Forecast Evaluation of Economic Sentiment Indicator for the Korean Economy*

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Abstract

The economic sentiment indicator (ESI) for the Korean economy is recently developed by combining the BSI and CSI components that have a high correlation with GDP growth and a leading feature with respect to GDP cycle. We evaluate the forecasting performance of the Korean ESI with respect to GDP growth and cycle. For this purpose we use Granger causality tests to show that the constructed ESI contains useful information in predicting GDP growth. Using a probit model, we also show that the ESI is helpful in monitoring and predicting the turning points of GDP.

Keywords: ESI, GDP, cycle, Granger causality, probit

1. Introduction

Survey data measuring economic agents' sentiment provide useful information to assess the current state of the economy and forecast short-term economic development. Besides the information itself that business and consumer surveys provide, the survey data have many advantages. They have an informational lead in that the data are available ahead of hard economic data like GDP and industrial production that are usually published with delays of 1 or 2 months. In addition, the survey data are generally available at monthly frequencies and hence suitable for reflecting volatile economic developments. Therefore, the survey data such as business survey index (BSI) and consumer survey index (CSI) are widely used as a key

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complement to quantitative statistics.

The BSI and CSI data consist of multiple component series that concern diverse facets of economic activity in different sectors of the economy. The demand to incorporate most of the information contained in multiple indicators into a single indicator has led to the construction of a composite indicator. The single composite indicator is useful to reflect economic agents' overall perception of economic activity. The European Commission (EC) has calculated an economic sentiment indicator (ESI) since 1985 at the EU and the euro-area level as well as at the individual EU member state level; see European Commission (2006) for a detailed description of the EC's ESI. Previous research on the construction and evaluation of composite confidence indicators include Stock and Watson (2002), Bruno and Malgarini (2002), Gayer (2005), Gayer and Genet (2006), Gelper and Croux (2007). Moon (2011) develops the ESI for the Korean economy that has officially published since June 2012. We extend Moon (2011) by adding the forecast evaluation of the ESI for the Korean economy. To evaluate the predictive content of the ESI with respect to GDP, Granger-causality tests (Granger, 1969) and a probit model are used. Related literatures that examine the forecast performance of the leading indicators in identifying turning points include Estrella and Mishkin (1998), Krystalogianni *et al*. (2004), Croce and Haurin (2009), and Coşar (2012) among others.

The rest of the paper is organized as follows. Section 2 describes the construction of the ESI for the Korean economy. In Section 3, we evaluate the forecast performance of the ESI with respect to GDP growth and cycle. Section 4 concludes with some remarks.

2. Construction of the Korean ESI

2.1 Data

To construct the Korean ESI, we use the monthly BSI and CSI data from 2003 to 2011 published by the Bank of Korea (BOK). While the monthly series of the BSI data are available from January 2003, those of the CSI data are only available from July 2008 as the BOK had conducted the survey of consumers on a quarterly basis before then. The BOK has conducted the survey of consumers on a monthly basis since July 2008 when Statistics Korea

(SK), a national statistics office that had conducted a separate survey of consumers, transferred its monthly compilation of the CSI to the BOK. Accordingly, we estimate the monthly series of the CSI data from January 2003 to June 2008 using temporal disaggregation, a process of deriving high frequency data from low frequency data. For the CSI components that exist both in the BOK and SK surveys, the monthly data are estimated so that the disaggregated series from the quarterly data of the BOK keep track of the movements of the SK's monthly data as a reference indicator. For the CSI components without a corresponding reference indicator in the SK survey, the monthly data are produced based on a smoothing method using ECOTRIM, the software released by Eurostat.

The BSI data consist of 30 component series in the manufacturing sector and 10 component series in the non-manufacturing sector. In each sector, half of the total component series provides the judgment for the current month, while another half represents the outlook for the next month. For the CSI data, 9 component series are considered, setting aside several component series that have recently been added. Hence there exists a total of 49 component series from the business and consumer survey data. Let us use these component series and their variable names interchangeably for convenience. The type of these 49 variables is the index moving around 100, ranging from 0 to 200. Each variable has 108 observations from January 2003 to December 2011.

GDP is used as a reference variable to represent the entire economy. In particular, the growth rate and cycle of GDP are used to consider short-term and long-term characteristics of the economy. However, since the monthly GDP data are not published, they are estimated using the temporal disaggregation by state space method. Then the GDP growth rate is measured by the year-on-year percentage change of monthly GDP series. The GDP cycle is extracted using the double Hodrick-Prescott (HP) filter. The HP filter is applied twice to achieve a smoothed de-trended cycle; removing a long-term trend from the seasonally adjusted GDP and then smoothing the de-trended GDP. The cycles of the 49 variables are extracted in the same fashion as the GDP cycle except for the de-trending procedure because the 49 component series have no trend.

2.2 Selection of the ESI components and weights

The ESI needs to be constructed to track GDP well so that it can be used as a useful complement to GDP. Should the ESI and GDP move differently, it may cause confusion in assessing the current state of the economy. So the ESI must be highly correlated with GDP. By the way, if the ESI tracks GDP with a lead of a few months, then the ESI will also be useful for predicting future GDP developments. Inherently the survey data related to respondents' expectations have the potential to have a leading property. This is because enterprisers and consumers tend to increase their production and consumption if they feel positive about the current and future economic situation. Therefore, the screening procedure is aimed at selecting informative components that are not only closely correlated with GDP but also detect turning points of economic movements earlier than GDP. Cross-correlation analysis and turning point analysis are used here.

Let z_{1t} be the reference variable and z_{it} be the i^{th} variable to compare with. Then the cross-correlation between the reference variable and the i^{th} variable shifted m months is defined as

$$\rho_{1i}(m) = \frac{Cov(z_{1t}, z_{it+m})}{\sqrt{Var(z_{1t})Var(z_{it})}}$$

for i=1,…,49. If m=0, then it is a contemporaneous correlation between the reference variable and the i^{th} variable. The maximum cross-correlation can be obtained from different choices of positive or negative integer values of m. If the maximum is found for negative m, then it means that the i^{th} variable has the largest correlation with the reference variable when it is shifted m months ahead. Here the sample cross-correlations between the GDP growth rate and each of the 49 variables are calculated. Denote the sample contemporaneous correlation by r_0, the maximum sample cross-correlation by $r_{\max}$ and the value of m with $r_{\max}$ by $t_{\max}$. A variable having a large $r_{\max}$ at the negative $t_{\max}$ is considered to have leading behavior.

The leading property is also examined in terms of the cyclical movement. The BUSY software based on the routine by Bry and Boschan (1971) can be used to detect the turning points. It identifies the turning points of the reference variable and then denotes the leading or lagging months of each of the 49 variables by negative or positive values at the reference turning points. However, the turning points produced by the BUSY software are not obvious in some periods, due to a relatively short length of time series. So only the turning points which are obviously identifiable even by the naked eye are considered. Variables with a negative sign at these time points are considered to have the leading property.

The preliminary screening of the individual variables is carried out in each of three sectors: manufacturing, non-manufacturing, and consumer. In each sector, the variables having high levels of cross-correlation and leading characteristics are pre-selected for further investigation. Under these criteria, the 9 variables in the manufacturing sector, 4 variables in the non-manufacturing sector and 5 variables in the consumer sector are pre-selected respectively.

In each sector, all possible combinations of the pre-selected variables are examined. There are 2^k-k-1 possible combinations when there exist k variables within a sector. In each combination, the variables are aggregated by a simple average of the standardized series, not the original series. This prior standardization is necessary to avoid the dominant effects of highly volatile variables on the composite indicator. The tracking performance of the aggregated series in relation to GDP is tested based on the cross-correlation and turning point analyses. The previous two criteria used in the preliminary screening are reapplied.

Among all combinations in each sector, a three-variable set (outlook for exports, capacity utilization and financial situation), a two-variable set (outlook for business conditions and financial situation) and another two-variable set (outlook for household income and spending decisions) are selected as the best combination respectively. Therefore, 7 variables among a total of 49 variables are finally selected to construct the ESI. The cross-correlation analysis and the turning point analysis to these 7 variables are given in Table 1. Overall, the selected variables show the leading property, which is consistent in the fact that these variables reflect anticipations.

Table 1. ESI Components

		Components	Cross-correlation			Turning point	
			r_0	r_{max}	t_{max}	Mean	Median
BSI	Manufacturing	Outlook for Exports	0.783	0.812	1	0.25	0.5
		Outlook for Capacity utilization	0.777	0.777	0	-1.25	-1.5
		Outlook for Financial situation	0.674	0.726	-2	-3.75	-3.0
	Non-manufacturing	Outlook for Business conditions	0.622	0.648	-1	-2.75	-2.5
		Outlook for Financial situation	0.611	0.680	-1	-3.75	-2.5
CSI		Outlook for Household income	0.466	0.534	-2	-4.25	-5.0
		Outlook for Spending decisions	0.591	0.624	-1	-5.75	-6.0

To determine the weights of the selected variables, principal component analysis is used. The first principal component explains about 82% of the total variance of the 7 variables. This means that the first principal component can replace the 7 variables without much loss of information. The coefficient of the first principal component measures the importance of the each variable to the first principal component, irrespective of the other variables. In particular, the relative sizes of importance are determined based on the squared coefficients which sum to 1. Based on the sum of the squared coefficients within the manufacturing and non-manufacturing sectors and the sum of those in the consumer sector, the weights of BSI and CSI parts are determined by 0.75 and 0.25.

Within the BSI part, the weights of the manufacturing and non-manufacturing sectors are determined based on the contributions to GDP growth. The contribution of the non-manufacturing sector to GDP growth is computed by excluding the industries for which the business survey is not conducted (agriculture, financial intermediation, public administration and defense, compulsory social security, education, health and social work, and other service activities). The average of the contributions over 2003 to 2011 is 1.62%p for the manufacturing sector and 0.98%p for the non-manufacturing sector, so the ratio of their relative magnitudes is almost 0.6 and 0.4. This ratio is stable for other time periods. Thus the weights within the manufacturing and non-manufacturing sectors are determined as 0.6 and 0.4.

Since the BSI part has a weight of 0.75 in total, the weights of the manufacturing and non-manufacturing sectors are finally allocated to 0.45 and 0.30. To sum up, the weights of the manufacturing, non-manufacturing and consumer sectors are set by 0.45, 0.30 and 0.25. Within each sector, the individual variables have equal weights as shown in Table 2.

Table 2. Weights allocated to the ESI Components

		Components	Weights	
BSI	Manufacturing	Outlook for Exports	0.150	0.45
		Outlook for Capacity utilization	0.150	
		Outlook for Financial situation	0.150	
	Non-manufacturing	Outlook for Business conditions	0.150	0.30
		Outlook for Financial situation	0.150	
CSI		Outlook for Household income	0.125	0.25
		Outlook for Spending decisions	0.125	

2.3 Calculation of the ESI

After determining the 7 informative variables (or components series) and the corresponding weights, the exact calculation of the ESI is made as follows.

Step 1: Standardize the original component series

$$Y_{i,t} = \frac{X_{i,t} - \overline{X}_i}{S}$$

where $X_{i,t}$ is the i^{th} component series observed at time t, $\overline{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{i,t}$ and

$S = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(X_{i,t} - \overline{X}_i)^2}$ for i=1,…,7.

Step 2: Aggregate the 7 standardized series using the weights

$$Z_t = \sum_{i=1}^{7} w_i Y_{i,t}$$

where w_i is a weight of the i^{th} component such that $\sum_{i=1}^{7} w_i = 1$.

Step 3: Scale Z_t to have a mean of 100 and a standard deviation of 10

$$ESI_t = \left(\frac{Z_t - \overline{Z}}{S_z}\right) \times 10 + 100$$

where $\overline{Z} = \frac{1}{T}\sum_{t=1}^{T} Z_t$ and $S_Z = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(Z_t - \overline{Z})^2}$.

The ESI value of 100 marks a long-term average over the time period from t=1,…,T. Values greater than 100 indicate an above-average position, while values below 100 indicate a below-average position. The fixed standard deviation of 10 implies that about 68% of the ESI values fall within a range between 90 and 110 assuming approximate normality.

Unlike the ESI, a value of 100 in the BSI and CSI data means the equal proportion of negative and positive opinions. In addition, the BSI and CSI data have often fallen below 100 due to the cautiousness of respondents, even when the economy is booming. The ESI solves this problem by rescaling in Step 3. Moreover, the ESI is easy to interpret because the long-term average of 100 plays a yardstick role for making judgments.

Note that the standardization in Steps 1 and 3 is carried out over the period from t=1,...,T. The end point T is extended every year to include up-to-date information, but does not change within a single year. For example, the ESI values from January to December in 2012 are calculated based on the standardization period from January 2003 to December 2011. But the ESI values in 2013 are computed using a new standardization period extended to December 2012, and the ESI values before 2013 are all revised at once at the beginning of 2013. That is, the revision of the ESI data is undertaken every year. This revision may confuse users, but it is inevitable in order to reflect the recent economic situation adequately. The cyclical component of the ESI is compiled to track the cyclical patterns of economic sentiment, and is calculated by removing seasonal and irregular components from the ESI.

3. Forecast Evaluation

3.1 Tracking performance of the ESI

Following the method described in Section 2, the ESI for the Korean economy are computed for the period of January 2003 to May 2012. Figure 1 shows that the ESI and GDP growth move closely together. Note that in Table 3 the ESI has a maximum cross-correlation of 0.726 when it is one month ahead of GDP.

Figure 1. ESI and GDP growth

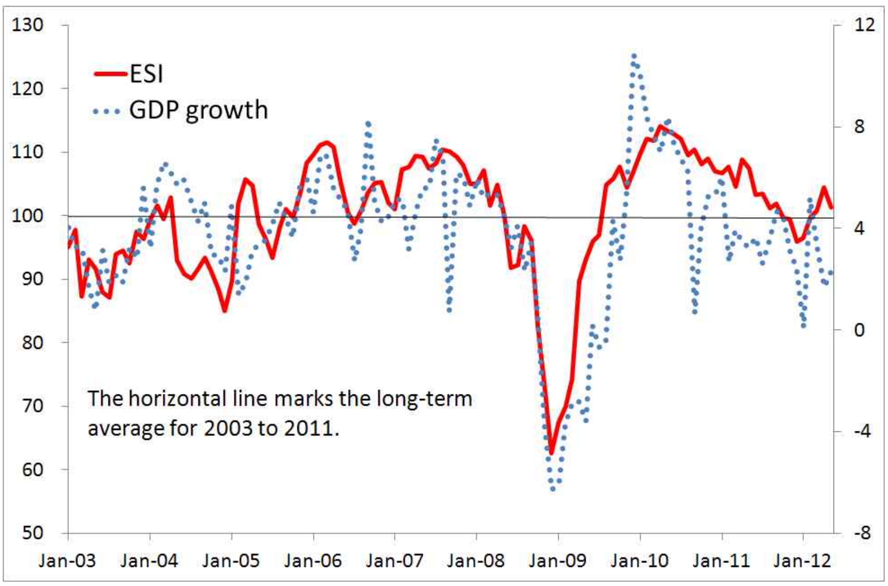
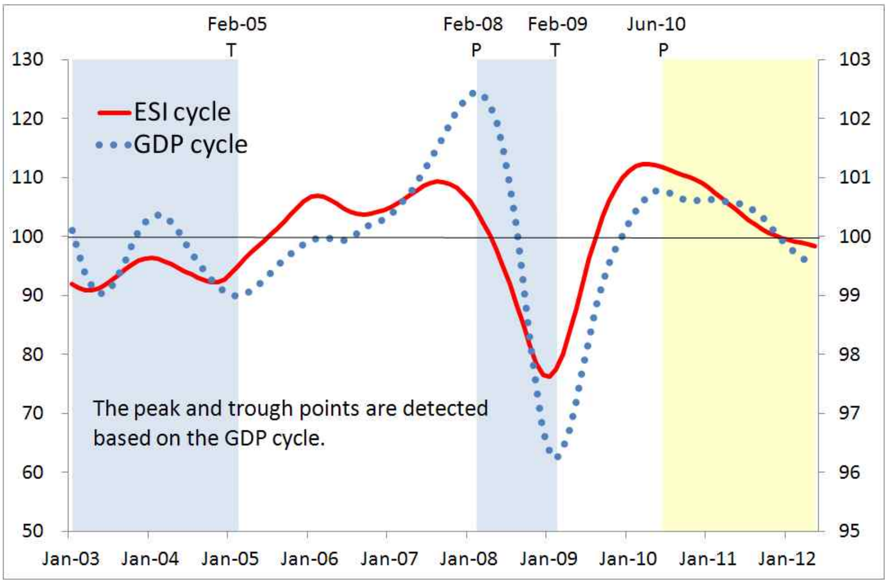


Table 3. Cross-correlation of ESI and GDP growth

Leading (-) or Lagging (+) Months												
-6	-5	-4	-3	-2	**-1**	0	1	2	3	4	5	6
0.382	0.500	0.575	0.639	0.699	**0.726**	0.713	0.671	0.564	0.431	0.316	0.203	0.124

The movements of the cyclical components of ESI and GDP are shown in Figure 2. Over the period of 9 years, the GDP cycle records two peaks in February 2008 and June 2010, and two troughs in February 2005 and 2009. The cyclical components of the ESI detects turning points 4 month, 6 months, 1 month, and 2 months ahead of the corresponding reference date, respectively, or about 3.25 months early on average. The leading feature of the cyclical movement is also found in the cross-correlation analysis of the cycles. The maximum cross-correlation is 0.852 when the cyclical component of ESI is 3 months ahead of GDP as shown in Table 4. Overall, the ESI tracks GDP well, being well correlated and co-moving with GDP with leads of a few months.

Figure 2. Cyclical components of ESI and GDP



Note: The decelerating phase starting in June 2010 is subject to change as more data are available.

Table 4. Cross-correlation of the cycles of the ESI and GDP

Leading (-) or Lagging (+) Months												
-6	-5	-4	**-3**	-2	-1	0	1	2	3	4	5	6
0.706	0.777	0.827	**0.852**	0.846	0.807	0.734	0.632	0.504	0.357	0.198	0.036	-0.121

3.2 Granger causality tests

In this subsection, the leading behavior of the ESI with respect to GDP growth is further examined using Granger-causality test. To see whether movements in the ESI precede movements in the GDP growth or vice versa, Granger-causality tests are carried out based on the lag lengths of 4, 5, and 6. As can be seen in Table 5, the null hypothesis that "ESI does not Granger-cause GDP growth" is rejected, while the null hypothesis that "GDP growth does not Granger-cause ESI" is not rejected, at a significance level of 5% for all choices of lag lengths, indicating the ESI precedes GDP growth. That is, the ESI shows significant positive contribution to explain future GDP growth, implying that the ESI is helpful in forecasting GDP growth.

Table 5. Granger causality tests

Lag	H_0: GDP growth does not Granger-cause ESI		H_0: ESI does not Granger-cause GDP growth		Results
	F-Statistic	Prob.	F-Statistic	Prob.	
4	2.200	0.074	3.379	0.012	ESI→GDP
5	1.877	0.105	2.592	0.030	ESI→GDP
6	1.355	0.241	2.689	0.019	ESI→GDP

3.3 Forecast using probit model

We use a probit model to further examine the leading property of the cyclical component of ESI with respect to that of GDP and then evaluate the forecast performance of the ESI in identifying the turning points of GDP. Suppose that a binary dependent variable, Y_t, takes on only values of one and zero as follows.

$$Y_t = \begin{matrix} 1,\ \text{if the economy is in deceleration period} \\ 0,\ \text{otherwise} \end{matrix}$$

Then the estimated probability of being in the deceleration period is of the form

$$P(Y_t = 1 \mid x, \beta) = F(\beta_0 + \beta_1 x_1 + \cdots \beta_k x_k)$$

where $x_1, \dots, x_k$ are k explanatory variables, $\beta_1, \dots, \beta_k$ are the corresponding regression coefficients and F is the cdf of a standard normal distribution, i.e.,

$$F(a) = \Phi(a) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{a} e^{-t^2/2} dt$$

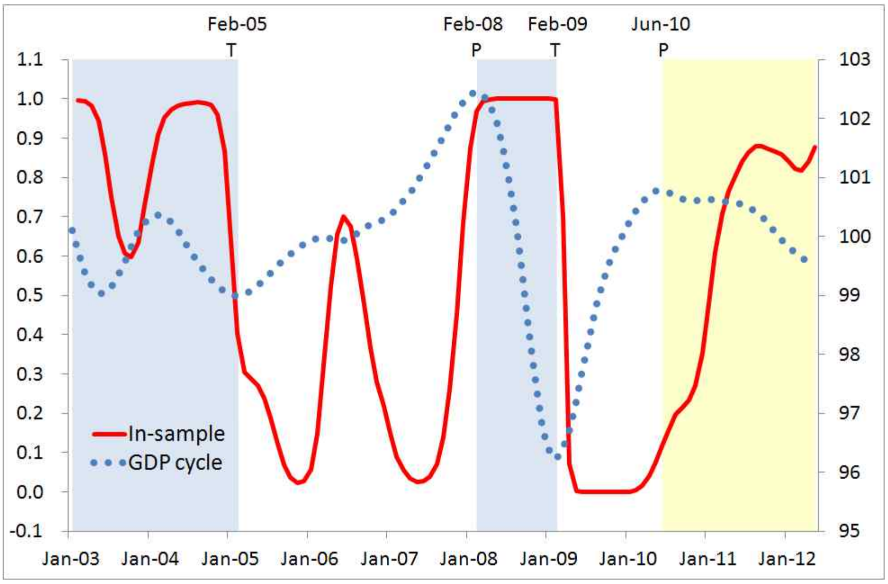
Here the deceleration period is determined based on the peak and trough points of the cyclical component of GDP. The contemporaneous and lagged values of the cyclical component of ESI are considered as explanatory variables. The number of lags is determined so as to minimize Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC). The cyclical component of ESI shifted 1 month ahead (ESIC(-1)) is included in our probit model as an explanatory variable along with its contemporaneous value (ESIC). Table 6 shows that the estimated model has 53% of the explanatory power and all explanatory variables are statistically significant. Note that the sign of estimated coefficient of ESIC(-1) is positive, implying that ESIC(-1) and the contemporaneous GDP cycle tend to move in the same direction.

Table 6. Probit model estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	17.873	3.363	5.315	0.000
ESIC	-1.476	0.274	-5.388	0.000
ESIC(-1)	1.301	0.251	5.182	0.000
McFadden R^2	0.530			

From the estimated probit model, the probability of being in the deceleration period can be computed for each observation of the data, which is called in-sample forecast. The probabilities from the in-sample forecast are plotted together with the GDP cycle in Figure 3. The estimated probabilities are shown to be high in the shaded areas of the deceleration. In particular, the estimated probabilities are close to 1 during the financial crisis from February 2008 to February 2009. Overall, our estimated probit model seems to successfully identify the deceleration phase.

Figure 3. Estimated probabilities and the GDP cycle

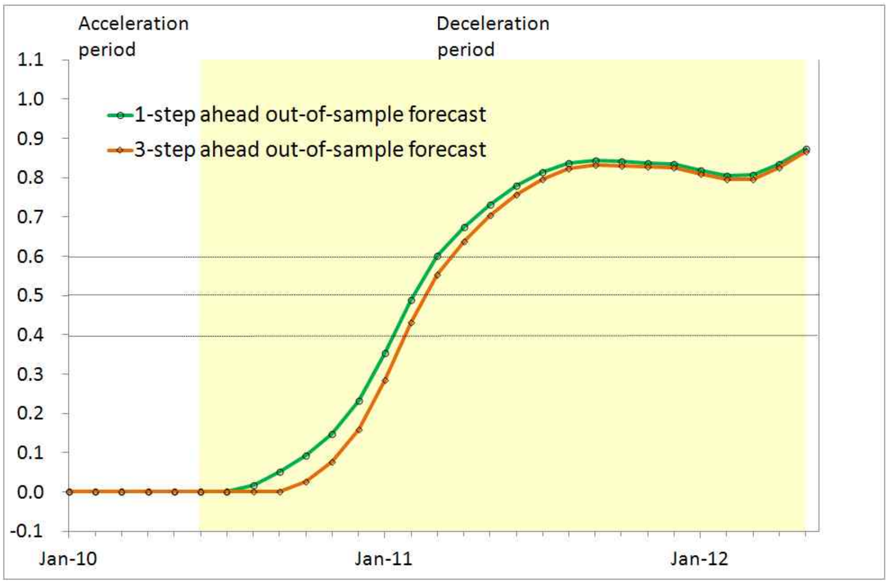


Note: The decelerating phase starting in June 2010 is subject to change as more data are available.

Recursive out-of-sample forecasts are made over the period from January 2010 to May 2012. In particular, the probabilities obtained from the 1-step and 3-step ahead out-of-sample forecasts are presented in Figure 4. The predictive power of these forecasts is evaluated by comparing a percentage of correct classification based on the cutoff value we specified. There are two kinds of correct classifications. One is that the predicted probability is greater than the cutoff and the observed $Y_t = 1$, and another is that the predicted probability is less than or equal to the cutoff and the observed $Y_t = 0$. The fraction of $Y_t = 1$ observations that are correctly predicted is called *sensitivity*, while the fraction of $Y_t = 0$ observations that are correctly predicted is called *specificity*. In this problem, the *sensitivity* is computed for the deceleration phase and the *specificity* for the acceleration phase. Moreover, a percentage of correct classification among total observations is computed.

Table 7 presents the forecast powers for the 1-step and 3-step ahead out-of-sample forecasts based on three cutoff values of 0.4, 0.5, and 0.6. All forecasts correctly identify the phase in the acceleration period from January 2010 to June 2010 for all three cutoff values. But the percentage of correct classification in the deceleration period depends on the choice of the cutoff. It is highest when the cutoff value is 0.4 since the smaller cutoff value is easier to declare the deceleration. Obviously the total forecast power tends to decrease as the cutoff value gets bigger. Comparing the out-of-sample forecast method, the 1-step ahead out-of-sample forecast has a higher forecast power than the 3-step ahead out-of-sample when the cutoff value is 0.6, but almost the same for the other cutoff values.

Figure 4. Probabilities from out-of-sample forecasts



Note: The decelerating phase starting in June 2010 is subject to change as more data are available.

Table 7. Out-of-sample forecast evaluation: probit model

Cutoff value	Phase	Percentage of correct classification	
		1-step ahead	3-step ahead
0.4	Deceleration	69.6	69.6
	Acceleration	100.0	100.0
	Total	75.9	75.9
0.5	Deceleration	65.2	65.2
	Acceleration	100.0	100.0
	Total	72.4	72.4
0.6	Deceleration	65.2	60.9
	Acceleration	100.0	100.0
	Total	72.4	69.0

4. Conclusions

We construct the ESI for the Korean economy in a similar fashion to the European Commission's; that is, we aggregate the standardized BSI and CSI component series by a weighted average and then rescale it to have a mean of 100 and a standard deviation of 10. However, we focus on selecting informative components of the BSI and CSI data and determining the weights so that the composite indicator has a high correlation with GDP growth and a leading feature with respect to GDP cycle.

We evaluate the forecasting performance of the Korean ESI with respect to GDP growth and cycle. The ESI turns out to have a good tracking performance as a leading indicator of GDP. Using the Granger causality tests we show that the constructed ESI precedes GDP growth, implying the former contains useful information in predicting GDP growth. Also, using a probit model, we show that the ESI is helpful in monitoring and predicting the turning points of GDP. The performance of our probit model could be further improved by adding more relevant economic variables as explanatory variables to the model. Overall, the recently developed ESI for the Korean economy is useful in forecasting short-term economic developments as well as in reflecting economic agents' overall perception of economic activity or conditions.

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