Forecasting Macroeconomic Variables Using Data Dimension Reduction Methods: The Case of Korea

Hyun Hak Kim*

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* Economist, Macroeconomics Team, Economic Research Institute, The Bank of Korea, 55 Namdaenunno, Jung-gu, Seoul 100-794, Korea, khdouble@bok.or.kr

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This paper investigates the usefulness of the factor model, which extracts latent information from a large set of data, in forecasting Korean macroeconomic variables. In addition to the well-known principal component analysis (PCA), we apply sparse principal component analysis (SPCA) to build a parsimonious model, and combine the estimated factors with various shrinkage methods, following Stock and Watson (2012) and Kim and Swanson (2013a), to forecast CPI inflation, GDP growth, exports, consumption and gross capital formation (GCF) of Korea from 2003:01 to 2012:12. Our major findings are that, in predicting growth rates, various hybrid models outperform benchmark models including an autoregressive model, and that this result becomes clearer as the forecast horizons lengthens. Specifically, in forecasting for more volatile periods like the global financial crisis during 2008-09, various hybrid models predict the inflection point better than AR model does. The auxiliary finding is that the main ingredients of Korean macroeconomic variables as indicated by SPCA include interest rates, construction orders received, and employment variables. Surprisingly, the monetary aggregates or price variables are never found to contribute to the principal components in our experiment.

Keywords: Prediction, Sparse Principal Component Analysis, Bagging, Boosting, Bayesian Model Averaging, Ridge Regression, Least Angle Regression, Elastic Net And Non-Negative Garrote

JEL Classification: C32, C53, G17

I. Introduction

As computation technologies are getting, remarkably, more powerful in recent decades, richer the quantity of financial and macroeconomic data becomes. Truly, there has been tremendous research, both in computation and theories, to keep pace with the enlarging amount of data, also called as 'big data'. In economics literature, one of the most widely applying field is the diffusion index methodology, also called factor model, which enable us to take a simpler and more sensible approach to extracting common component underneath dynamic evolution of a large number of variables. More specifically, many studies adopt the so-called 'dimension reduction' methods in the forecasting context, including Stock and Watson (2002), who used principal component analysis (PCA) in constructing factors. Such factors are "a few" latent variables which explain the variances in a large set of variables. To be more specific, let X be a time-series predictor matrix of N variables, and extract $r(< N)$ unobserved common factors F from X. Using the common factors thus extracted with PCA, Stock and Watson (2002) forecasted US macroeconomic variables. PCA-based factor models have generated an extensive literature, including Armah and Swanson (2010, 2011), Artis et al. (2002), Bai and Ng (2002, 2006, 2009), Boivin and Ng (2005, 2006) and Stock and Watson (2005, 2006, 2012). Meanwhile, Kalman Filtering (KF) has also been used in constructing factors for forecasting: e.g. by Banerjee and Marcellino (2008), and Dufour and Stevanovic (2010), who suggest that KF works better than PCA under certain conditions.

There are also many empirical studies that predict individual country variables using the factor model described above. For examples from advanced countries, Angelini, Bańbura and Rünstler (2008) predicted the euro area's macroeconomic variables, Bessec (2012) did the same for French GDP, den Reijer (2005) for Dutch macroeconomic variables, Schumacher (2007) for German GDP, and Schneider and Spitzer (2004) for Austrian GDP.[1] There have been numerous cases for

1) Other cases from the advanced economies include Kapetanios, Labhard and Price (2007) for macroeconomic variables in England, Godbout and Lombardi (2012) for Japanese macroeconomic variables, both Gosselin and Tkacz (2001) and Cheung and Demers (2007) for Canadian GDP and inflation, and

emerging countries as well,[2] but no research has yet forecast Korean macroeconomic variables using this kind of factor model although Lee (2004) applied PCA in forecasting the inflection point of the Korean economy's business cycle.[3]

In spite of PCA's good forecasting performance, it is very hard to tell exactly what any individual factor implicates. To overcome this problem, we apply sparse principal component analysis (SPCA), which enables us to extract parsimonious factor loadings following Kim and Swanson (2013b). In SPCA a small number of variables are selected to construct "sparse" factors which help analyze the composition of such factors. However, these sparse factors are based on the covariance structure of a predictor set, and do not tell the relationships between the dependent variables and the explanatory ones. Stock and Watson (2012) use various shrinkage methods to pick appropriate factors among the principal components. In light of this, following Bai and Ng (2008, 2009), Stock and Watson (2012), and Kim and Swanson (2013a), we implement a forecasting model in which factors are selected using various shrinkage methods including bagging, boosting, Bayesian model averaging, simple model averaging, ridge regression, least angle regression, elastic net and non-negative garotte. Kim and Swanson (2013a) have shown in their empirical work that models based on these shrinkage methods have produced better predictions.

In this paper, we first estimate unobserved factors at the time t, $\widehat{F}_t$, using PCA and SPCA and then forecast a target variable $\widehat{Y}_t$, with these given factors using various shrinkage methods. This "hybrid" model works well and outperforms benchmark models such as AR model for US macroeconomic variables in Kim and Swanson (2013b). We follow their approach with Korean macroeconomic variables. To the best of our knowledge, no research has as of yet forecast Korean macro-

Matheson (2006) for macroeconomic variables in New Zealand.

2) Examples include Ajevskis and Davidsons (2008) for Latvian GDP, Cheng and Lin (2011) for Taiwanese macroeconomic variables, Chow and Choy (2008) for Singaporean's GDP, Gupta and Kabundi (2011) for South African macroeconomic variables, Ibarra-Ramirez (2010) for the Mexican inflation rate, Kunovac (2007) for Croatian inflation, Rogleva (2011) for Bulgarian GDP, and Stakėnas (2012) for Lithuanian GDP.

3) As well as forecasting macroeconomic variables, research including Engle et al. (2012) and Marcucci (2008) have investigated high frequency financial variables, and shown empirically that models that consider factors facilitate better forecasting than the simple autoregressive model.

economic variables using data dimension reduction methods. This paper empirically assesses the predictive accuracies of various linear models and diffusion index models combined with various shrinkage methods. This comparison allows us to provide new evidence on the usefulness of the factor model in Korea as well as on various related issues such as whether model averaging outperforms, as is usually found to be the case. The variables that we predict include a variety of macroeconomic variables useful for evaluating the state of the economy such as CPI inflation, GDP growth, consumption, exports and gross capital formation (GCF).

The rest of the paper is organized as follows. The next section introduces the forecasting framework, along with a briefly describing the various shrinkage models. Section 3 explains how the sparse principal component analysis is implemented. Section 4 discusses the data and means of determining the number of factors, and Section 5 presents interpretations of the sparse principal components. The empirical results are then provided in Section 6, and concluding remarks are given in Section 7.

Ⅱ. Forecasting Model

Stock and Watson (2002) suggest the following model, in which factors are added into the ordinary autoregressive model;

$$Y_{t+h} = W_t\beta_W + F_t\beta_F + \epsilon_{t+h}, \tag{1}$$

where Y_{t+h} is the $h-$step ahead forecast value, W_t are the constants and the lagged values of the dependent variable, F_t is a vector of factors, and ϵ_t is the error term. This model is called the factor augmented autoregression (FAAR) or simply ‘factor model’ in the existing research.

The estimation of (1) consists of two steps. The first step extracts factors, F_t from the estimation of the following equation:

$$X = F\Lambda' + e, \tag{2}$$

where X is a $T \times N$ matrix, F is a $T \times r$ matrix, and Λ is an $N \times r$ matrix, also called a loading vector. A principal component of PCA is a linear combination of all variables. More specifically, PCA considers the variances within a predictor set, X, in the sense that a principal component is constructed as a linear combination of all explanatory variables with non-zero coefficients like the following,

$$P_i = a_{1i}X_1 + a_{2i}X_2 + \ldots + a_{Ni}X_N, \tag{3}$$

where P_i is the i-th principal component, and all coefficients, $a_{1i},\ldots,a_{Ni}$, also called loadings, are non-zero. Even though various literature show that PCA works very well in forecasting, it is difficult to tell what each factor implies. SPCA, in contrast, produces sparse loadings. More specifically, some of the loadings in equation (3) are not non-zero in SPCA. This means that limited subset of the variables is used in constructing components, enabling us to interpret what each component indicates. And this SPCA is applied to construct factors and its loadings of (2).

Once factor F_t is estimated through PCA or SPCA, estimated factor $\widehat{F}_t$ becomes an explanatory variable. The next step is then to estimate the parameters (β_W, β_F) of (1). Since factors are constructed without considering the dependent variable, we use shrinkage methods to give more weight to the selected factors. Brief introductions of shrinkage methods are provided as follow (see Kim and Swanson (2013a,b) for more details):

- Bagging (Bootstrap Aggregating): Bagging, introduced by Breiman (1996), makes bootstrapped samples from an original set, forecasts the target variable from each bootstrapped sample, and then takes the average of these forecasts, which becomes the bagging predictor. Stock and Watson (2012) modify bagging to make the algorithm similar to an ordinary shrinkage method by including a shrinkage factor, and apply it for forecasting U.S. macroeconomic variables under the FAAR model.
- Boosting: Introduced by Freund and Schapire (1997), boosting is a procedure

that builds on a user-determined set of functions (e.g. least square estimators), often called “learners”, and uses this set iteratively on filtered data by reducing the residuals in the previous iteration. Boosting is not strictly speaking a shrinkage method, but it resembles the procedure of bagging and is known to perform well in the forecasting literature (see Bai and Ng (2009)).

- Ridge Regression: Ridge, introduced by Hoerl and Kennard (1970), is one of the earliest versions of a penalized regression. By imposing an L_2 penalty on loss function it gives very tiny, but not zero, coefficients on less important variables. This is similar to following methods, which are penalized regressions characterized by a L_1 penalty function, which directly gives zero coefficients to the selected variables.[4)]
- Least Angle Regression (LARS): This method was introduced by Efron et al. (2004). LARS, like stepwise regressions, uses the residuals obtained after regressing the target variable on one of the explanatory data and constructs the first estimate, and then decides whether that each series can be part of the active set or not. Possible explanatory variables are incrementally examined, of which only some have corresponding non-zero coefficients then participate in making the final LARS estimate.
- Elastic Net (EN): Zou and Hastie (2005) introduced EN to overcome the problems found in LARS when T is larger than N. EN is basically similar to LARS as a penalized regression, but uses L_1 and L_2 penalties simultaneously.
- Non-negative Garrote (NNG): Breiman (1995) introduced this method, and Yuan and Lin (2007) modified the algorithm using EN. Since NNG is based on the least square estimator, its use in simple implementation is advantageous.

We also consider an autoregressive model (AR), an autoregression with exogenous variables (ARX), and a combined autoregressive distributed lag (CADL) as benchmark models. We in addition estimate the FAAR model, equivalent to equation (1) using the least square, and carry out the same estimation without lagged terms, which is called principal component regression (PCR). Also considered in

4) See Hoerl and Kennard (1970) for L_2 penalty and Tibshirani (1996) for L_1 penalty.

the sequel is Bayesian Model Averaging (BMA), known in the relevant literature as the best performer in an empirical sense. Table 1 lists all of the estimation methods used in this paper. The methods ranging from FAAR to NNG in Table 1 are based on the FAAR framework of (1), while AR, ARX and CADL do not contain any factors. We also refer to the models from Bagg to NNG as "hybrid" models, since they combine factors with shrinkage methods in their estimations.

In summary, we estimate $\widehat{F_t}$ as a first step using PCA and SPCA, and then estimate $\widehat{\beta_W}$, $\widehat{\beta_F}$ using various shrinkage methods as a second step to forecast $\widehat{Y_{t+h}}$.[5)]

Table 1: Models and Methods Used in Forecasting Experiment

Method	Description
AR	Autoregressive model with lags selected by the SIC
ARX	Autoregressive model with exogenous regressors
CADL	Combined autoregressive distributed lag model
FAAR	Factor augmented autoregressive model estimated by OLS
PCR	Principal component regression
Bagg	Bootstrap aggregating
Boost	Component boosting
BMA1	Bayesian Model Averaging with g-prior=1/T
BMA2	Bayesian Model Averaging with g-prior=1/N2
Ridge	Ridge regression
LARS	Least angle regression
EN	Elastic net
NNG	Non-negative garotte
Mean	Arithmetic mean of all above

Notes: This table summarizes the model specification and estimations used in the construction of prediction models.

5) Kim and Swanson (2013b) consider the dynamics in the factors, and show that they do not help to improve predictive accuracy, and we therefore also decide not to consider them as well.

Ⅲ. Sparse Principal Component Analysis

We skip explanation of PCA, as it was already been discussed in various literature. As explained in the previous section, the principal components are linear combinations of variables that are ordered by covariance contribution. As a result, the loading coefficients are all nonzero, making it difficult to interpret what each component represents. SPCA aids in the interpretation of PCA by restricting some coefficients at zero, we thus have components that are the linear combinations of only some of the variables. Joliffe et al. (2003), at first, suggested SCoTLASS for constructing modified principal components with possible zero loadings but the constraint of the method does not ensure convexity so that the estimation is computationally expensive. Then Zou et al. (2006) developed a regression optimization framework to derive sparse loading coefficients, and named it SPCA, which has less computational burden and we follow their approach in the spirit of Kim and Swanson (2013b).

Suppose we derive factors, F via ordinary PCA. In particular, a standardized data matrix, X can be decomposed to UDV' by singular value decomposition. In ordinary PCA, F, is defined as UD, and V becomes the loading. We then consider a simple regression problem like (2) to obtain sparse loadings by letting F_i, the i-th principal component be a dependent variable and X be explanatory variables. That is, the SPCA problem can be switched to a penalized regression problem. Zou et al. (2006) suggested the following regression type criterion to obtain sparse loadings by solving the problem: Let X_t be the t-th row vector of X; then for any positive value of η,

$$\left(\widehat{\delta}_j, \widehat{\lambda}_j\right) = \operatorname{argmin}_{\delta_i, \lambda_j} \sum_{t=1}^{T} \| X_t - \delta_j \lambda_j{}' X_t \|^2 + \eta \| \lambda_j \|^2 \tag{4}$$

$$\text{subject to } \| \delta_j \|^2 = 1.$$

Then $\widehat{\lambda}_j$ becomes the estimator of the j-th loading, λ_j. We can then simply extend (4) to derive a whole sequence of PCs. However, the penalty parameter η is applied to all variables, and this means that we do not have sparsity yet. By giving a lasso penalty[6] term, which is the L_1 penalty, we can consider the following penalized regression problem in obtaining the sparse loadings:

$$(\widehat{\Delta},\widehat{\Lambda}) = \arg\min_{\Delta,\Lambda} \sum_{t=1}^{T} \| X_t - \Delta\Lambda' X_t \|^2 + \eta \sum_{j=1}^{r} \| \lambda_j \|^2 + \sum_{j=1}^{r} \eta_{1,j} \| \lambda_j \|_1 \qquad (5)$$

$$\text{subject to } \Delta'\Delta = I_r,$$

where Λ is an $N \times r$ matrix with column λ_j, and Δ is also an $N \times r$ orthogonal constraint, so that $\widehat{\lambda}_j$ is the estimator of the j-th factor loadings, λ_j. See Zou et al. (2006) and Kim and Swanson (2013b) for more computational details. The SPCA algorithm, which solves (5) as follows.

Algorithm *Sparse Principal Component Analysis*

1. Let Δ be the factor loadings of the first r principal components.
2. Given Δ, solve the following regression problem for $j = 1, 2, \ldots, r$.
   $\lambda_j = \arg\min_{\lambda} (\delta_j - \lambda)' X' X (\delta_j - \lambda) + \eta \| \lambda \|^2 + \eta_{1,j} \| \lambda \|_1$
3. For each fixed $\Lambda = [\lambda_1, \ldots, \lambda_r]$, do the singular value decomposition on $X'X\Lambda = UDV'$, then update $\Delta^* = UV'$
4. Repeat steps 2-3 until convergence. In the final loop, Δ^* becomes the sparse factor loadings.

There are two parameters for obtaining sparse loadings and in practice, the choice of η is known not to affect the result much. However, the sparsity of loadings depends greatly upon another parameter, η_j. Shen and Huang (2007) introduce two ways of selecting the tuning parameters. The first method is K-fold Cross Validation (CV) which chooses the degree of sparsity where a given CV is minimized. The other is using the cumulative percentage of the explained variance (CPEV) of the first r PCs. The degree of sparsity as the largest parameter can be selected where the CPEV does not drop too much (for example, by less than 5% or 10%) from its peak value. For computational brevity we follow this second approach,

6) See Tibshirani (1996) for details about the lasso (least absolute shrinkage and selection operator) penalty

which Shen and Huang (2007) state also works reasonably well.

IV. Data and Estimation

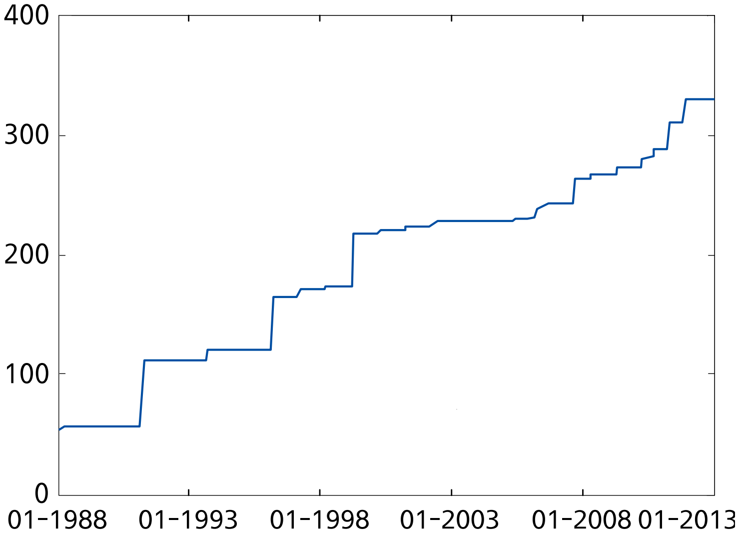
We do not restrict which series are included in the predictor set, since the purpose of this paper is extracting useful information from a large set of data. We therefore collect all available monthly series from 1970. We consider both aggregate and disaggregate series at the same level since multicollinearity does not occur in the construction of factors using PCA (see Stock and Watson (2002)).

We collect 617 monthly series from January 1970 to December 2012 and categorize them into 12 groups: interest rates, imports/exports, prices, money, exchange rates, orders received, inventories, housing, retail and manufacturing, employment, industrial production, and stocks. Among these, we pick 340 series which do not have missing values and have at least 120 observations.[7] The variables selected are listed in Appendix 1.

Since most of the data are available only in recent periods, and their starting dates are various, we only consider a rolling estimation scheme where we have 120 observations as the rolling window. When a series completes 120 observations, it is eligible for inclusion in the predictor set used in the estimation. We therefore have a set of predictors that increases in size from period to period.

7) In the estimation, we consider 120 for the size of the in-sample, and for that reason we limit the data to those with at least 120 observations.

Figure 1: Number of Variables Included in Estimation



Notes: The solid line shows the number of variables actually used in each period of estimation in the out-of-sample forecasting experiment. Since many series were not available in the past, only some of them have been used in the estimation.

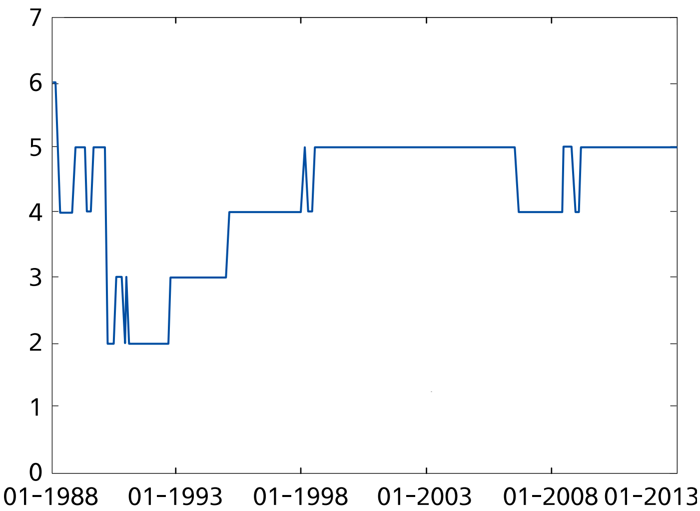
Figure 1 shows this increasing number of available variables over our out-of-sample period. In November 1987, we have only 58 available series, but by the end of the period, it reaches 340. In this sense, for more a precise forecasting experiment, we need to consider a real-time dataset. We leave this to future research since a real-time dataset for Korea has not yet been established. Having a limited amount of available data in the early periods, we consider a forecasting experiment only for the recent 10 years, which is from 2002:01 to 2012:12. Note that all variables are assumed to be stationary for implementing PCA, and we therefore transform the data appropriately following Stock and Watson (2012).

The purpose of estimating principal components is reducing the data dimension, which means that we have to choose a "small" number of components that contain a large enough amount of information from the predictor set. Bai and Ng (2002) provide one solution to the problem of choosing the number of factors in the use of ordinary PCA. They establish convergence rates for factor estimates under consistent estimation of the number of factors, r, and propose panel criteria to consistently estimate the number of factors. Bai and Ng (2002) defined selection criteria of the form $PC(r) = V(r, \hat{F}) + rh(N, T)$ where $h(\bullet)$ is a penalty function. In this paper, the following version is used (see Bai and Ng (2002) for more details):

$$SIC(r) = V(r, \hat{F}) + r\widehat{\sigma}^2\left(\frac{(N+T-r)\ln(NT)}{NT}\right) \quad (6)$$

where $\widehat{\sigma}^2$ is $(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{e}_{i,t}^2$ and $\hat{e}$ is the estimator of e in (2). The consistent estimate of the number of factors is $\hat{r} = \operatorname{argmin}_{0 \leqq r \leqq r_{\max}} SIC(r)$. We use this criterion in choosing the number of factors in the sequel.

Figure 2: Number of Factors Determined by BN



Notes: The solid line shows the number of factors determined by Bai and Ng (2002), where these factors are estimated using principal component analysis at each time of forecast. This time-varying number of factors is used in the actual forecast.

Figure 2 shows the number of factors determined by Bai and Ng (2002) at each time of forecasting. We truncate the earlier sample periods for brevity and between four and five factors are selected consistently after 1995. Alhough there are continuous inputs of new series in constructing the factors, the appropriate number of factors does not seem to be affected. The above discussion is for PCA, and as there is no literature on determining the number of factors for SPCA, we use the same number of factors in PCA in the sequel.

V. Comparison of Two Principal Components

As explained in the previous section, many loadings by SPCA become zero, unlike in ordinary PCA. That is, the less important variables have coefficients of zero and principal components (or factors) consist of a small number of variables, which enables us to interpret what the factors are composed of.

Table 2 shows the selected loadings of the first two components of PCA and SPCA. For the readers' convenience, the first column corresponds to the numbers in the full list of all predictors in the appendix. Columns PC1 and PC2 denote the loadings of PC, and SPC1 and SPC2 those of sparse PC. Note that all variables participate in the composition of the principal components, so that all loading coefficients are non-zero. Since over 300 variables are included in composing one component, it is very difficult to confirm how each component works in the set.

Table 2: First Two Loadings of PC and SPC in December 2012

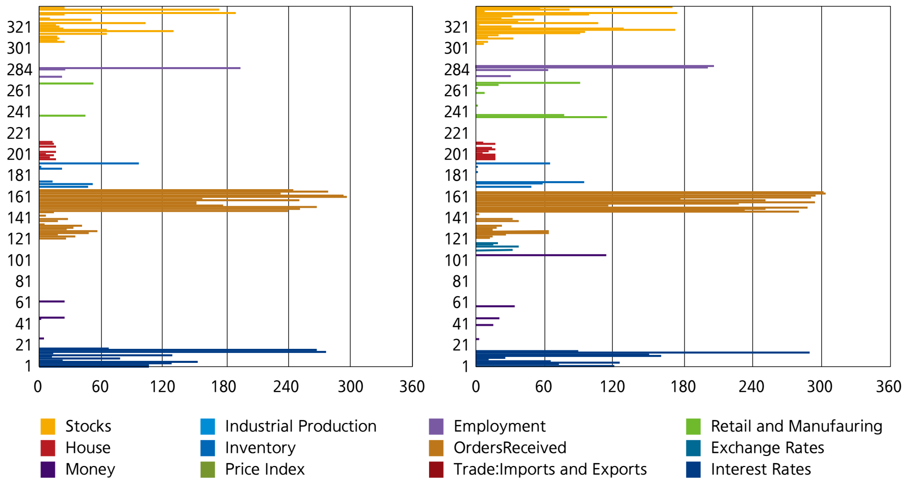
No.	Class	Variable	PC1	PC2	SPCA1	SPCA2
1	Interest Rates	Uncollateralized Call Rate	−0.685	−0.601	0	0
19	Trade	Unit Value Index of Imports	−0.600	−0.691	0	0
43	Trade	Unit Value Index of Exports	−0.771	−0.493	0	0
66	Price	Producer Price Index−All	−0.052	−0.721	0	0
74	Price	Consumer Price Index−All	0.191	−0.667	0	0
81	Price	Housing Price Index	−0.285	−0.431	0	0
87	Money	In Circulation	−0.222	0.097	0	0
110	Exchange Rates	Won Per Japanese Yen	0.781	−0.239	0	0
123	Order Received	Machinery	0.149	0.041	−0.077	0
153	Order Received	Domestic Construction−Private	−0.425	−0.100	0.054	0
168	Inventory	Total Index	−0.332	−0.727	0	0
197	Housing	Unsold−Seoul	0.166	0.108	−0.033	0.301
214	Retails and Manufacturing	Wholesale and Retail Sales Index−All	−0.668	−0.047	0	0
249	Retails and Manufacturing	Manufacturing Operation Ratio Index	−0.788	0.177	0	0
276	Employment	Unemployed−More than 12 Months.	−0.120	0.471	−0.0213	0.1815
283	Employment	Unemployment Rate	−0.031	0.325	0	0
304	Stocks	KOSDAQ Construction Index	−0.830	0.425	0	0

Notes: This table indicates the factor loadings of the first two components of PCA and SPCA. Due to limited space, we only show the loadings of selected variables. The first column shows the index numbers used in the list in the Appendix. The second one specifies the class each variable belongs to (we divide all variables into 12 classes). Since SPCA makes many variables' loadings zero, only some of the variables have nonzero loadings.

On the other hand, only a few variables participate in the composition of the components in SPCA. The first SPC in Table 2 consists of four variables and the other variables' coefficients are all zero. The actual first component consists of 47 variables out of 340 variables in total, and we report only a part of them for the sake of brevity in Table 2. SPCA enables us to construct a more parsimonious model, which is believed to give more accurate prediction according to Diebold (1998) and Clark and McCraken (2009). To analyze which variables are included the most in constructing factors, we count how many times each variable participates in each out-of-sample prediction.

Figure 3 shows the numbers of inclusion of variables with non-zero coefficients in the first two sparse principal components over the out-of-sample period (which is from 1982:01 to 2012:12). The left panel is for the first component and the right one for the second. 340 variables are categorized into 12 groups in the figure, with each group having the same colored bar. The most selected group is 'Orders Received' and the most selected variable in this group for both of the components is the Value of Construction Orders Received. Aggregate 'Construction Orders Received' is considered one of the components of a leading indicator, and its disaggregate series are frequently chosen in sparse principal components. This gives useful insight for future research in analyzing which series play bigger roles in the economy. Other frequently chosen variables include ones from the interest rates and the employment groups. Among interest rates, US interest rates such as Treasury Note Yield are the most selected. This may be an evidence showing that the Korean economy is affected by foreign economies, especially the US. We also include the Japanese government bond rate in our set, which does not seem as influential as the US Rates. In the employment group, the unemployment and employment rates are as expected the most chosen. Stock-related variables are frequently selected but we could not conclude which index is predominantly included over the out-of-sample periods. Surprisingly, price and money variables, which may be considered more important ex ante, are never chosen.

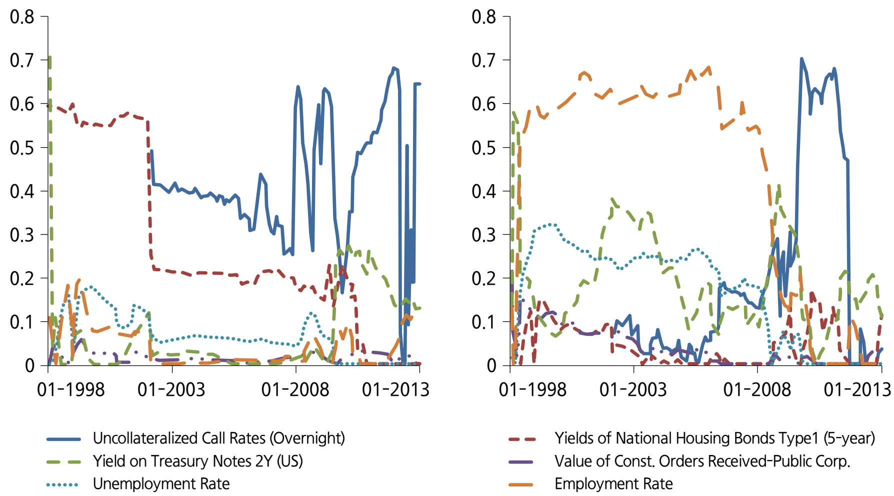
Figure 3: Number of Variables with Non-zero Coefficients in Constructing the First Two Sparse Principal Components



Notes: See the Appendix for the description of variables. The left panel shows the frequencies of inclusions of the explanatory variables in the first sparse principal component through the out-of-sample forecasting experiment, and the right panel the frequencies for the second sparse principal component. The vertical axis of each panel indicates the index number of variables from the Appendix. Variables from the same groups are in the same color. For example, Domestic Construction Order Received – Roads and Bridges, index #163, is included in construction of the first sparse principal component in 297 times out of 300 out-of-sample periods.

To see how influential each variable is over the experiment period, we plot the changes in loadings of selected variables as shown in Figure 4. Due to the limited data availability, the changes in factor loadings before 1998 are too dramatic, and we therefore exclude the results of those periods. The Uncollateralized Call Rates have remained highly influential over time, except in the beginning of the sample period (because call rates were not in the dataset at that time). In this regard, the main proxy of the first component seems to be the Overnight Call Rates in the period when all predictors are included. Considering the interactions among the interest rate variables, it is not surprising that there is a shift in importance among them. Note that the weight of the US T-Note yield has risen since the 2007-08 Financial Crisis, which may indicate that influences from overseas have increased after the crisis.

Figure 4: Factor Loadings of Selected Variables in First Two Components



Notes: See notes to Figure 3. The left panel shows the changes in loadings of the selected variables of the first sparse principal component and the right one the second sparse principal component over 1998:01-2012:12.

In the first component, variables other than interest rates have had relatively smaller weights. In the second component, however, the value of construction orders received had more weight at the beginning of the sample period. On the other hand, the importance of the employment rate had been high in the earlier period of out-of-sample experiment but dropped after the recent financial crisis in 2008 with the importance of call rates increasing during the crisis. Number of Unsold Houses in Lots, which is included in constructing factors from 2011:09, dominates the other variables in the second component.[8] Moreover, the weight of the Yield of US T-Note fluctuates moderately even after other interest rate variables are included, and that of the employment rate, which had risen to take a dominant position in the component, dropped during the 2007-08 financial crisis. Although the variables of the Value of Construction Orders are selected the most during experiment periods, they are not considered as important now as they were in the

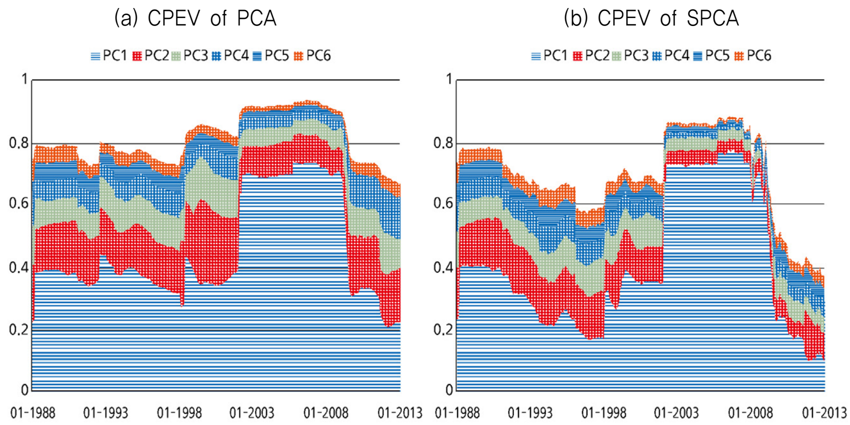
8) Note that we do not plot it in the figure, due to data availability, but it is necessary to monitor in the future.

past. We can conclude that the main part of the first component is interest rates, although the relative importance among interest rates have not yet been specified. In the second component, it is not clear which variable is more dominant than the others in our sample period.

As sparse principal components consist of a smaller number of variables, they may not explain the variations in the predictor set as much as ordinary principal components do. To see this difference, we draw the cumulative percentages of explained variance (CPEV) in Figure 5. Once a group of variables get in the dataset considered, as shown in Figure 1, its percentage changes dramatically in both principal component cases.[9] However, there was a big jump in percentages in 2002 even though there were no huge increases in sets of available variables. And this high explanatory power was maintained until the Financial Crisis in 2008. This power is jointly analyzed with the forecasting accuracy of the FAAR model in the following section. The CPEV of the six sparse components have been diminishing in recent periods more dramatically than those of the six ordinary components have. Since we do not so far have any consensus on a method of determining the number of sparse components, we keep the same number of ordinary principal components and leave to future research the task of deciding an appropriate number of sparse factors to explain an satisfactory amount of variances in the predictor.

9) Since our predictor set is expanding over time, there are jumps in the CPEV.

Figure 5: Cumulative Percentage of Explained Variance of Components



Notes: See the notes to Figures 3 and 4. This figure plots the cumulative percentages of the explained variances of the components using PCA in Panel (a) and SPCA in Panel (b) over the forecasting experiment period.

VI. Experimental Results

1. Experimental Setup

To measure the performances of the models, we use the mean square forecasting error (MSFE) method. The MSFE of the i-th model for h-step ahead is

$$MSFE_{i,h} = \sum_{t=R-h+2}^{T-h+1} (Y_{t+h} - \hat{Y}_{i,t+h})^2 \tag{7}$$

where R is a rolling window of a rolling scheme, T is the number of total observations, Y_{t+h} is the observed value at $t+h$, and $\hat{Y}_{i,t+h}$ is the predicted value at $t+h$ of the i-th model. We test the performance of the model by defining how it differs statistically from an autoregressive model, in accordance with Diebold and Mariano (1995, hereafter DM). The null hypothesis of the test is that the two models' prediction errors are identical, and is defined as

$$H_0 : E\left[l\left(\epsilon^1_{t+h|t}\right)\right] - E\left[l\left(\epsilon^2_{t+h|t}\right)\right] = 0 \tag{8}$$

where $\epsilon^i_{t+h|t}$ is the prediction error of the i-th model, and $l(\bullet)$ is the quadratic loss function. For example, if a statistic under the null hypothesis as in (4) is negative and significantly different from zero, we decide that model 2 outperforms model 1. The statistic of the DM test is

$$DM = \frac{1}{P}\sum_{i=1}^{P}\frac{d_t}{\hat{\sigma}_{\bar{d}}} \tag{9}$$

where $d_t = \left(\widehat{\epsilon^1_{t+h|t}}\right)^2 - \left(\widehat{\epsilon^2_{t+h|t}}\right)^2$, $\bar{d}$ is the mean of d_t, $\hat{\sigma}_{\bar{d}}$ is the heteroskedasticity and autocorrelation robust estimator of the standard deviation of $\bar{d}$, and $\widehat{\epsilon^1_{t+h|t}}$ and $\widehat{\epsilon^2_{t+h|t}}$ are the estimators of the prediction errors, $\epsilon^1_{t+h|t}$ and $\epsilon^2_{t+h|t}$. In this paper, we set the autoregressive as the first model and each of all the others as the second one.

We consider the following as our target variables: consumer price index (CPI), GDP, consumption, exports and gross capital formation (GCF). Since GDP, consumption, exports and GCF are quarterly data, they are interpolated using the Industrial Production, Retail Sales Value, Value of Exports and Total Equipment indexes respectively, based on the method of Chow and Lin (1971). In line with data availability, we implement out-of-sample forecasting for prices, and consumption from 1982:11, GDP from 1992:11, exports from 2000:05 and GCF from 2007:07. Due to a shortage of data, we only consider the recent ten years' out-of-sample forecasting. We make a month, a quarter, half-a-year and a year ahead forecasts, which are denoted by $h = 1, 3, 6$ and 12 respectively.

2. Results: Consumer Price Index

Table 3 reports the mean square forecasting errors (MSFEs) of the forecasts for month-on-month consumer price index inflation in the recent 10-year out-of-sample experiment. Entries in the first row, corresponding to our benchmark AR model, are the actual MSFEs, while the following entries are the relative MSFEs compared to those of AR model. That is, numerical values less than unity indicate cases in which the alternative model has a lower point MSFE than AR model. For example, in the one month ahead forecast, the relative MSFE of the FAAR model is 0.868, meaning that the real MSFE is 86.8% that of AR model. Entries in bold denote the "best" performing models under the given factor methods and forecast horizons. Entries in red indicate the lowest-MSFE models between PCA and SPCA in the given forecast horizons. For example, in the one quarter ahead forecast, Mean has the lowest MSFE in both principal component methods but Mean of PCA is highlighted in red since it has lower MSFE than that of SPCA. The results of the DM predictive accuracy test between the benchmark model and the other models, listed in the first column of the table, are reported using single star (denoting rejection at the 10% level) and a double star (denoting rejection at the 5% level).

Table 3: Relative MSFEs for Month-on-Month CPI Inflation

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.001	0.002	0.002	0.001	0.001	0.002	0.002	0.001
ARX	1.046	1.263	1.189	1.447*	1.046	1.263	1.189	1.447*
CADL	1.190	1.419**	1.108	1.061	1.190	1.419**	1.108	1.061
FAAR	0.868	0.986	1.050	1.035	0.872	0.900	0.913*	0.913
PCR	0.901	1.064	1.009	1.222**	0.956	1.105*	0.787*	0.962
Bagg	1.001	0.975	0.986	**0.923**	0.923	0.893	0.898	0.907
Boost	0.944	1.008	1.007	1.022	0.973	1.054*	0.982	1.002
BMA1	0.935	0.998	1.005	1.008	0.994	1.054*	0.981	1.004
BMA2	0.922	0.997	1.008	1.019	0.997	1.064	0.975	1.015
Ridge	0.904*	0.997	1.018	1.031	0.854	0.925*	0.821	0.828
LAR	0.960	1.004	1.008	0.992	0.986	1.053	0.984	1.026
EN	0.960	1.004	1.008	0.992	0.986	1.051	0.984	1.023
NNG	0.962	1.006	1.017	1.001	0.994	1.066	0.979	1.003
Mean	**0.883***	**0.972***	**0.984**	0.983	0.802**	0.870	0.814*	0.805

Notes: Numerical entries in this table indicate the mean square forecasting errors (MSFEs) of forecasting methods in the first column. Entries in the first row are actual MSFE of AR model while all following entries are relative MSFEs, compared to those of AR model, such that numerical values less than unity indicate cases in which the alternative model has a lower point MSFE than AR. Entries in bold denote the "best" performing models for the given forecast horizons. Entries in red denote better models, between PCA and SPCA. The results of Diebold and Mariano (1995)'s predictive accuracy tests, for which the null hypothesis is that of equal predictive accuracy between the benchmark model (defined to be the AR), and the model listed in Table 1, are reported using a single star (denoting rejection at the 10% level), and a double star (denoting rejection at the 5% level). Note that numerical entries for AR, ARX and CADL in PCA and SPCA are identical each other since those benchmark models do not involve factor or shrinkage methods.

With the exception of the one year ahead forecasts of PCA, Mean has the lowest MSFE in other horizons. Considering that model averaging or model combination outperforms other models in various literature, this is not surprising. However, applying this model in practice is a different story because the choice of which models to adopt or how to combine them matters. We discuss issues regarding this combination in the future research.

In one month ahead forecasts, the hybrid models (except Bagg) outperform AR model when PCA is used as the factor estimation method, altough only some of them outperform AR model as the forecast horizon lengthens. Bagging of PCA has the lowest MSFE in one year ahead forecast, and also has relatively lower ones in a quarter and half-a-year ahead forecasts. Overall, we cannot pick a dominant model among the hybrid models for the given forecast horizons and factor methods. However, we confirm that the mean of many forecasts work well in any case, especially when the factors are estimated by SPCA.

Table 4: Relative MSFEs for Year-on-Year CPI Inflation

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.002	0.006	0.010	0.012	0.002	0.006	0.010	0.012
ARX	1.505*	1.000	1.000	1.000	1.505*	1.000	1.000	1.000
CADL	1.189*	1.105	1.145**	1.873**	1.189*	1.105	1.145**	1.873**
FAAR	1.140	1.126	0.705*	0.398**	1.113	1.090	0.900	0.971
PCR	1.519*	1.027	0.746	0.387**	6.593**	1.927*	1.055	1.369**
Bagg	2.520**	2.286**	0.991	0.947	1.060	1.043	1.360*	1.718**
Boost	1.075	1.120	0.803*	0.461**	0.993	1.005	0.937	0.941
BMA1	1.061	1.234	0.847	0.485**	1.024	1.054	0.974	1.163*
BMA2	1.066	1.227	0.821	0.499**	1.035	1.066	0.993	1.164*
Ridge	1.074	1.249	0.880	0.398**	1.060	1.018	0.955	1.015
LAR	1.007	1.019	0.959**	0.959**	0.984	0.991	0.983*	1.047*
EN	1.007	1.018	0.959**	0.959**	0.984	0.991	0.984*	1.044*
NNG	1.017	1.016	0.975**	0.996	**0.981**	0.998	0.990	1.007
Mean	0.944*	0.928	0.686**	0.540**	1.039	**0.975**	**0.890**	**0.916**

Notes: See notes to Table 3.

Table 4 shows the relative MSFE for year-on-year CPI inflation over the same period in the previous year like Table 3. The overall performances of the one month and one quarter ahead forecasts of the hybrid models are not dominant over those of AR model. Especially, no one month or one quarter ahead forecasts of any of the hybrid models using PCA ever outperform AR model. In the meantime, some of the models using SPCA work better than AR model in given forecast horizons. However, as the forecasting horizon becomes longer, in half-a-year and one year ahead forecasts, the hybrid models show much better statistics than AR model does. Specifically, in a year ahead forecast, the relative MSFE of FAAR under PCA is about 60% lower than that of AR. Mean of PCA in this longer forecast horizons also works much better than that shorter forecast horizons. As can be seen later, this results is similar for all the other variables. Overall, we can conclude that FAAR and PCR work relatively well in longer forecast horizons when the factors are estimated by PCA.

3. Results: GDP growth rate

Entries in Tables 5 and 6 are the relative MSFEs of the forecasts for the GDP growth rate over the previous month and over the same month in the previous year, respectively. Interestingly, Table 5 shows that, for any forecast horizons, the models using SPCA work better than those using PCA. However, the best-MSFE model in SPCA is not significantly different from the MSFE of AR model. The forecasting of month-on-month growth rates shows results similar to those for CPI inflation. That is, for shorter forecast horizons, not many methods beat AR model in forms of MSFE but for longer horizons, the methods using PCA perform better. However, the best models, especially when using PCA, are generally the means of all the other models (Mean). This again confirms the well-known result that model averaging or forecast combination works well in practice.

Table 5: Relative MSFEs for Month-on-Month GDP Growth

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.027	**0.030**	**0.031**	**0.033**	0.027	0.030	0.031	0.033
ARX	1.059	1.149	1.211	1.105	1.059	1.149	1.211	1.105
CADL	1.086	1.025	1.037	1.021	1.086	1.025	1.037	1.021
FAAR	1.086	1.050	1.052	1.093	1.046	1.052	1.021	1.061
PCR	1.242	1.061	1.034	1.043	1.267	1.032	0.968	0.935
Bagg	1.043	1.017	1.005	1.019	1.016	1.019	1.018	1.016
Boost	1.026	1.012	1.013	1.007	1.056	0.996	0.994	0.994
BMA1	1.022	1.005	1.007	1.012	1.060	0.997	0.993	0.993
BMA2	1.028	1.011	1.014	1.016	1.059	0.996	0.990	0.993
Ridge	1.036	1.013	1.014	1.039	1.019	1.001	0.988	0.988
LAR	1.012	1.018	1.020	1.009	1.026	1.000	0.994	1.001
EN	1.012	1.018	1.020	1.009	1.026	1.000	0.994	1.001
NNG	1.014	1.020	1.033	1.009	1.020	1.005	0.989	1.008
Mean	**0.988**	1.011	1.017	1.002	0.987	0.998	0.993	0.979

Notes: See notes to Table 3.

Table 6: Relative MSFEs for Year-on-Year GDP Growth

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.048	0.062	0.061	0.064	0.048	0.062	0.061	0.064
ARX	0.955	0.822	0.943	0.906	0.955	0.822	**0.943**	0.906
CADL	1.135	1.243	1.230	1.640*	1.135	1.243	1.230	1.640*
FAAR	1.160*	0.857	0.825	0.735	0.991	0.894	0.979	0.957
PCR	1.167*	0.925	0.837	0.883	1.250	1.031	1.215	0.912
Bagg	1.368	0.885	1.006	0.941	1.014	1.025	1.079	**0.788***
Boost	1.009	1.013	0.825	0.790	1.002	1.068	1.218**	0.980
BMA1	1.014	1.055	0.835	0.812	1.009	1.107	1.312**	1.054
BMA2	1.017	1.030	0.836	0.859	1.010	1.106*	1.311**	1.052
Ridge	1.012	1.042	0.844	0.743	1.006	1.099	1.259*	0.935
LAR	1.002	0.971	0.952	0.923**	0.999	1.005	1.011	0.918*
EN	1.002	0.971	0.952	0.922**	0.999	1.005	1.011	0.918*
NNG	1.004	0.969	0.970	0.988*	1.001	0.995	1.007	0.990*
Mean	**0.951**	0.855	0.801*	0.723*	0.941*	0.941*	1.008	0.851**

Notes: See notes to Table 3.

4. Results: Consumption

Tables 7 and 8 report the relative MSFEs of the forecasts for consumption over the previous month and over the same month in the previous year respectively. Note that the results in both tables are for the recent five years' out-of-sample forecasting experiment due to the data availability of the corresponding series when implementing interpolation. In Table 7, not many hybrid models work better than AR model for any forecast horizons, as is already known from the previous forecasts. However, Bagg performs well and has the lowest MSFE in one month and one quarter ahead forecasts using all types of factor methods. In year-on-year consumption growth rate forecast as in Table 8, the models using PCA work better. Moreover, as shown in the previous forecasts, the performances of the hybrid models seem better with the longer forecast horizons, although they are not as good as in CPI inflation or the GDP growth rate percent.

Table 7: Relative MSFEs for Month-on-Month Consumption Growth

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.010	0.013	0.013	0.012	0.010	0.013	0.013	0.012
ARX	1.881*	1.312*	1.290	1.309	1.881*	1.312*	1.290	1.309
CADL	1.083	1.000	0.995	1.020	1.083	1.000	0.995	1.020
FAAR	1.035	1.066	1.142	1.090	1.045	1.142	1.006	0.954
PCR	1.406	1.059	1.148	1.123	1.395	1.045	1.096	1.147
Bagg	**0.994**	**0.997**	1.010	**0.997**	0.952	0.990	1.037	1.032
Boost	1.007	1.027	1.019	1.037	0.978	0.993	1.019	1.023
BMA1	0.997	1.018	1.019	1.016	1.006	1.015	1.004	1.038
BMA2	1.002	1.025	1.034	1.024	1.015	1.021	1.009	1.040
Ridge	1.000	1.023	1.041	1.027	1.021	1.018	1.016	1.039
LAR	1.000	1.037	1.022	1.045	0.991	1.024	1.014	1.011
EN	1.000	1.036	1.021	1.043	0.991	1.024	1.014	1.010
NNG	1.007	1.052	1.047	1.072	0.988	1.015	1.049	0.996
Mean	1.022	1.028	1.030	1.024	1.019	1.009	1.014	0.971

Notes: See notes to Table 3.

Table 8: Relative MSFEs for Year-on-Year Consumption Growth

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.022	0.024	0.024	0.028	**0.022**	**0.024**	0.024	0.028
ARX	1.424	1.119	1.370	0.909	1.424	1.119	1.370	0.909
CADL	1.049	1.084	0.982	1.074	1.049	1.084	0.982	1.074
FAAR	1.349	1.200	0.894	0.832	1.140	1.464	1.313	1.068
PCR	1.317	1.111	0.856	1.080	1.731	1.885*	1.497	1.199
Bagg	1.466	1.628*	1.983	1.123	1.027	1.014	0.943	0.975
Boost	1.043	1.262	1.249	0.822	1.029	1.325	1.006	1.001
BMA1	1.049	1.399	1.403	0.936	1.024	1.455	1.133	1.164
BMA2	1.033	1.350	1.466	0.978	1.033	1.464	1.153	1.154
Ridge	1.117	1.241	0.989	0.875	1.042	1.428	1.104	1.040
LAR	1.002	0.994	0.988	0.878	1.017	1.161	**0.920***	0.960
EN	1.002	0.994	0.988	0.878	1.017	1.160	0.921*	0.960
NNG	1.029	0.999	1.006	0.967	1.051*	1.087	0.960	0.977
Mean	0.977	0.976	0.928	0.696	1.008	1.140*	0.925	**0.799**

Notes: See notes to Table 3.

5. Results: Exports

Table 9 shows the MSFEs of the forecasts of exports over the previous month. We can find that Mean outperforms in many cases, like with other variables. With respect to the year-on-year export growth rate, we do not find that the predictions for longer horizons are more precise than those for shorter ones, different from cases of other variables. This implicates that forecasting for exports is more difficult than other variables. Ridge has the smallest MSFE in a year ahead forecasts but shows worse results than AR in shorter horizons. We can therefore not conclude that this method is a good 'stable' performer. In the meantime, Mean still shows a good performance for the longer forecast horizons. Since the result for year-on-year growth rate resemble those of consumption like Table 8, we skip the result for brevity.

Table 9: Relative MSFEs for Month-on-Month Growth in Exports

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.108	0.108	0.113	0.101	0.108	0.108	0.113	0.101
ARX	1.210	1.647**	1.561**	1.554*	1.210	1.647**	1.561**	1.554*
CADL	1.069	1.120	0.995	1.022	1.069	1.120	0.995	1.022
FAAR	1.320	1.050	1.149*	1.198	1.346	**0.989**	1.019	1.195
PCR	1.024	1.005	0.976	1.028	1.188	1.342**	1.106	1.308
Bagg	1.237	0.991	1.034	1.020	1.188	1.232*	1.029	1.113
Boost	1.038	1.003	1.026	1.010	1.077	1.201**	1.016	1.003
BMA1	1.077	1.016	1.034	1.029	1.104	1.401**	0.999	1.055
BMA2	1.084	1.002	1.048	1.049	1.112	1.426**	1.008	1.078
Ridge	1.078	0.973	1.056	1.062	1.137	1.270*	1.028	1.069
LAR	0.967	1.015	1.007	0.989	1.018	1.096**	1.007	1.017
EN	0.967	1.015	1.007	0.989	1.018	1.096**	1.007	1.016
NNG	0.993	0.989	1.025	0.983	1.003	1.054*	1.020	1.023
Mean	0.939	0.958	1.001	**0.970**	**0.988**	1.048	**0.979**	0.964

Notes: See notes to Table 3.

6. Results: Gross Capital Formation

Tables 10 and 11 report the relative MSFEs of the forecasts for gross capital formation (GCF)[10] over the previous month and over the same month in the previous year respectively. Similarly to in other cases, in the month-on-month forecast, the models estimated by SPCA work better than those for PCA. Surprisingly, FAAR, PCA and Bagg in SPCA perform much better than they do in any other cases. Those models track the high volatility of the rate of month-on-month growth of GCF in March-May 2009, July 2011 and July 2012 well, and these exceptions to the general results make huge differences in relative MSFEs in Table 10. As a result, those models under SPCA perform best among all models, and the dominance of SPCA over PCA in the month-on-month growth rates is thus confirmed again. In Table 11, PCR models under PCA have the lowest MSFE for every horizon and differ significantly from AR model except in a month ahead forecast. Although many hybrid models are significantly better than AR, FAAR and PCR, which do not shrink factors, also work well. It can also be interpreted that the estimated factors are sufficient for forecasting the target variables well, and that we may not need a more parsimonious model for the Korean macroeconomic data in order to improve the predictive accuracy.

10) Note that, given the data availability, the results are based on the recent five years' out-of-sample forecasting experiment.

Table 10: MSFEs for Month-on-Month Growth in GCF

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.523	0.602	0.645	0.471	0.523	0.602	0.645	0.471
ARX	0.878	**0.823**	0.891	1.294	0.878	0.823	0.891	1.294
CADL	0.953	0.987	0.984	0.985	0.953	0.987	0.984	0.985
FAAR	**0.857**	0.949	0.882	0.959	0.410	0.276	0.138	0.223
PCR	1.117	0.950	**0.876***	1.013	0.521	0.460	0.286*	0.396
Bagg	0.978	0.877	1.063	1.003	0.373	0.344	0.222	0.167
Boost	0.945	1.019	0.936*	0.934	0.989	1.127	1.108	1.087
BMA1	0.943	1.035	0.923*	0.939	1.002	1.139	1.130	1.093
BMA2	0.927	0.999	0.912*	0.943	1.007	1.139	1.134	1.099
Ridge	0.902	0.916	0.915*	0.943	0.371	0.323	0.190	0.235
LAR	1.013	1.050	0.960*	0.969	0.996	1.155	1.093	1.080
EN	1.013	1.049	0.960*	0.969	0.996	1.135	1.094	1.079
NNG	1.005	1.016	0.953*	0.977	0.993	1.016	1.013	1.022
Mean	0.895	0.927	0.899*	**0.928**	0.350	0.308	0.151	0.210

Notes: See notes to Table 3.

Table 11: MSFEs for Year-on-Year Growth in GCF

Method	PCA				SPCA			
	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
AR	0.495	0.955	1.584	1.805	0.495	0.955	1.584	1.805
ARX	1.105	0.699*	1.032	1.000	1.105	0.699*	1.032	1.000
CADL	0.913	0.823*	0.805*	0.869	0.913	0.823*	0.805*	0.869
FAAR	0.715	0.484*	0.314*	0.377**	0.919	**0.801**	**0.727***	0.769
PCR	0.714	0.448*	0.307*	0.357**	1.549*	1.208	1.125	0.917
Bagg	3.572**	1.958*	0.978	0.668**	1.003	0.844	1.065	**0.724****
Boost	0.878*	0.577*	0.412**	0.387**	0.955	0.878	1.100	1.000
BMA1	0.829*	0.546*	0.409*	0.389**	0.981	0.869	1.160	1.301*
BMA2	0.828*	0.555*	0.414**	0.392**	0.981	0.876	1.161	1.285*
Ridge	0.820**	0.555*	0.370*	0.395**	0.940	0.910	1.150	0.998
LAR	0.970	0.871*	0.798*	0.848**	0.984	0.929*	0.941	1.002
EN	0.970	0.871*	0.798*	0.848**	0.983	0.931*	0.942	1.003
NNG	0.948*	0.956**	0.962**	0.978**	0.958	0.940	0.997	0.981
Mean	0.818**	0.583**	0.510**	0.473**	**0.884***	0.815*	0.962	0.853**

Notes: See notes to Table 3.

Ⅶ. Concluding Remarks

We investigate the usefulness of factor augmented autoregressive models with various dimension reduction methods for Korean macroeconomic variables. We forecast five variables — consumer inflation, GDP growth, consumption, exports and gross capital formation — using data dimension reduction methods such as principal component analysis (PCA) and sparse principal component analysis (SPCA), combined with various shrinkage methods. First, we analyze the composition of Korean macroeconomic variables using SPCA. The main ingredients are interest rates, values of construction orders received, and employment variables. Notably, the weights of variables from the interest rates and the employment groups have been increasing, while those from the values of construction orders received has been decreasing.

The findings in the above forecasting experiment can be summarized as follows; In the one month ahead predictions, hybrid models outperform the benchmark models, including autoregression, for both month-on-month and year-on-year growth. However, we cannot pick one specific model which dominates others; As the forecast horizon lengthens, the forecasts for the year-on-year growth rate improve compared to those for month-on-month growth. And while no individual model can outperform the others for month-on-month growth (although the hybrids give better predictions than the benchmark), in the case of the year-on-year growth FAAR or PCR show the lowest MSFEs, especially for GDP and GCF, which becomes clearer with longer forecast horizons.

In most of the cases that we consider, the hybrid models give better predictions than the benchmark models, regardless of the factor estimation methods. But in comparing of the two methods, PCA gives more accurate predictions than SPCA under the same forecasting framework in our out-of-sample experiment. Our finding is thus contrary to general consensus, that more parsimonious model leads to a better forecast. This may be because a tuning parameter of SPCA, which controls the sparsity of loadings, may affect the quality of forecasts under SPCA. We leave more precise calibrations of tuning parameters to further research. A careful approach is required for applying factor methods in the sequel, in line with the following considerations. First, as we do not use real-time data, there must be a gap between the revised data and the first released. The model performance in longer forecast horizons may change if the model is estimated based on the first-released data. Second, we see that FAAR and PCR models work very well in many cases, but also that the mean of other models (Mean) works well universally. However, there also remain issues regarding model averaging, such as what models we should use and how we should combine them. We need to work further on these issues to ensure more accurate predictions.

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Appendix: List of predictors

#	Class	Type	Variable
1	Interest Rates	Domestic Interest Rates	Uncollateralized Call Rates(Overnight)
2			Uncollateralized Call Rates(Overnight, Direct Interbank Transactions)
3			Uncollateralized Call Rates(Overnight, Intermediated Transactions)
4			Yields on CD(91-day)
5			Yields on CP(91-day)
6			Yields of National Housing Bonds Type1(5-year)
7			Yields of Treasury Bonds(1-year)
8			Yields of Treasury Bonds(3-year)
9			Yields of Treasury Bonds(5-year)
10			Yields of Treasury Bonds(10-yer)
11			Yields of Monetary Stab. Bonds(2-year)
12			Yields of Financial Debentures(1-year)
13			Yields of Financial Debentures(3-Year)
14			Yields of Corporate Bonds : O.T.C (3-year, BBB-)
15		Major International Interest Rates	C/D(90days)(USA)
16			T/N(2years)(USA)
17			T/N(5years)(USA)
18			Govt.Bond(5years)(Japan)
19	Imports and Exports	Value Indexes of Imports	Total
20			Consumer Goods
21			Cereal
22			Direct Consumer Goods
23			Durable Consumer Goods
24			Electric Machine for Domestic Purpose
25			Nondurable Consumer Goods
26			Crude Material & Fuel
27			Fuel
28			Crude Oil
29			Mineral
30			Light-industrial Crude Material
31			Textile Yarn & Thread
32			Chemicals
33			Iron & Steel Product
34			Non Ferreous Metal
35			Capital Goods

#	Class	Type	Variable
36	Imports and Exports	Value Indexes of Imports	Machinery & Precision equipment
37			Precision Equipment
38			Electric · electronic Machine
39			Information&communication's Equipment
40			Semi–conductor
41			Excluding Crude Petrolum
42		Value Indexes of Exports	Unit Value Index of Export
43			Foods and Direct Consumer Goods
44			Fish & Shellfish
45			Crude Material & Fuels
46			Petroleum & Petroleum Products
47			Light–industry Products
48			Textile Yarn & Thread
49			Woven & Textile Fabrics
50			Clothing
51			Tyres & Inner Tube
52			Gold
53			Paper & Paperboard
54			Heavy–industry Products
55			Chemicals
56			Iron & Steel Product
57			Machinery & Precision Equipment
58			Precision Equipment
59			Electric · electronic Machine
60			Electric machine for Domestic Purpose
61			Information & Communication Equiment
62			Semi–conductor
63			Passenger Car
64			Excl. Semicond. Inform & Comm. Equip.
65			to Hong Kong
66	Price	Production Price Index	All
67			Commodities
68			Agricultural, Forest & Marine Products
69			Services
70			Transportation
71			Financial Services
72			Leasing & Renting
73			Other Services

#	Class	Type	Variable
74	Price	Consumer Price Index	Total Item
75			Food and Non-Alcoholic Beverages
76			Housing, Water, Electricity, Gas and Other Fuels
77			Furnishings, household equipment and routine household maintenance
78			Recreation and culture
79			Restaurants and hotels
80			Miscellaneous goods and services
81		Housing Purchase Price Index	All Groups
82			All Groups(Seoul)
83			Detached Dwelling
84			Row House
85			Apartment
86			Apartment(Seoul)
87	Money	Money & Banking (Monetary Aggregates, Deposits, Loans & Discounts etc.)	Bank Notes and Coins in Circulation(End Of)
88			Monetary Base(End Of)
89			M1(Narrow Money, End Of)
90			M1-MMF(End of)
91			M2(Broad Money, End Of)
92			Lf(End Of)
93			L(End of)
94			Seasonally Ajusted M1(End of)
95			Seasonally Ajusted M2(End of)
96			Seasonally Adjusted Lf(End Of)
97			Seasonally Adjusted L(End of)
98			Total Deposits of CBs & SBs. (End Of)
99			Time & Savings Deposits of CBs & SBs. (End Of)
100			Loans of CBs & SBs(End Of)
101			Turnover Ratio of Demand Deposits, CBs & SBs
102		Loans & Discounts By Fund	Total Loans(CBs & SBs)
103			Equipment
104			Operation
105			Loans With Banking Funds
106			Loans With Govt Funds
107		Loans and Discounts of the Bank of Korea	TOTAL
108			AGGR.LOANS PROV (TOTAL)
109			AGGR.LOANS PROV (LOCAL)

#	Class	Type	Variable
110	Exchange Rates	Arbitraged Rates of Major Currencies Against Won, Longer Frequency	Won per Japan Yen(100Yen)
111			Won per Euro
112			Won per United Kingdom Pound Sterling
113			Won per Canadian Dollar
114			Won per Swiss Franc
115			Won per Hongkong Dollar
116			Won per Sweden Swdish Krona
117			Won per Australian Dollar
118			Won per Denmark Danish Krone
119			Won per Norwagian Krone
120			Won per Saudi Riyal
121	Value of Orders	Value of Machinery Orders Received	Total Value Ordered
122			Domestic Demand
123			Government and Public
124			Private Demand
125			Manufacturing
126			Non-Manufacturing
127			Agencies
128			Overseas Demand
129			Engines
130			Special Purpose Machinery
131			Metal Cutting and Forming
132			General Purpose Machinery
133			Communication Equipment
134			Electrical Machinery
135			Motor Vehicles
136			Precise Process Control Equipment
137			Total Value Ordered(Excluding Vessels)
138			Domestic Demand(Excluding Vessels)
139			Government and Public(Excluding Vessels)
140			Private Demand(Excluding Vessels)
141			Overseas Demand(Excluding Vessels)
142			Total Value Ordered (Excluding Vessels · Internal conversion engine for vessels)
143			Domestic Demand (Excluding Vessels · Internal conversion engine for vessels)
144			Government and Public (Excluding Vessels · Internal conversion engine for vessels)
145			Private Demand (Excluding Vessels · Internal conversion engine for vessels)

#	Class	Type	Variable
146			Overseas Demand (Excluding Vessels · Internal conversion engine for vessels)
147	Value of Orders	Value of Domestic Construction Orders Received	Total Orders Received
148			Public
149			Central Government
150			Local Government
151			Public Corporation
152			Other Public Body
153			Private
154			Manufacturing
155			Non-Manufacturing
156			Building
157			Dwellings
158			Offices and Stores
159			Factory and Storage
160			Public Offices
161			Others
162			Civil Engineering
163			Roads and Bridges
164			Water Supply and Sewerage
165			Generation of Electricity
166			Land Development
167			Installation of Machinery
168	Inventory	Inventory Index by Industry	All Groups
169			Mining & Manufacturing
170			Mining and quarrying
171			Mining of Coal, Crude Petroleum and Natural Gas
172			Mining of Non-metallic Minerals, Except Fuel
173			Manufacturing
174			Manufacture of Food Products
175			Manufacture of Beverages
176			Manufacture of Tobacco Products
177			Manufacture of Textiles, Except Apparel
178			Manufacture of wearing apparel, Clothing Accessories and Fur Articles
179			Tanning and Dressing of Leather, Manufacture of Luggage and Footwear
180			Manufacture of Wood and of Products of Wood and Cork ; Except Furniture
181			Manufacture of Pulp, Paper and Paper Products

#	Class	Type	Variable
182	Inventory	Inventory Index by Industry	Manufacture of Coke, hard-coal and lignite fuel briquettes and Refine
183			Manufacture of chemicals and chemical products (except pharmaceuticals
184			Manufacture of Rubber and Plastic Products
185			Manufacture of Other Non-metallic Mineral Products
186			Manufacture of Basic Metal Products
187			Manufacture of Fabricated Metal Products, Except Machinery and Furniture
188			Manufacture of Electronic Components, Computer, Radio, Television and
189			Manufacture of Medical, Precision and Optical Instruments, Watches and
190			Manufacture of electrical equipment
191			Manufacture of Other Machinery and Equipment
192			Manufacture of Motor Vehicles, Trailers and Semitrailers
193			Manufacture of Other Transport Equipment
194			Manufacture of Furniture
195			Other manufacturing
196	Housing	Number of Unsold Houses in Lots	Whole Country
197			Seoul
198			Busan
199			Daegu
200			Incheon
201			Gwangju
202	Housing	Number of Unsold Houses in Lots	Daejeon
203			Ulsan
204			Gyeonggi-do
205			Gangwon-do
206			Chungcheongbuk-do
207			Chungcheongnam-do
208			Jeollabuk-do
209			Jeollanam-do
210			Gyeongsangbuk-do
211			Gyeongsangnam-do
212			Jeju-do
213			(National Capital Region)
214	Wholesale and Retail Sales	Wholesale and Retail Sales Index	All Groups
215			Sale of Motor Vehicles and Parts
216			Sale of Motor Vehicles
217			SaleofMotorVehiclePartsand two-wheeled vehicle

#	Class	Type	Variable
218	Wholesale and Retail Sales	Wholesale and Retail Sales Index	Wholesale Trade
219			Brokerage of Inductrial Agricultural Raw Materials
220			Wholesale of Food, Beverages and Tobaccos
221			Wholesale of Household Goods
222			Wholesale of Machinery Equipment and Supplies
223			Wholesale of Construction Materials and Hardware
224			Other Specialized Wholesale
225			Retail Trade
226			Retail Sale in Non-Specialized Stores
227			Retail Sale of Foods, Beverages and Tobacco in Specialized Stores
228			Retail Sale of Textiles, Clothing and Footwear Goods
229			Retail Sale of Fuel
230			Retail Sale not in Stores
231	Manufacturing	Manufacturing Production Index by Special Classification	All Items
232			Capital Goods
233			Manufacturing Equipment
234			Electricity
235			Communication
236			Transportation Equipment
237			Agriculture
238			Construction
239			Office
240			Others
241			Intermediate Goods
242			Manufacturing
243			Construction
244			Fuel and Electricity
245			Others
246			Consumers' Goods
247			Durable Consumers' Goods
248			Non-Durable Consumers' Goods
249		Manufacturing Operation Ratio Index Manufacturing Operation Ratio Index	Manufacture
250			Food Products
251			Beverages Products
252			Tobacco Products
253			Petroleum Products
254			Manufacture of wearing apparel, Accessories and Fur Articles

#	Class	Type	Variable
255	Manufacturing	Manufacturing Operation Ratio Index Manufacturing Operation Ratio Index	Tanning and Dressing of Leather, Luggage and Footwear
256			Manufacture of Wood and of Products of Wood and Cork
257			Pulp, Paper and Paper Products
258			Coke, hard-coal and lignite fuel briquettes and Refined Petroleum Products
259			Chemicals and chemical products
260			Rubber and Plastic Products
261			Non-metallic Mineral Products
262			Basic Metal Products
263			Fabricated Metal Products
264			Electronic onents, Computer, Radio, Television and Communication Equipment and Apparatuses
265			Medical, Precision and Optical Instruments, Watches
266			Electrical Equipment
267			Other Machinery and Equipment
268			Motor Vehicles, Trailers and Semitrailers
269			Other Transport Equipment
270			Other manufacturing
271	Employment	Unemployed	Total
272			Less than 3mo.
273			More than 3mo. And Less than 6mo.
274			More than 6mo. And Less than 12mo.
275			More than 6mo.
276			More than 12mo.
277		Labor Force	Pop.15 Years Old and Over
278			Economically Active Pop.
279			Employed Persons
280			Unemployed Persons
281			Not Economically Active Pop.
282			Participation Rate
283			Unemployment Rate
284			Employment Rate
285	Output	Production Index by Industry	All Groups
286			Mining and Manufacturing
287			Mining
288			Manufacturing
289			Publishing activities
290			Total index(Including Publishing activities)

#	Class	Type	Variable
291	Output	Shipment Index by Industry Shipment Index by Industry	All Groups
292			Mining and Manufacturing
293			Mining
294			Manufacturing
295			Electricity, gas
296			Publishing activities
297			Total index(Including Publishing activities)
298	Misc		Total Equipment Index
299			Leading Composite Index
300			Coincident Composite Index
301			Lagging Composite Index
302			Cycle of Coincident Composite Index
303			Cycle of Leading Composite Index
304	Stocks	KOSPI	KOREA KOSPI 100 INDEX (KOSPI100)
305			KOREA KOSPI 50 INDEX (KOSPI50)
306			KOSPI 200 INDEX (KOSPI2)
307			KOSPI BANKS INDEX (KOSPBANK)
308			KOSPI CHEMICALS INDEX (KOSPCHEM)
309			KOSPI COMMUNICATION INDEX (KOSPCOMM)
310			KOSPI CONSTRUCTION INDEX (KOSPCONS)
311			KOSPI DISTRIBUTION INDUS (KOSPWHOL)
312			KOSPI ELECTRIC & ELE EQU (KOSPELEC)
313			KOSPI ELECTRICITY & GAS (KOSPELGS)
314			KOSPI FINANCE INDEX (KOSPFIN)
315			KOSPI FOOD & BEVERGE IX (KOSPFBEV)
316			KOSPI INDEX (KOSPI)
317			KOSPI INSURANCE INDEX (KOSPINSR)
318			KOSPI Iron & Metal Pr IX (KOSPBMET)
319			KOSPI LARGE CAP INDEX (KOSPLMKC)
320			KOSPI MACHINERY INDEX (KOSPMACH)
321			KOSPI MANUFACT INDU INDX (KOSPMAN)
322			KOSPI MEDIC SUPPLIES IDX (KOSPMED)
323			KOSPI MEDICAL & PREC MAC (KOSPMDEQ)
324			KOSPI MID CAP INDEX (KOSPMMKC)
325			KOSPI NONMETALLIC MINRL (KOSPNMET)
326			KOSPI PAPER & WOOD INDEX (KOSPPPRD)
327			KOSPI SECURITIES INDEX (KOSPSEC)
328			KOSPI SERVICES INDEX (KOSPSERV)

#	Class	Type	Variable
329	Stocks	KOSPI	KOSPI SMALL CAP INDEX (KOSPSMKC)
330			KOSPI TEXTILE & WEAR APP (KOSPTXAP)
331			KOSPI TRANSPORT & STRGE (KOSPTRAN)
332			KOSPI TRANSPORT EQUIPMT (KOSPTREQ)
333		KOSDAQ	KOSDAQ 100 INDEX (KOSD100)
334			KOSDAQ CONSTRUCTION INDEX (KOSCNST)
335			KOSDAQ DISTRIB SRVC INDEX (KOSDIST)
336			KOSDAQ FINANCE INDEX (KOSFINC)
337			KOSDAQ INDEX (KOSDAQ)
338			KOSDAQ IT COMPOSITE INDEX (KOSITCP)
339			KOSDAQ MANUFACTURING INDEX (KOSMANU)
340			KOSDAQ OTHERS INDEX (KOSOTHR)

<Abstract in Korean>

김현학*

본고는 대용량의 데이터로부터 유용한 정보를 추출하는 팩터 모형(factor model)이 국내 거시경제 변수들을 전망하는데 있어 유용한지 살펴보았다. 이를 위해 널리 알려진 주성분분석(PCA) 외에 조금 더 간소한 모형을 구축하기 위해 설명력이 큰 소수의 변수들로 구성된 주성분을 추출하는 Sparse 주성분분석(Sparse PCA)에 Stock and Watson (2012)와 Kim and Swanson (2013a)에서 사용한 축약(shrinkage)방법을 결합하여 혼합 예측 모형을 구성하고 2003년부터 2012년까지 물가, GDP, 수출, 소비 그리고 총자본형성을 예측하여 보았다. 분석 결과 변수들의 전기대비 및 전년 동기대비 성장률 예측에서 혼합모형들이 자기회귀모형에 비해 나은 예측력을 보이는 것으로 나타났다. 혼합모형의 예측력은 전년 동기대비 성장률의 경우, 그리고 예측 시계가 길어질수록 더 좋아지는 것으로 분석되었다. 특히 큰 변동성을 보이는 경제 위기 시에 자기회귀모형에 비해 혼합모형들은 각 변수들의 변곡점을 더 잘 예측하는 것으로 나타났다.

* 한국은행 경제연구원 거시경제연구실 전문연구원, khdouble@bok.or.kr