j)}$, $j = 1, \ldots, m$, from the earlier MCMC procedure to construct $g(\mathbf{\Theta})$. The sampling distribution we used is

$$g(\mathbf{\Theta}) \sim \mathrm{N}\big(\mu_{\mathbf{\Theta}_u}, \Sigma_{\mathbf{\Theta}_u}\big),$$

with

$$\mu_{\mathbf{\Theta}_u} = \frac{1}{m}\sum_{j=1}^{m}\mathbf{\Theta}_u^{(j)}, \qquad \Sigma_{\mathbf{\Theta}_u} = \frac{1}{m}\sum_{j=1}^{m}\mathbf{\Theta}_u^{(j)}\mathbf{\Theta}_u^{(j)\prime} - \mu_{\mathbf{\Theta}_u}\mu_{\mathbf{\Theta}_u}'.$$

It produces very accurate results.

In our Bayesian framework, the leave-one-out cross-validation measure is equivalent to the posterior probability of observing firm $i$'s responses given all the observed data, leaving out the observation of firm $i$. We construct two cross-validation measures: $V_{I,u}$ for the decision indicator $I_i$ and $V_{t,u}$ for the firm's survival time $t_i$. Again, $u = 1, 2, 3, 4$ corresponds to Model I, II, III, and IV, respectively. Let $\mathbf{X}_i = (\mathbf{X}_{0,i}, \mathbf{X}_{1,i})$, we define

$$V_{I,u} \triangleq \sum_{i=1}^{n}\log(v_{I,u,i}) \qquad \text{and} \qquad V_{t,u} \triangleq \sum_{i=1}^{n}\log(v_{t,u,i}),$$

where

$$v_{I,u,i} = \int P(I_i|\mathbf{X}_i, \mathbf{Z}_i, c_i, \mathbf{W}_s, s_i, \mathbf{\Theta}_u, M = u) \times P(\mathbf{\Theta}_u|I_j, T_j^*, X_j, Z_j, c_j, \mathbf{W}_s, s_j, j \neq i, M = u)\, d\mathbf{\Theta}_u$$

and

$$v_{t,u,i} = \int P(T_i^*|I_i, \mathbf{X}_i, \mathbf{Z}_i, c_i, \mathbf{W}_s, s_i, \mathbf{\Theta}_u, M = u) \times P(\mathbf{\Theta}_u|I_j, T_j^*, X_j, Z_j, c_j, \mathbf{W}_s, s_j, j \neq i, M = u)\, d\mathbf{\Theta}_u.$$

Using $\mathbf{\Theta}_u^{(\ell)}$, $\ell = 1, \ldots, m$, generated from the earlier MCMC estimation procedure for models $u = 1, \ldots, 4$, we can estimate $v_{I,u,i}$ and $v_{t,u,i}$ using importance sampling. Specifically, let

$$\begin{aligned} w_{u,i}^{(\ell)} \propto{}& P\big(\mathbf{\Theta}_u^{(\ell)}|I_j, T_j^*, X_j, Z_j, c_j, \mathbf{W}_s, s_j, \\ & j = 1, \ldots, n, j \neq i, M = u\big) \\ & /P\big(\mathbf{\Theta}_u^{(\ell)}|I_j, T_j^*, X_j, Z_j, c_j, \mathbf{W}_s, s_j, j = 1, \ldots, n, M = u\big) \end{aligned}$$

for $i = 1, \ldots, n$. We have

$$\begin{aligned} v_{I,u,i} &= E[P(I_i|\mathbf{X}_i, \mathbf{Z}_i, c_i, \mathbf{W}_s, s_i, \mathbf{\Theta}_u, M = u)| \\ &\quad \text{all records except } i\text{th record}] \\ &= E[w_{u,i}P(I_i|\mathbf{X}_i, \mathbf{Z}_i, c_i, \mathbf{W}_s, s_i, \mathbf{\Theta}_u, M = u)|\text{all records}] \\ &\approx \frac{\sum_{\ell=1}^{m} w_{u,i}^{(\ell)}P(I_i|\mathbf{X}_i, \mathbf{Z}_i, c_i, \mathbf{W}_s, s_i, \mathbf{\Theta}_u^{(\ell)}, M = u)}{\sum_{\ell=1}^{m} w_{u,i}^{(\ell)}}. \end{aligned}$$

And $v_{t,u,i}$ can be obtained similarly.

In view of our model specification, it would be cumbersome and time consuming to obtain the leave-one-out cross-validation measure using a traditional likelihood approach, as parameters need to be reestimated for each set of observations. Under the Bayesian framework with the use of important sampling procedure, we could make use of samples generated during in model estimation procedure and reduce computation time substantially.

# 4. EMPIRICAL RESULTS

## 4.1 Parameter Estimates

Table 3 presents, for each parameter, the estimated posterior mean and standard deviation for Model specifications I, II, III, and IV. We tabulate parameter estimates for the decision model in Panel A, those for the hazard model for firms with withdrawn IPOs in Panel B, and those for the hazard model for firms with completed IPOs in Panel C.

Model I constitutes the most comprehensive model. In this specification, we include all the covariates $\mathbf{Z}_i$, as well as $L_i$ in the decision model. The annual market return is included as a time-varying covariate $\mathbf{W}_s$ in both hazard models of bankruptcy in addition to the variables in $\mathbf{X}_i$.

As indicated by the high significance level of the coefficient $\eta$, $L_i$ is highly predictive of increased likelihood for firms to complete their offerings. This is evidence consistent with that this anticipated effect of "withdrawal" is an important determinant of a firm's decision on whether to complete its IPO. Figure 1 shows the marginal posterior distribution of $\eta$. It is seen that almost the entire posterior distribution of $\eta$ is above zero.

Other variables in the decision model with $r_0(\theta)$ greater than 19 or less than 0.05 include REV, DUSEP, CMRank, and RET30, showing that the firms are more likely to complete their IPO if they have higher revenue prior to the offerings, low need to paying off debt, higher underwriter ranking, and better market conditions.

There is a significant positive time dependence of bankruptcy rate for firms with completed IPOs, as the time dependence parameter $p_1$ in the hazard model is significantly above the value of one. For those firms, the likelihood of bankruptcy at time $t$, conditioned upon duration up to time $t$, is increasing in $t$. The finding is consistent with an initial positive, but not lasting, benefit of a successful IPO. On the other hand, there is no significant time dependence of survival rates for firms with withdrawn IPOs, as the time dependence parameter $p_0$ is not significantly different from one. Figure 2 shows the estimated posterior distributions for the time independence parameters $p_0$ and $p_1$ of Model I.

In Model I, among the set of ex ante variables observable at the time of the offering, the underwriter ranking (CMRank) emerges as a highly significant variable in predicting a higher survival rates for firms with withdrawn IPOs. This is consistent with the fact that firms, with the certification of a high-quality banker, could suffer less reputation loss after IPO withdrawal. On the other hand, the underwriter ranking has no significant impact to the firms with completed IPOs.

In Model I, among firms with completing IPOs, profitable firms (right after IPO) exhibit better performance, as ROAaft is significantly predictive of higher post-IPO survival time. ROA is not significant among the firms with withdrawn IPOs. On the other hands, smaller firms (low AST) exhibit a higher survival rate for firms with withdrawn IPOs, but not significant for those with completed IPOs.

Figure 3 presents the boxplot of the posterior distribution of the parameter estimate of the time-varying variable MKT for Models I and III. It shows that the time-varying market return is significantly predictive of postcompleted-IPOs survival rate, but not postwithdrawn-IPO survival rate.

Table 3. Posterior mean and standard deviation of Bayesian estimation of switching hazard models of bankruptcy

| | Model I | Model II | Model III | Model IV |
|---|---|---|---|---|
| Panel A: decision model to withdraw IPOs | | | | |
| CONSTANT | 7.34 (5.42) | 7.14 (5.55) | 11.43* (3.37) | 11.62* (3.45) |
| $\eta$ | 10.64* (3.51) | 9.71* (4.41) | – | – |
| VENTURE | −0.01 (0.92) | 0.09 (0.88) | 1.27* (0.31) | 1.29* (0.31) |
| REV | 0.29* (0.12) | 0.30* (0.12) | 0.43* (0.09) | 0.43* (0.09) |
| DUSEP | −1.02* (0.31) | −1.02* (0.32) | −0.77* (0.28) | −0.77* (0.29) |
| log(MKCAP) | −0.48 (0.35) | −0.44 (0.35) | −0.55* (0.22) | −0.56* (0.23) |
| CMRank | 0.29* (0.16) | 0.25 (0.15) | −0.06 (0.06) | −0.06 (0.06) |
| RET30 | 6.87* (3.48) | 6.92* (3.50) | 6.28* (3.34) | 6.30* (3.37) |
| NumIPOs | −0.35 (0.24) | −0.39 (0.24) | −0.35 (0.23) | −0.35 (0.23) |
| DEBT | −1.45 (0.96) | −1.43 (0.97) | −2.30* (0.44) | −2.29* (0.45) |
| Panel B: Hazard model of bankruptcy for firms with withdrawn IPOs | | | | |
| $p_0$ | 0.73 (0.19) | 0.81 (0.20) | 0.79 (0.21) | 0.84 (0.21) |
| CONSTANT | 3.74* (0.85) | 3.65* (0.74) | 2.48* (0.90) | 2.60* (0.76) |
| VENTURE | −0.47 (0.61) | −0.40 (0.55) | −0.34 (1.00) | −0.20 (0.96) |
| CMRank | 0.27* (0.12) | 0.24* (0.10) | 0.33* (0.17) | 0.31* (0.15) |
| DEBT | 0.73 (0.66) | 0.72 (0.60) | 1.06 (0.95) | 0.99 (0.92) |
| AST | −0.38* (0.17) | −0.35* (0.16) | −0.17 (0.29) | −0.15 (0.27) |
| ROA | 0.42 (0.34) | 0.41 (0.29) | 0.65 (0.70) | 0.62 (0.63) |
| MKT | 1.30 (3.67) | – | 1.56 (3.78) | – |
| Panel C: Hazard model of bankruptcy for firms with completed IPOs | | | | |
| $p_1$ | 1.54* (0.23) | 1.71* (0.24) | 1.56* (0.24) | 1.71* (0.25) |
| CONSTANT | 4.03* (0.48) | 3.96* (0.42) | 3.78* (0.44) | 3.73* (0.41) |
| VENTURE | 0.40 (0.27) | 0.38 (0.24) | 0.06 (0.24) | 0.05 (0.22) |
| CMRank | 0.05 (0.04) | 0.05 (0.03) | 0.07 (0.04) | 0.06 (0.04) |
| DEBTaft | 0.16 (0.38) | 0.18 (0.36) | −0.25 (0.63) | −0.23 (0.57) |
| ASTaft | −0.24 (0.15) | −0.23 (0.12) | −0.14 (0.14) | −0.13 (0.13) |
| ROAaft | 2.08* (0.70) | 1.89* (0.65) | 1.24 (0.92) | 1.13 (0.84) |
| MKT | 1.27* (0.78) | – | 1.20* (0.77) | – |

NOTE: Posterior means are presented with standard deviation in the parenthesis. Parameters marked with * are significantly different from zero (or one for $p_0$ and $p_1$) at 5% level.

In Model II, we include all the independent variables $\mathbf{Z}_i$, as well as $L_i$ in the decision model, but exclude the annual market return in both hazard models of bankruptcy. As a result, all the covariates in the model are time invariant.

Model II shows a similar significance level to the coefficient $\eta$, indicating $L_i$ as highly predictive of increased likelihood for firms to complete their offerings. Again, this is an evidence consistent with the existence of "feedback" from the anticipated ef-

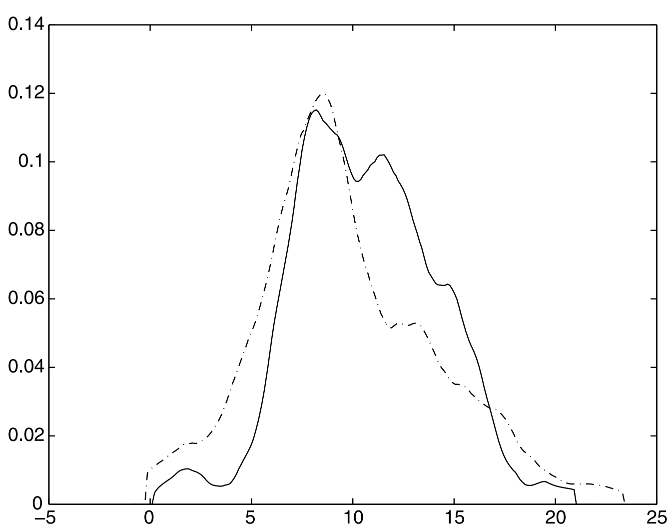


Figure 1. Estimated posterior density function of parameter $\eta$. The dashed line is for Model I, the solid line is for Model II.

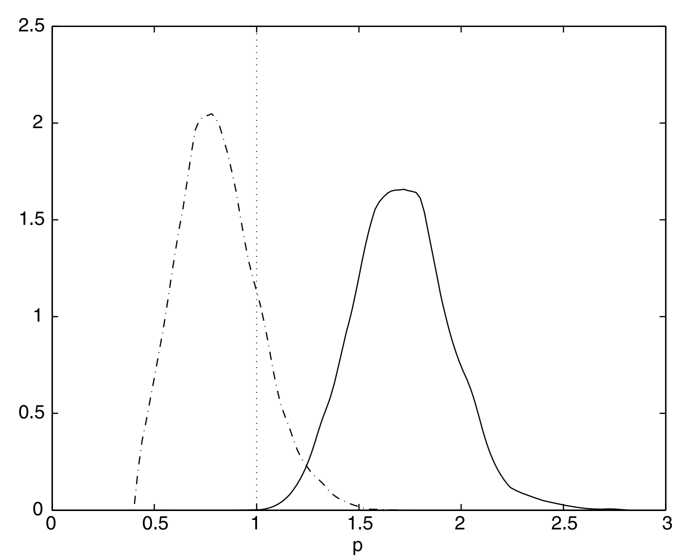


Figure 2. Estimated posterior density function of parameter $p_0$ and $p_1$ for Model I. The dashed line is $p_0$, the solid line is for $p_1$. The dotted line is constant 1.

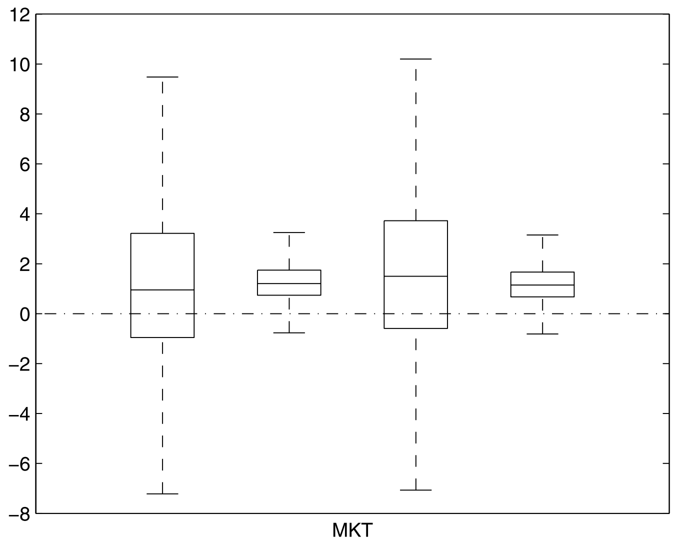


Figure 3. Boxplots of the estimate posterior distribution of parameter $\zeta_0$ and $\zeta_1$ for time varying variable MKT. From left to right, the boxes are for $\zeta_0$ in Model I, $\zeta_1$ in Model I, $\zeta_0$ in Model III, and $\zeta_1$ in Model III, respectively. The dotted line shows constant 0.

fect of "withdrawal" to a firm's decision on whether to complete its IPO.

Comparing Model I and Model II, we can see that all variables, except CMRank in the decision model, have the same significant/nonsignificant status. The coefficient of the CMRank variable in the decision model only changed slightly. Note that CMRank is still significant in the hazard model for postwithdrawn-IPO firms.

Model III, with almost identical specification to Model I, excluded $L_i$ as a covariate in the decision model, under the assumption that there is no feedback on the "anticipated" effect of withdrawal. In this model, the estimation of a firm's decision model to withdraw and two hazard models of bankruptcy are estimated independently. Results from the model closely correspond to those presented in Busaba, Benveniste, and Guo (2001). Similar to what is reported by Busaba, Benveniste, and Guo (2001), a firm with larger revenue, filing its IPO in better market condition are more likely to complete its offering as scheduled. A firm with larger expected market capitalization, with a primary use of proceeds to pay down debt, filing its IPO with more active market (with a higher number of contemporaneous number of IPO offerings), and with higher leverage, are more likely to withdraw its offering. The underwriter quality, however, is not significantly predictive of firm's withdrawal decision. The underwriter ranking remains as a highly significant variable in predicting a higher survival rates for firms with withdrawn IPOs. The significance of other variables in predicting postwithdrawal survival is quite low in this model. On the completed IPO side, the time dependence parameter $p_1$ remains significantly above the value of one in the hazard model of bankruptcy for firms with completed IPOs. The time-varying annual market return is also significant in predicting post-IPO survival. All other variables are not significant.

Model IV, with similar specification to Model III, excludes the annual market return in both hazard models of bankruptcy. It shows very similar results as Model III.

Table 4. Posterior model probabilities and leave-one-out prediction fitness for different models

| Model type | Posterior model prob | $V_{I,u}$ | $V_{t,u}$ |
|---|---|---|---|
| Model I | 0.0005 | −224.1 | −326.1 |
| Model II | 0.749 | −224.5 | −324.5 |
| Model III | 0.0002 | −225.7 | −327.7 |
| Model IV | 0.250 | −225.9 | −326.1 |
| Model V | – | −226.1 | −327.7 |

## 4.2 Model Comparison Results

We provide statistics on which model best describes the observed data. An equal probability prior is used on the set of models $\{u = 1, 2, 3, 4\}$. The posterior model probability estimation procedure used 500,000 Monte Carlo draws. We report the results in Table 4. They indicate that the time-invariant model with feedback (Model II) is the model with the highest posterior model probability, which is much higher than those of the other three models. Results of our cross-validation measures are mixed. In making out-of-sample prediction for the decision to withdraw an IPO, the $V_{I,u}$ is slightly in favor of Model I over Model II, while the prediction for survival time $V_{t,u}$ is in favor of Model II.

We also compare our model with a simple model, in which we first estimate the survival models for the withdrawn-IPO firms and complete-IPO firms separately using a MCMC procedure, ignoring the decision bias. In this simple model, the time-varying covariates $\mathbf{W}_s$ are included. Then we estimate the conditional expectation of the loss function by

$$L_i^* = E(L_i|\text{data}) \approx \frac{1}{m}\sum_{j=1}^{m} L_i(\boldsymbol{\Theta}_j),$$

where $\boldsymbol{\Theta}_1, \ldots, \boldsymbol{\Theta}_m$ are $m$ samples of parameters generated in the MCMC procedure, $L_i$ is the loss function defined in (5), $L_i(\boldsymbol{\Theta}_j)$ denotes the value is calculated using parameter $\boldsymbol{\Theta}_j$. Treating $L_i^*$ as observed values, we estimate a logistic regression model for the decision model

$$P(I_i = 1) = \frac{\exp\{\alpha + \boldsymbol{\gamma}'\mathbf{Z}_i + \eta L_i^*\}}{1 + \exp\{\alpha + \boldsymbol{\gamma}'\mathbf{Z}_i + \eta L_i^*\}}. \tag{8}$$

For our dataset, the estimated $\eta$ is not significantly different from zero ($p$-value $= 0.28$). The difference between this model and the ones we proposed shows the strong impact of selection bias and the importance of joint modeling and estimation, taking into account of the feedback mechanism. In Table 4, we also report the leave-one-out prediction fitness for this model, labeled as Model V. The $V_{I,u}$ is calculated under a Bayesian version of model (8), due to computational convenience. The $V_{t,u}$ is the same as that of Model III, since Model III also ignores the feedback in the survival model. Smaller values of $V_{I,u}$ and $V_{t,u}$ show that the model is not as good as the others.

We present the full set of Bayesian statistics, including posterior mean, standard deviation, 95% Bayesian interval, and the posterior odds ratios $r_0(\theta)$ and $r_1(\theta)$, defined in (7), for Model II in Table 5. The implications of our empirical results from Model II are as the following. Because withdrawn IPOs

Table 5. Bayesian inference for Model II

| Variable | Mean | Standard deviation | Bayesian interval (95%) | $r_0(\theta)$ | $r_1(\theta)$ |
|---|---|---|---|---|---|
| Panel A: Decision model to withdraw IPOs | | | | | |
| CONSTANT | 7.14 | 5.55 | (−3.90, 17.76) | 8.61 | – |
| $\eta$ | 9.71 | 4.41 | (0.41, 17.89) | Inf | – |
| VENTURE | 0.09 | 0.88 | (−1.72, 1.69) | 1.36 | – |
| REV | 0.30 | 0.12 | (0.06, 0.55) | 113.22 | – |
| DUSEP | −1.02 | 0.32 | (−1.65, −0.40) | 0.00 | – |
| log(MKCAP) | −0.44 | 0.35 | (−1.10, 0.26) | 0.12 | – |
| CMRank | 0.25 | 0.15 | (−0.05, 0.55) | 17.34 | – |
| RET30 | 6.92 | 3.50 | (0.07, 13.80) | 44.14 | – |
| NumIPOs | −0.39 | 0.24 | (−0.87, 0.08) | 0.05 | – |
| DEBT | −1.43 | 0.97 | (−3.28, 0.56) | 0.08 | – |
| Panel B: Hazard model of bankruptcy for firms with withdrawn IPOs | | | | | |
| $p_0$ | 0.81 | 0.20 | (0.42, 1.16) | – | 0.20 |
| CONSTANT | 3.65 | 0.74 | (2.31, 5.28) | Inf | – |
| VENTURE | −0.40 | 0.55 | (−1.56, 0.64) | 0.28 | – |
| CMRank | 0.24 | 0.10 | (0.06, 0.45) | 1708.40 | – |
| DEBT | 0.72 | 0.60 | (−0.37, 1.94) | 9.35 | – |
| AST | −0.35 | 0.16 | (−0.67, −0.09) | 0.00 | – |
| ROA | 0.41 | 0.29 | (−0.12, 1.04) | 18.00 | – |
| Panel C: Hazard model of bankruptcy for firms with completed IPOs | | | | | |
| $p_1$ | 1.71 | 0.24 | (1.24, 2.14) | – | Inf |
| CONSTANT | 3.96 | 0.42 | (3.12, 4.80) | Inf | – |
| VENTURE | 0.38 | 0.24 | (−0.10, 0.86) | 16.48 | – |
| CMRank | 0.05 | 0.03 | (−0.02, 0.11) | 12.50 | – |
| DEBTaft | 0.18 | 0.36 | (−0.55, 0.88) | 2.40 | – |
| ASTaft | −0.23 | 0.12 | (−0.46, 0.03) | 0.05 | – |
| ROAaft | 1.89 | 0.65 | (0.62, 3.22) | 245.91 | – |

are usually associated with firms of questionable quality, it is often believed that the issuers cannot withdraw freely without taking undesirable consequences. In addition, at times benefits of public equity can overwhelmingly outweigh those of other financing sources so that the opportunity cost of cancelling the public offerings is high. In such cases, the option value for firms to cancel their offerings is minimal. The issue of whether there will be unwanted consequences after an IPO withdrawal is studied in this paper. By measuring the postwithdrawal and post-IPO performance using the subsequent survival rates of issuing firms, the analysis in this paper provides for the first time the evidences that a firm's performance deteriorates after withdrawal, with everything else being equal. Our results also indicate that this "anticipated" cost of withdrawal is an important determinant of a firm's decision to complete its offering. In Figure 4 we show the marginal distribution of the anticipated cost $L_i$, ignoring the differences in covariates, for completed IPO companies and the withdrawn IPO companies, respectively, under Model II. It seems that a company is unlikely to withdraw its IPO offering if the anticipated cost of such an action is high. The difference between average $L_i$ of the two groups is 0.09, while the posterior mean for $\eta$ is 9.71. This difference approximately translates to an odds ratio of $e^{0.09\times 9.71} = 2.40$ in the decision model (4), given all other covariates are the same.

The analysis also shows new evidence that firms with offerings underwritten by high-ranked bankers, survive significantly longer after withdrawal of their offerings. We do not, however, find such correlation on firms with completed offerings. Our finding is consistent with that firms, with the certification of a

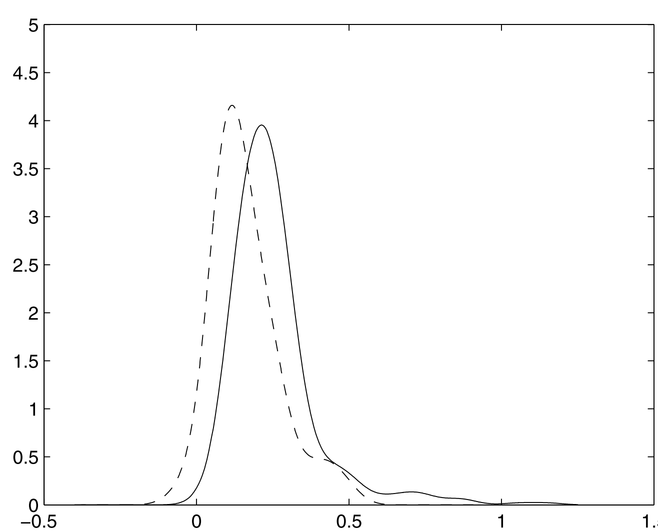


Figure 4. Marginal distribution of the estimated loss $L^*$ for completed IPO companies (solid line) and withdrawn IPO companies (dashed line), under Model II. The expected benefits of going through with the IPO is concentrated on larger values for the firms that complete IPO.

high-quality banker, could suffer less reputation loss after incidence of IPO withdrawal.

Our analysis on the post-IPO survival rates indicates a significant positive time dependence of bankruptcy rate for firms with completed IPOs. This finding is consistent with the "immediate" benefit of going public for firms that elect to complete their offerings; such benefit, however, diminishes over time.

## 5. CONCLUSION

This study extends the existing econometric models in order to examine the self-selectivity in a firm's decision to withdraw its IPO. Using post-IPO and postwithdrawal duration data of bankruptcy, we report that the firm managers are forward-looking and apprehensive of postwithdrawal consequences, and the corresponding anticipated effect serves as "feedback" to their decision to withdraw an offering. We also uncover different sets of determinants for post-IPO and postwithdrawal hazard rates of bankruptcies, and provide new insights to the going-public process.

We also develop a Bayesian estimation strategy, which is powerful in our experiment design in working with complex nonlinear likelihood function, making inference from limited sample size, and conducting model comparison. Our econometric specifications and the accompanying estimation procedure is widely applicable to studies which examine timing information of postevent performance and firm's preevent decision making. Given the pervasive self-selectivity in corporate transactions, we believe that application of our analysis will greatly improve our understanding on the economic consideration behind managerial consideration.

## APPENDIX: ESTIMATION VIA MCMC

Detailed and general descriptions of the MCMC algorithm can be found in Robert and Casella (1999) and Liu (2001) and references therein. Here we use an iterative componentwise Metropolis–Hastings method to draw samples from the posterior distribution

$$P(\alpha, \eta, \boldsymbol{\gamma}, \boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1, p_0, p_1 | \text{data}).$$

For simplicity, we use $P(\cdot)$ to denote $P(\cdot|\text{data})$ in the following.

Specifically, in the MCMC procedure, random samples are drawn from the posterior distribution by iteratively updating several components in the parameter space. Each updating is done with a Metropolis–Hastings move of the component, while fixing the value of all other components to their value in the previous iteration. In the analysis, 300,000 total iterations were carried out, with the first 100,000 samples discarded as burning period. For each component, five Metropolis–Hastings steps were run before moving to the next component.

The parameters are partitioned into three components, $(\alpha, \eta, \boldsymbol{\gamma})$, $(\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0, \boldsymbol{\zeta}_1)$, and $(p_0, p_1)$. In the following we provide the details on each updating.

(1) *Draw* $\alpha, \eta, \boldsymbol{\gamma}$. We have

$$\log[P(\alpha, \eta, \boldsymbol{\gamma}|\text{rest})] = -\sum_{i=1}^{n} \log\{1 + \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}\} + \sum_{i:I_i=1} \{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\} - 0.5\boldsymbol{\phi}'\Sigma_1^{-1}\boldsymbol{\phi} + C_1,$$

where $\boldsymbol{\phi} \triangleq (\alpha, \eta, \boldsymbol{\gamma}')'$, $C_1$ is a term that does not depend on $\boldsymbol{\phi}$. We define $A_1(\boldsymbol{\phi})$ as the first-order derivation of $\log[P(\alpha, \eta, \boldsymbol{\gamma}|\text{rest})]$, that is,

$$A_1(\boldsymbol{\phi}) = -\sum_{i=1}^{n} \frac{\exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}}{1 + \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}} H_i + \sum_{i:I_i=1} H_i - \Sigma_1^{-1}\boldsymbol{\phi},$$

where $H_i = (1, L_i, \mathbf{Z}_i')'$. Then a proposal move $\boldsymbol{\phi}_{new}$ is generated from

$$\mathrm{N}(\mu(\boldsymbol{\phi}), \Sigma(\boldsymbol{\phi})) = \mathrm{N}\left(\boldsymbol{\phi} + \rho\frac{A_1(\boldsymbol{\phi})}{|A_1(\boldsymbol{\phi})|}, \rho^2 E\right),$$

where $E$ is the identity matrix, $\rho$ is a small positive value. We used $\rho = 0.03$ in this analysis. The proposed values $\boldsymbol{\phi}_{new}$ is accepted with probability

$$\min\left\{1, \frac{T(\boldsymbol{\phi}_{new}, \boldsymbol{\phi})P(\boldsymbol{\phi}_{new}, \text{rest})}{T(\boldsymbol{\phi}, \boldsymbol{\phi}_{new})P(\boldsymbol{\phi}, \text{rest})}\right\},$$

where $T(\boldsymbol{\phi}, \boldsymbol{\phi}_{new})$ is the transition probability of moving $\boldsymbol{\phi}$ to $\boldsymbol{\phi}_{new}$, which is

$$T(\boldsymbol{\phi}, \boldsymbol{\phi}_{new}) = \frac{1}{\sqrt{|2\pi\Sigma(\boldsymbol{\phi})|}} \exp\{-0.5(\boldsymbol{\phi}_{new} - \mu(\boldsymbol{\phi}))' \times \Sigma^{-1}(\boldsymbol{\phi})(\boldsymbol{\phi}_{new} - \mu(\boldsymbol{\phi}))\}.$$

The reverse transition probability is calculated with

$$T(\boldsymbol{\phi}_{new}, \boldsymbol{\phi}) = \frac{1}{\sqrt{|2\pi\Sigma(\boldsymbol{\phi}_{new})|}} \exp\{-0.5(\boldsymbol{\phi} - \mu(\boldsymbol{\phi}_{new}))' \times \Sigma^{-1}(\boldsymbol{\phi}_{new})(\boldsymbol{\phi} - \mu(\boldsymbol{\phi}_{new}))\},$$

where

$$\mu(\boldsymbol{\phi}_{new}) = \boldsymbol{\phi}_{new} + \rho\frac{A_1(\boldsymbol{\phi}_{new})}{|A_1(\boldsymbol{\phi}_{new})|}$$

and $\Sigma(\boldsymbol{\phi}_{new}) = \rho^2 E$.

(2) *Draw* $\boldsymbol{\beta}_0, \boldsymbol{\beta}_1, \boldsymbol{\zeta}_0$, *and* $\boldsymbol{\zeta}_1$. For notation simplicity, let $\boldsymbol{\psi} \triangleq (\boldsymbol{\beta}_0', \boldsymbol{\zeta}_0', \boldsymbol{\beta}_1', \boldsymbol{\zeta}_1')$. We have

$$\begin{aligned}
&\log[P(\boldsymbol{\psi}|\text{rest})] \\
&\quad = \sum_{i:c_i=1} \log(S_{I_i,i}(T_i^*)) + \sum_{i:c_i=0} \log(S_{I_i,i}(T_i^*) - S_{I_i,i}(T_i^*+1)) \\
&\qquad - \sum_{i=1}^{n} \log\{1 + \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}\} + \sum_{i:I_i=1} \{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\} \\
&\qquad - 0.5\boldsymbol{\psi}'\Sigma_2^{-1}\boldsymbol{\psi} + C_2,
\end{aligned}$$

where $C_2$ is a term that does not depend on $\boldsymbol{\psi}$. We define $B_1(\boldsymbol{\psi})$ as the first-order derivation of $\log[P(\boldsymbol{\psi}|\text{rest})]$. We have

$$\begin{aligned}
B_1(\boldsymbol{\psi}) &= \begin{pmatrix} \sum_{i:c_i=1, I_i=0} \frac{F_{0,i}(T_i^*)}{S_{0,i}(T_i^*)} \\ \sum_{i:c_i=1, I_i=1} \frac{F_{1,i}(T_i^*)}{S_{1,i}(T_i^*)} \end{pmatrix} \\
&\quad + \begin{pmatrix} \sum_{i:c_i=0, I_i=0} \frac{F_{0,i}(T_i^*) - F_{0,i}(T_i^*+1)}{S_{0,i}(T_i^*) - S_{0,i}(T_i^*+1)} \\ \sum_{i:c_i=0, I_i=1} \frac{F_{1,i}(T_i^*) - F_{1,i}(T_i^*+1)}{S_{1,i}(T_i^*) - S_{1,i}(T_i^*+1)} \end{pmatrix} \\
&\quad - \sum_{i=1}^{n} \frac{\eta\exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}}{1 + \exp\{\alpha + \eta L_i + \boldsymbol{\gamma}'\mathbf{Z}_i\}} \frac{\partial L_i}{\partial \boldsymbol{\psi}} \\
&\quad + \eta \sum_{i:I_i=1} \frac{\partial L_i}{\partial \boldsymbol{\psi}} - \Sigma_2^{-1}\boldsymbol{\psi},
\end{aligned}$$

where

$$F_{I_i,i}(T_i^*) = \begin{pmatrix} \frac{\partial S_{I_i,i}(T_i^*)}{\partial \beta_{I_i}} \\ \frac{\partial S_{I_i,i}(T_i^*)}{\partial \zeta_{I_i}} \end{pmatrix}.$$

A proposal move $\boldsymbol{\psi}_{new}$ is generated from

$$\mathrm{N}\left(\boldsymbol{\psi} + \rho\frac{B_1(\boldsymbol{\psi})}{|B_1(\boldsymbol{\psi})|}, \rho^2 E\right),$$

where $E$ is identity matrix, $\rho$ is a small positive value. We used $\rho = 0.03$ in this analysis. The proposal $\boldsymbol{\psi}_{new}$ is accepted with probability

$$\min\left\{1, \frac{T(\boldsymbol{\psi}_{new}, \boldsymbol{\psi})P(\boldsymbol{\psi}_{new}, \text{rest})}{T(\boldsymbol{\psi}, \boldsymbol{\psi}_{new})P(\boldsymbol{\psi}, \text{rest})}\right\},$$

where

$$T(\boldsymbol{\psi}, \boldsymbol{\psi}_{new}) = \frac{1}{\sqrt{|2\pi\,\Sigma(\boldsymbol{\psi})|}} \exp\{-0.5(\boldsymbol{\psi}_{new} - \mu(\boldsymbol{\psi}))' \times \Sigma^{-1}(\boldsymbol{\psi})(\boldsymbol{\psi}_{new} - \mu(\boldsymbol{\psi}))\}$$

and

$$T(\boldsymbol{\psi}_{new}, \boldsymbol{\psi}) = \frac{1}{\sqrt{|2\pi\,\Sigma(\boldsymbol{\psi}_{new})|}} \exp\{-0.5(\boldsymbol{\psi} - \mu(\boldsymbol{\psi}_{new}))' \times \Sigma^{-1}(\boldsymbol{\psi}_{new})(\boldsymbol{\psi} - \mu(\boldsymbol{\psi}_{new}))\},$$

where

$$\mu(\boldsymbol{\psi}) = \boldsymbol{\psi} + \rho\frac{B_1(\boldsymbol{\psi})}{|B_1(\boldsymbol{\psi})|}, \qquad \mu(\boldsymbol{\psi}_{new}) = \boldsymbol{\psi}_{new} + \rho\frac{B_1(\boldsymbol{\psi}_{new})}{|B_1(\boldsymbol{\psi}_{new})|},$$

and $\Sigma(\boldsymbol{\psi}) = \Sigma(\boldsymbol{\psi}_{new}) = \rho^2 E$.

(3) *Draw* $p_0, p_1$. Here we use a grid system for $p_0$ and $p_1$. Specifically, $p_0$ and $p_1$ take values in interval [0.4, 3], and $\delta_p = 0.02$ as grid width. We draw $\widetilde{p}_i = p_i + \delta_p$ or $p_i - \delta_p$ with probability 0.5. Then we accept $\widetilde{p}_i$ as new $p_i$ with probability $\min\{1, \frac{P(\widetilde{p}_i,\text{rest})}{P(p_i,\text{rest})}\}$.

*[Received November 2008. Revised March 2010.]*

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