A Comparison Study of Forecasting Accuracy of Econometric Models on Domestic Freight Demand in South Korea

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Abstract: This study compares the forecasting accuracy of five econometric models on domestic freight demand in South Korea. These applied five models are as follows: Ordinary Least Square model, Partial Adjustment model, Reduced Auto-regressive Distributed Lag model, Vector Auto-regressive model, Time Varying Parameter model. Estimating models and forecasting are carried out based on annual data of domestic freight demand and an index of industrial production during 1970~2011. As a result, Time Varying Parameter model showed the best accuracy for forecasting the period having large fluctuation, whereas the VAR model seems better performance for forecasting the period with gradual change.

Keywords: Econometric Model, Forecasting Accuracy comparisons, Freight Demand

1. INTRODUCTION

Estimates of future trip demand are provided as a basic reference for transportation and logistics planning as well as operation management. The accuracy or reliability of estimated future trip demand is an important and sensitive issue for running transportation projects. The well-known method for estimating trip demand is a sequential demand model of 4-step: Generation - Distribution - Mode choice - Assignment. In this model, as errors can accrue during the sequential process, it is important to forecast demand accurately in generation process. The trip generation model, as well as other direct demand models, is estimated based on the relationship between trip demand and socioeconomic index. In the past, these models were estimated using cross-sectional data, but recently, according to the data accumulation various econometric models have been applied using time-series and panel data. In addition, transportation planners may be required to estimate socioeconomic index directly using econometric models when these basis data for demand analysis are not provided. Thus, the forecasting performance comparison between econometric models may be an interesting topic in the transportation field. In this study, five econometric models are estimated using the relationship between socioeconomic activity and domestic freight demand in South Korea, and then forecasting performance is compared. Applied econometric models are as follows: 1)Ordinary Least Square model, 2)Partial Adjustment model, 3)Reduced Autoregressive Distributed Lag model, 4)Vector Autoregressive model, 5)Time Varying Parameter model. The recent papers related to this topic are as follows.

Song, Witt and Jensen (2003) evaluated the econometric models based on the forecasting performance of inbound tourism to Denmark. The applied models are 1) Ordinary Least Square model (OLS), 2)Wickens-Breuch error correction model, 3)Johansen error correction model, 4)Reduced Autoregressive Distributed Lag Model (ReADLM), 5)Time Varying Parameter model (TVP), 6)Vector Autoregressive model (VAR), 7)ARIMA model, 8)Naïve no-change model. Consequently, the TVP model and the OLS model appeared to be the most accurate at the one-year-ahead forecasting and four-year-ahead forecasting respectively. Shen *et al.* (2009) applied state of the art econometric models to modeling and forecasting freight demand in UK and compared forecasting accuracy among these models. The applied models are 1)OLS model, 2)Partial Adjustment (PA) model, 3)ReADLM, 4)VAR model, 5)TVP model, 6)Structural Time Series model (STSM). The rankings of the forecasting accuracy of the models were different, depending on the compared commodities. At the aggregate level (total freight demand), STSM appeared to be the most accurate at the one-year-forecast and three-year-forecast. At the five-year-ahead forecast, PA model and ReADLM appeared to be the most accurate forecasting model.

2. THEORETICAL MODELS

There are various econometric models usually applied in macroeconomics such as OLS, AR, MA, ARMA, VAR, VEC, State space model. In this paper, commonly used 1)OLS model, 2)PA model and 3)ReADLM which have the form of AR (auto-regressive) and are often used to estimate demand in transportation field, 4)VAR model which has the vector form of AR model, 5)TVP model that is a representative model with state space form, these five models were applied. For the specification and diagnostic tests, the Ramsey RESET test for mis-specification (Ramsey, 1969), the Jarque-Bera test for non-normaility (Jarque and Bera, 1980), White heteroscedasticity test (White, 1980), and the Lagrange Multiplier test for serial correlation (Breusch, 1978 and Godfrey, 1978) were used.

2.1 Ordinary Least Square (OLS) Regression model

$$y_t = \alpha + \sum_{i=1}^{I} \beta_i \; x_{it} + \varepsilon_t \tag{1}$$

This is a most commonly used model in regression analysis. y_t is the dependent variable, x_{it} is the explanatory variable, α, β are the coefficients, ε_t indicates random error term distributed normally and independently with zero means and constant variance. It is assumed that data (time) series are stationary. When data series are non-stationary, spurious regression may occur. Unit-root test is used to check whether data series are stationary or not. If it is not, the issue can be solved through the difference process.

2.2 Partial Adjustment (PA) model

$$y_t = \delta\alpha + \sum_{i=1}^{I} \delta\beta_i \; x_{it} + (1-\delta) y_{t-1} + \delta\varepsilon_t \tag{2}$$

This model has a form of being first order lagged endogenous variable on right side. y_t is the dependent variable, x_{it} is the explanatory variable, α, β are the coefficients, ε_t indicates stochastic random error term distributed normally and independently. δ is known as the adjustment parameter, where $0 < \delta \leq 1$. The closer it is to 1 the faster the speed of adjustment. When δ is zero, y_t is equal to y_{t-1} and it means that there is no change. When δ is equal to 1, all changes of y_t are completed in time t and it means that there is no lagged effect. For detailed application of PA model refer to Dargay and Hanly (2002).

2.3 Reduced Auto-regressive Distributed Lag Model (ReADLM)

$$y_t = \alpha + \sum_{i=1}^{I}\sum_{j=0}^{J}\beta_{ij}x_{i,t-j} + \sum_{j=0}^{J}\varphi_j\, y_{t-j} + \varepsilon_t \tag{3}$$

The equation above is the form of a general Autoregressive Distributed Lag Model (ADLM). α, β, φ are the coefficients, J is the lag length and is determined by experimentation but generally J=1 for annual data (Thomas, 1997). From the estimated ADLM model, insignificant variables are eliminated sequentially. Specifically, the most insignificant coefficient of variable is removed and a reduced model is re-estimated. This method is repeated until all coefficients are significant at significance level 5% and have the correct signs (Song, Witt and Jensen, 2003). In this study, J=1 was applied because even when J was not equal to 1, other lagged variables except first order lagged variable were removed in reduction procedure.

2.4 Vector Auto-Regressive (VAR) model

$$\begin{cases} y_t = \alpha_{00} + \sum_{j=1}^{J}\beta_{0j}\, y_{t-j} + \sum_{i=1}^{I}\sum_{j=1}^{J}\varphi_{0j}x_{i,t-j} + \varepsilon_{0t} \\ x_{1t} = \alpha_{10} + \sum_{j=1}^{J}\beta_{1j}\, y_{t-j} + \sum_{i=1}^{I}\sum_{j=1}^{J}\varphi_{1j}x_{i,t-j} + \varepsilon_{1t} \\ \vdots \\ x_{It} = \alpha_{I0} + \sum_{j=1}^{J}\beta_{Ij}\, y_{t-j} + \sum_{i=1}^{I}\sum_{j=1}^{J}\varphi_{Ij}x_{i,t-j} + \varepsilon_{It} \end{cases} \tag{4}$$

The equation above is the form of reduced form VAR model. ε_{it} is stochastic random error term distributed normally and independently, but the covariance between errors in each equation is not equal to zero. This form can be estimated using the least square method, so estimates in each equation are the same with the result from the least square method. In addition, all variables are dealt with an endogenous variable in VAR model, and in predicting future estimates, the future values of independent variables are not necessary unlike other models. The lag length that is an important issue in VAR model is determined through the Akaike Information Criterion (AIC) or Schwarz criterion (SC).

2.5 Time Varying Parameter (TVP) model

$$y_t = \beta_{0t} + \sum_{i=1}^{I}\beta_{it}\, x_{it} + \varepsilon_t \tag{5.1}$$

$$\beta_{it} = \beta_{it-1} + \mu_{it} \quad i = 0,1,\cdots,I \tag{5.2}$$

In the TVP model, a constant and coefficients of variables varies depending on time, in other words, coefficients are dealt with unobserved variables. This model has state space form. Equation (5.1) and (5.2) are known as the observation equation and the state equation respectively. In state space model, coefficients are estimated using the Kalman filter algorithm that is recursive procedure for computing the optimal estimate of unobserved state variable with two steps: prediction and updating. ε_t and $\mu_t$indicate random error terms distributed normally and independently with zero means and constant variance.

3. DATA

There are various socioeconomic indexes related to freight demand. The study of TRB(2011) shows that GDP (Gross Domestic Product), IIP (Index of Industrial Production) and fuel price are good explanatory variables of freight demand. GDP is a derived statistic based on IIP and it means that GDP and IIP are highly correlated. In this paper focusing on the comparison of the forecasting performance between five econometric models, IIP that is a proxy index of economic production was selected as an explanatory variable for the convenience of model estimation, especially in VAR model. Fuel price was applied as a dummy variable to reflect oil shock event.

This study is carried out based on the annual domestic freight demand data and annual IIP (2005=100) data during the period 1970~2011. The time series of IIP obtained from Statistics Korea (KOSTAT) were disconnected, and through the adjustment process to constant level (2005=100) time series have been connected. Freight demand data of ton unit was obtained from Korea Transport DataBase (KTDB). Figure 1 shows the annual trends of domestic freight demand. The share of freight demand by road is higher than that by other modes. Total domestic freight demand has steadily increased until 1997 and showed some fluctuations afterwards.

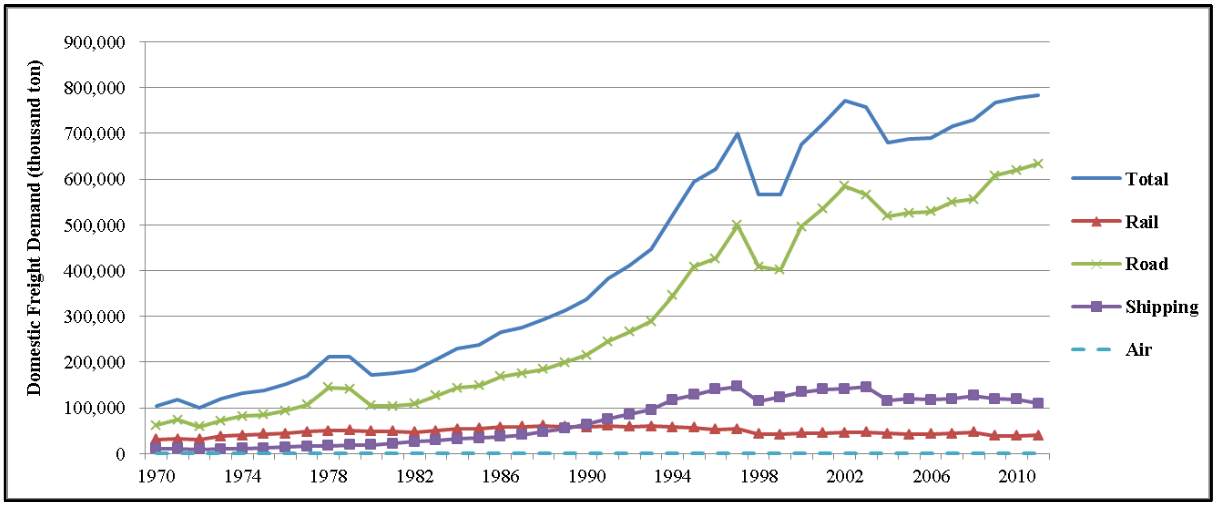

Figure 1 1970-2011 Domestic freight demand in South Korea

For model construction, Log-Log (Log linear) form was applied to explain the relationship between dependent variable and explanatory variables. In log-log form, the coefficient of a variable becomes elasticity. The following equation is a general function form applied in models.

$$\mathrm{Ln(TON)}_t = \mathrm{f(\ Ln(IIP)}_t\ , Dummy\ variables\ ) \tag{6}$$

$\mathrm{Ln(TON)}_t$ indicates a natural logarithm value of domestic freight demand in year t. IIP refers to an Index of Industrial Production. Additionally dummy variables are included in the models to reflect one-off events. Initially, five dummy variables were considered: DUM74 and DUM80 to represent first and second oil price shock, DUM98 to represent Asian financial crisis, DUM203 and DUM208 to represent truckers strike in 2003 and 2008. However, in the initial estimation results, DUM74, DUM203 and DUM208 were not significant. This result may be due to that the economy of South Korea was less affected by the first oil shock in 1974 and that the effect of truckers' strikes didn't appear sufficiently in the annual data because truckers' strikes were short-term. Thus, two dummy variables, DUM80 to reflect second oil price shock (DUM80=1 in 1980-81 and 0 otherwise) and DUM98 (DUM98=1 in 1998-99 and 0 otherwise) to reflect Asian financial crisis, were finally selected.

4. MODEL ESTIMATION

The Applied five models were estimated using EVIEWS 7.1. The estimation results of five models over the period 1970~2011 are presented in Table 1.

Table 1 Estimation results of five models (1970~2011)

	OLS	PA	ReADLM	VAR		TVP
	ΔLn(TON)	Ln(TON)	Ln(TON)	ΔLn(TON)	ΔLn(IIP)	Ln(TON)
Ln(TON(-1))		0.794** (0.080)	0.863** (0.080)			
ΔLn(TON(-1))				-0.249 (0.158)	-0.499** (0.150)	
ΔLn(TON(-2))				-0.069 (0.160)	0.034 (0.152)	
Ln(IIP)		0.103* (0.046)	0.548** (0.185)			0.456** (0.019)
ΔLn(IIP)	0.492** (0.149)					
Ln(IIP(-1))			-0.466* (0.188)			
ΔLn(IIP(-1))				0.098 (0.202)	0.461* (0.192)	
ΔLn(IIP(-2))				0.151 (0.203)	0.208 (0.193)	
Constant	0.011 (0.020)	2.345* (0.873)	1.482 (0.888)	0.062* (0.025)	0.063* (0.024)	11.300** (0.089)
DUM80	-0.131* (0.052)	-0.180* (0.055)	-0.134* (0.055)	-0.203** (0.060)	-0.120* (0.057)	-0.125** (0.043)
DUM98	-0.154** (0.052)	-0.112 (0.058)	-0.125* (0.054)	-0.182** (0.057)	-0.021 (0.054)	-0.131 (0.125)
Adj. R^2	0.407	0.988	0.989	0.307	0.229	
S.E.	0.071	0.074	0.070	0.073	0.069	
LMSC	0.385	5.210	3.343	11.413*		
HETRO	2.613	15.815	21.311	44.728		
NORM	23.066**	0.215	2.736	1.590		
RESET	1.294	5.407**	6.685**			

- Δ indicates 1st difference and IIP(-1) means first order lagged variable of IIP.
- Values in parentheses are standard error.
- Not relevant; ** Significant at 1% level; * Significant at 5% level.
- LMSC: Lagrange multiplier test for Serial correlation, HETRO: White's heteroscedasticity test, NORM: Jarque-Bera normality test, RESET : Ramsey's misspecification test

Before estimating the models, Augmented Dicky-Fuller Unit root test and Cointegration test were carried out to check whether the time series data are stationary or not. The results showed that first differenced data were stationary and data were not cointegrated. Therefore, in estimating OLS and VAR model first differenced data were used to avoid spurious regression. In TVP model, when both constant and the coefficients of variable are set as time-varying or random walk coefficient, the result shows that the variance of estimated errors are not unique. Thus, constant was set as fixed coefficient and the coefficient of IIP was set as random walk parameter.

The result in table 1 shows that adjusted R-square statistics of OLS and VAR model using differenced data were relatively lower than that of PA model and ReADLM. Estimated coefficients of IIP and DUM80 and DUM98 were significant as a whole. For the diagnostic tests, OLS model and VAR model failed Jarque-Bera normality test and serial correlation test respectively. PA model and ReADLM didn’t pass the Ramsey’s misspecification test.

5. EX POST FORECASTING COMPARISON

In this study, the forecasting accuracy of the models for one-year ahead, three-year ahead, five-year ahead was compared. To compare the forecasting performance between applied five models, two periods during 1986~1992 and 2002~2011 were set. These two forecasting periods were classified according to whether there is a fluctuation of observed freight demand or not. For each model and in each period, recursive forecasting method was used to obtain forecasts from estimated model. For instance, each model is estimated during the period 1970~2001 and then each model is used to forecast freight demand during the period 2002~2011. In the next, models are re-estimated during the period 1970~2002 and used to forecast freight demand during the period 2003~2011. This procedure is continued until each model is re-estimated for 1970~2010 and used to forecast freight demand in 2011. This procedure is repeated 10 times for the period 2002~2011 and 7 times for the period 1986~1992. From the recursive forecasting method, 10 one-year ahead forecasts, 8 three-year ahead forecasts, 6 five-year ahead forecasts were obtained for the forecasting period 2002~2011, and 7 one-year ahead forecasts, 5 three-year ahead forecasts, 3 five-year ahead forecasts were gained for 1986~1992. As an evaluation measure of forecasting accuracy, Mean Absolute Percentage Error (MAPE) and Root Mean Square Percentage Error (RMSPE) were used because these are not affected by the units of the variables.

$$\text{MAPE}(\%) = \frac{\sum \frac{|y_{est} - y_{obs}|}{y_{obs}}}{n} \times 100 \tag{7}$$

$$\text{RMSPE}(\%) = \sqrt{\frac{\sum((y_{est} - y_{obs})/y_{obs})^2}{n}} \times 100 \tag{8}$$

Before obtaining estimates, it should be noted that VAR model doesn’t require future values of IIP to obtain future freight demand because both variables are dealt with an endogenous variable. For example, for the forecasting period 1986~1992, the OLS model estimated using data over the period 1970~1985 requires the value of IIP in 1986~1992 to forecast the estimate of freight demand in 1986~1992; however, VAR model doesn’t require the values of IIP in 1986~1992 because VAR model estimates both the values of IIP and freight demand in 1986~1992. For fair comparison of the five models, we tried to apply the values of IIP estimated from VAR model to other four models as the input values of IIP during the forecasting period instead of actual values.

Table 2 and 3 represent the forecasting error of the applied five models for 2002~2011 and 1986~1992. The overall results in both tables show that the short-term forecasting is more accurate than the long-term forecasting as a matter of course. In 2002~2011, the forecasting performance of the TVP model was the highest for one-year ahead, three-year ahead and five-year ahead forecasts. The forecasting performance of OLS model followed the TVP. ReADLM and VAR model including a relatively large number of lagged variables shows lower forecasting performance than that of other models. In 1986~1992, the period that there is almost no fluctuation, the forecasting performance showed conflicting results. VAR was the most accurate model for one-year ahead, three-year ahead and five-year ahead. OLS model was the second rank for one-year ahead and ReADLM occupied the second for three-year and five-year ahead. TVP model showed the lowest forecasting performance over the period 1986~1992.

Table 2 Forecasting performance of the models over the period 2002~2011

Horizon	Measure	OLS	PA	ReADLM	VAR	TVP
1-year ahead	MAPE	6.699%(2)	7.120%(3)	10.911%(5)	9.726%(4)	6.326%(1)
	RMSPE	9.229%(3)	8.748%(2)	13.213%(5)	12.078%(4)	8.647%(1)
3-year ahead	MAPE	21.096%(2)	23.278%(3)	35.258%(5)	28.633%(4)	14.848%(1)
	RMSPE	24.237%(2)	24.988%(3)	38.446%(5)	31.763%(4)	18.102%(1)
5-year ahead	MAPE	37.472%(2)	38.144%(3)	65.247%(5)	50.278%(4)	24.849%(1)
	RMSPE	39.839%(3)	39.166%(2)	68.138%(5)	52.883%(4)	26.825%(1)

- Figures in parenthesis are the rankings.

Table 3 Forecasting performance of the models over the period 1986~1992

Horizon	Measure	OLS	PA	ReADLM	VAR	TVP
1-year ahead	MAPE	4.049%(2)	5.187%(4)	4.531%(3)	3.634%(1)	8.673%(5)
	RMSPE	4.575%(2)	6.516%(4)	4.951%(3)	4.395%(1)	10.872%(5)
3-year ahead	MAPE	7.949%(3)	8.220%(4)	6.781%(2)	4.447%(1)	11.110%(5)
	RMSPE	8.950%(3)	9.712%(4)	8.404%(2)	5.424%(1)	13.171%(5)
5-year ahead	MAPE	11.353%(5)	10.476%(3)	7.250%(2)	4.120%(1)	10.780%(4)
	RMSPE	13.182%(5)	11.761%(4)	8.176%(2)	4.882%(1)	11.435%(3)

- Figures in parenthesis are the rankings.

6. CONCLUSION

This study compared the forecasting accuracy of five econometric models on domestic freight demand in South Korea. The applied five models were Ordinary Least Square model, Partial Adjustment model, Reduced Autoregressive Distributed Lag model, Vector Autoregressive model and Time Varying Parameter model. The estimating models and forecasting were carried out based on annual data of domestic freight demand and an index of industrial production during 1970~2011. Freight demand was forecasted twice for the period 1986~1992 and 2002~2011. These periods were classified by the sharpness of fluctuation of observed freight demand data. Considered the characteristic of VAR model, the values of IIP for the forecasting period were first estimated using VAR model and then, these values, instead of actual values, were put into other 4 models to forecast the estimates of freight demand.

In period 2002~2011, TVP was the most accurate model for one-year, three-year and five-year ahead forecasts. VAR model showed the lowest accuracy and the rapid increase of forecast error according to the increase of forecasting horizons. In 1986~1992, the period that there is almost no fluctuation, VAR showed the best forecasting performance for one-year, three-year, and five year ahead forecasts. It is considered that the conflicting results of ReADLM and VAR model in two forecasting periods may be due to the power of lagged variables. OLS, most commonly used models, showed the performance of the medium in both forecasting periods. The result of this study was not exactly consistent with that of previous studies showing that TVP model has better performance for short-term forecasting, whereas PA model has relatively good forecasting accuracy in the long-run. However, this study showed that it seems appropriate to use TVP model for forecasting series or period showing large fluctuation, while VAR and ReADLM model seems good forecasting performance for the series or period showing gradual changes. This information can be used as the reference of econometric model selection for forecasting the trip demand or socioeconomic index.

REFERENCES

Breusch, T. (1978). Testing for autocorrelation in dynamic linear models, *Australian Economic Papers*, 17, 334-355.

Dargay, J. M. and Hanly, M. (2002). The demand for local bus services in England, *Journal of Transport Economics and Policy*, 36(1), 73-91.

Enders, W. (2009). *Applied Econometric Time Series, 3rd Edition*. John Wiley & Sons Inc., Kendallville.

Godfrey, L. G. (1978). Testing for higher order serial correlation in regression equations when the regressors contain lagged dependent variables, *Econometrica*, 46, 1303-1310.

Jarque, C. M. and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals, *Economic Letters*, 6, 255-259.

Statistics Korea (KOSTAT) (2013). Annual Report on Industrial Production. Available at URL: http://kostat.go.kr/portal/korea/kor_pi/6/4/index.actioa?bmode=read&seq=464.

Korea Transport DataBase (KTDB) (2013). Domestic Freight Transportation Volume. Available at URL: http://www.ktdb.go.kr/html/common/sub_main.jsp?menu_id=C01000000&1depth=4&2depth=1.

Ramsey, J. B. (1969). Test for specification errors in classical linear least squares regression analysis, *Journal of the Royal Statistical Society*, Series B, 31, 350-371.

Song, H., Witt, S. F. and Jensen, T. C. (2003). Tourism forecasting: accuracy of alternative econometric models, *International Journal of Forecasting*, 19, 123-141.

Shen, S., Fowkes, A. S., Johnson, D. H. and Whiteing, A. E. (2009). Econometric modeling and forecasting of freight transport demand in Great Britain, refereed paper presented at the European Transport Conference, Noordwijkerhout, the Netherlands, October 5-7, 2009.

Thomas, R. L. (1997). *Modern econometrics: an introduction*, Addison-Wesley, Harlow.

Transportation Research Board (TRB) (2011). Identification and Evaluation of Freight Demand Factors, National Cooperative Freight Research Program.

White, H. (1980). A heteroscedasticity-consistent covariance matrix estimator and a direct test of heteroscedasticity, *Econometrica*, 48, 817-838.