



A Predictive System for International Trade Growth

CHON Sora



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HYUN Jung Taik
President

Korea Institute for International Economic Policy
370 Sicheong-daero, Sejong-si, 30147, Korea
Tel: (8244) 414-1114 Fax: (8244) 414-1001
www.kiep.go.kr

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CHON Sora

**KOREA INSTITUTE FOR
INTERNATIONAL ECONOMIC POLICY (KIEP)**

Building C, Sejong National Research Complex, 370,
Sicheong-daero, Sejong-si, Korea
Tel: 82-44-414-1251 Fax: 82-44-414-1144
URL: <http://www.kiep.go.kr>

HYUN Jung Taik, President

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EXECUTIVE SUMMARY

The objective of this paper is to suggest a new predictive system for international trade, based on an unobserved component model. We employ the predictive system developed by Pástor and Stambaugh (2009), which is unlike other conventional predictive regression models. This paper derives an equivalent linear predictive regression from the predictive system, and explains why the proposed predictive system is able to achieve superior out-of-sample predictive power. When predictors are imperfect in an estimated equation, the equation fails to utilize all information from the predictors' past history, and unexplained variations are captured by residuals in the estimated equation. With the use of the predictive system, we can more effectively deal with the dynamics of imperfect predictors.

For empirical illustration, we show that, in the case of Korea's export and import growth rates, the predictive system has better out-of-sample predictive powers than the conventional regressions based on Root Mean Squares Error (RMSE). Results from an out-of-sample analysis show that, compared to the benchmark model, the predictive system improves forecast precision by 18.90% for the export growth rate, and by 7.95% for the import growth rate.

Keywords: Predictive System, Time-Series Analysis, Unobserved Component Model

JEL classification: F17, C53, C32, C22

CONTRIBUTORS

CHON Sora

Associate Research Fellow at the Korea Development Institute (KDI) since 2016. Prior to joining KDI, She worked at Korea Institute for International Economic Policy (KIEP). Her fields of research are macroeconomics and applied econometrics. She received her B.A. and M.A. degree in Economics from Korea University and her Ph.D. degree in Economics from University of Washington.

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1. Introduction

The importance of accurately forecasting trade growth has grown significantly since the global financial crisis of 2008. Forecasting of trade growth rates is important for policy makers, whose job is to design effective trade policy, and for businesses, who want to make prudent investment decisions. Various reduced-form econometric models have been used to forecast world trade growth for exports and imports by using one of the time-series approaches (e.g., Algieri 2011; Angelini *et al.* 2010, 2011; Guichard and Rusticelli 2011; Keck *et al.* 2009; Lehmann 2009). One advantage of using a time series approach in forecasting international trade growth is that it is a relatively simple way to achieve predictive power comparable to that of many major institutions, such as the International Monetary Fund (IMF) or the Organization for Economic Cooperation and Development (OECD) (See Keck *et al.* 2009).

In a seminal paper, Keck *et al.* (2009) used time series analysis to forecast international trade growth of major advanced economies, and to show that the most useful model among the various time series approaches is the Autoregressive Distributed lags (ADL) model, with real GDP growth rate as an ad-

ditional predictor. Also, Kargbo (2007) employed time-series forecasting models to estimate agricultural exports and imports in South Africa. He confirmed that the Vector Auto-Regressive (VAR) model outperforms both ADL and the Auto-Regressive Moving-Average (ARMA) process. However, there is still no consensus on which model among the time series approaches is best for explaining the movement of international trade.

Conventional predictive regressions, such as the ADL, VAR, or ARMA models use lagged variables in their models, including other exogenous regressors as predictors. If the predictors are imperfect in an estimated equation, in the sense that true expected variations of exports and imports cannot be well approximated by a linear function of finite lagged macro-economic fundamentals, it fails to utilize all information from their past history. The unexplained variation of future expectations is captured by residuals in the equation, and it is serially correlated. This results in inefficiency of predictive ability based on the conventional predictive regressions. To avoid these problems, Pástor and Stambaugh (2009) developed an alternative predictive system by using the Unobserved Component (UC) model to deal with the imperfect predictors with an application to expected returns.

UC models have been widely used in analyzing many macroeconomic variables for the analysis of inflation rate, GDP, and exchange rates (See. e. g, Harvey 1989, 1990, 1997; Kim and Nelson 1999). For example, Clark (1987) employed a version of the UC approach to examine quarterly U.S. real GNP and monthly industrial production. He attempted to investigate the relative magnitude of unobserved stochastic trend components and the cyclical component. Most recently, Luo and Startz (2014) applied the UC model to decompose the U.S. real GDP to explain the relative importance of trend components and cyclical components in understanding the movement of the U.S. macro economy.

The UC model has not yet become popular among scholars studying international trade. However, Algieri (2011) applied the UC approach to explain ex-

port volume behaviors and explanatory variables in traditional trade models. In addition to foreign demand and price competitiveness, non-price competitiveness can play a significant role in explaining structural relationships in export volumes. Thus, he suggested use of the UC approach to capture the underlying non-price competitiveness in modelling export equations in the case of the Euro and its competitors.

The objective of this paper is to suggest a new predictive system for international trade based on the UC model, and we focus on Korean export and import growth rates as an empirical illustration. Using the predictive system introduced by Pástor and Stambaugh (2009), it is possible to deal with the unobserved innovations of residuals in an estimated equation. Since the underlying true economic decisions made by economic agents is not known to the econometricians, predictors are limited to capturing the dynamics of the future expectation of growth rates, conditional on the available information. Due to the uncertainty of structural models based on using the conventional regressions, relationships between economic fundamentals and future expectations cannot be well represented by a linear function of the predictors. These unexplained variations, if captured by residuals in the estimated equation, can be easily accounted for using the UC approach, by letting the process of imperfect predictors be a stochastic component.

This paper contributes to the literature in two ways. First, it extends the UC approach suggested by Pástor and Stambaugh (2009) to forecast Korean international trade growth rates. This paper demonstrates a linear predictive regression equivalent to the predictive system developed by Pástor and Stambaugh (2009), and provides an explanation of fundamental reasons why the proposed predictive system is able to achieve superior out-of-sample predictive power. When persistence of both predictors and future expectations are similar, the conventional linear predictive regression would be a special case of the predictive system. Thus, this system shows a flexible way to forecast trade growth rates in the presence of imperfect proxy variables. Second, by computing the

root mean squares error (RMSE) with other methods, the predictive system achieves better out-of-sample forecasts for Korea's export and import growth rates. Compared to the benchmark ADL model analysis of Korea's export and import growth rates, the proposed prediction system improves forecast precision by 18.90% for exports and by 7.95% for imports.

The policy implication of this paper is that the predictive system would be a useful tool to perform a short-term forecast for Korea's trade growth. It would assist in designing better trading plans with other countries in preparation for future trade flow changes. It is well known that the movement of Korean exports plays an important role in explaining most of the fluctuations of Korea's macro-economy. The change in trade growth is transmitted through direct and indirect channels, such as income and wealth effects to the overall macro-economy. Thus, in order to develop a suitable macro trade policy, it is important to project future exports and imports accurately.

The organization of this paper is as follows. Section 2 briefly reviews the conventional predictive regression approaches based on time series analysis, such as the ADL, ARMA, and VAR models. In Section 3, we introduce an alternative system for predicting Korean export growth rate. The unobserved component model developed by Pástor and Stambaugh (2009) allows us to overcome some of the limitations present in existing predictive models. Section 4 explains in detail the estimation procedure for forecasting international trade. We show the empirical results for Korean export and import growth in Section 5, compute the Root Mean Squares Error (RMSE), and visually describe the one-step ahead out-of-sample forecasts of Korean export growth rate based on each model. Section 6 concludes this paper and discusses policy implications.

2. Overview of the Conventional Productive Regression

Popular time-series forecasting conventional models are autoregressive distributed lag (ADL) models, or autoregressive and moving-average models (ARMA), and Vector Auto-Regressive (VAR) model. In the followings, we briefly explain model specifications of these conventional approaches.

ADL (p,q) models

An ADL model to forecast trade growth rates is given as:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^p \Delta y_{t-i} + \sum_{j=0}^q z_{t-j} + \epsilon_t, \quad (1)$$

where Δy_t is a stationary international trade growth at time t. p and q are the orders of the autoregressive process and lags of Δy_t and z_t , respectively. z_t is a stationary possible predictor for the trade growth rate, which is exogenously given. The above ADL specification includes the q^{th} order lags of z_t as well as its contemporaneous value. The critical assumption of the above specification is that the errors, ϵ_t are not correlated with the explanatory variables in the equation with zero conditional mean and constant variance.

ARMA (p,q) models

An ARMA model to estimate is given as:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^p \Delta y_{t-i} + \sum_{j=0}^q e_{t-j}, \quad (2)$$

where p and q are the orders of the autoregressive process and moving average processes of Δy_t , respectively. We assume that e_t is a white noise process. In order to select the order of p and q , we examine the auto-correlation and partial auto-correlation function following Box-Jenkins procedure. Among the possible ARMA models, we can choose the best candidate model based on either the Akaike Information Criterion (AIC) or Schwarz Bayesian information criterion.

VAR (k) models

A VAR model to forecast trade growth rates is represented by:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \dots + \Phi_k Y_{t-k} + \epsilon_t, \quad (3)$$

where $Y_t = [\Delta y_t, \Delta y_{t-1}, \dots, \Delta y_{t-k+1}, z_t, z_{t-1}, \dots, z_{t-k+1}]'$; Φ_0 is a vector of constants; and Φ_1, \dots, Φ_k are vectors of coefficients. Without loss of generality, it is guaranteed that one can estimate the above VAR model by regressing each equations based on Ordinary Least Squares (OLS).

3. Model Specification

One of the major concerns of the above predictive approaches is that because the underlying structural economy is not known to the econometricians, the available predictors for the estimation is limited to perfectly explain the dynamics of future expectation. In order to resolve this problem, we consider the following the predictive system, which is suggested by Pástor and Stambaugh (2009):

$$\Delta y_{t+1} = \mu_t + u_{t+1}, \quad (4)$$

$$\mu_{t+1} = (1 - \alpha)E_\mu + \alpha\mu_t + v_{t+1}, \quad (5)$$

$$x_{t+1} = (1 - \beta)E_x + \beta x_t + \omega_{t+1}, \quad (6)$$

where Δy_{t+1} and x_{t+1} represent the observation of interest, which is the international growth rate and the predictor at time t ; μ_t represents the expected Δy_t at time t ; u_{t+1} presents the unpredicted part of Δy_{t+1} at time t . In the simple dynamic system, we assume that μ_{t+1} which captures the expected variations in the time series Δy_{t+1} follows an AR(1) process with the unconditional mean E_μ .¹ The dynamics of the observable predictor x_{t+1} are also described by an AR(1) process with the unconditional mean E_x where the persistence parameter β is not necessarily same as another persistence parameter α in equation (2).² The covariance matrix of the three shocks follows a multivariate normal distribution:

$$\begin{bmatrix} u_t \\ v_t \\ \omega_t \end{bmatrix} \sim i. i. d. N \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_u^2 & \sigma_{uv} & \sigma_{u\omega} \\ \sigma_{vu} & \sigma_v^2 & \sigma_{v\omega} \\ \sigma_{\omega u} & \sigma_{\omega v} & \sigma_\omega^2 \end{bmatrix} \right) \quad (7)$$

¹ μ_t can be interpreted as the mean of Δy_{t+1} , which is unobservable expected mean of Δy_{t+1} .

² We assume the dynamics of the future expectation and the predictors follow AR(1) as in Pástor and Stambaugh (2009), and it is possible to extend for a general AR(p) case.

Note that it is assumed that x_{t+1} is uni-variate to obtain underlying understanding on the above predictive system. However, in practice, more flexible specifications for x_{t+1} can be incorporated like restricted or unrestricted VAR models.

3-1. Comparison with a Conventional Predictive Regression

As discussed in the previous section, in macroeconomic or finance literature, linear predictive regression models have been a workhorse in forecasting important economic variables of interest. The conventional predictive regression model is given by:

$$\Delta y_{t+1} = \alpha + bx_t + e_{t+1}, \quad (8)$$

where the observation and the observable predictor are denoted by Δy_{t+1} and x_t as before. We use the notation x_t to explain various predictors used in Section 2, such as the exogenous regressors z_t and its own lags, the lagged values as well as the moving-averaged processes of Δy_t . And e_{t+1} is one-step-ahead forecast error. Now, we show that the linear predictive regression model is a special case of the predictive system by Pástor and Stambaugh (2009). Suppose that the correlation between v_{t+1} and ω_{t+1} is perfect and the two persistent parameters α and β are identical. As the two shocks are perfectly correlated in the particular case, they can be expressed as $v_{t+1} = b\omega_{t+1}$. Therefore, according to equations (5) and (6)

$$\begin{aligned} (1 - \alpha L)\mu_{t+1} &= (1 - \alpha)E_\mu + v_{t+1} \\ &= (1 - \alpha)E_\mu + b\omega_{t+1} \\ &= (1 - \alpha)E_\mu + b(1 - \beta L)(x_{t+1} - E_x) \\ &= (1 - \alpha)E_\mu + b(1 - \alpha L)(x_{t+1} - E_x), \end{aligned} \quad (9)$$

which results in $\mu_{t+1} = (E_\mu - bE_x) + bx_{t+1}$. This implies that the predictive system leads to the following result:

$$\begin{aligned}\Delta y_{t+1} &= \mu_t + u_{t+1} \\ &= (E_\mu - bE_x) + bx_t + u_{t+1} \\ &= a + bx_t + e_{t+1},\end{aligned}\tag{10}$$

where $a = E_\mu - bE_x$ and $e_{t+1} = u_{t+1}$. It can be easily shown that the predictive regression model extensively used in the literature can be obtained by restricting the model parameters in the adopted predictive system.

3-2. Why Does the Predictive System Produce Better Forecasting Performance?

In this section, we provide the fundamental reason why the predictive system allows us to obtain a superior prediction for a time series variable. Before starting to investigate the underlying source of a better prediction, it is worth mentioning that v_{t+1} and ω_{t+1} are not perfectly correlated and also the persistence parameters α and β are not same in general. Using equation (5)

$$\begin{aligned}\mu_{t+1} &= (1 - \alpha)E_\mu + \alpha\mu_t + v_{t+1} \\ &= (1 - \alpha)E_\mu + \alpha\mu_t + \sigma_v \frac{\rho_{v\omega}}{\sigma_\omega} \omega_{t+1} + \sigma_v \sqrt{(1 - \rho_{v\omega}^2)} \eta_{t+1} \\ &= (1 - \alpha)E_\mu + \alpha\mu_t + \sigma_v \frac{\rho_{v\omega}}{\sigma_\omega} (1 - \beta L)(x_{t+1} - E_x) \\ &\quad + \sigma_v \sqrt{(1 - \rho_{v\omega}^2)} \eta_{t+1} \\ &= E_\mu + \sigma_v \frac{\rho_{v\omega}}{\sigma_\omega} \frac{(1 - \beta L)}{(1 - \alpha L)} (x_{t+1} - E_x) \\ &\quad + \sigma_v \sqrt{(1 - \rho_{v\omega}^2)} \frac{1}{(1 - \alpha L)} \eta_{t+1}, \\ &= E_\mu + \sigma_v \frac{\rho_{v\omega}}{\sigma_\omega} \theta(L)(x_{t+1} - E_x)\end{aligned}\tag{11}$$

$$\begin{aligned}
& +\sigma_v\sqrt{(1-\rho_{v\omega}^2)}\frac{1}{(1-\alpha L)}\eta_{t+1} \\
= & E_\mu + \sigma_v\frac{\rho_{v\omega}}{\sigma_\omega}\left[\sum_{j=0}^{\infty}\theta^j(x_{t+1-j}-E_x)\right] \\
& +\sigma_v\sqrt{(1-\rho_{v\omega}^2)}\left[\sum_{k=0}^{\infty}\alpha^k\eta_{t+1-k}\right]
\end{aligned}$$

Therefore, we have:

$$\begin{aligned}
\Delta y_{t+1} & = \mu_t + u_{t+1} \\
& = E_\mu + \sigma_v\frac{\rho_{v\omega}}{\sigma_\omega}\left[\sum_{j=0}^{\infty}\theta^j(x_{t+1-j}-E_x)\right] \\
& \quad +\sigma_v\sqrt{(1-\rho_{v\omega}^2)}\left[\sum_{k=0}^{\infty}\alpha^k\eta_{t-k}\right] + u_{t+1},
\end{aligned} \tag{12}$$

where the observation Δy_{t+1} is a function of the infinite lags of the predictor x_t , and η_t is i.i.d. Different from the conventional predictive regression model where only the current predictor x_t is used, the dynamic system given by equations (4), (5), and (6) fully utilizes all past history of the predictor in a parsimonious way.

4. Estimation Procedure

4-1. A State-Space Representation

In order to estimate equation (4)-(6), we are able to employ the maximum likelihood estimation (MLE) method based on the Kalman filter. We now consider a following state space representation as follows.³

Measurement Equation

$$\begin{bmatrix} \Delta y_{t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & I_k \end{bmatrix} \begin{bmatrix} \Delta y_{t+1} \\ \mu_{t+1} \\ x_{t+1} \end{bmatrix} \quad (13)$$

$$(\tilde{y}_t = H\beta_t)$$

Transition Equation

$$\begin{bmatrix} \Delta y_{t+1} \\ \mu_{t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} \mu \\ \psi_0 \\ \Phi_0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 \\ 0 & \psi & 0 \\ 0 & 0 & \Phi \end{bmatrix} \begin{bmatrix} \Delta y_t \\ \mu_t \\ x_t \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_{t+1} \\ v_{t+1} \\ \omega_{t+1} \end{bmatrix} \quad (14)$$

$$(\beta_t = \tilde{\mu} + F\beta_{t-1} + Re_t, e_t \sim i.i.d N(0, Q))$$

Then, the log-likelihood function to be maximized is:

$$\begin{aligned} \ln L(\Psi_{\tilde{y}}) &= \sum_{t=1}^T \ln(f(\tilde{y}_t | I_{t-1})) \\ &= \sum_{t=1}^T \ln \left(\frac{1}{\sqrt{2\pi f_{t|t-1}}} \exp \left(-\frac{(\tilde{y}_t - \tilde{y}_{t|t-1})^2}{2f_{t|t-1}} \right) \right), \end{aligned} \quad (15)$$

³ In general, there are more than one of specifying a system in state-space models, which means one is able to specify an alternative representation.

where $\Psi_{\tilde{y}}$ is the vector of parameters to be estimated, $\tilde{y}_{t|t-1} = E(\tilde{y}_t|I_{t-1})$, and $f_{t|t-1}$ is the variance of $\tilde{y}_{t|t-1}$. I_{t-1} means the information set up to time t-1. The last two terms are obtained from the following Kalman filter recursion.⁴

The Kalman filter recursion provides us the mean squares linear estimate of the variables of our interest from the state vector. By using the above state space representation we can rewrite the mean squares estimates, $\eta_{t+1|t}$, and its precision, $f_{t+1|t}$, of one-step-ahead forecasts as follows:

$$\eta_{t+1|t} = \tilde{y}_{t+1} - E[\tilde{y}_{t+1}|I_t], \quad (16)$$

$$P_{t+1|t} = E[\tilde{y}_{t+1} - \tilde{y}_{t+1|t}][\tilde{y}_{t+1} - \tilde{y}_{t+1|t}]' \quad (17)$$

4-2. Forecasting Evaluation

In order to properly evaluate the forecasting performance of the proposed predictive system we compute the root mean squares error (RMSE). The measure is defined as⁵:

$$RMSE = \sqrt{\sum_{t=1}^T \frac{(\Delta y_{t+1} - E_t \Delta y_{t+1})^2}{T}}, \quad (18)$$

where T is sample size. The RMSE depends on the scale of the variables, and it is a widely used measure of the differences between the actual data and the predicted values by the model. Also, we perform the out-of-sample forecasts for the growth rate of Korean exports and imports for an empirical application, and it is computed by using recursive way. The recursive forecasts mean we ex-

⁴ The Kalman filter procedure is provided in appendix.

⁵ See e.g., Kargbo (2007) for details.

and windows to compute the out-of-sample forecast. An initial sample (T) is used to estimate model, the one-step ahead out-of-sample forecasts would be computed starting after the initial sample T_0+1 .

5. Empirical Application

5-1. Data

The variables used in this study are the quarterly-based Korean exports and imports of goods and services, world real GDP, Korea's real GDP, and the oil price. For the world real GDP, in order to focus on the impact of the GDP on Korea major trading partner, such as the United States, China, Japan, ASEAN, and EU, we consider the weighted average real GDP based on the size of trade volume. For the oil price, we use the petroleum average crude oil price, which is a composite of the Dubai, UK Brent, and West Texas Intermediate petroleum prices, in dollars per barrel. The sample period covers from 1999:1 to 2015:3 ⁶, and all variables are seasonally adjusted. Total values of Korea's exports and imports are obtained from the Korea International Trade Association. World GDP, Korea's real GDP and oil prices are obtained from Information Handling Services (IHS), the Bank of Korea and the World Bank, respectively.

We check the existence of the unit roots of the each variable, so we consider the Augmented Dickey-Fuller (ADF) tests for all variables. The estimated equation for the test of ADF is given as:

$$\Delta y_t = \gamma_0 + \gamma_1 t + \gamma_2 y_{t-1} + \delta_1 \Delta y_{t-1} + \dots + \delta_{p-1} \Delta y_{t-p+1} + \epsilon_{y,t} \quad (19)$$

where $\epsilon_{y,t}$ is assumed to be a white noise process. The null is $H_0: \gamma_2 = 0$ against $H_0: \gamma_2 < 0$ and if the null hypothesis is rejected, there is a unit root in the process in y_t . As in Table 1, under the null hypothesis that the series have unit roots we cannot reject the null for the all variables. Thus, to eliminate the

⁶ In order to focus on the behavior of Korea's trade growth rate in the recent periods, we chose the sample periods after the Asian financial crisis.

non-stationarity of these time series data, we use the first order log-differenced series. Figure 1-5 show the quarterly growth rate of Korea's exports and imports, the world real GDP, Korea's real GDP, the oil price. Additionally, we consider the unit root test for the possible structural break with all first order log-differenced variables. With the transformed series, we are able to reject the null hypothesis of a unit root with a break in intercept as in Table 2.

Next, we check the correlograms of Korea's export and import growth rate, which shows the auto-correlation and partial auto-correlation functions. The results are given in Figure 6 and 7. Based on Box-Jenkins approaches, one would select AR(1), MA(1), and ARMA(1,1) model. We found that the best model to explain Korea's export growth rate is AR(1) and ARMA(1,1) for the import growth from Schwarz Bayesian information criterion. And we also confirm this by checking Akaike Information criterion (AIC).

5-2. The Predictability of the Export Growth Rate

The dependent variable, Δy_t , is the first differenced quarterly log of exports of goods and services in Korea. The growth rate of exports, the world GDP, and the oil price are also estimated by using the VAR model simultaneously. And we include the oil price as an additional predictor, as in Keck, *et al.* (2009), by assuming that the oil price is an important factor to represent foreign demand growth. In order to compare the forecast ability of the proposed method with conventional predictive regression, we considered the ADL, ARMA, and VAR models as benchmark cases. For comparisons of predictive power, we reported the Root Mean Squared Errors (RMSE) from each model. We used the first 40 observations as initial samples and we extrapolated from the data beyond the initial sample period using the estimated parameters.

The explanatory variables of the ADL model that we considered are two lagged values of growth rate of Korean exports; one lags of the growth rate of the oil price, and the other lags of the growth rate of world real GDP. We did

not include the contemporaneous values of the oil price growth rate and the growth rate of the world real GDP, due to the possible endogeneity in the estimated regression equation. The results from the ADL model are described in Figure 8. The black line represents the actual data, and the dotted line shows the out-of-sample forecast from the ADL model. And, we also show the confidence band of the out-of-sample forecast in Figure 8-11.

The ARMA model we used is Auto-Regressive of the order 1 model, and the lag selection is based on Schwartz Bayesian information criteria. The last conventional model is the VAR model of order 2. The results of the ARMA model have worse RMSE than those of VAR, ADL, and the proposed methods. The RMSEs are 3.612, 4.092, and 3.900 for the ADL, ARMA, and VAR, respectively. That from the proposed predictive regression is 2.929.

Figure 8-11 depicts the performance of each model presented in this paper, and we consider one-step-ahead conditional expectations of Korea's export growth rate from each model in comparison with the actual data. For the proposed model, one-step-ahead conditional expectations are obtained from the Kalman filter recursion, based on the state-space model, conditional on the maximum likelihood estimates of the parameters. For the ADL, ARMA, and VAR models, one-step-ahead forecasts are obtained by the fitted values in the estimated regression equations. In Figure 8-11, we visually show the forecasts' precision by using plotting confidence bands of each models.

5-3. The Predictability of the Import Growth Rate

Similar to the examination of the prediction for the Korea's export growth rate in the previous section, we compare the relative performance of each models for Korea's import growth rate. Δy_t is Korea's import growth rate. For the ADL model, we use two lags of the oil growth rate, one lag of Korea's import growth rate, and one lag of Korea's real GDP growth rate as predictors. Also, we select the ARMA (1,1) model, which is the best model to approximate

the world representation of Korea's import growth rate based on AIC. Last, we consider the VAR of order 2.

The estimation results are summarized in Table 4. We compare the out-of-sample performance of each model with the proposed predictive system. The RMSEs are 0.930, 1.121, and 1.018 for the ADL, ARMA, and VAR, respectively. The RMSE from the proposed predictive regression is 0.856. Figure 12-15 presents one-step-ahead forecasts of Korea's import growth rate from each model, in comparison with the actual data. Also, in order to consider the significance of the forecasts, we show confidence bands for the estimates of each model. Different from the case of Korea's export growth rate, all models that we use based on time-series approaches perform well, and closely fit the actual data.

In general, for the prediction of trade growth rate, the RMSE from the proposed method reveals the smallest RMSE, and its confidence bands are relatively narrower than other conventional predictive regressions as in Figure 11 and 15. And the estimated values, based on the Kalman filter recursion of the proposed methods, capture well the true data process compared to the fitted values in the conventional predictive regression for both cases.

6. Conclusion and Policy Implications

This paper suggests a new predictive system for international trade when the available predictors are imperfect, which means that future expectations of exports and imports cannot be accurately represented by a linear function of finite lagged macro-economic variables. Due to the unexplained variations in an estimated regression, this results in inefficiency of predictive ability based on the conventional predictive regressions. By employing the predictive system suggested by Pástor and Stambaugh (2009), the problem of the imperfect proxies can be easily overcome. The proposed methods for international trade growth incorporate the UC approach to deal with the unexplained parts from the imperfect predictors, letting these be a stochastic process. We can estimate jointly the unobservable relationship between the future expectations of the international trade growth rate and the dynamics of the predictors.

Furthermore, this paper derives a condition for a linear predictive regression equivalent to the predictive system by Pástor and Stambaugh (2009). We provide a theoretical reason why the predictive system achieves out-of-sample predictive power that is superior to the conventional regression. When persistence of both the predictors and the future expectations are much the same, the conventional linear predictive regression would be a special case of the predictive system.

For an empirical illustration, we focus on the Korea's export and import growth rates, comparing our predictive system's performance to the conventional predictive regressions such as ADL, ARMA, and the VAR model. By evaluating RMSE, we show that the proposed predictive system produces the smallest RMSE in Korea's international trade growth rate. Therefore, results from out-of-sample analysis indicate that the proposed predictive system is a superior method to forecast the growth rate of Korea's exports, as well as its imports. Forecast accuracy has increased, based on RMSE, by 18.90% for export growth rate and by 7.95% for import growth rate, using the ADL model as

a benchmark case.

Finally, the policy implication of this paper is that the predictive system proposed herein could be a practicable means for policy makers to project the short-term of Korea's trade growth rate precisely. In particular, the unusual drop in Korea's exports in recent years emphasizes the need to better forecast trade flow, since exports in Korea play a significant role in understanding the fluctuations of Korea's real GDP. A trade slowdown affects Korea's macro-economy through the spillover channels, such as an income and a wealth effect. Thus, the initial step in order to suggest appropriate trade policy decisions is to predict accurately the future trade growth rate. Equipped with precise future forecasts, policy makers will be able to prepare for changes in future export behavior.

The principal limitation of this paper is that, due to the short spans of the data period, we were only able to focus on short-term forecasts in Korea. In this paper, we aim to provide a new suggestion to predict international trade growth based on the UC framework. Therefore, a possible future research direction would be the extension for comparisons between short and long horizons' forecasts, and in the long horizon case, to incorporate the long-run equilibrium condition, if possible. Another possible extension for future research in this area would be the application of the UC approach to the trade growth rates of other countries. We leave thorough investigation of these topics for future research.

TABLES

Table 1. Results of Unit Root Tests

	ADF test statistic	P-value
Export	-0.993	0.751
World real GDP	1.800	0.997
Oil Price	-2.006	0.287
Import	-1.268	0.639
Korea's real GDP	-1.912	0.648

Note: P-values for the ADF test statistic is based on the MacKinnon (1996) one-sided p-values. Each lag length is determined by the Akaike information criterion (AIC).

Source: Author's calculations.

Table 2. Unit Root Tests with Structural Break in Mean for the Transformed Variables in Conventional Predictive System

	ADF test statistic	P-value
Export growth rate	-5.899	<0.01
World real GDP growth rate	-9.926	<0.01
Oil Price growth rate	-8.106	<0.01
Import growth rate	-7.221	<0.01
Korea's real GDP growth rate	-6.488	<0.01

Note: P-values for the ADF test statistic is based on the MacKinnon (1996) one-sided p-values. Each lag length is determined by the Akaike information criterion (AIC).

Source: Author's calculations.

Table 3. Forecast Evaluation Based on Out-of-Sample Analysis: Export Growth

	Root Mean Squares Error (RMSE)
ADL	3.612
ARMA	4.092
VAR	3.900
Proposed	2.929

Note: ADL means Auto-regressive Distributed Lag model; ARMA means Auto-regressive and moving average process; VAR represents Vector Auto-regressive model; and Proposed represents the predictive system employed in this paper. For evaluating RMSE, we use 40 observations as initial samples and expand the window to compute the out-of-sample forecast.

Source: Author's calculations.

Table 4. Forecast Evaluation Based on Out-of-Sample Analysis: Import Growth

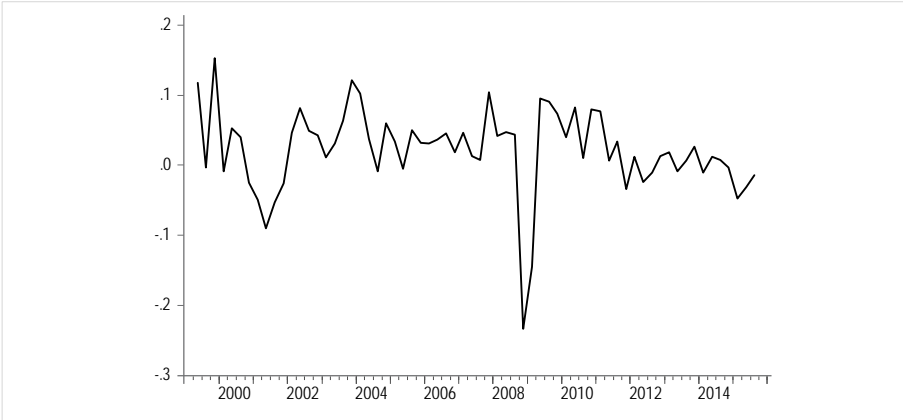
	Root Mean Squares Error (RMSE)
ADL	0.930
ARMA	1.121
VAR	1.018
Proposed	0.856

Note: ADL means Auto-regressive Distributed Lag model; ARMA means Auto-regressive and moving average process; VAR represents Vector Auto-regressive model; and Proposed represents the predictive system employed in this paper. For evaluating RMSE, we use 40 observations as initial samples and expand the window to compute the out-of-sample forecast.

Source: Author's calculations.

FIGURES

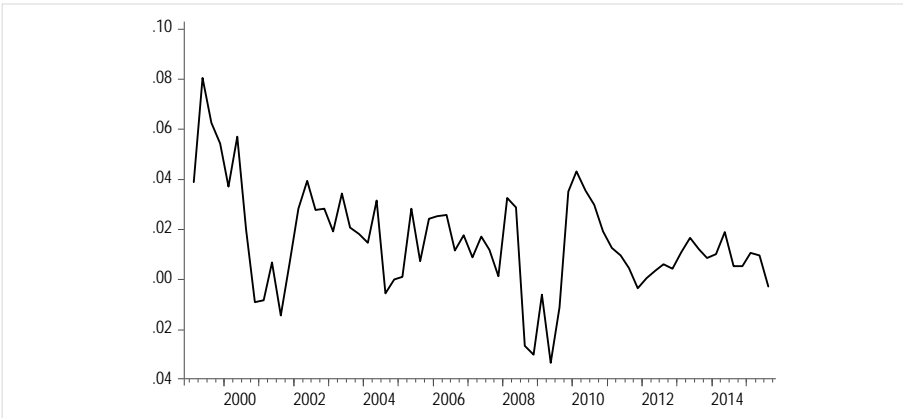
Figure 1. Growth Rate of Export Values of Good and Services in Korea



Note: The sample covers from 1999:1 to 2015:3, and is seasonally adjusted. We obtain the growth rate by differencing the logarithm of the total export value.

Source: Author's calculations.

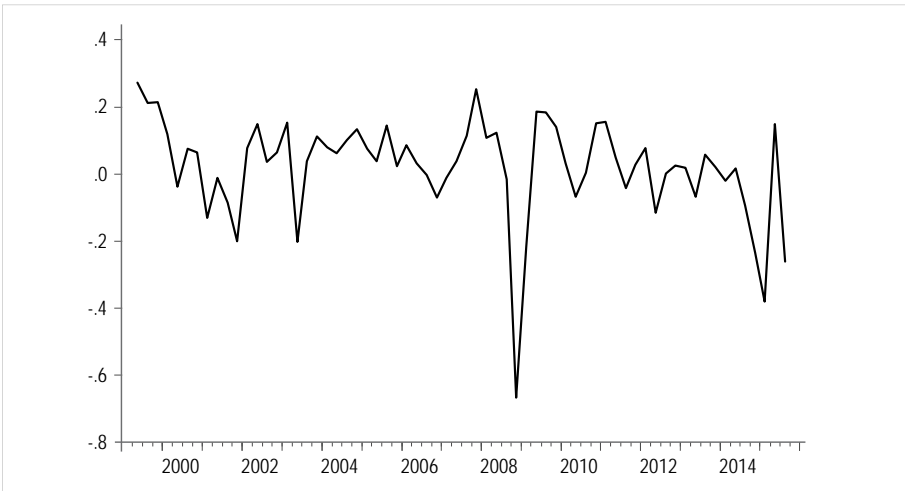
Figure 2. Growth Rate of Import Values of Good and Services in Korea



Note: The sample covers from 1999:1 to 2015:3, and is seasonally adjusted. We obtain the growth rate by differencing the logarithm of the total Import value.

Source: Author's calculations.

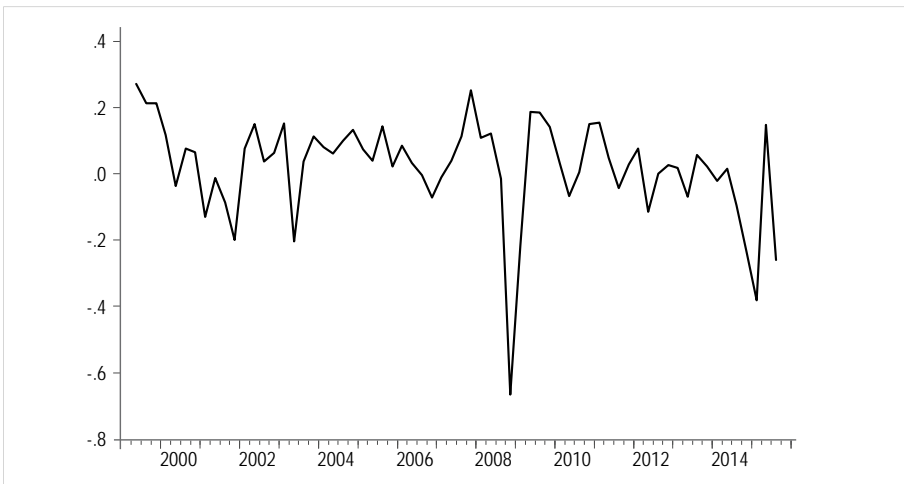
Figure 3. Growth Rate of Average Crude Oil Prices



Note: The sample covers from 1999:1 to 2015:3, and is seasonally adjusted. We obtain the growth rate by differencing the logarithm of the oil price.

Source: Author's calculations.

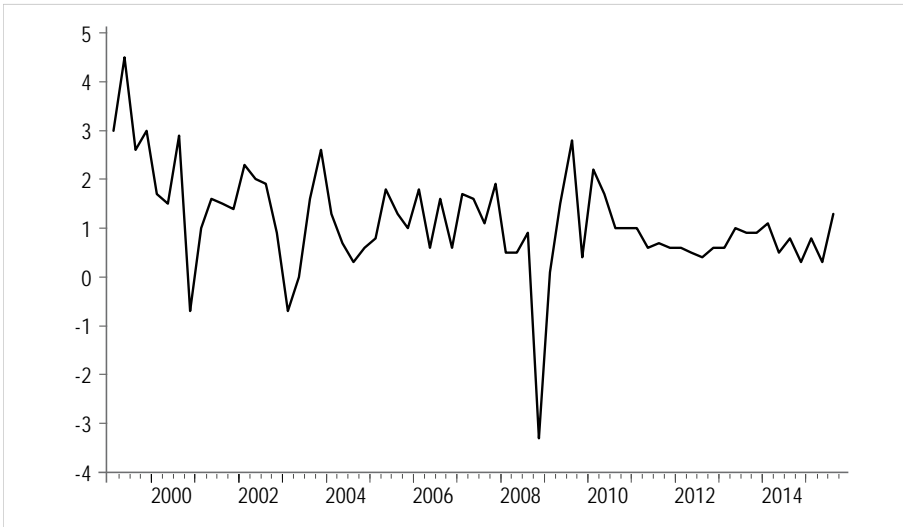
Figure 4. Growth Rate of World Real GDP



Note: The sample covers from 1999:1 to 2015:3, and is seasonally adjusted. We obtain the growth rate by differencing the logarithm of the world real GDP. We consider the weighted averaged real GDP based on the size of the trade volume with major trading partners such as the US, China, Japan, ASEAN, EU.

Source: Author's calculations.

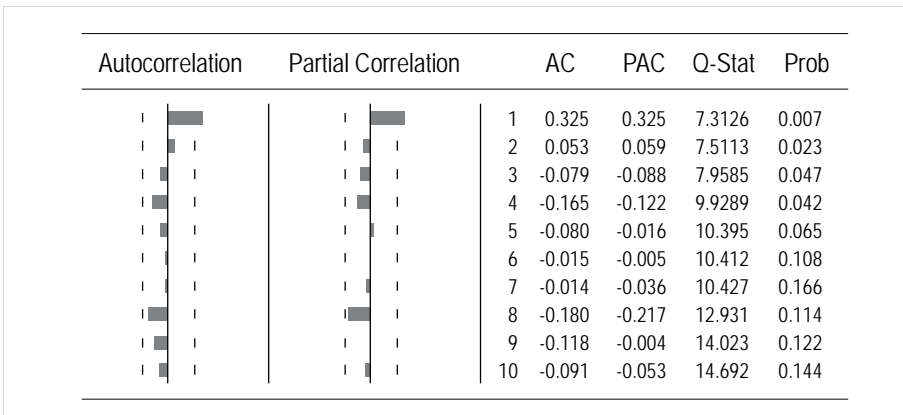
Figure 5. Growth Rate of Korea's Real GDP



Note: The sample covers from 1999:1 to 2015:3, and is seasonally adjusted. We obtain the growth rate by differencing the logarithm of Korea's real GDP.

Source: Author's calculations.

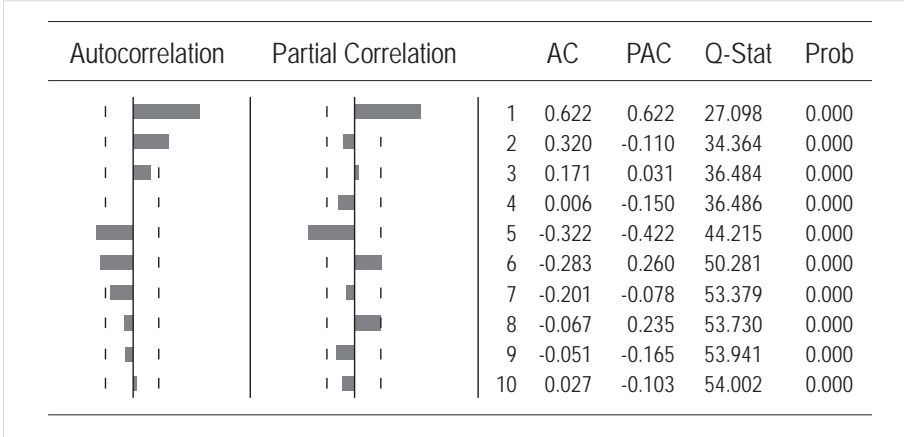
Figure 6. Correlogram of Growth Rate of Export Values of Good and Services in Korea



Note: AC means autocorrelation; PAC means partial autocorrelation; and Q-stat and Prob represent the Ljung-Box Q-statistics and their p-values.

Source: Author's calculations.

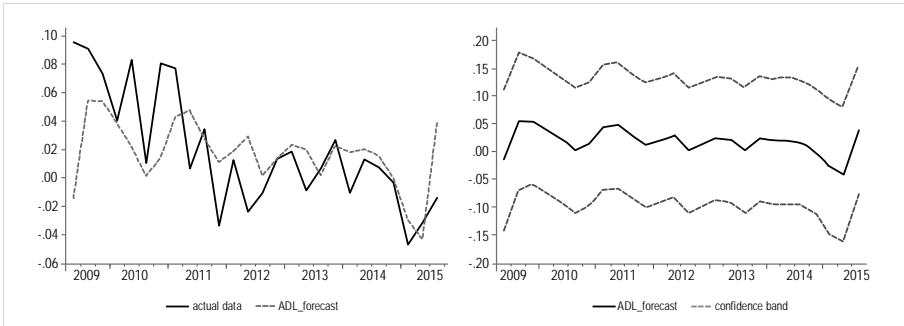
Figure 7. Correlogram of Growth Rate of Import Values of Good and Services in Korea



Note: AC means autocorrelation; PAC means partial autocorrelation; and Q-stat and Prob represent the Ljung-Box Q-statistics and their p-values.

Source: Author's calculations.

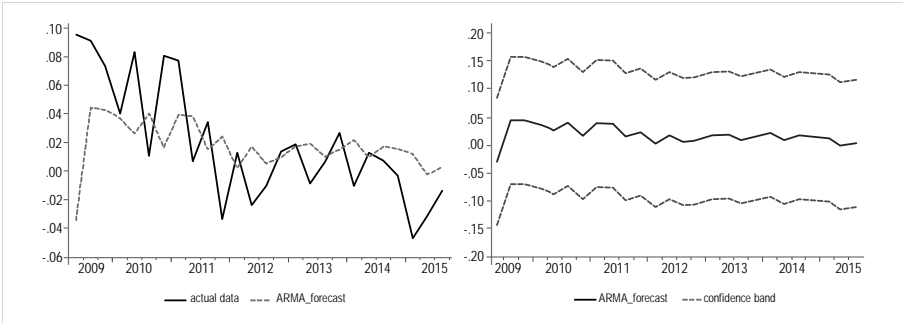
Figure 8. Out-of-sample Forecast of Growth Rate of Exports: ADL Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from ADL model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on ADL model.

Source: Author's calculations.

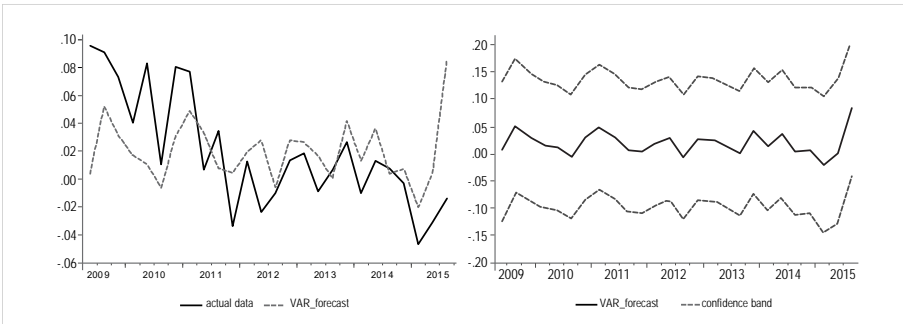
Figure 9. Out-of-sample Forecast of Growth Rate of Exports: ARMA Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from ARMA model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on ARMA model.

Source: Author's calculations.

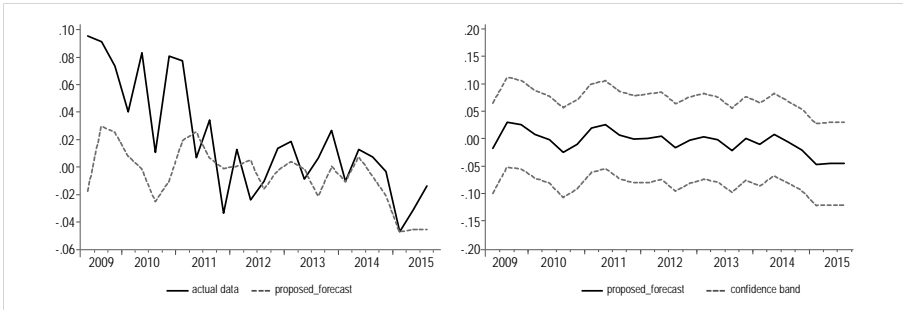
Figure 10. Out-of-sample Forecast of Growth Rate of Exports: VAR Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from VAR model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on VAR model.

Source: Author's calculations.

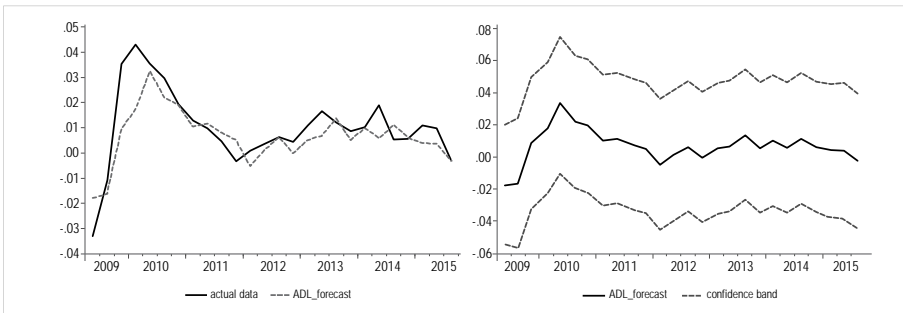
Figure 11. Out-of-sample Forecast of Growth Rate of Exports: the Proposed



Note: The black line represents the actual data, and the dotted line represents the fitted values from the proposed predictive system in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on the proposed predictive system.

Source: Author's calculations.

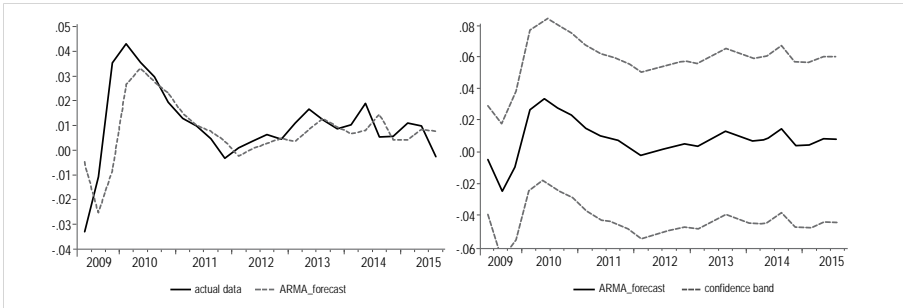
Figure 12. Out-of-sample Forecast of Growth Rate of Imports: ADL Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from ADL model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on ADL model.

Source: Author's calculations.

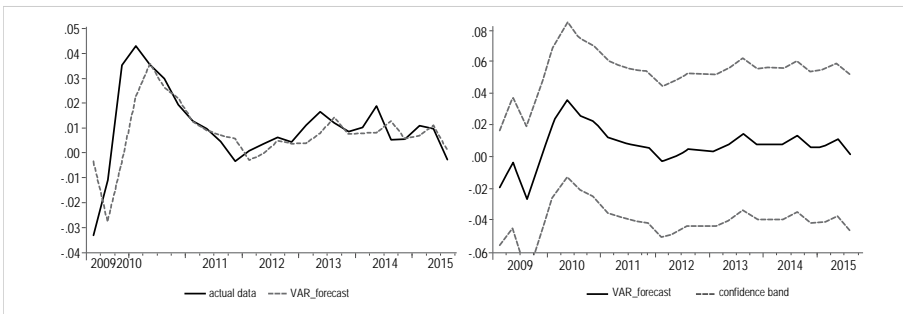
Figure 13. Out-of-sample Forecast of Growth Rate of Imports: ARMA Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from ARMA model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on ARMA model.

Source: Author's calculations.

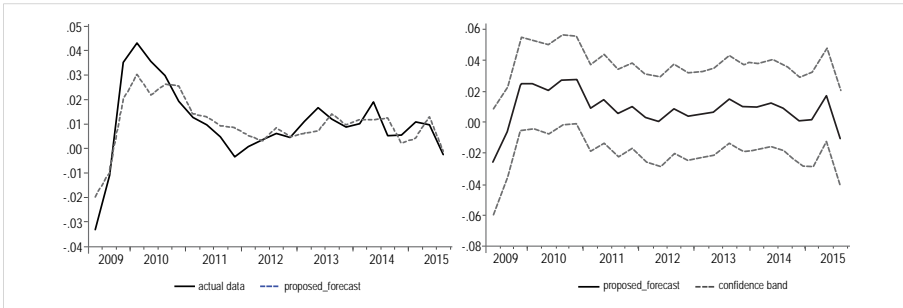
Figure 14. Out-of-sample Forecast of Growth Rate of Imports: VAR Model



Note: The black line represents the actual data, and the dotted line represents the fitted values from VAR model in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on VAR model.

Source: Author's calculations.

Figure 15. Out-of-sample Forecast of Growth Rate of Imports: the Proposed



Note: The black line represents the actual data, and the dotted line represents the fitted values from the proposed predictive system in the left window. The dotted line in the right window shows the confidence bands for the out-of-sample forecast based on the proposed predictive system.

Source: Author's calculations.

APPENDIX

The Kalman filter recursion for (13) and (14) would be:

Kalman Filter

$$\beta_{t|t-1} = \tilde{\mu} + F \beta_{t-1|t-1}, \quad (20)$$

$$P_{t|t-1} = F P_{t-1|t-1} F' + RQR', \quad (21)$$

$$\eta_{t|t-1} = \tilde{y}_t - H \beta_{t|t-1}, \quad (22)$$

$$f_{t|t-1} = HP_{t|t-1}H', \quad (23)$$

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1}H'f_{t|t-1}^{-1} \eta_{t|t-1}, \quad (24)$$

$$P_{t|t} = P_{t|t-1} + P_{t|t-1}H'f_{t|t-1}^{-1}HP_{t|t-1}, \quad (25)$$

where $\beta_{t|t-1} = E(\beta_t|I_{t-1})$; $P_{t|t-1} = \text{Var}(\beta_{t|t-1})$; $\beta_{t|t}$
 $= E(\beta_{t|t})$; and $P_{t|t} = \text{Var}(\beta_{t|t})$.

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국문요약

본 연구에서는 비관측 요소모형(unobserved component model)을 이용하여 국제 무역을 예측하기 위한 새로운 접근법을 제안하고 있다. 이를 위해 통상적인 예측 회귀모형과 달리 Pátor and Stambaugh(2009)의 예측 시스템을 응용하였다. 본 연구에서는 예측 시스템과 동일한 선형 예측 회귀모형을 도출하고, 예측 시스템이 보다 우수한 표본 외(out-of-sample)의 예측력을 가질 수 있음을 증명하였다. 그 이유는 예측 변수가 추정모형에서 불완전한 경우 추정방정식이 예측변수의 과거자료로부터 도출되는 충분한 정보를 활용하지 못하므로 추정모형의 잔차항에 추가적인 설명력이 남아 있기 때문이다. 따라서 예측 시스템을 사용함으로써 불완전한 예측변수의 동태성을 보다 효율적으로 다룰 수 있게 되었다.

실증분석으로 한국의 수출입 증가율을 분석한 결과, 예측 시스템을 사용할 경우 통상적인 회귀모형에 비해 Root Mean Squares Error(RMSE)로 평가한 표본 외 예측력이 더 뛰어났다. 분석 결과에 따르면, 비교 대상 모형에 비해 예측 시스템은 수출 증가율의 경우 18.9%, 수입 증가율의 경우 7.95% 예측정확도를 개선하는 것으로 나타났다.

핵심용어: 예측 시스템, 시계열 모형, 비관측 요소모형

천소리(千소리)

고려대학교 경제학과 졸업

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A Predictive System for International Trade Growth

CHON Sora

The objective of this paper is to suggest a new predictive system for international trade, based on an unobserved component model. We employ the predictive system developed by Pástor and Stambaugh (2009), which is unlike other conventional predictive regression models. This paper derives an equivalent linear predictive regression from the predictive system, and explains why the proposed predictive system is able to achieve superior out-of-sample predictive power. When predictors are imperfect in an estimated equation, the equation fails to utilize all information from the predictors' past history, and unexplained variations are captured by residuals in the estimated equation. With the use of the predictive system, we can more effectively deal with the dynamics of imperfect predictors. For empirical illustration, we show that, in the case of Korea's export and import growth rates, the predictive system has better out-of-sample predictive powers than the conventional regressions based on Root Mean Squares Error (RMSE). Results from an out-of-sample analysis show that, compared to the benchmark model, the predictive system improves forecast precision by 18.90% for the export growth rate, and by 7.95% for the import growth rate.

