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Sequential Updating of Price Elasticities of Traffic Demand Incorporating Regional Differences Based on a Hierarchical Bayesian Approach

Makoto CHIKARAISHI
Ph.D. Candidate
Transportation engineering Laboratory,
IDEC, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima
739-8529, Japan
Fax: +81-82-424-6957
E-mail: chikaraishi@hiroshima-u.ac.jp

Akimasa FUJIWARA
Professor
Transportation engineering Laboratory,
IDEC, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima
739-8529, Japan
Fax: +81-82-424-6921
E-mail: afujiw@hiroshima-u.ac.jp

Junyi ZHANG
Associate Professor
Transportation engineering Laboratory,
IDEC, Hiroshima University
1-5-1, Kagamiyama, Higashi-Hiroshima
739-8529, Japan
Fax: +81-82-424-6919
E-mail: zjy@hiroshima-u.ac.jp

Abstract: This paper proposes a method for sequential updating of the short-run and long-run price elasticities of traffic demand incorporating regional differences based on hierarchical Bayesian approach. The elasticities are treated as uncertain elements and updated to make an adjustment of our expectations/beliefs in the behavioral responses. As an empirical analysis, the updating is demonstrated from January through August in 2008 by using monthly traffic volume data on 54 expressway routes in Japan, which include two notable periods: the outdated temporary tariff rate (during April 2008) and the rapid increase of gasoline price (until August 2008). The results show that, even within a year, the short-run and long-run elasticities are quite unstable across space and over time, and underscore that we should make a continued observation of both short-run and long-run elasticities in order to monitor the change of behavioral responses to gasoline price fluctuations.

Key Words: *price elasticity, regional differences, hierarchical Bayesian approach, sequential updating*

1. INTRODUCTION

During 2008, substantial fluctuations of gasoline price were observed all over the world. The price soared until around August 2008, and then dramatically decreased. The gasoline price fluctuations at high levels have undeniable effects on various aspects of travel behavior in various places. Especially during the August 2008 when gasoline price peaked, traffic levels were remarkably reduced. In United States, travel on all roads and streets changed by -5.6% (or -15.0 billion vehicle miles) compared to that in August 2007 (U.S. Department of Transportation: Federal Highway Administration, 2008). In Japan, traffic volumes changed by -8.5% on Metropolitan expressways during this period, compared with those in August 2007. Additionally, in Japan, temporary tariff rate (25.1 Yens per liter) was outdated during April 2008, and it was restored from May 2008. Thus, the gasoline price fluctuations in Japan in 2008 were caused not only by the relation between supply and demand, but also by policy decisions. These facts imply that prediction of the gasoline price in future is quite difficult because there are many factors that go into determining the gasoline price, while the impacts on travel behavior have been certainly observed. These underscore the need to continuously monitor the impacts of gasoline price fluctuations on travel behavior, and to timely reflect the latest information of gasoline price into transportation planning, e.g., the re-review of the existing traffic demand forecasting.

In this context, the price elasticity of traffic demand is a useful indicator, which indicates the marginal change of traffic demand per unit change of gasoline price. As Goodwin (1992) mentioned, elasticities have the great attractions of being empirically estimable, reasonably easily understood, and directly usable for policy assessment. Accordingly, a number of researchers have examined the elasticities of, for example, gasoline consumption (e.g., Drollas, 1984; Schimek, 1996), traffic level (e.g., Schimek, 1996; Johansson and Schipper, 1997), and demand for public transport (e.g., Currie and Phung, 2007), with respect to oil/gasoline price (comprehensive reviews can be found in, for example, Goodwin (1992), Goodwin *et el*. (2004), and Graham and Glaister (2002, 2004)).

The price elasticity of traffic demand gives useful insights that may help predicting the impacts of gasoline fluctuations on the travel demand as well as the effectiveness of, for example, introducing environmental taxes (OECD, 2000). However, some recent studies have pointed out that the elasticities would not be stable for several reasons. First, the elasticities could vary over time (e.g., Hughes *et al*., 2008). Typically, the value of estimated price elasticity depends on data-related issues (e.g., data interval, period, and data type). Especially as for data interval, while a majority of the price elasticity estimates is derived from models based on national data on a yearly basis, this would lose information of the gasoline price fluctuations occurred within a year by taking aggregate average. Thus, it is clear that more detailed data is required when we attempt to capture the impacts of current gasoline price fluctuations occurred within the year of 2008. Second, the behavioral responses would vary with the spatial conditions (e.g., Tanishita, 2005), such as the quality of public transport service as an alternative mode. Third, the effects of an x% increase in the price would not be equal to x% increase in the demand, i.e., the behavioral responses would be asymmetry with respect to upward and downward price changes (e.g., Dargay and Gately, 1997). Fourth, the behavioral responses would depend on the types of price changes, such as a change of tax system, the interplay of supply and demand, and so on (OECD, 2000). The above-mentioned matters imply that there would be no unique price elasticity, and the elasticity seems to be uncertain. Moreover, the above-mentioned factors would be intricately interrelated, and thus it seems to be difficult to pinpoint the exact cause. In this sense, it would be better to continuously confirm whether price elasticity of traffic demand change or not rather than seeking a unique causal factors through some sort of hypothesis testing. In other words, it might be better to update the elasticity as quickly as possible in order to make an adjustment of our prior expectations of price elasticity sequentially. However, to the authors' knowledge, relevant methodologies have not been satisfactory developed in existing studies.

Under such circumstances, this paper attempts to develop a method for sequential updating of the short-run and long-run price elasticities of traffic demand incorporating regional differences based on hierarchical Bayesian approach. The proposed method incorporates regional differences of price elasticities by using a random coefficient model, which is estimated as a hierarchical Bayesian model, and takes into account temporal changes through a Bayesian updating to make an adjustment of our expectations/beliefs about the elasticities. In other words, the method aims at following the tracks of behavioral responses (i.e., the elasticities) through this updating system, just like a sequential monitoring of actual phenomena through some sorts of devices, repeated questionnaires, and so on. In empirical analysis, we focus on the impacts of outdated temporary tariff rate (during April 2008) and the rapid increase of gasoline price (until August 2008) on the behavioral responses. We will use monthly traffic volume data of some major expressways in Japan, which would be one of the most suitable data to capture the latest traffic situation, because the data is rapidly-available from inflow/outflow traffic volume on tollgate with a high degree of accuracy. Although the data is rather approximate measures and could not represent general situation perfectly, it would be eligible for quick monitoring of the change of behavioral responses. In empirical analysis, we use the data of 54 expressway routes, and the updating will be demonstrated from January through August in 2008. The paper highlights the spatiotemporal stabilities/ changes of the price elasticities.

This paper is organized as follows. The next chapter describes the model development to obtain the elasticity of each region through hierarchical Bayesian approach, and the Bayesian updating method for adjusting our prior expectations/beliefs of price elasticities. Chapter 3 describes the data used in this study. In Chapter 4, the developed model is estimated, and updating results are described and discussed. Finally, this study is concluded in Chapter 5.

2. METHODOLOGICAL FRAMEWORK

To calculate the short-run and long-run price elasticities, a partial adjustment model has been widely used. Short-run elasticity refers to responses made within one period of the data, while long-run elasticity refers to the asymptotic end state when the responses are completed (i.e., reaching the appropriate equilibrium). The rationale is that states of conflict between the desired change and the actual change would prevent reaching appropriate equilibrium level, and then only a portion of the desired change in behavior between periods would be realized. The partial adjustment model is composed of two parts, and in this study the following model structure is assumed:

$$\ln\left(Q_{imy}\right)-\ln\left(Q_{im(y-1)}\right)=\lambda\left(\ln\left(Q^{*}_{imy}\right)-\ln\left(Q_{im(y-1)}\right)\right) \tag{1}$$

$$\ln\left(Q^{*}_{imy}\right)=\theta_{i0}+\theta_{i2}\ln\left(P_{imy}\right)+\theta_{i3}T_{my}+e_{imy} \tag{2}$$

where Q^{*}_{imy} is the desired level of Q_{imy} which is the traffic volume on expressway route i during month m of year y; λ represents “adjustment speed” which would lies between 0 and 1 because of the states of conflict mentioned above. When λ gets closer to 1, the adjustment of traffic level would be completed immediately. $Q_{im(y\text{-}1)}$ is the traffic volume in the same period of last year, and therefore λ would be annual adjustment speed toward the desired traffic level. P_{imy} is the pump price of regular gasoline in the region (at prefecture level) around route i during month m of year y (if a corresponding route passes through more than one prefecture, the average price of these prefectures will be used), and T_{my} is time for representing trend of traffic demand. θ_{i0}, θ_{i2} and θ_{i3} are unknown parameters. e_{imy} is random error term. Here, although there might be the other influential factors affecting traffic volumes (e.g., the number of automobiles), we could not introduce these factors because these data are not available on a monthly basis. In the future, it is necessary to confirm whether ignoring these factors leads to biased estimates or not.

By substituting eq. (2) into eq. (1), we obtain the following equation:

$$\ln\left(Q_{imy}\right)=\beta_{i0}+\beta_{i1}\ln\left(Q_{im(y-1)}\right)+\beta_{i2}\ln\left(P_{imy}\right)+\beta_{i3}T_{my}+\varepsilon_{imy} \tag{3}$$

where $\beta_{i0} = \lambda\theta_{i0}$, β_{i1} = 1-λ, $\beta_{i2} = \lambda\theta_{i2}$, and $\beta_{i3} = \lambda\theta_{i3}$. ε_{imy} represents λe_{imy} which is assumed as $\varepsilon_{imy} \sim N(0, \sigma^2{}_0)$. As we can confirm, this formulation is intrinsically linear in the parameters (β_{i0}, β_{i1}, β_{i2}, β_{i3}), and we will estimate β_{i0}, β_{i1}, β_{i2} and β_{i3} instead of λ, θ_{i0}, θ_{i2} and θ_{i3}. The short-run price elasticity is given by β_{i2} according to the definition of the elasticity, i.e., [(% change in traffic demand) / (% change in gasoline price)] = [(dQ/Q)/(dP/P)] = [dln(Q)/dln(P)]. The long-run elasticity is defined as β_{i2}/(1-β_{i1}) which represents the states fully adjusted to the desired change with the assumption of stable demand structure. Here, the assumption of stable demand structure would not hold over time as mentioned above (and also our results indicate unstable demand structure as shown later), and thus the long-run elasticity would not be realistic. However, it is still interesting to examine what would happens if the demand structure does not change over time, especially for a better understanding of the behavioral responses to gasoline price fluctuations.

To incorporate the regional (route) differences into eq. (1), the unknown parameters β_{i0}, β_{i1}, β_{i2} and β_{i3} are treated as random coefficients. Here, one can employ a simple way to obtain the route-specific elasticities by estimating the model for each route separately. However, Maddala et al. (1997) pointed out that such separate estimations could give wrong signs and are highly unstable in the context of energy demand at the state level of the USA. To resolve this problem, Maddala et al. (1997) applied a random coefficient model to obtain the elasticities for each state, and confirmed that these elasticities gave much more reasonable parameter values. Following their empirical results, this study attempts to apply a similar random coefficient model.

Suppose that $\boldsymbol{\beta_i}$ (=(β_{i0}, β_{i1}, β_{i2}, β_{i3})) is distributed normally with mean $\boldsymbol{\mu}$ (=(μ_0, μ_1, μ_2, μ_3)) and covariance matrix $\sum$ as follows:

$$(\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}) = (\mu_0 + \gamma_{i0}, \mu_1 + \gamma_{i1}, \mu_2 + \gamma_{i2}, \mu_3 + \gamma_{i3}) \tag{4}$$

$$(\gamma_{i0}, \gamma_{i1}, \gamma_{i2}, \gamma_{i3}) \sim N(0, \Sigma), \quad \Sigma = \begin{bmatrix} \sigma_{\beta 0}^2 & \sigma_{\beta 01} & \sigma_{\beta 02} & \sigma_{\beta 03} \\ \sigma_{\beta 01} & \sigma_{\beta 1}^2 & \sigma_{\beta 12} & \sigma_{\beta 13} \\ \sigma_{\beta 02} & \sigma_{\beta 12} & \sigma_{\beta 2}^2 & \sigma_{\beta 23} \\ \sigma_{\beta 03} & \sigma_{\beta 13} & \sigma_{\beta 23} & \sigma_{\beta 3}^2 \end{bmatrix} \tag{5}$$

where μ_0, μ_1, μ_2 and μ_3 represent route average effects of corresponding explanatory variables, while γ_{i0}, γ_{i1}, γ_{i2} and γ_{i3} represent route-specific differences from the average effects. This extended partial adjustment model allows us to calculate route-specific price elasticity, i.e., the short-run elasticity is given by μ_2+γ_{i2} (=β_{i2}) for route i, and the long-run elasticity is defined as μ_2+γ_{i2}/(1-μ_1+γ_{i1}) for route i.

The route i's probability density in eq. (3) with random coefficients can be written as follows:

$$L_i(\boldsymbol{Q_i}, \boldsymbol{x_i} \mid \boldsymbol{\mu}, \Sigma, \sigma_0) = \int_{\boldsymbol{\beta_i}} \prod_{my \in TT_i} f(Q_{imy}, x_{imy} \mid \boldsymbol{\beta_i}, \sigma_0) p(\boldsymbol{\beta_i} \mid \boldsymbol{\mu}, \Sigma) d\boldsymbol{\beta_i} \tag{6}$$

where $\boldsymbol{x_i}$ is route-specific data of explanatory variables (e.g, $\boldsymbol{x_1}$ ={$\boldsymbol{Q_{1m(y\text{-}1)}}$, $\boldsymbol{P_{1my}}$, $\boldsymbol{T_{my}}$ | $my \in TT_i$}) and x_{imy} represents the set of explanatory variables for each sample; TT_i is total observing period of traffic volume; f (Q_{imy}, x_{imy} | $\boldsymbol{\beta_i}$, σ_0) represents the probability density for each sample which is conditional on $\boldsymbol{\beta_i}$. It is assumed to be normally distributed with a mean [ln(Q_{imy}) − β_{i0} − β_{i1}ln($Q_{im(y\text{-}1)}$) − β_{i1}ln(P_{imy}) −$\beta_{i3}T$] and variance σ^2_0. p($\boldsymbol{\beta_i}$ | $\boldsymbol{\mu}$, $\sum$) denotes the four-dimensional normal density for $\boldsymbol{\beta_i}$ given mean $\boldsymbol{\mu}$ and covariance $\sum$. Here, it should be noted that, for the autoregressive nature of traffic demand, although $Q_{im(y\text{-}1)}$ might be able to accommodate the annually autoregressive nature of traffic demand for each route, this study could not take into account serial correlations of the error term, because, in a random coefficient model, a single error term is introduced for representing the residuals in all the routes. The development of the method for accommodating such correlation effects customized to the situation in each route in the context of a random coefficient model still remains to be solved in the future. The likelihood for all routes can be defined as follows:

$$L(\boldsymbol{\mu}, \Sigma, \sigma_0 \mid \boldsymbol{Q}, \boldsymbol{x}) = \prod_{i \in I} L_i(\boldsymbol{Q}_i, \boldsymbol{x}_i \mid \boldsymbol{\mu}, \Sigma, \sigma_0) \quad (7)$$

To obtain the estimated parameter set $\{\hat{\boldsymbol{\mu}}, \hat{\Sigma}, \hat{\sigma}_0\}$, in this study, the hierarchical Bayesian procedure based on Markov Chain Monte Carlo (MCMC) method is applied. This method incorporates prior distribution assumptions and, based upon successive sampling from posterior distributions of the model parameters, yields a chain which is then used for making point and interval estimations. Although there are several alternative ways to maximize this likelihood function such as restricted maximum likelihood method and maximum simulated likelihood method (Goldstein, 2003; Train, 2003), the hierarchical Bayesian approach would be desirable, given the extension to updating of our expectations/beliefs of price elasticities as shown later.

In the Bayesian formulation, we combine prior information about all parameters with the likelihood based on the data. These parameters are regarded as random variables described by probability distributions. Suppose the prior distributions on, $\boldsymbol{\mu}$ is normal distribution [$p(\boldsymbol{\mu}) \sim N(\boldsymbol{\mu}_0, \boldsymbol{V}_{\boldsymbol{\mu}})$; $\boldsymbol{\mu}_0$ and $\boldsymbol{V}_{\boldsymbol{\mu}}$ are given parameters], $\sum$ is inverted Wishart distribution [$p(\sum) \sim$ Wishart $(c, \sum_0)^{-1}$; c and $\sum_0$ are given parameters], and $\sigma^2{}_0$ is inverted Gamma distribution [$p(\sigma_0) \sim$ Gamma$(a, b)^{-1}$; a and b are given parameters]. These prior distributions correspond to conjugate prior distributions, which mean that the posterior distributions can be specified within the same distributional families as the prior distributions (Gill, 2008). In this case, we can derive the conditional posterior distributions analytically as described later (see eq.(10)). Besides, each $\boldsymbol{\beta}_i$ is considered to be a parameter along with $\boldsymbol{\mu}$ and $\sum$ for fast and simple sampling (Train, 2003). This additional procedure creates "hierarchical" sampling procedure, and then we could gain the parameters $\boldsymbol{\beta}_i$ for each route directly from successive sampling. Note that, when we assign non-informative prior densities for all given parameters, the estimated parameters would be equivalent to these obtained through the above-mentioned maximum likelihood methods (Goldstein, 2003; Train, 2003). Based on the above-mentioned settings, the joint posterior density of all the parameters conditioned on observed data can be written as follows:

$$\pi(\boldsymbol{\beta}_1, \ldots, \boldsymbol{\beta}_I, \boldsymbol{\mu}, \boldsymbol{\Sigma}, \sigma_0 \mid \boldsymbol{Q}, \boldsymbol{x}) \propto \prod_{i \in I} \prod_{my \in TT_i} f(Q_{imy}, x_{imy} \mid \boldsymbol{\beta}_i, \sigma_0) p(\boldsymbol{\beta}_i \mid \boldsymbol{\mu}, \boldsymbol{\Sigma}) p(\boldsymbol{\mu}) p(\boldsymbol{\Sigma}) p(\sigma_0) \quad (8)$$

Without loss of generality, eq. (6) can be rewritten by using $\boldsymbol{\gamma}_i$ $(=(\gamma_{i0}, \gamma_{i1}, \gamma_{i2}, \gamma_{i3}))$ as follows:

$$\pi(\gamma_1, \ldots, \gamma_I, \boldsymbol{\mu}, \boldsymbol{\Sigma}, \sigma_0 \mid \boldsymbol{Q}, \boldsymbol{x}) \propto \prod_{i \in I} \prod_{my \in TT_i} f(Q_{imy}, x_{imy} \mid \gamma_i, \boldsymbol{\mu}, \sigma_0) p(\gamma_i \mid \boldsymbol{\Sigma}) p(\boldsymbol{\mu}) p(\boldsymbol{\Sigma}) p(\sigma_0) \quad (9)$$

Sampling from this posterior is obtained using software WinBUGS (Bayesian inference Using Gibbs Sampling (Lunn *et al*., 2000)) in this study. A sampling of each parameter is taken, conditional on the other parameters as follows:

Step1: Set the initial values, $\boldsymbol{\mu}^{(0)}, \Sigma^{(0)}$ and $\sigma_0^{(0)}$.

Step2: Repeat the following procedures (t = 1,2,…).

(a) Sampling $\boldsymbol{\mu}^{(t)}$ from $\pi(\boldsymbol{\mu} \mid \boldsymbol{\gamma}_1^{(t-1)}, \ldots, \boldsymbol{\gamma}_I^{(t-1)}, \Sigma^{(t-1)}, \sigma_0^{(t-1)}, \boldsymbol{Q}, \boldsymbol{x})$

(b) Sampling $\boldsymbol{\gamma}_i^{(t)}$ from $\pi(\boldsymbol{\gamma}_i \mid \boldsymbol{\mu}^{(t)}, \Sigma^{(t-1)}, \sigma_0^{(t-1)}, \boldsymbol{Q}, \boldsymbol{x})$

(c) Sampling $\Sigma^{(t)}$ from $\pi(\Sigma \mid \boldsymbol{\mu}^{(t)}, \boldsymbol{\gamma}_1^{(t)}, \ldots, \boldsymbol{\gamma}_I^{(t)}, \sigma_0^{(t-1)}, \boldsymbol{Q}, \boldsymbol{x})$

(d) Sampling $\sigma_0^{2(t)}$ from $\pi(\sigma_0^2 \mid \boldsymbol{\mu}^{(t)}, \boldsymbol{\gamma}_1^{(t)}, \ldots, \boldsymbol{\gamma}_I^{(t)}, \boldsymbol{\Sigma}^{(t)}, \boldsymbol{Q}, \boldsymbol{x})$

Step3: Obtain these samples after the chain has converged.

where,
$$\begin{aligned}
&\pi(\boldsymbol{\mu} \mid \gamma_1,\ldots,\gamma_I,\Sigma,\sigma_0,\boldsymbol{Q},\boldsymbol{x}) \sim N\left(\boldsymbol{A}^{-1}\left\{\textstyle\sum_{i\in I}\boldsymbol{x}_i^T(\boldsymbol{Q}_i-\boldsymbol{x}_i\gamma_i)+\sigma_0^2\boldsymbol{V}_\mu^{-1}\boldsymbol{\mu}_0\right\},\sigma_0^2\boldsymbol{A}^{-1}\right)\\
&\pi(\boldsymbol{\gamma}_i \mid \boldsymbol{\mu},\Sigma,\sigma_0,\boldsymbol{Q},\boldsymbol{x}) \sim N\left(\boldsymbol{B}^{-1}\left\{\boldsymbol{x}_i^T(\boldsymbol{Q}_i-\boldsymbol{x}_i\boldsymbol{\mu})\right\},\sigma_0^2\boldsymbol{B}^{-1}\right)\\
&\pi(\Sigma \mid \boldsymbol{\mu},\gamma_1,\ldots,\gamma_I,\sigma_0,\boldsymbol{Q},\boldsymbol{x}) \sim Inverse-Wishart\left(I+c,\textstyle\sum_{i\in I}\boldsymbol{\gamma}_i^T\boldsymbol{\gamma}_i+\Sigma_0\right)\\
&\pi(\sigma_0^2 \mid \boldsymbol{\mu},\gamma_1,\ldots,\gamma_I,\Sigma,\boldsymbol{Q},\boldsymbol{x}) \sim Inverse-Gamma\left(N/2+a,\textstyle\sum_{i\in I}\boldsymbol{S}_i/2+b\right)\\
&\boldsymbol{S}_i=(\boldsymbol{Q}_i-\boldsymbol{x}_i\boldsymbol{\mu}-\boldsymbol{x}_i\boldsymbol{\gamma}_i)^T(\boldsymbol{Q}_i-\boldsymbol{x}_i\boldsymbol{\mu}-\boldsymbol{x}_i\boldsymbol{\gamma}_i),\ \boldsymbol{A}=\textstyle\sum_{i\in I}\boldsymbol{x}_i^T\boldsymbol{x}_i+\sigma_0^2\boldsymbol{V}_\mu^{-1},\ \boldsymbol{B}=\boldsymbol{x}_i^T\boldsymbol{x}_i+\sigma_0^2\Sigma^{-1}
\end{aligned} \tag{10}$$

The first some values from the chain will be discarded as the "burn-in" phase and the result will be shown based on the samples obtained after the chain has converged to the joint posterior distribution. Geweke diagnostic, as mentioned in Section 4, will be used to judge whether the obtained samples are converged or not. Note that, when we assign non-informative prior densities for all given parameters, the estimated parameter $\hat{\boldsymbol{\mu}}$ would be equivalent to BLUE (Best Linear Unbiased Estimator), and $\hat{\boldsymbol{\gamma}}_i$ would be equivalent to BLUP (Best Linear Unbiased Prediction) originally shown by Henderson (1950). As with BLUP, $\hat{\boldsymbol{\gamma}}_i$, which represents route differences from the average, can be referred to "shrinkage estimator" which is a compromise estimate between the unstable heterogeneous estimate (which could be obtained by separate estimate for each route) and the untenable homogeneity estimate (which could be obtained by pooled estimate (i.e., without considering regional differences)). The degree of shrinkage depends on the reliability of inference for each route, e.g., if the great number of sample for each route, the estimate would be less shrunk, and vice versa. In other words, this shrinkage means that a certain route estimates borrow "strength" from the other route estimates (Kreft and de Leeuw, 1998). Here, it should be noted that, although the route-specific elasticities $\hat{\boldsymbol{\mu}}+\hat{\gamma}_i$ for each route are interrelated through covariance matrix $\hat{\Sigma}$ as described in eq. (10), this doesn't mean that the model reflects spatial correlations among routes. In this study, we assume that there are no spatial correlations among routes, considering that usually there are little competing expressway routes in the neighborhood, especially in the case of aggregated traffic volume used in this study. Nonetheless, because there is a possibility that there exist some spatial correlations especially in a high dense network area (i.e., urban expressway routes), we must confirm whether there exist spatial correlations or not as well as the interactions with competing ordinary roads in the future.

The quite similar "shrinkage" mechanism can be observed in the given parameters in prior distributions (i.e., $\boldsymbol{\mu}_0$, $\boldsymbol{V}_\mu$, a, b, c, and Σ_0) when we assign the informative prior distributions, which is called Bayesian shrinkage. The difference is that BLUP makes shrinkage toward "average" from separate estimates for each of route, while Bayesian shrinkage is toward the given parameters in the priors. Thus, when we assign informative priors based on our prior expectations/beliefs, the posterior distributions would be shrunk back to the prior distributions away from the posteriors with non-informative priors. For example, if we have the strong belief on $\boldsymbol{\mu}$, which means that a certain our expectation value is set for $\boldsymbol{\mu}_0$ with high confidence ($\boldsymbol{V}_\mu\rightarrow 0$ i.e., $\boldsymbol{V}^1_\mu\rightarrow\infty$), the sampling form $\pi(\boldsymbol{\mu}\mid\gamma_1,\ldots,\gamma_I,\Sigma,\sigma_0,\boldsymbol{Q},\boldsymbol{x})$ in eq. (10) would strongly depends on the prior because $\sigma^2_0\boldsymbol{V}^1_\mu\boldsymbol{\mu}_0$ and $\sigma^2_0\boldsymbol{V}^1_\mu$ become the dominant in the sampling process in $\pi(\boldsymbol{\mu}\mid\gamma_1,\ldots,\gamma_I,\Sigma,\sigma_0,\boldsymbol{Q},\boldsymbol{x})$ in eq. (10). This Bayesian shrinkage property offers a comprehensive way of routine updating/learning that is not dependent upon any particular assumptions when the updating is started with the non-informative prior at initial stage. Suppose we obtain new information $Q_{i(m+1)y}$, $x_{i(m+1)y}$ at TT_i +1. In this case, the joint posterior distribution can be written as follows:

$$
\begin{aligned}
&\pi\left(\gamma_1,\ldots,\gamma_I,\boldsymbol{\mu},\boldsymbol{\Sigma},\sigma_0 \mid \boldsymbol{Q},\boldsymbol{x},Q_{i(m+1)y},x_{i(m+1)y}\right)\\
&\qquad\propto \prod_{i\in I}\prod_{my\in TT_i+1} f\left(Q_{imy},x_{imy}\mid \boldsymbol{\gamma_i},\boldsymbol{\mu},\sigma_0\right)p(\boldsymbol{\gamma_i}\mid \boldsymbol{\Sigma})p(\boldsymbol{\mu})p(\boldsymbol{\Sigma})p(\sigma_0)\\
&\qquad\propto \prod_{i\in I} f\left(Q_{i(m+1)y},x_{i(m+1)y}\mid \boldsymbol{\gamma_i},\boldsymbol{\mu},\sigma_0\right)\pi\left(\gamma_1,\ldots,\gamma_I,\boldsymbol{\mu},\boldsymbol{\Sigma},\sigma_0 \mid \boldsymbol{Q},\boldsymbol{x}\right)\\
&\qquad\propto [\text{Likelihood based on new information}]\\
&\qquad\qquad\qquad\times[\text{Previous posterior (= new prior)}]
\end{aligned}
\tag{11}
$$

The joint posterior distribution with new information therefore can be obtained by multiplying the likelihood function based only on the new information ($Q_{i(m+1)y}$ and $x_{i(m+1)y}$) by the joint posterior up to previous period TT_i. More specifically, to update our posterior, i.e., to improve our state of expectations/beliefs, we simply treat the previous posterior as a prior and proceed to calculate using a likelihood function from new data (Figure 1). This cycle of prior to posterior can be repeated in infinitum, and our expectations/beliefs continue to update the posterior when new information is available. In fact, this idea is quite similar with the sequential monitoring of the actual phenomena: a sequential monitoring through some sorts of devices, repeated questionnaires, etc., is conducted in order to monitor the change of phenomena under study. Otherwise, sequential monitoring would not be needed. In a similar fashion, this updating system aims at capturing the changes of the behavioral responses over time. The needs for paying attention to the changes of responses are clear because the elasticities seem to be unstable, as pointed out by a number of studies (e.g., Dargay and Gately, 1997; Tanishita, 2005; Hughes *et al*., 2008). In the next section, we will demonstrate the updating of the short-run and long-run elasticities from January through August 2008.

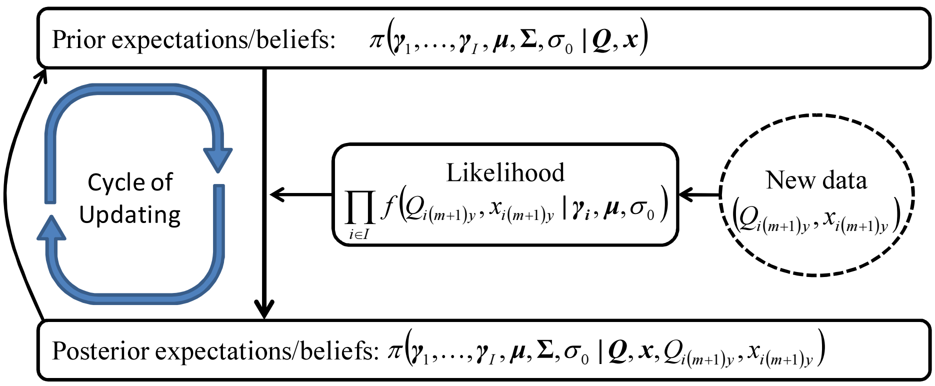


Figure 1 Bayesian updating

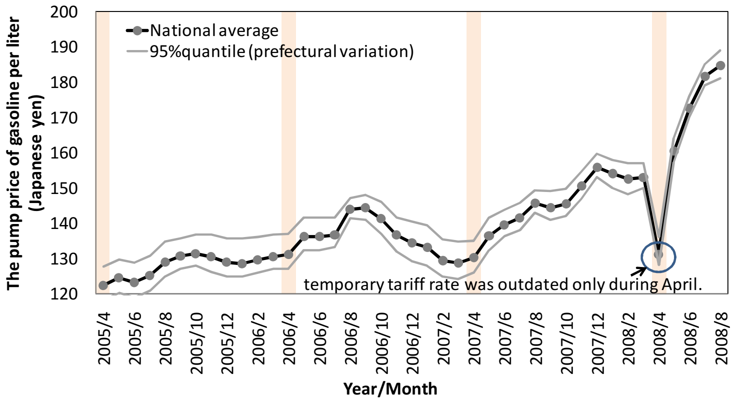
3. DATA

In empirical analysis, we use the expressway traffic volume data from three data sources in Japan as shown in Table 1. The traffic volume data include all types of vehicle (i.e., private vehicle, business track, bus, etc). The reason for employing traffic volume data is that the data is rapidly-available from inflow/outflow traffic volume on tollgate with a high degree of accuracy. As shown in Table 1, totally 54 routes are used in the empirical analysis: 3 routes are from Metropolitan Expressway, 42 routes from East Nippon Expressway, and 9 routes from West Nippon Expressway. The data of Metropolitan Expressway and East Nippon Expressway are available from their web sites. The periods of observed traffic volume data differ from source to source. Here, the traffic volume data of the first 12-month period can be used only as the objective variables in the model estimation, and these as 12-month lagged explanatory variables are missing variables. To deal with these missing variables, in this study, data augmentation technique is applied, which is originally proposed by Tanner and Wong (1987). Note that we use this method only for Metropolitan Expressway data and East Nippon Expressway data, and traffic volume data of the first 12-month period in West Nippon Expressway are removed from the samples used in the model estimation (because the number of samples in West Nippon Expressway data are higher than the other data sources, we assume that enough reliable results could be obtained without data augmentation). The data augmentation technique is summarized in the following. To simplify the expression, a set of unknown parameters are rewritten as $\boldsymbol{\theta}$ (= $\{\gamma_1,\ldots,\gamma_I,\boldsymbol{\mu},\boldsymbol{\Sigma},\sigma_0\}$), observed data as $\mathbf{Y}_{\text{obs}}$, and missing data as $\mathbf{Y}_{\text{mis}}$ (i.e., the first 12-month lagged variables for Metropolitan Expressway and East Nippon Expressway), and thus the posterior $\pi(\gamma_1,\ldots,\gamma_I,\boldsymbol{\mu},\boldsymbol{\Sigma},\sigma_0 \mid \boldsymbol{Q},\boldsymbol{x})$ can be rewritten as $\pi(\boldsymbol{\theta} \mid \mathbf{Y}_{\text{obs}},\mathbf{Y}_{\text{mis}})$. The data augmentation algorithm consists of two parts: 1) the imputation step (I-step), which imputes the missing values given all the observed data and current set of parameters, i.e., $\pi(\mathbf{Y}_{\text{mis}} \mid \mathbf{Y}_{\text{obs}},\boldsymbol{\theta})$ is corresponding to I-step, and 2) posterior step (P-step), in which the parameters of the model are drawn from posterior distribution given the complete data formed from the I-step, i.e., $\pi(\boldsymbol{\theta} \mid \mathbf{Y}_{\text{obs}},\mathbf{Y}_{\text{mis}})$ is corresponding to P-step. In this algorithm, the missing values could be regarded as one of the unknown parameters, and thus the idea of data augmentation is a straightforward extension of the above-mentioned sampling procedure (adding the imputation process in the same way of the sampling of other unknown parameters). The imputations would be conducted under the missing at random assumption. More detailed explanation of the data augmentation can be found in, for example, Daniels and Hogan (2008). As mentioned later, the impacts of the data augmentation on the parameters are not so significant in the empirical analysis, while the goodness-of-fit is slightly improved.

Gasoline prices from April 2005 through August 2008 in Japan are shown in Figure 2. We can confirm that gasoline price basically have remained on the upward trend during this period. The highest price is around 185 Yens in August 2008. We can also confirm that the price increase/decrease by outdated tariff rate in April 2008 show sharp declines than the others.

Table 1 Data used in this study

Data	Source
Traffic volume by route on a monthly basis 3 routes in total (2005.4-2008.8)	Metropolitan Expressway Company Limited. (http://www.shutoko.jp/)
Traffic volume by route on a monthly basis 42 routes in total (2006.4-2008.8)	East Nippon Expressway Company Limited. (http://www.e-nexco.co.jp/)
Traffic volume by route on a monthly basis 9 routes in total (2004.4-2008.8)	West Nippon Expressway Company Limited. (survey by branch office of Chugoku region)
Pump price of regular gasoline by prefecture on a monthly basis (2005.4-2008.8)	The Oil Information Center of the Institute of Energy Economics, Japan (http://oil-info.ieej.or.jp/index.html)



Note: One US dollar is equal to 98.5 Japanese yen on October 30, 2008.

Figure 2 Gasoline prices from April 2006 to August 2008 in Japan

4. MODEL ESTIMATION AND UPDATING RESULTS

4.1 Estimation Results

In the empirical analysis, we totally estimate four models: 1) OLS with pooled data (i.e., it does not reflect route differences) as a benchmark, 2) Bayesian estimation with the pooled data for checking the effects of data augmentation, 3) OLS for each of route separately as one of the most common way for representing regional differences, and 4) hierarchical Bayesian estimation (random coefficient model) proposed in Chapter 2. OLS estimations were carried out using 1,170 samples (samples including missing variables were excluded), while Bayesian estimations were carried out using 1,710 samples (missing data were imputed by the data augmentation). In Bayesian estimation, the non-informative prior distributions are given for all parameters, and we specify a total of 3,600,000 iterations in order to obtain 10,000 draws: the first 600,000 for burn-in to mitigate start-up effects and 3,000,000 after convergence, of which every 300 samples is retained. Although the number of iterations is relatively high than usual, it makes the estimated elasticities for each of route remarkably stable even when we conduct the iterations with different initial values, and the amount of correlation among the samples is quite low. In order to check the convergence, Geweke diagnostic (Geweke, 1992) is used in this study (for other diagnostics and the discussion of the model convergence, please refer to Gill (2008)). The Geweke diagnostic takes two non-overlapping parts (the first 0.1 and last 0.5 proportions) of the samples and compares the means of both, using a difference of means test to see if the two parts of the chain are from the same distribution (null hypothesis). The test statistic is a standard Z-score with the standard errors adjusted for autocorrelation. The estimation results with full dataset (to August 2008) are shown in Table 2. Geweke diagnostics in estimation results of “Bayesian (pooled)” and “Bayesian (shrinkage)” indicate that the parameter chains are well-converged.

Based on the comparison between the estimation results of “OLS (pooled)” and “Bayesian (pooled)” in Table 2, the influences of data augmentation seem to be quite small. The estimated coefficients are almost the same between them as well as short-run elasticity and long-run elasticity, while the R^2 is slightly improved. This implies that we might not need to impute the missing data when we only focus on whether there exist biases in estimated elasticities or not, while data augmentation might be needed from the perspective of the model prediction accuracy. On the other hand, the estimated short-run and long-run elasticities vary according to whether regional (route) differences are considered or not, even when we focus on the average price elasticities: the short-run (long-run) elasticities in pooled estimations are -0.218 and -0.219 (-26.9 and -27.1), while the averages of the short-run (long-run) elasticities taking into account regional differences are -0.116 and -0.120 (-0.925 and -0.917). Considering the estemated short-run (long-run) elasticities in previous studies are about -0.2 (-0.8) in previous studies (e.g., Goodwin, 1992; Goodwin *et el*., 2004; Graham and Glaister, 2002: note that these values vary from case to case, and there are few empirical evidences based on expressway traffic volume data), the estimated elasticities taking into account regional differences seem to be more realistic. In addition, the estimated elasticities in “OLS (separate)” also seem to be unrealistic when we focus on the elasticity of each route. Especially in the long-run elasticities, the values vary from -145.1 to 289.7, while these in “Bayesian (shrinkage)” are between -3.306 to -0.505. These results are quite consistent with the results of Maddala *et al*. (1997) in which the price elasticities of energy demand was analyzed. Their empirical estimations underscore that 1) pooled estimates give a very high coefficient of the lagged dependent variable, 2) the separate estimates are hard to interpret and has several wrong signs, and 3) the estimates using random coefficient model (i.e., shrinkage estimators) give much reasonable parameter values. Our results also indicate that the shrinkage estimation based on random coefficient approach would be a more reasonable way to obtain the price elasticities than other estimation methods. The comparison of goodness-of-

Table 2 Estimation results of the models

Explanatory variables		OLS (pooled) param	S.E.	t value	Bayesian (pooled)[a] mean	S.E.	Geweke
Constant	μ_0	0.110	0.022	5.06	0.132	0.013	-0.399
Lagged dependent variable (year-ago month)	μ_1	0.992	0.002	568.68	0.992	0.001	0.580
Gasoline price	μ_2	-0.219	0.043	-5.12	-0.218	0.036	0.250
Time (trend)	μ_3	8.5.E-04	4.6.E-04	1.86	8.6.E-04	3.8.E-04	-0.364
Short-run elasticity [$=\mu_2$]			-0.219			-0.218	
Long-run elasticity [$=\mu_2/(1-\mu_1)$]			-27.1			-26.9	
Number of sample			1170			1710	
R^2			0.9965			0.9971	
-2*log likelihood with posterior means of params			-			-3537.33 [d]	
DIC (Deviance Information Criterion)			-			-3262.92	

Explanatory variables		OLS (separate) mean[b]	var[c]	min/max	Bayesian (shrinkage)[a] mean	S.E.	Geweke
Constant	μ_0	0.723	0.688	(-2.49/3.54)	0.723	0.118	0.899
Lagged dependent variable (year-ago month)	μ_1	0.875	0.034	(0.05/1.20)	0.870	0.026	-1.083
Gasoline price	μ_2	-0.116	0.035	(-1.11/0.18)	-0.120	0.029	0.720
Time (trend)	μ_3	-1.5.E-04	4.9.E-05	(-0.01/0.03)	1.0.E-04	9.4.E-04	-1.149
Variance of β_{i0}	$\sigma^2_{\beta 0}$	-	-	-	0.414	0.096	1.269
Variance of β_{i1}	$\sigma^2_{\beta 1}$	-	-	-	0.024	0.005	1.367
Variance of β_{i2}	$\sigma^2_{\beta 2}$	-	-	-	0.015	0.007	-0.605
Variance of β_{i3}	$\sigma^2_{\beta 3}$	-	-	-	3.8.E-05	8.3.E-06	0.031
Covariance between β_{i0} and β_{i1}	$\sigma_{\beta 01}$	-	-	-	-0.094	0.022	-1.279
Covariance between β_{i0} and β_{i2}	$\sigma_{\beta 02}$	-	-	-	-0.074	0.022	0.151
Covariance between β_{i0} and β_{i3}	$\sigma_{\beta 03}$	-	-	-	0.003	0.001	0.937
Covariance between β_{i1} and β_{i2}	$\sigma_{\beta 12}$	-	-	-	0.017	0.005	-0.094
Covariance between β_{i1} and β_{i3}	$\sigma_{\beta 13}$	-	-	-	-7.4.E-04	1.8.E-04	-0.664
Covariance between β_{i2} and β_{i3}	$\sigma_{\beta 23}$	-	-	-	-5.3.E-04	1.9.E-04	0.298
Short-run elasticity [$=\beta_{i2}$] av. (min./max.)			-0.116 (-1.113 / 0.182)			-0.120 (-0.770 / -0.021)	
Long-run elasticity [$=\beta_{i2}/(1-\beta_{i1})$] av. (min./max.)			-0.925 (-145.1 / 289.7)			-0.917 (-3.306 / -0.505)	
Number of sample			1170 (all 54 routes)			1710	
R^2			0.8226 (0.148, 0.989)			0.9991	
-2*log likelihood with posterior means of params			-			-5749.83 [d]	
DIC (Deviance Information Criterion)			-			-4962.04	

Notes: [a] estimated with data augmentation for the lagged dependent variable.
[b] the average of parameters among 54 routes.
[c] the variance of parameters among 54 routes.
[d] because the likelihood is difined based on density function, the log-likelihood can be positive.

fit R^2 also supports the accuracy of the shrinkage estimation. Thus, we could say that the random coefficient approach presented in this paper is a better way when our interest is in obtaining the price elasticity of traffic demand for each route. In addition, considering this shrinkage mechanism within the Bayesian framework, we can straightforwardly extend the inference to updating of the price elasticities as mentioned in previous chapter. In the next section, the updating will be demonstrated from January through August in 2008.

4.2 Updating Results of Short-Run and Long-Run Elasticities

The updating is started with non-informative prior distributions for all parameters as well as the estimations in previous section, and therefore the updating results in August are equal to the estimation results as shown in Table 2. This analysis especially focuses on the impacts of outdated temporary tariff rate (during April 2008) and the rapid increase of gasoline price (until August 2008).

The updating results of the short-run and long-run elasticities are shown in Tables 3 and 4, respectively. First, the updating results of the average short-run and long-run elasticities are discussed. As shown in the bottom parts of Tables 3 and 4, the short-run and long-run elasticities are highly unstable during this period: the average values vary from -0.178 to -0.066 for the short-run elasticity, and from -2.416 to -0.672 for the long-run elasticity. Especially in April and May, the short-run and long-run elasticities dramatically decrease, while these in January through March are relatively stable. The results indicate that the increases in traffic due to decreases in the gasoline prices (due to outdated temporary tariff rate during April) are smaller than our expectations specified with the data until March. Note that the reason why the impact of outdated temporary tariff rate continues up to May might arise from the time lag between the purchase of gasoline and its use, although this still remains a matter of speculation. From June, in the opposite direction from the adjustments in April and May, our expectations of the short-run and long-run elasticities are again upwardly-revised with increasing the gasoline prices. This means that traffic reductions in June through August are greater than our expectations specified with the data until May. The results indicate that both the short-run and long-run elasticities are quite unstable over time even at the average level, yet there seems to be some tendencies: a) the behavioral responses to the decreases of gasoline prices would be less sensitive than those to the increases, and/or, b) the behavioral responses are dependent on the types of price changes. Although it would be difficult to determine which is more dominant based on this analysis, at least the results indicate that there might be asymmetric/irreversible responses. The price irreversibility had been confirmed by Dargay and Gately (1997), yet they provide only year-based evidence, which would be difficult to distinguish the irreversible effects from other factors, such as transport infrastructure development, economic changes, innovation of technology, and so on. Our results indicate that, even within a year, there are some asymmetric responses to the changes of gasoline price. Relating to this, interestingly, the early results of congestion charging in London also indicate that the price elasticities were higher than expected, i.e., traffic reductions were greater than forecast (Goodwin, 2004). Including this real-world example, the mechanisms of behavioral responses to the gasoline price fluctuations seem very complicated. Accordingly, further updating results of the price elasticities would deserve continued attention, especially to the sharp decline of gasoline price from September 2008.

Next, we consider the regional (route) differences of the updating results of the short-run and long-run elasticities. The graphical representations of the updating results are shown in Figure 3. From the Figure, we can confirm that regional differences are gradually narrowed over time, although the estimated variance parameter for representing regional differences, σ^2_{i2}, is still statistically significant as shown in Table 2. Besides, in order to confirm how much the estimated short-run and long-run elasticities as of January are applicable over time, we conduct simple linear regression analyses: the unit of analysis is each route, the objective variable is the elasticity of each month, and the explanatory variable is the elasticity in January. The results are shown in Figure 4. It is found that, a) if the R^2 and regression coefficient are nearly one, the elasticities of all routes are quite stable over time; b) if the R^2 is close to one but the coefficient is not, a elasticity of a certain route changes in the same direction as the other; c) if the R^2 falls below one at a certain level, the directions of changes are different from route to route; d) if the R^2 and regression coefficient are nearly zero, the directions of changes among routes would be random. From this standpoint, based on Figure 4, it is confirmed that the short-run and long-run elasticities of all routes are quite stable over time from January to March. In April and May, the coefficients of short-run elasticities notably decreased, while the R^2 are nearly one. This implies that the impacts of outdated

Table 3 Updating results of short-run elasticities from January to August in 2008

Expressway [prefecture][a]	Updating results of short-run elasticities in 2008:							
	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.
Data source: Metropolitan Expressway Company Limited.								
Saitama routes [Saitama]	-0.240	-0.267	-0.300	-0.164	-0.164	-0.192	-0.140	-0.184
Kanagawa routes [Kanagawa]	-0.054	-0.059	-0.068	-0.030	-0.033	-0.089	-0.055	-0.088
Tokyo routes [Tokyo]	-0.048	-0.053	-0.050	-0.029	-0.025	-0.080	-0.048	-0.090
Data source: East Nippon Expressway Company Limited.								
Keiyo Road [Tokyo-Chiba]	-0.095	-0.059	-0.064	-0.026	-0.024	-0.084	-0.050	-0.086
Daisan Keihin Road [Tokyo-Kanagawa]	-0.131	-0.098	-0.114	-0.023	-0.022	-0.079	-0.045	-0.081
Tokyo-Gaikan Exp. [Tokyo-Saitama-Chiba]	-0.117	-0.076	-0.089	-0.004	-0.006	-0.068	-0.033	-0.074
Yokohama Yokosuka Road [Kanagawa]	-0.128	-0.074	-0.084	-0.014	-0.013	-0.075	-0.038	-0.081
Yokohama Shindo [Kanagawa]	-0.132	-0.086	-0.097	-0.023	-0.020	-0.081	-0.044	-0.081
Tokyo Bay Aqualine [Kanagawa-Chiba]	-0.162	-0.145	-0.148	-0.033	-0.041	-0.110	-0.079	-0.135
Chiba Togane Road [Chiba]	-0.171	-0.137	-0.153	-0.060	-0.055	-0.114	-0.063	-0.096
Tokyo Bay Aqualine (accessway) [Chiba]	-0.075	-0.051	-0.036	-0.053	-0.066	-0.139	-0.105	-0.163
Tateyama Exp. [Chiba]	-0.174	-0.147	-0.162	-0.064	-0.063	-0.114	-0.067	-0.107
Shin-Kuko Exp. [Chiba]	-0.127	-0.096	-0.106	-0.043	-0.039	-0.104	-0.090	-0.111
Futtsu-Tateyama Road [Chiba]	0.197	0.143	0.172	0.089	0.053	-0.040	-0.144	-0.238
Higashi-Kanto Exp. [Chiba-Ibarabi]	-0.125	-0.091	-0.104	-0.034	-0.026	-0.090	-0.052	-0.089
Higashi Mito Road [Ibaragi]	-0.139	-0.108	-0.117	-0.089	-0.062	-0.124	-0.076	-0.102
Kita-Kanto Exp. [Gunma-Tochigi-Ibaragi]	-0.129	-0.098	-0.179	-0.336	-0.279	-0.270	-0.196	-0.193
Joshin-Etsu Exp. [Gunma-Nagano-Niigata]	-0.148	-0.106	-0.124	-0.025	-0.022	-0.091	-0.053	-0.090
Ken-O Exp. [(Kanto)]	0.063	0.140	0.153	0.071	0.057	-0.062	-0.076	-0.150
Joban Exp. [(Kanto)-(Tohoku)]	-0.112	-0.075	-0.094	-0.016	-0.013	-0.076	-0.041	-0.082
Tohoku Exp. [(Tohoku)-(Kanto)]	-0.096	-0.060	-0.072	-0.006	-0.005	-0.069	-0.037	-0.077
Nagano Exp. [Nagano]	-0.263	-0.222	-0.222	-0.063	-0.055	-0.127	-0.094	-0.108
Kan-Etsu Exp. [Niigata-(Kanto)]	-0.095	-0.053	-0.067	-0.016	-0.013	-0.076	-0.047	-0.087
Hokuriku Exp. [Niigata-Toyama]	-0.165	-0.134	-0.145	-0.084	-0.073	-0.131	-0.086	-0.119
Nihonkai-Tohoku Exp. [Niigata-Yamagata-Akita]	-0.178	-0.163	-0.157	-0.116	-0.101	-0.179	-0.141	-0.157
Senen Road [Miyagi]	-0.171	-0.131	-0.149	-0.083	-0.070	-0.123	-0.086	-0.121
Sendai-Tobu Road [Miyagi]	-0.173	-0.137	-0.145	-0.078	-0.072	-0.121	-0.085	-0.123
Sendai-Hokubu Road [Miyagi]	-0.097	-0.056	-0.052	-0.034	-0.024	-0.089	-0.056	-0.087
Yamagata Exp. [Miyagi-Yamagata]	-0.116	-0.070	-0.087	-0.014	-0.001	-0.073	-0.046	-0.083
Yonezawa Nan-Yo Road [Yamagata]	-0.071	-0.030	-0.028	0.028	0.036	-0.033	-0.019	-0.047
Ban-Etsu Exp. [Fukushima-Niigata]	-0.205	-0.161	-0.181	-0.043	-0.036	-0.103	-0.068	-0.105
Tohoku-Chuo Exp. [Fukushima-Yamagata]	-0.132	-0.099	-0.094	0.007	0.008	-0.062	-0.045	-0.079
Kotoka Noshiro Road [Akita]	-0.135	-0.106	-0.095	-0.048	-0.040	-0.113	-0.089	-0.131
Akita Gaikan Road [Akita]	-0.087	-0.069	-0.052	-0.034	-0.016	-0.095	-0.078	-0.107
Yuzawa-Yokote Road [Akita]	-0.047	-0.003	0.002	0.042	0.037	-0.060	-0.054	-0.093
Akita Exp. [Akita-Iwate]	-0.131	-0.098	-0.098	-0.046	-0.033	-0.106	-0.080	-0.113
Kamaishi Exp. [Iwate]	-0.005	0.024	0.043	0.051	0.042	-0.058	-0.040	-0.075
Hachinohe Exp. [Iwate-Aomori]	-0.167	-0.118	-0.118	0.002	-0.002	-0.069	-0.042	-0.063
Aomori Exp. [Aomori]	-0.130	-0.111	-0.103	-0.042	-0.035	-0.111	-0.091	-0.117
Momoishi Road [Aomori]	-0.070	-0.107	-0.116	-0.129	-0.099	-0.162	-0.131	-0.120
Sasson Exp. [Hokkaido]	-0.124	-0.101	-0.109	-0.036	-0.033	-0.104	-0.086	-0.105
Fukagawa-Rumoi Exp. [Hokkaido]	-0.010	0.058	0.051	0.084	0.063	-0.042	-0.043	-0.065
Hokkaido Exp. [Hokkaido]	-0.088	-0.057	-0.071	0.003	0.001	-0.073	-0.059	-0.084
Doto Exp. [Hokkaido]	-0.393	-0.360	-0.296	-0.220	-0.142	-0.210	-0.173	-0.136
Hidaka Exp. [Hokkaido]	-0.049	0.024	0.022	0.066	0.078	-0.003	0.002	-0.021
Data source: West Nippon Expressway Company Limited. (Chugoku region)								
Chugoku Exp. [(Chugoku)]	-0.071	-0.079	-0.094	-0.024	-0.013	-0.068	-0.036	-0.067
Hiroshima-Iwakuni Road [Hiroshima]	-0.119	-0.139	-0.137	-0.060	-0.065	-0.130	-0.104	-0.137
Hiroshima Exp. [Hiroshima]	-0.193	-0.199	-0.210	-0.115	-0.095	-0.138	-0.114	-0.158
Okayama Exp. [Okayama]	-0.084	-0.099	-0.092	-0.015	-0.013	-0.078	-0.054	-0.082
Sanyo Exp. [Okayama-Hiroshima-Yamagichi]	-0.012	-0.019	-0.022	0.015	0.022	-0.042	-0.018	-0.058
Matsue Exp. [Shimane]	-0.989	-0.951	-0.927	-0.546	-0.478	-0.503	-0.422	-0.319
Hamada Exp. [Shimane-Hiroshima]	-0.019	-0.017	0.032	-0.010	0.029	-0.038	-0.038	-0.097
Yonago Exp. [Tottori-Okayama]	-0.087	-0.081	-0.079	-0.006	0.014	-0.051	-0.023	-0.036
San-In Exp. [Tottori-Shimane-Yamaguchi]	-2.669	-2.694	-2.706	-1.591	-1.396	-1.275	-1.050	-0.770
Average (μ_2)	-0.178	-0.151	-0.153	-0.076	-0.066	-0.127	-0.095	-0.120
Route Variance ($\sigma^2_{\beta 2}$) [differences between 54 routes]	0.174	0.179	0.181	0.068	0.054	0.040	0.028	0.015

[a] If the number of corresponding prefectures are more than three, we only show a wide-area region name with ().

Table 4 Updating results of long-run elasticities from January to August in 2008

Expressway [prefecture][a]	Updating results of long-run elasticities in 2008:							
	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.
Data source: Metropolitan Expressway Company Limited.								
Saitama routes [Saitama]	-3.894	-3.426	-3.604	-1.521	-1.401	-1.757	-1.271	-1.167
Kanagawa routes [Kanagawa]	-2.441	-1.933	-2.137	-0.659	-0.674	-1.901	-1.149	-1.376
Tokyo routes [Tokyo]	-2.270	-1.825	-1.717	-0.657	-0.553	-1.899	-1.107	-1.477
Data source: East Nippon Expressway Company Limited.								
Keiyo Road [Tokyo-Chiba]	-2.832	-1.864	-1.963	-0.592	-0.523	-1.928	-1.109	-1.400
Daisan Keihin Road [Tokyo-Kanagawa]	-3.259	-2.570	-2.835	-0.555	-0.538	-2.126	-1.195	-1.473
Tokyo-Gaikan Exp. [Tokyo-Saitama-Chiba]	-3.196	-2.356	-2.675	-0.129	-0.187	-2.306	-1.158	-1.546
Yokohama Yokosuka Road [Kanagawa]	-2.858	-1.971	-2.131	-0.324	-0.290	-1.839	-0.953	-1.297
Yokohama Shindo [Kanagawa]	-3.092	-2.257	-2.459	-0.521	-0.459	-1.942	-1.072	-1.353
Tokyo Bay Aqualine [Kanagawa-Chiba]	-2.754	-2.642	-2.574	-0.636	-0.693	-1.751	-1.053	-1.026
Chiba Togane Road [Chiba]	-2.945	-2.452	-2.575	-0.897	-0.814	-1.722	-1.026	-1.139
Tokyo Bay Aqualine (accessway) [Chiba]	-1.840	-1.449	-0.957	-0.683	-0.714	-1.374	-0.926	-0.897
Tateyama Exp. [Chiba]	-3.131	-2.810	-2.854	-1.003	-0.948	-1.809	-1.033	-1.108
Shin-Kuko Exp. [Chiba]	-1.662	-1.260	-1.291	-0.453	-0.384	-1.038	-0.770	-0.768
Futtsu-Tateyama Road [Chiba]	-4.091	-5.031	-7.040	16.174	1.677	-0.972	-0.930	-0.819
Higashi-Kanto Exp. [Chiba-Ibarabi]	-2.986	-2.306	-2.512	-0.698	-0.557	-1.965	-1.149	-1.380
Higashi Mito Road [Ibaragi]	-1.890	-1.478	-1.348	-0.732	-0.521	-1.036	-0.650	-0.712
Kita-Kanto Exp. [Gunma-Tochigi-Ibaragi]	-2.391	-1.835	-2.027	-1.484	-1.191	-1.212	-0.878	-0.759
Joshin-Etsu Exp. [Gunma-Nagano-Niigata]	-2.934	-2.312	-2.422	-0.502	-0.417	-1.742	-1.013	-1.194
Ken-O Exp. [(Kanto)]	-4.221	-4.402	-4.368	-6.633	-10.928	-3.703	-1.659	-1.385
Joban Exp. [(Kanto)-(Tohoku)]	-3.128	-2.269	-2.552	-0.408	-0.337	-2.038	-1.091	-1.416
Tohoku Exp. [(Tohoku)-(Kanto)]	-3.108	-2.118	-2.335	-0.175	-0.140	-2.116	-1.119	-1.541
Nagano Exp. [Nagano]	-2.400	-2.093	-2.041	-0.667	-0.579	-1.271	-0.887	-0.861
Kan-Etsu Exp. [Niigata-(Kanto)]	-3.003	-1.925	-2.164	-0.414	-0.315	-2.054	-1.198	-1.469
Hokuriku Exp. [Niigata-Toyama]	-2.671	-2.174	-2.130	-0.954	-0.796	-1.434	-0.915	-0.974
Nihonkai-Tohoku Exp. [Niigata-Yamagata-Akita]	-2.191	-1.856	-1.680	-0.879	-0.757	-1.247	-0.935	-0.861
Senen Road [Miyagi]	-2.448	-1.949	-2.010	-0.856	-0.704	-1.293	-0.876	-0.914
Sendai-Tobu Road [Miyagi]	-2.728	-2.234	-2.328	-0.952	-0.834	-1.494	-1.003	-1.048
Sendai-Hokubu Road [Miyagi]	-1.308	-0.795	-0.683	-0.310	-0.230	-0.911	-0.582	-0.692
Yamagata Exp. [Miyagi-Yamagata]	-2.213	-1.490	-1.602	-0.252	-0.016	-1.316	-0.802	-1.043
Yonezawa Nan-Yo Road [Yamagata]	-1.214	-0.536	-0.458	0.517	0.704	-0.734	-0.369	-0.712
Ban-Etsu Exp. [Fukushima-Niigata]	-2.719	-2.264	-2.317	-0.627	-0.522	-1.490	-0.959	-1.039
Tohoku-Chuo Exp. [Fukushima-Yamagata]	-1.720	-1.265	-1.203	0.111	0.129	-1.090	-0.686	-0.859
Kotoka Noshiro Road [Akita]	-2.153	-1.678	-1.458	-0.545	-0.435	-1.191	-0.848	-0.801
Akita Gaikan Road [Akita]	-1.342	-0.981	-0.685	-0.331	-0.160	-0.910	-0.683	-0.736
Yuzawa-Yokote Road [Akita]	-1.067	-0.088	0.053	1.092	0.875	-1.109	-0.760	-0.880
Akita Exp. [Akita-Iwate]	-2.148	-1.625	-1.506	-0.561	-0.406	-1.254	-0.880	-0.933
Kamaishi Exp. [Iwate]	-0.177	0.729	1.252	1.224	0.836	-0.899	-0.565	-0.683
Hachinohe Exp. [Iwate-Aomori]	-2.055	-1.595	-1.569	0.043	-0.031	-1.342	-0.787	-0.996
Aomori Exp. [Aomori]	-1.663	-1.280	-1.112	-0.397	-0.324	-0.995	-0.741	-0.741
Momoishi Road [Aomori]	-0.729	-0.831	-0.750	-0.593	-0.442	-0.726	-0.572	-0.505
Sasson Exp. [Hokkaido]	-2.539	-1.970	-1.971	-0.572	-0.518	-1.568	-1.136	-1.166
Fukagawa-Rumoi Exp. [Hokkaido]	-0.914	-4.383	-3.073	-2.230	-1.913	3.437	-3.161	-3.306
Hokkaido Exp. [Hokkaido]	-2.644	-1.771	-1.991	0.077	0.032	-1.925	-1.294	-1.462
Doto Exp. [Hokkaido]	-2.055	-1.866	-1.508	-0.858	-0.589	-0.856	-0.694	-0.569
Hidaka Exp. [Hokkaido]	-1.160	1.101	1.090	5.783	22.041	-2.010	0.221	-2.317
Data source: West Nippon Expressway Company Limited. (Chugoku region)								
Chugoku Exp. [(Chugoku)]	-3.720	-2.706	-2.987	-0.606	-0.342	-1.972	-1.057	-1.494
Hiroshima-Iwakuni Road [Hiroshima]	-2.797	-2.462	-2.445	-0.860	-0.848	-1.635	-1.180	-1.171
Hiroshima Exp. [Hiroshima]	-3.670	-3.054	-3.128	-1.279	-1.073	-1.654	-1.204	-1.157
Okayama Exp. [Okayama]	-2.418	-1.992	-1.901	-0.268	-0.229	-1.413	-0.900	-1.078
Sanyo Exp. [Okayama-Hiroshima-Yamagichi]	-1.121	-1.010	-1.117	0.580	0.854	-1.849	-0.774	-1.639
Matsue Exp. [Shimane]	-2.085	-1.957	-1.889	-0.973	-0.857	-0.898	-0.746	-0.568
Hamada Exp. [Shimane-Hiroshima]	-0.607	-0.381	0.877	-0.141	0.531	-0.770	-0.577	-0.880
Yonago Exp. [Tottori-Okayama]	-2.525	-1.844	-1.800	-0.131	0.313	-1.292	-0.604	-1.066
San-In Exp. [Tottori-Shimane-Yamaguchi]	-3.266	-3.185	-3.211	-1.624	-1.456	-1.321	-1.083	-0.809
Average ($\mu_2/[1-\mu_1]$)	-2.416	-2.027	-1.967	-0.791	-0.672	-1.295	-0.907	-0.917
Route Variance [differences between 54 routes]	0.807	1.155	1.657	6.960	11.913	0.726	0.172	0.207

[a] If the number of corresponding prefectures are more than three, we only show a wide-area region name with ().

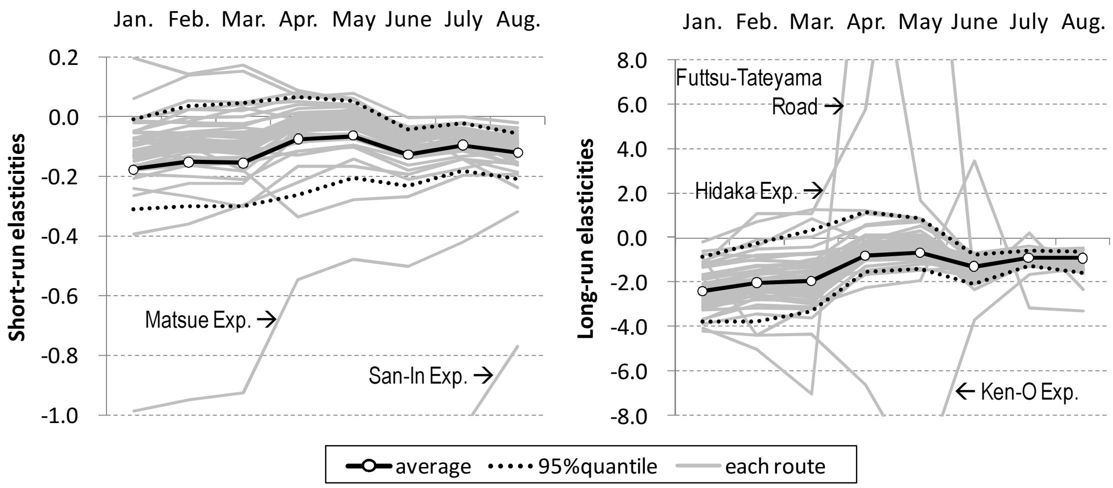


Figure 3 Trajectories of the elasticities for each route from January to August in 2008

Short-run Elasticities

$E_{i(\text{Jan.})} = 1.0000 \times E_{i(\text{Jan.})} \quad R^2 = 1.000$

$E_{i(\text{Feb.})} = 0.9847 \times E_{i(\text{Jan.})} \quad R^2 = 0.992$

$E_{i(\text{Mar.})} = 0.9893 \times E_{i(\text{Jan.})} \quad R^2 = 0.991$

$E_{i(\text{Apr.})} = 0.5708 \times E_{i(\text{Jan.})} \quad R^2 = 0.940$

$E_{i(\text{May})} = 0.4976 \times E_{i(\text{Jan.})} \quad R^2 = 0.937$

$E_{i(\text{June})} = 0.5033 \times E_{i(\text{Jan.})} \quad R^2 = 0.932$

$E_{i(\text{July})} = 0.4041 \times E_{i(\text{Jan.})} \quad R^2 = 0.919$

$E_{i(\text{Aug.})} = 0.3269 \times E_{i(\text{Jan.})} \quad R^2 = 0.732$

Long-run Elasticities

$E_{i(\text{Jan.})} = 1.0000 \times E_{i(\text{Jan.})} \quad R^2 = 1.000$

$E_{i(\text{Feb.})} = 0.8239 \times E_{i(\text{Jan.})} \quad R^2 = 0.904$

$E_{i(\text{Mar.})} = 0.8587 \times E_{i(\text{Jan.})} \quad R^2 = 0.893$

$E_{i(\text{Apr.})} = 0.0830 \times E_{i(\text{Jan.})} \quad R^2 = 0.007$

$E_{i(\text{May})} = 0.2156 \times E_{i(\text{Jan.})} \quad R^2 = 0.026$

$E_{i(\text{June})} = 0.5894 \times E_{i(\text{Jan.})} \quad R^2 = 0.821$

$E_{i(\text{July})} = 0.3716 \times E_{i(\text{Jan.})} \quad R^2 = 0.824$

$E_{i(\text{Aug.})} = 0.4217 \times E_{i(\text{Jan.})} \quad R^2 = 0.782$

Note) "$E_{i(\bullet)}$" represents the elasticity of route i in month ($\bullet$).

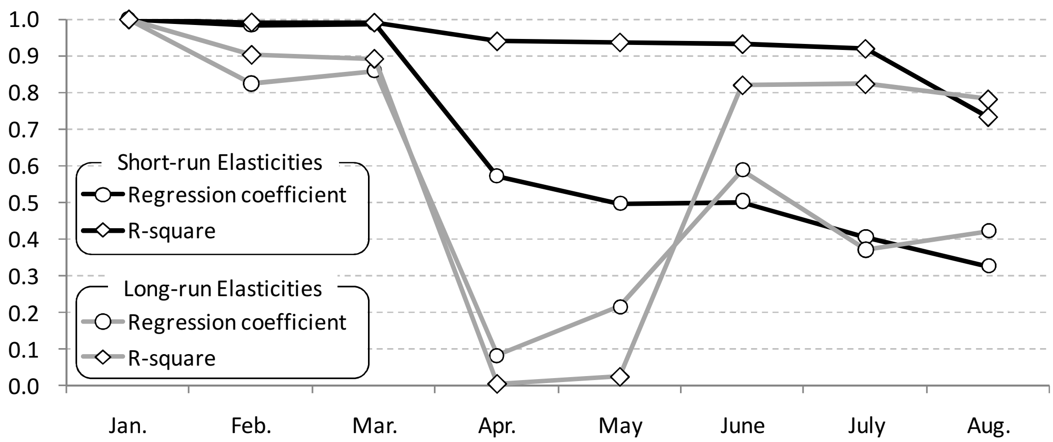


Figure 4 Linear regression results with the elasticities in January as an explanatory variable

temporary tariff rate on the short-run elasticities are quite high, but the directions of changes are not different from route to route. On the other hand, the R^2 and coefficients of long-run elasticities are quite close to zero in April and May. The results indicate that the long-run elasticity for each of route dramatically and randomly changed from the elasticities specified with the data until March. But then, the R^2 and coefficients of long-run elasticities return to a certain levels from June. In this sense, the outdated temporary tariff rate may only cause episodic change on long-run elasticities. As a general trend, assuming the changes of long-run elasticities in April and May as isolated cases, all R^2 and coefficients are gradually reduced from one. In August 2008, the R2/coefficients of short-run and long-run elasticities become 0.732/0.327, and 0.782/0.422, respectively. Thus, it could be said that the changes of the short-run and long-run elasticities certainly occur in each route, and these are different for different routes. In other words, the elasticities are quite unstable across space and over time. The results indicate that the further monitoring of elasticity changes needs to be continued with the consideration of regional differences.

5. CONCLUSIONS

This paper developed a new method for sequential updating of the short-run and long-run price elasticities of traffic demand incorporating regional differences based on hierarchical Bayesian approach, in which the elasticities are treated as uncertain elements and updated to make an adjustment of our expectations/beliefs in the behavioral responses. In the proposed method, the updating cycle can be repeated in infinitum theoretically as long as new data is available. As an empirical analysis, the updating is demonstrated from January to August in 2008 by using monthly traffic volume data on 54 expressway routes in Japan, which would be one of the most suitable data to capture the latest traffic situation. The data include two notable periods: the outdated temporary tariff rate (during April 2008) and the rapid increase of gasoline price (until August 2008). The paper highlights the spatiotemporal stabilities and changes of the price elasticities.

The empirical results indicate that, even within a year, the short-run and long-run elasticities are quite unstable across space and over time. Even at average level (i.e., taking aggregate average over the 54 routes), the short-run and long-run elasticities vary from -0.178 to -0.066 and from -2.416 to -0.672, respectively. The results also show two important possible reasons of the changes of behavioral responses: a) the behavioral responses to the decreases of gasoline prices would be less sensitive than those to the increases, and/or, b) the behavioral responses are dependent on the types of price changes, although more extensive analyses are needed before giving any general conclusions. Moreover, the changes of the elasticities are quite different for different routes. These results underscore that we should make a continued observation of behavioral responses, just like a sequential monitoring of actual phenomena through some sorts of devices, repeated questionnaires, and so on. Our proposed updating method can provide a monitoring framework for capturing the tracks of the behavioral responses over time and across space to monitor the changes of the responses.

Due to the data availability, this study dealt with traffic volume as an indicator of demand. We will attempt to employ environmentally related indicators such as vehicle-kilometer and fuel consumption. Moreover, the proposed updating method can be easily applied to capture the tracks of other elasticities, such as income elasticities, price elasticities of demand for public transport and so on, if we can obtain suitable monthly data. On the other hand, the proposed method should be further improved in several respects. From an academic perspective, in the updating process, we assume the importance of information at each time point is equivalent to the other. However, the passing of time would induce a loss in the value of information. How to incorporate this into the current updating system is of considerable value. Exploring the performance of random coefficient models with different distributions and different sample sizes is also important future tasks. Another important future issue is about the existence of other potential contributing factors, such as type of vehicle, economic conditions, and the experimental ETC (Electronic Toll Collection) toll discount. In addition, since some of expressways are connected with each other to form a network, the effects of such network should be clarified based on O-D (Origin-Destination) information. While the monthly traffic volume data on expressway allow us to examine the current state of elasticities quickly, a lot of data related to other contributing factors (e.g., the effects of car ownership, special events, and major accidents in the surrounding area of a certain route) are not available at this moment. In the future, we must confirm whether ignoring these factors lead to biased estimates or not.

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