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A Structural Model of Entry and Exit in the Export Market: A Bayesian Model Application

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Abstracts

Most research on estimating dynamic optimal choice model has been using conventional econometric methods such as Maximum Likelihood (ML) Method and Generalized Method of Moment (GMM). It is well known that when the model has many state variables, the estimation becomes difficult due to the well-known "Curse of Dimensionality". In this paper, we applied a new estimation technique that is based on the Bayesian estimation to confront this issue. To show the effectiveness of the Bayesian dynamic programming estimation algorithm, we first simulate the model of entry and exit in the export market, and then estimate back the parameters of the model based on simulated data. It enables us to solve the dynamic programming problem and estimate the parameters simultaneously instead of sequentially. This new method makes the computational burden of estimating the dynamic programming model on the same order of magnitude as those of estimating static model. We estimated a simple model of entry and exit behavior in the export market. We used the Bayesian dynamic programming method suggested by Imai, Jain, and Ching (2001) and successfully estimate back the true parameter from the simulated data.

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Ⅰ. Introduction

Roberts and Tybout (1997) estimated an econometric model of plants' decision to export in Columbian industries using plant level panel data. They estimate a dynamic model, where plants make a discrete decision of whether or not to export, explicitly taking into account present as well as future benefits of exporting and not exporting. The model includes serial correlation in the shocks to the export profit. They estimate the parameters of the model together with the parameters describing the future benefits of the export choices. Because their estimation was not based on the full solution of the model, they could not recover some structural parameters. Das, Roberts and Tybout (2001) used a full solution based estimation method to estimate the sunk entry costs faced by heterogeneous potential exporters. They use the two stage maximum likelihood method to estimate the parameters that govern the evolution of exporting profit and export market participation rules. They also found that sunk entry costs are substantial, and vary across heterogeneous plants in terms of domestic market output level. In addition, plant expectations and history of exporting status are important determinants of current exporting decision.

Both Roberts and Tybout (1997) and Das, Roberts and Tybout (2001) emphasize the role of heterogeneity, in particular, unobserved heterogeneity in explaining the different export entry and exit behavior of firms. But so far, most of the empirical works which use full solution based estimation adopt a very simplified form of Heckman and Singer (1984) unobserved types specification. That is, they typically assume a few unobserved types only. This is because, in order to estimate a dynamic structural model with, say n observed or unobserved types, for each likelihood computation, the researcher has to solve for the dynamic programming problem n times.

To overcome the computational burden mentioned above, we use the Bayesian solution and estimation technique advocated by Imai, Jain and Ching (2002), which they solve the dynamic programming problem and estimate the parameters *simultaneously* instead of *sequentially*. They claim that the new method makes the computational burden of estimating the dynamic programming models on the same order of magnitude as those of estimating the static models. The Bayesian method of estimating a static model with random effects has been well developed in papers such as McCulloch and Rossi (1994). Hence, extending their estimation method by including the unobserved heterogeneity would enable me to solve for and estimate a dynamic structural model with continuous random effects heterogeneities.

In this paper, we apply the recently developed Bayesian Dynamic Programming estimation method proposed by Imai, Jain and Ching (2002) to the estimation of the above dynamic model of export entry and exit. We estimate a very simple model of entry/exit behavior in the export market. Preliminary estimation results indicate that the Bayesian Dynamic Programming approach works well for estimating the dynamic entry and exit models. We will include explicitly the heterogeneous characteristics of firms in later research. In section 2, we describe the empirical model to be estimated. The estimation method is described next section in detail. In this section, we mention how to apply the Bayesian method in the structural model and compare the differences between the method done by previous work and the new kind of Bayesian estimation method. Section 4 shows the result of estimation briefly.

Ⅱ. Model

We estimate a simple dynamic discrete choice model of entry and exit in the export market. This firm is either an incumbent or an entrant.

The current profit of an incumbent, if he decides to stay, is a simple sum of the constant term α and a profit shock ϵ_{it}.

$$\pi_{it} = \alpha + \epsilon_{it}$$

Here, we assume that the profit shock is *i.i.d.* over time and over firms. We also assume that the fixed entry cost to be F_i. When a firm exits from the export markets, it earns an exit value, which we denote to be X_i. Here, we assume X_i to be zero. We define the binary variable y_{it} to take a value of 1 if the plant i exports at year t, and 0 otherwise. Then, the period-t profit of plant i from export is:

$$u_{it} = \begin{cases} \pi_{it} & \text{if} \quad y_{it} \quad \text{and} \quad y_{it-1} = 1 \\ \pi_{it} - F_i & \text{if} \quad y_{it} \quad \text{and} \quad y_{it-1} = 0 \\ 0 & \text{if} \quad y_{it} = 0 \end{cases}$$

At period t, a plant chooses $y_{it} \in \{0,1\}$ that maximizes the expected present value of profit. This maximized profit is represented by

$$V_{it}(\epsilon_{it}) = \max_{y_{it}} E_t(\sum_{j=t}^{\infty} \beta^{j-t} u_{it})$$

where β is the discount factor, and we assume $0 < \beta < 1$. Then, the Bellman equation can be expressed as

$$V_{it}(\epsilon_{it}, y_{it-1}) = \max_{y_{it}}\{u_{it}(y_{it}, y_{it-1}, \epsilon_{it}) + \beta E V_{t+1}(y_{it}, \epsilon_{it+1})\}$$

There exists a unique $V_{it}(\cdot)$ that solves the Bellman equation each period, and the policy function is given by

$$f_{it}(\epsilon_{it}, y_{it-1}) = \arg\max_{y_{it}}\{u_{it}(y_{it}, y_{it-1}, \epsilon_{it}) + \beta E V_{t+1}(y_{it}, \epsilon_{it+1})\}$$

Ⅲ. Estimation strategy

The previous researches of dynamic discrete choice model such as Hotz and Miller (1993), Geweke and Keane (2000) estimated the parameters without solving the dynamic optimization problem. Hotz and Miller (1993) present a new estimator called the Conditional Choice Probability (CCP) estimator. They represent the expected value function in terms of utility payoffs, choice probabilities, and probability transitions of choices and outcomes. They estimate the structural parameters by using non-parametric estimates of these future choice probabilities and transition functions in place of their true values. Geweke and Keane (2000) also estimate the dynamic structural model without solving the dynamic programming problem. Instead of using the exact expected value function that would have been calculated from DP solution, they assume the value function takes polynomial form of the state variables.[1)]

1) Without solving the expected value function, they simply assume that it takes a polynomial form of value function. They estimate the polynomial function and use the fitted value of the dependent variable as the expected value function. They try to match the right polynomial value function, and find that the 6-th order polynomials of value function explains better than any other type of polynomials. But, it still causes the bias on the

In this paper we will not adopt any assumptions on the expected value function cited above. That is, the estimation process is based on the full solution of the model. To show the effectiveness of the Bayesian DP estimation algorithm, we first simulate the model of entry and exit in the export market, and then estimate back the parameters of the model based on the simulated data. The first step is to solve a dynamic programming problem to generate the decision rule in the export market. Since there are only two alternatives, entry (stay in) or exit (stay out), it is straightforward to solve the dynamic programming problem mathematically. The steps are described in detail below.

Given true values of parameters, we need to solve the dynamic programming problem to generate the data. Here is how to generate the artificial data.

(i) Set the true value of α and the fixed cost.

(ii) Given true parameters, draw the random shocks $\epsilon_{m} \sim N(0, \Sigma_{\epsilon})$

(iii) Given true parameters and random shocks, calculate

$$V_t^{s+1}(\epsilon_t, y_{t-1}=1) = \max\{u_t(y_{t-1}=1, y_t=1, \epsilon_{2t}) + \beta E V_{t+1}^s(y_t=1, \epsilon_{t+1}), u_t(y_{t-1}=1, y_t=1, \epsilon_{1t}) + \beta E V_{t+1}^s(y_t=1, \epsilon_{t+1})\}$$ and

$$V_t^{s+1}(\epsilon_t, y_{t-1}=0) = \max\{u_t(y_{t-1}=0, y_t=1, \epsilon_{2t}) + \beta E V_{t+1}^s(y_t=1, \epsilon_{t+1}), u_t(y_{t-1}=0, y_t=0, \epsilon_{1t}) + \beta E V_{t+1}^s(y_t=0, \epsilon_{t+1})\}$$

Where, ϵ_{1t} and ϵ_{2t} be the profit shocks to the potential entrant and incumbent

(iv) Repeat (i) through (iii) M times and take averages to derive the expected value function for the next iteration.

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estimators compare to the exactly computed value functions.

$$EV^{s+1}(\epsilon, y, \alpha) = \frac{1}{M}\sum_{m=1}^{M} V^{s+1}(\epsilon_m, y, \alpha)$$

In the simulation exercise, we set the simulation size M to be 2,000.

(v) Repeat (i) through (iv) until the expected value function converges.

$Max_y |EV^{s+1}(\epsilon, y, \alpha) - E^s V(\epsilon, y, \alpha)| < \delta$, where δ is some small number, say 0.001.

By following the above steps, we can get the expected value function. Then, we can generate the behaviors of firms whether it enters or exits in the export market. That is, for y_{it-1},

$$\begin{aligned} y = 1 \quad \text{if } & u_{it}(y_{it} = 1, y_{it-1}) = 0, \epsilon + \beta EV_{it+1}(y_{it} = 1, \epsilon) \\ & > u_{it}(y_{it} = 0, y_{it-1} = 0, \epsilon) + \beta EV_{it+1}(y_{it} = 0, \epsilon) \end{aligned}$$

$y = 0$ otherwise

where $EV_{it+1}(\bullet)$ is the expected value function calculated from step (v).

Similarly conditions hold for $y_{it-1} = 1$.

Given the data set generated from above steps, we do estimate the model with the Bayesian dynamic programming routine. Before mentioning the estimation procedure, let us specify some assumptions on prior distribution over the fixed cost and the variance of profit shocks.

We assume the prior of the exporting profit α and F_i are normally distributed.

$$\alpha \sim N(\underline{\alpha}, A_\alpha^{-1})$$

$$F_i \sim N(\underline{F}, A_F^{-1})$$

We further assume an independent Wishart prior for the precision of the profit shocks. Denote $G = (\Sigma_\epsilon)^{-1}$. Then,

$$G \sim W(v, V)$$

Since we are solving the dynamic programming problem and estimate the parameters simultaneously instead of sequentially, the Emax function and the parameter values will be updated at the same time in each iteration.

The estimation steps are described as follows.

Given the generated profit shocks and the value of Emax function, we conduct data augmentation and Gibbs sampling procedures. The Gibbs sampler was developed and has been applied in the literatures of complex stochastic models. When the model has large numbers of variables involved, direct specification of a joint distribution is not feasible. But, the Gibbs sampler allows us to generate random draws from the marginal density without having to compute it.

Gibbs sampling is a Markov Chain Monte Carlo (MCMC) simulation method for approximating joint and marginal distributions by sampling from conditional distributions. If we are given the complete set of conditional densities, denoted $f(\theta_n|\theta_{-n})$, $n = 1, 2, \ldots, k$ and $\theta_{-n} = \{\theta_1, \ldots, \theta_{n-1}, \theta_{n+1}, \ldots, \theta_k\}$. Then the Gibbs sampling technique enable us to generate a sample $\theta_1^i, \theta_2^i, \ldots, \theta_k^i$ from the joint density $f(\theta_1, \ldots, \theta_k)$ without requiring that we know either the joint density or the marginal densities $f(\theta_n)$. Given a set of initial values of parameters $\theta_1^0, \theta_2^0, \theta_3^0, \ldots, \theta_k^0$, we draw next parameter values by conditioning on past values as follows. $\theta_1^1 \sim f(\theta_1|\theta_2^0, \theta_3^0, \ldots, \theta_k^0)$, $\theta_2^1 \sim f(\theta_2|\theta_1^1, \theta_3^0, \ldots, \theta_k^0)$, $\theta_3^1, \ldots,$ $\theta_k^1 \sim f(\theta_k|\theta_1^1,$ $\theta_2^1, \ldots, \theta_{k-1}^1)$. After i such iterations we would arrive at $(\theta_1^i, \theta_2^i, \ldots, \theta_k^i)$. Geman and Geman (1984) show that joint and marginal distribution of generated $(\theta_1^i, \theta_2^i, \ldots, \theta_k^i)$ converge at an exponential rate to the joint and marginal distribution of

$\theta_1, \theta_2, ..., \theta_k$ as i goes to infinity. Thus the joint and marginal distribution of $\theta_1, \theta_2, ..., \theta_k$ can be approximated by the empirical distributions of M simulated values. McCulloch and Rossi (1994) suggest plotting the estimates of the posterior densities over Gibbs iterations. If these estimated densities show little variation with additional Gibbs iteration, one may conclude that the Gibbs sampling has converged.

Let us see how the Gibbs sampling method can be applied in this model. Denote

$$V^{in}(y_{it}, \theta^s) = \alpha^s - F_i(1 - y_{it-1}) + \beta EV^s(y_{it} = 1, \epsilon_{t+1}, \alpha^s) \text{ and}$$
$$V^{out}(y_{it}, \theta^s) = \beta EV^s(y_{it} = 0, \epsilon_{t+1}, \alpha^s)$$

where θ^s is defined to be the vector of parameters at s^{th} iteration.

Consider a firm who decides whether to enter or stay in the export market, or to exit or stay out of the export market. Since we assume that we cannot observe the profit shocks, we have to draw ϵ_{1t} and ϵ_{2t}, under the constraint that the shocks are consistent with the observed entry and exit behavior of the firm. That is, if a firm chooses to stay in or enter into the export market at period t, draw a new exogenous shock $\xi_{it} = \epsilon_{2t} - \epsilon_{1t}$ such that it satisfies the condition

$$\xi_{it} \geq V^{out}(y_{it}^d, \alpha^s) - V^{in}(y_{it}^d, \alpha^s)$$

Similarly, if the data shows that a firm chooses to exit or stay out in the market at period t, draw ξ_{it} such that

$$\xi_{it} < V^{out}(y_{it}^{d}, \alpha^{s}) - V^{in}(y_{it}^{d}, \alpha^{s})$$

we define Y_{it} to be as follows.

$$\begin{aligned} Y_{it} &\equiv (V^{in}(\bullet) - \beta EV^{s}(Y_{it} = 1, \epsilon, \alpha^{s})) \\ &\quad - (V^{out}(\bullet) - \beta EV^{s}(Y_{it} = 0, \epsilon, \alpha^{s})) \\ &= \alpha^{s} - F_i(1 - y_{it-1}) \quad + \xi_{it}\, \xi_{it} \sim N(0, \Sigma) \end{aligned}$$

In this model set up, first we draw the latent variable Y_{it} conditional on α and G. Next, we can draw α conditional on G and new drawn Y_{it} in the previous step. Finally, G can be drawn by conditioning on new drawn Y_{it}, and α from the first and second steps respectively. By sampling consecutively from the three steps of conditional posterior distributions, we will see these draws will converge to a single draw from the posterior distribution. This process is repeated to obtain additional draws from the posterior. We will see this procedure in detail below.

The first step is to draw N conditionals of $Y|\alpha^{s}, G^{s}$. This step is the data augmentation described above. The second step is to draw α^{s+1} given Y, G^{s}. Notice that $Y = \{Y_i\}_{i-1}^{N}$ was generated by data augmentation. To make the errors standard normal distributed, we premultiply C', Cholesky root of G^{s}, to both sides of equation. That is,

$$\begin{aligned} &C'Y_i = C'X_i\alpha + C'\xi_i \\ &\Rightarrow Y_i^{*} = X_i^{*}\alpha + \xi_i^{*}, \quad \xi_i^{*} \sim N(0, 1) \\ &\text{or } \; Y^{*} = X^{*}\alpha + \xi^{*}, \quad \xi^{*} \sim N(0, I) \end{aligned}$$

α is the vector of parameters of interest.

The conditional posterior over the parameter values of α has the following normal distribution.

$$\alpha^{s+1} | Y, G^{s} \sim N(\hat{\alpha}, \Sigma_{\alpha}) \text{ where } \Sigma_{\alpha} = (X^{*'} X^{*} + A_{\alpha})^{-1}$$
$$\text{and } \Sigma_{\alpha} = (X^{*'} Y^{*} + A_{\alpha} \underline{\alpha})^{-1}.$$

The third step for the sampler is to draw G^{s+1} conditional on Y and α^{s+1} derived from the first and second step respectively. This step requires the standard Bayesian analysis of a covariance matrix and Wishart theory. Up to the second step, we observe new normally distributed random shocks from substituting Y and α in the equation $\xi_i = Y_i - X_i \alpha^{s+1}$. Then, we draw G^{s+1} from the following Wishart distribution that we define to be $W(a, B)$. i.e.

$$G^{s+1} | \alpha^{s+1}, Y \sim W(v+N, V + \sum_{i=1}^{N} \xi_i \xi_i') \equiv W(a, B)$$

Here is how to draw from a Wishart distribution $W(a, B)$ when B is $p \times p$ matrix, which means there are p choices for the firms. Let $B^{-1} = SS'$. Let T be a lower triangular $p \times p$ matrix with entries T_{ij}, which are independently drawn from standard normal for $i > j$ and from $\sqrt{\chi^2_{(n-p+1)}}$ for diagonal elements. Let $\tilde{V} = TT'$, where $\tilde{V} = W(v, I)$. Then, we can draw from a Wishart distribution by letting $B = S\tilde{V}S$.

As we mentioned so far, we draw from each of the $N+2$ conditional distributions one by one by following three steps we mentioned above. As we keep iterating above three steps, these draws will converge to a single draw from the posterior distribution.

Finally, we describe the expected value function iteration step. It is derived as

$$EV^{s+1}(y_{it},\epsilon)=\frac{\sum_{j=Max s-M,1}^{s} V(y_{it},\epsilon_j,\alpha_j)K_h(\alpha_j-\alpha_{s+1})}{\sum_{j=Max s-M,1}^{s} K_h(\alpha_j-\alpha_{s+1})}$$

where $K(\bullet)$ is the Gaussian kernel function such that

$$K_h(\alpha_j-\alpha_{s+l})=(2\pi)^{-\frac{L}{2}}\prod_{l=1}^{L}\exp[-\frac{1}{2}(\frac{\alpha_{i,j}-\alpha_{l,s+1}}{h_l})^2]$$

In the Bayesian estimation, we calculate the expected value function by simply taking the average over the past M values when the parameter value α_j was very close to α_{s+1}. Pakes and McGuire (2000) show that this kind of Bellman equation step and the expected value function step overcome the "Curse of Dimensionality" problem. By following these step mentioned above so far, we will get the $s+1^{th}$ parameter value and the expected value functions.

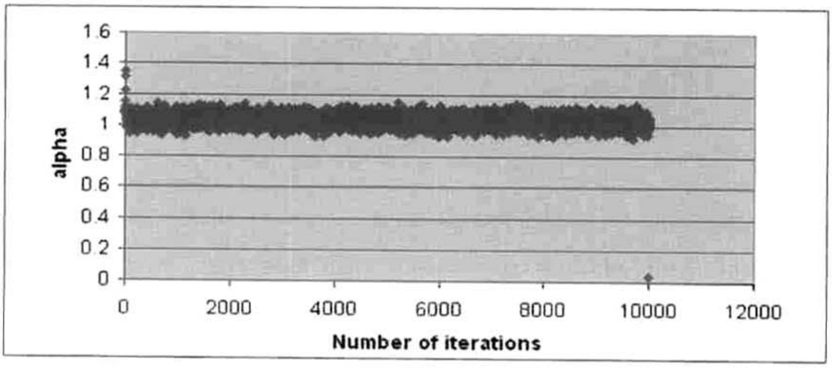
Ⅳ. Estimation Result

We set the true parameters for the model to be $\alpha=1.0$, and $F=1.0$. We first solve the dynamic programming problem numerically to derive the two expected value functions, one for incumbents and the other for potential entrants. With these values, we generate artificial data of entry and exit choices. Then, we estimate back the true parameter values by using the simulated data. We set the discount rate, β, to be 0.9 and do not estimate it. We set the initial guess of the expected value functions to be zero. The profit shocks are normally distributed with mean zero and variance 1. The Gibbs sampling was conducted 10,000 times. The results are shown in table 1 and the Gibbs sampler output is shown in figures 1. The posterior average of α is 1.032, very close to true parameter 1. We can see that the Gibbs sampler of α converges to the true value almost immediately.[2] In figures 2 and 3, we plot the expected values derived during the Gibbs sampling iteration. We can see that the expected values converge to the true value at the same time as the Gibbs sampler of α converges to its true value. In that sense, our Bayesian DP algorithm estimates the parameter and solves the DP problem simultaneously, and not subsequently.

【Table 1】 Estimated parameter value (standard error in parenthesis)

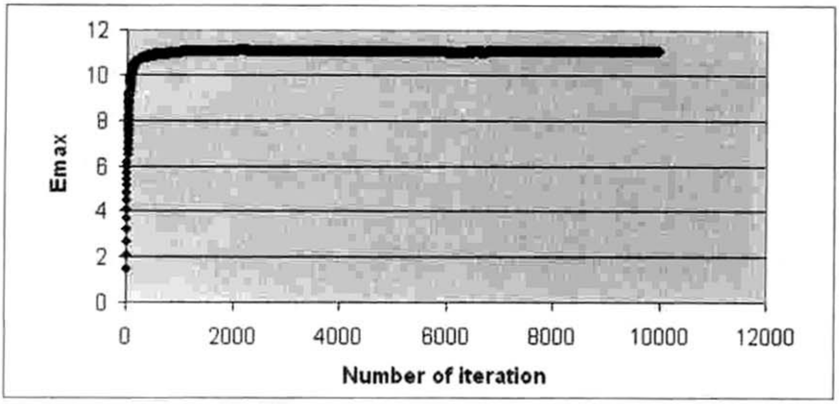
Parameter	True values	Estimated values
α	1	1.032(0.032)

【Figure 1】 The Gibbs draws of estimator

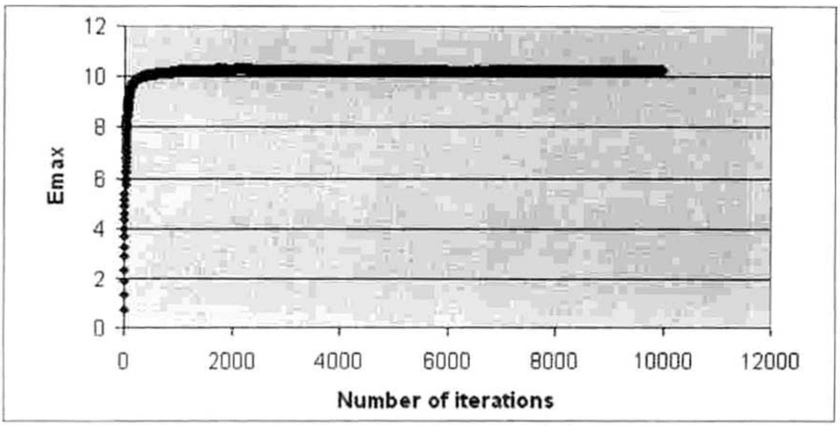


2) The purpose of this paper is to introduce and show a new estimation algorithm to solve the dynamic programming problem. We do not explicitly compare its efficiency with other conventional economic models in this paper. At the last iteration, alpha goes to zero because we set the firm exit at the last stage.

【Figure 2】 The Emax of incumbents



【Figure 3】 The Emax of outsiders



Ⅴ. Conclusion

Most research on estimating dynamic optimal choice models has been using conventional econometric methods such as Maximum Likelihood (ML) Method and Generalized Method of Moments (GMM). It is well known that when the model has many state variables, the estimation becomes computationally difficult due to the "Curse of Dimensionality". Imai, Jain and Ching (2001) recently advocated a new estimation algorithm that is based on the Bayesian estimation technique. It enables us to solve the dynamic programming problem and estimate the parameters simultaneously instead of sequentially. This new method makes the computational burden of estimating the dynamic programming model on the same order of magnitude as those of estimating static model.

In this paper, we estimate a simple model of entry and exit behavior in the export market. We use the Bayesian Dynamic Programming method suggested by Imai, Jain and Ching (2001) and successfully estimate back the true parameter from the simulated data. In the future, we will consider an expanded model to investigate the relationship between domestic market conditions and the entry-exit choice in the export market. Roberts and Tybout (2001) examined firms' dynamic behavior only in the export market. But, obviously most of the producers sell their products both in the domestic market and in the foreign market. Under this situation, we consider the domestic demand changes as a factor that causes the export condition to change. In addition to this assumption, we will consider random effects of an entry cost and an exit cost.

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수출시장 진출입의 구조분석: 베이지언 모형 적용

송 백 훈*

논문초록

동태적 적정선택모형에 관한 많은 연구가 최빈우도법(ML) 및 일반화적률법(GMM) 등 일반적인 계량경제학적 접근법에 기초한다. 하지만, 상태변수가 많아질수록 이와 같은 계량추정법은 규모의 저주(Curse of Dimensionality)로 알려진 문제에 직면한다. 본 고에서는 이러한 문제를 해결하기 위한 베이지언 추정에 기초한 새로운 추정기술을 적용한다. 베이지언 동태프로그래밍 추정법의 효율성을 보여주기 위하여, 먼저 수출시장에서의 진출입모형을 시뮬레이션한다. 그 이후, 시뮬레이션 데이터에 기초하여 모형의 변수를 재추정한다. 본 추정법은 규모의 저주 문제를 해결하면서 동태 프로그래밍 문제를 풀 수 있도록 해주며, 단계별 추정이 아닌 동시 추정을 가능하게 해준다.

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