Forecasting Financial Stress Indices in Korea: A Factor Model Approach

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We propose factor-based out-of-sample forecast models for the financial stress index and its 4 sub-indices developed by the Bank of Korea. We employ the method of the principal components for 198 monthly frequency macroeconomic data to extract multiple latent factors that summarize the common components of the entire data set. We evaluate the out-of-sample predictability of our models via the ratio of the root mean squared prediction errors and the Diebold-Mariano-West statistics. Our factor models overall outperform the random walk model in forecasting the financial stress indices for up to 1-year forecast horizon. Our models also perform fairly well relative to a stationary autoregressive model especially when the forecast horizon is short, which is practically useful because financial crises often occur abruptly with no systemic warning signals. Parsimonious models with small number of factors perform as well as bigger models. Overall, our findings imply that not only financial data but also real activity variables can help out-of-sample forecast the vulnerability in the financial markets.

Keywords: Financial stress index, Principal component analysis, PANIC, In-sample fit, Out-of-sample forecast, Diebold-Mariano-West Statistic

JEL Classification: C53, G17, C38

1. Introduction

Financial market crises often occur abruptly and quickly spread to other sectors of the economies and even to other countries. For example, the bankruptcy of Lehman Brothers on September 15, 2008 resulted in the collapse of financial markets not only in the U.S. but also in other countries including Korea. These crises tend to come to a surprise realization with no systemic warnings. Since they create harmful long-lasting effects on real activities even after the financial system becomes stabilized, it would be useful to have an instrument, say an Early Warning Signal (EWS), which can provide timely information on the vulnerability in financial markets in the near future.

For this purpose, it is crucially important to find a measure of financial market vulnerability, which quantifies the potential risk that prevails in financial markets. One popularly used measure in the literature is the Exchange Market Pressure index (EMP). Since the work of Girton and Roper (1977), many researchers use this index to develop EWS mechanisms to detect money market turbulence across countries. See Tanner (2002) for a review.

One other measure that is rapidly gaining popularity is financial stress indices (FSTI)¹⁾. Unlike the EMP index that is based on exchange rate depreciation and reserves changes, the FSTI is constructed using a broad range of financial market key variables. There's an array of work that provides regional financial stress indices such as Grimaldi (2010), Grimaldi (2011), Hollo et al. (2012), and Islami and Kurz-Kim (2013) for the Euro area as well as for individual countries such as Greece (Louzis and Vouldis, 2011), Sweden (Sandahl et al., 2011), Canada (Illing and Liu, 2006), Denmark (Hansen, 2006), Switzerland (Hanschel and Monnin, 2005), Germany (Van Roye, 2011), Turkey(Cevik et al., 2013), Colombia (Morales and Estrada, 2010), and Hong Kong (S.Yiu et al., 2010). There are currently 12 FSTI type data available for the U.S. financial market (Oet et al., 2011) including four indices produced by the U.S. Federal Reserve system.

Conventional approaches to predict financial crises include the following. Frankel and Saravelos (2012), Eichengreen et al. (1995), and Sachs et al. (1996)

1) Bank of Korea produces financial stability indices as FSI so that financial stress indices are abbreviated to FSTI.

use linear regressions to test the statistical significance of various economic variables on the occurrence of crises. Other group of researches employs discrete choice model approaches, either parametric probit or logit regressions (Frankel and Rose, 1996; Cipollini and Kapetanios, 2009) or nonparametric signals approach (Kaminsky et al., 1998; Brüggemann and Linne, 1999; Edison, 2003; Berg and Pattillo, 1999; Bussiere and Mulder, 1999; Berg et al., 2005; El-Shagi et al., 2013; Christensen and Li, 2014).

Some of recent studies started to investigate what economic variables help predict financial market vulnerability proxied by newly developed FSTIs. For instance, Christensen and Li (2014) propose a model to forecast the FSTIs developed by IMF for 13 OECD countries, utilizing 12 economics leading indicators and three composite indicators. They used the signal extraction approach proposed by Kaminsky et al. (1998). Slingenberg and de Haan (2011) constructed their own FSTIs for 13 OECD countries and investigated what economic variables have predictive contents for the FSTIs via linear regression models, finding no clear linkages between economic variables and the FSTIs. Misina and Tkacz (2009) investigated the predictability of credit and asset price movements for financial market stress in Canada. Kim and Shi (2015) implemented forecasting exercises for the FSTI in the U.S. using a similar methodologies used in this paper.

The present paper seeks possible mechanisms to predict financial market vulnerability in Korea using a broad range time series macroeconomic data. We propose factor-based prediction models to out-of-sample forecast the financial stress index and its four sub-indices for the bond market, the foreign exchange market, the stock market, and the financial industry in Korea. Instead of using individual data series, we employ the method of the principal components (Stock and Watson, 2002) to extract multiple common factors from 198 monthly frequency time series data from October 2000 to December 2013. We categorized these 198 variables into 13 groups that include an array of nominal and real activity variables. We evaluate the out-of-sample forecast predictability of our models in comparison with two benchmark models, the nonstationary random

walk (RW) and a stationary autoregressive (AR) models, via the ratio of the root mean square prediction errors (*RRMSPE*) and the Diebold-Mariano-West (*DMW*) test statistics.

Our major findings are as follows. First, our factor models overall outperform the RW model for most FSTI. Our models also perform reasonably well over the AR model especially for cases with short forecast horizons. Our model performed the best for the foreign exchange market over the RW model. That is, *RRMSPE* was substantially greater than one (smaller mean squared prediction errors of our models) and the *DMW* test rejects the null of equal predictability for majority cases of the forecast horizons from 1 month to 1 year. Second, parsimonious models with just one single factor perform as well as bigger models that include up to 8 common factors. Especially, the first common factor that represent both the nominal and real activity variables seems to be sufficient to beat the RW model. Third, the fixed rolling window scheme tends to perform similarly well as the recursive approach when we choose the 70% split point. Overall, our findings imply that not only financial data but also real activity macroeconomic data help out-of-sample forecast the vulnerability in the financial markets.

The rest of the paper is organized as follows. Section 2 describes the econometric model and the out-of-sample forecasts schemes as well as the evaluation methods we employ in the present paper. In Section 3, we provide data descriptions and preliminary analyses for latent common factor estimates. Section 4 reports our major findings from in-sample fit analyses and out-of-sample forecast exercises. Section 5 concludes.

2. The Econometric Model

Let $x_{i,t}$ be a macroeconomic variable $i \in \{1, 2, \dots, N\}$ at time $t \in \{1, 2, \dots, T\}$.

$$x_{i,t} = c_i + \lambda_i' \mathbf{F}_t + e_{i,t}, \quad (1)$$

where c_i is a fixed effect intercept, $\mathbf{F}_t = [F_{1,t} \cdots F_{r,t}]'$ is an $r \times 1$ vector of *latent* common factors, and $\lambda_i = [\lambda_{i,1} \cdots \lambda_{i,r}]'$ denotes an $r \times 1$ vector of factor loading

coefficients for $x_{i,t}$. $e_{i,t}$ is the idiosyncratic error term. All variables other than those in percent (interest rates, unemployment rates, etc.) are log-transformed.

Estimation is carried out via the method of the principal components for the first-differenced data. As Bai and Ng (2004) show, the principal component analysis estimators for $\mathbf{F}_t$ and λ_i are consistent irrespective of the order of $\mathbf{F}_t$ as long as $e_{i,t}$ is stationary. However, if $e_{i,t}$ is an integrated process, a regression of $x_{i,t}$ on $\mathbf{F}_t$ is spurious. To avoid this problem, we apply the method of the principal components to the first-differenced data. That is, we rewrite (1) by the following.

$$\Delta x_{i,t} = \lambda_i' \Delta \mathbf{F}_t + \Delta e_{i,t} \quad (2)$$

for $t = 2, \dots, T$. Let $\Delta \mathbf{x}_i = [\Delta x_{i,1} \dots \Delta x_{i,T}]'$ and $\Delta \mathbf{x} = [\Delta \mathbf{x}_1 \dots \Delta \mathbf{x}_N]$. We first normalize the data before the estimations, since the method of the principal components is not scale invariant. Taking the principal components method for $\Delta \mathbf{x} \Delta \mathbf{x}'$ yields factor estimates $\Delta \hat{\mathbf{F}}_t$ along with their associated factor loading coefficients $\hat{\lambda}_i$. Estimates for the idiosyncratic components are naturally given by the residuals $\Delta \hat{e}_{i,t} = \Delta x_{i,t} - \hat{\lambda}_i' \Delta \hat{\mathbf{F}}_t$. Level variables are then recovered by re-integrating these estimates,

$$\hat{e}_{i,t} = \sum_{s=2}^t \Delta \hat{e}_{i,s} \quad (3)$$

for $i = 1, 2, \dots, N$. Similarly,

$$\hat{\mathbf{F}}_t = \sum_{s=2}^t \Delta \hat{\mathbf{F}}_s \quad (4)$$

After obtaining latent factor estimates, we employ the following regression model. Abstracting from deterministic terms,

$$fsi_{t+j} = \beta_j' \Delta \hat{\mathbf{F}}_t + \alpha_j fsi_t + u_{t+j}, \quad j = 1, 2, \dots, k \quad (5)$$

That is, we implement direct forecasting regressions for the j -period ahead financial stress index (fsi_{t+j}) on (differenced) common factor estimates ($\Delta \hat{\mathbf{F}}_t$) and the

current value of the index (fsi_t), which belong to the information set (Ω_t) at time t . Note that (5) is an AR (1) process for $j = 1$, extended by exogenous common factors $\Delta \hat{\mathbf{F}}_t$. This formulation is based on our preliminary unit-root test results for the FSTIs that show strong evidence of stationarity.²⁾ Applying the ordinary least squares (OLS) estimation for (5) yields the following j -period ahead forecast for the financial stress index.

$$\widehat{fsi}_{t+j|t}^F = \beta_j' \Delta \hat{\mathbf{F}}_t + \hat{\alpha}_j fsi_t \quad (6)$$

To statistically evaluate our factor models, we employ the following nonstationary random walk (RW) model as a (no change) benchmark model.

$$fsi_{t+1} = fsi_t + \varepsilon_{t+1} \quad (7)$$

It is straightforward to show that (7) yields the following j -period ahead forecast.

$$\widehat{fsi}_{t+j|t}^R = fsi_t, \quad (8)$$

where fsi_t is the current value of the financial stress index.

In addition to the RW model, we also employ the following stationary AR (1) model as an alternative benchmark model.

$$fsi_{t+j} = \alpha_j fsi_t + \varepsilon_{t+j}, \quad (9)$$

where α_j is the coefficient on the current FSTI in the direct regression for the j -period ahead FSTI variable, which yields the following j -period ahead forecast.

$$\widehat{fsi}_{t+j|t}^{AR} = \hat{\alpha}_j fsi_t, \quad (10)$$

For evaluations of the prediction accuracy of our models, we use the ratio of the root mean squared prediction error (*RRMSPE*), that is, *RMSPE* from the benchmark model divided by *RMSPE* from the factor model. Note that our factor model performs better than the benchmark model when *RRMSPE* is

2) ADF test results are available upon request.

greater than 1.

Also, we employ the Diebold-Mariano-West (*DMW*) test for further statistical evaluations of our models. For the *DMW* test, we define the following function.

$$d_t = L(\varepsilon_{t+j|t}^A) - L(\varepsilon_{t+j|t}^F), \quad (11)$$

where $L(\cdot)$ is a loss function from forecast errors under each model, that is,

$$\varepsilon_{t+j|t}^A = fsi_{t+j} - \widehat{f}si_{t+j|t}^A \quad (A = RW, AR), \quad \varepsilon_{t+j|t}^F = fsi_{t+j} - \widehat{f}si_{t+j|t}^F \quad (12)$$

One may use either the squared error loss function, $(\varepsilon_{t+j|t}^j)^2$, or the absolute loss function, $|\varepsilon_{t+j|t}^j|$.

The *DMW* statistic to test the null of equal predictive accuracy, $H_0 : Ed_t = 0$, is given as follows.

$$DMW = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}}, \quad (13)$$

where $\bar{d}$ is the sample mean loss differential, $\bar{d} = \frac{1}{T - T_0} \sum_{t=T_0+1}^T d_t$, and $\widehat{Avar}(\bar{d})$ denotes the asymptotic variance of $\bar{d}$,

$$\widehat{Avar}(\bar{d}) = \frac{1}{T - T_0} \sum_{i=-q}^q k(i, q) \hat{\Gamma}_i \quad (14)$$

$k(\cdot)$ is a kernel function where T_0/T is the split point in percent, $k(\cdot) = 0$, $j > q$, and $\hat{\Gamma}_j$ is j^{th} autocovariance function estimate.³⁾ Note that our factor model (5) nests the stationary benchmark model in (9) with $\beta_j = 0$. Therefore, we use critical values proposed by McCracken (2007) that re-center the distribution of the test statistic for this case. For the *DMW* statistic with the random walk benchmark (7), which is not nested by (5), we use the asymptotic critical values, which are obtained from the standard normal distribution.

3) Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

3. Data Descriptions and Factor Estimations

3.1. Data descriptions

We use the financial stress index (FSTI) data to assess the vulnerability in financial sectors in Korea. Financial stress or the vulnerability in financial markets to a financial crisis may be measured by the level of uncertainty in the financial market and/or expected financial losses that could be incurred to financial intermediaries in the economy. Early Warning Indicators (EWI) and Financial Condition Indices (FCI) share similar information as FSTIs in the sense that they all measure the current financial conditions in the economy, though the purposes of those indices are somewhat different.⁴⁾

Earlier attempts to develop FSTIs were done by the Bank of Canada in 2003 and the Swiss National Bank in 2004, while the Kansas City Fed and the St. Louis Fed in the U.S. also started using FSTIs since 2008. In Korea, the Bank of Korea developed FSTIs in 2007 and started to report the indices on a yearly basis in their Financial Stability Report. We estimated monthly frequency FSTI data based on the Bank of Korea. Korea's FSTI data is based on 4 sub-indices for the bond market (FSTI-Bond), financial stability report the foreign exchange market (FSTI-FX), the stock market (FSTI-Stock), and the financial industry (FSTI-Industry). Index ranges from 0 to 100 and it reaches to 100 when financial stress is at peak, such as Asian Financial Crisis in 1997.

Each sub-index is constructed as follows. The FSTI-Bond is based on an array of credit spreads, long-short interest rate spreads, and covered interest rate differentials (CID). The FSTI-FX is obtained utilizing the volatility and the growth rate of the Korean Won-U.S. Dollar exchange rate as well as the growth rate of Korea's foreign exchange reserves. The FSTI-Stock is constructed based on the volatility and the growth rate of KOSPI (Korea Composite Stock Price Index), and the volatility and growth rate of the KOSPI trade volume. Lastly, the FSTI-Industry

4) For example, most EWIs are designed to predict the occurrence of a financial crisis using qualitative response model framework such as the probit model. FCIs focus more on how financial variables react to changes in the market conditions.

Figure 1: Financial Stress Index (Dashed) and 4 Sub-Indices

is based on the volatility and the betas of financial intermediaries' stocks, and the spread between the average bond yields issued by financial intermediaries and the treasury bond yield.

As we can see in Figure 1, all sub-indices show overall similar movements as the FSTI total index. FSTI-Bond exhibits much lower volatility than FSTI, while FSTI-Stock shows the highest volatility. All indices imply extremely high degree vulnerability during the recent financial crisis that began in 2008.

We obtained all necessary macroeconomic time series data from Kim (2013), which are used to extract latent common factors for our out-of-sample forecast exercise. Observations are monthly frequency and span from October 2000 to December 2013. We categorized 198 time series data into 13 groups as summarized in Table 1.

Group #1 that includes 14 time series data represents a set of nominal interest

Table 1: Macroeconomic Data Descriptions

Group ID	Data ID	Data Descriptions
#1	1–14	Domestic and World Interest Rates
#2	15–35	Exports / Imports Prices
#3	36–54	Producer / Consumer / Housing Prices
#4	55–71	Monetary Aggregates
#5	72–83	Bilateral Exchange Rates
#6	84–110	Manufacturers' / Construction New Orders
#7	111–117	Manufacturers' Inventory Indices
#8	118–136	Housing Inventories
#9	136–157	Sales and Capacity Utilizations
#10	158–171	Unemployment / Employment / Labor Force Participation
#11	172–180	Industrial Production Indices
#12	181–186	Business Condition Indices
#13	187–198	Stock Indices

rates. Groups #2 through #4 include prices and monetary aggregate variables, while group #5 covers an array of bilateral nominal exchange rates. Note that these groups overall represent the nominal sector variables. On the contrary, group #6 through #11 entail various kinds of real activity variables such as manufacturers' new orders, inventory, capacity utilizations, and industrial production indices. The last two groups represent business condition indices and stock indices in Korea, respectively.

3.2. Latent factors and their characteristics

We estimated up to 8 latent common factors by applying the method of the principal components to 198 macroeconomic data series after differencing and normalizing them. Estimated (differenced) common factors, $\Delta F_1, \Delta F_2, \dots, \Delta F_8$, are reported in Figure 2. We also report level common factors F_1 through F_8 in Figure 3 that are obtained by re-integrating differenced common factors.

We first note a dramatic decline in the first common factor F_1 around the beginning of the Great Recession in 2008. Similarly, the second common factor F_2 exhibits an abrupt down-ward movement about the same time. All estimated

Figure 2: Factor Estimates: Differenced Factors

common factors *in levels* exhibit highly persistent dynamics, indicating nonstationary stochastic processes. Therefore, it seems to be appropriate to employ the method of the principal components to the data after differencing

Figure 3: Factor Estimates: Level Factors

them to ensure the stationarity of the data.

To see what variables represent each of these latent factors more closely, we report the factor loading coefficient (λ_i) estimates in Figure 4. We also provide the

Figure 4: Factor Loading Coefficients Estimates

marginal R^2 analysis by regressing each variable $x_{i,t}$ on each common factor $\Delta \hat{F}_i$ to get R^2 values. Results are reported in Figure 5.

To investigate the nature of the first common factor, we plot F_1 and its

Figure 5: Marginal R^2 Analysis

associated factor loading coefficients ($\lambda_{i,1}$) together in Figure 6. We first note that the factor loading coefficients for the first four groups and the last three groups are dependent upon F_1 in a positive way, whereas groups #5, #6, and #8 are

Figure 6: Common Factor #1 and its Factor Loading Coefficients

substantially but negatively associated with it. These observations imply that F_1 represents both the nominal variables (interest rates, prices, nominal exchange rates, and stock prices) and real activity variables (new orders, industrial production, and business condition indices). Factor loading coefficients imply positive associations between Interest rates and prices (inflation rates), which seems to be consistent with the Fisher effect. Domestic prices are negatively related with nominal exchange rates (relative prices of the domestic currency), which also seem plausible.

As we can see in Figure 7, the second common factor seems to closely represent groups #5, #6, and #9 through #12, which are real sector variables with an exception of group #5. F_2 is overall positively related with the majority of the variables in these groups. For instance, the factor loading coefficients ($\lambda_{i,2}$) for nominal exchange rates (group #5) are positive, which implies that a depreciation

Figure 7: Common Factor #2 and its Factor Loading Coefficients

of Korean won ($\Delta x_{i,t} > 0$) are associated with an increase in real activities ($\Delta F_2 > 0$) in Korea, $\lambda_{i,2} \Delta F_2 > 0$. Similarly, new orders, sales, industrial production, and business condition indices groups have positive coefficients. Among the group #10, unemployment variables have negative coefficients, while employment variables tend to exhibit positive ones. Overall, F_2 seems to represent real sector variables.

In what follows, our in-sample-fit analysis demonstrates a non-negligible role of the fourth common factor F_4 in explaining FSTIs.

4. Forecasting Exercises

4.1. In-Sample fit analysis

We implement an array of least squares estimations for the following equation, employing alternative combinations of estimated common factors $\{\Delta\hat{F}_1, \Delta\hat{F}_2, \dots, \Delta\hat{F}_8\}$ as explanatory variables.

$$fsi_{t+j} = \beta_j' \Delta \hat{\mathbf{F}}_t + u_{t+j}, \quad j = 0, 1, 2, \dots, k \quad (15)$$

We report our in-sample fit analyses in Table 2 for the contemporaneous case ($j = 0$).⁵⁾

We employed an R^2 -based selection method for one-factor models to an 8-factor full model to find the best combination of explanatory variables. The first common factor $\Delta\hat{F}_1$ seems to play the most important role in explaining variations in all financial stress indices with an exception of FSTI-Bond. The second common factor $\Delta\hat{F}_2$ explains negligibly small portion of variations in FSTI. Overall, one or two factor models seem to be sufficient to obtain a good in-sample fit for each financial stress index.

Since R^2 increases as more variables are included, this R^2 -based selection method always pick the full model as the best one. So, we considered two alternative selection methods. The adjusted R^2 selection method chose a 7-factor model, while a step-wise selection method (Specific-to-General rule) selected a 6-factor model for FSTI. For FSTI-FX, whereas a 5-factor model was chosen by these two methods. It turns out, however, that fairly small models such as 1 through 3-factor models are good enough to perform well in out-of-sample forecast exercises as will be shown in the next section.

5) Regressions for the 1-, 3-, and 6-month ahead FSTI yield similar results.

Table 2: In-Sample Fit Analysis for Selection of Factors

Financial Stress Index		
#Factors	Factors	R^2
1	$\Delta F1$	0.233
2	$\Delta F1, \Delta F4$	0.331
3	$\Delta F1, \Delta F4, \Delta F5$	0.365
4	$\Delta F1, \Delta F4, \Delta F5, \Delta F8$	0.388
5	$\Delta F1, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.409
6 [†]	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.421
7 [*]	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.426
8	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.429

Financial Stress Index: Bond		
#Factors	Factors	R^2
1	$\Delta F4$	0.036
2	$\Delta F4, \Delta F5$	0.054
3 [†]	$\Delta F1, \Delta F4, \Delta F5$	0.068
4 [*]	$\Delta F1, \Delta F4, \Delta F5, \Delta F8$	0.079
5	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F8$	0.083
6	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F6, \Delta F8$	0.084
7	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F8$	0.085
8	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.085

Financial Stress Index: Foreign Exchange		
#Factors	Factors	R^2
1	$\Delta F1$	0.324
2	$\Delta F1, \Delta F4$	0.373
3	$\Delta F1, \Delta F4, \Delta F7$	0.395
4	$\Delta F1, \Delta F4, \Delta F6, \Delta F7$	0.405
5 ^{*†}	$\Delta F1, \Delta F4, \Delta F5, \Delta F6, \Delta F7$	0.414
6	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F6, \Delta F7$	0.417
7	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.419
8	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.419

Financial Stress Index: Stock		
#Factors	Factors	R^2
1	$\Delta F1$	0.235
2	$\Delta F1, \Delta F4$	0.357
3	$\Delta F1, \Delta F4, \Delta F8$	0.388
4	$\Delta F1, \Delta F4, \Delta F7, \Delta F8$	0.417
5	$\Delta F1, \Delta F4, \Delta F6, \Delta F7, \Delta F8$	0.438
6	$\Delta F1, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.456
7	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.471
8 ^{*†}	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.479

Table 2: In-Sample Fit Analysis for Selection of Factors

Financial Stress Index: Financial Industry		
#Factors	Factors	R^2
1	$\Delta F1$	0.189
2	$\Delta F1, \Delta F4$	0.260
3	$\Delta F1, \Delta F4, \Delta F5$	0.322
4	$\Delta F1, \Delta F4, \Delta F5, \Delta F7$	0.352
5	$\Delta F1, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.378
6	$\Delta F1, \Delta F2, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.395
7	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F7, \Delta F8$	0.410
8 ^{*†}	$\Delta F1, \Delta F2, \Delta F3, \Delta F4, \Delta F5, \Delta F6, \Delta F7, \Delta F8$	0.421

Note: * and † denote the chosen model by the adjusted R^2 method and the specific to general rule, respectively.

4.2. Out-of-Sample forecast exercises and model evaluations

We implement out-of-sample forecast exercise using two methods. We first employ a conventional recursive forecast scheme. That is, we start forecast exercise with an out-of-sample forecast of FSTI using the initial 70% observations. Then, we add one additional new observation to the sample and implement another forecast of the next index observation using this expanded set of observations. We repeat this procedure until we forecast the last observation. We implement this scheme for up to 12 month forecast horizons, $j = 1, 3, 6, 9, 12$. The second scheme is a fixed size rolling window method that repeats forecasting by adding one additional observation with the same split point but dropping one earliest observation, maintaining the same sample size, 70% of total observations.

For statistical evaluations of our factor model, we employ two benchmark models, the random walk (RW, no change) model and a stationary AR (1) model. We evaluate our factor model performances relative to these benchmark models using the following two popular measures.

First, we report the ratio of the root mean square prediction error, $RRMSPE$, of each of the benchmark models to that of our factor models. Note that the factor model outperforms the benchmark model when the $RRMSPE$ is greater than one. Second, we employ the DMW statistics with asymptotic critical values when the random walk model is used, while the critical values from McCracken (2007) were

used when the AR model is used because the AR model is nested by our factor models.

Our forecast exercise results for FSTI are reported in Table 3. To save space, we report results with three 1-factor models, two two-factor models, and one three-factor model, which are chosen based on our in-sample fit analyses in previous section.

We first note that our factor models outperform the RW model for all forecast horizons from 1-month to 1-year. *RRMSPE* is greater than one for all cases. Our factor models outperform the benchmark model with the *DMW* test for many cases. For example, the *DMW* test rejects the null of equal predictability at the 10% significance level for 24 out of 30 cases both with the recursive method and the rolling window method. Especially, we find strong out-of-sample forecast performances when the forecast horizon is equal to or greater than 3 months.

It turns out that our factor models also perform reasonably well in comparison with the stationary AR (1) benchmark model. *RRMSPE* is greater than one for majority cases when the recursive method is employed, whereas our models perform relatively poorly when the rolling window method is used. Interestingly, the 1-factor model with $\Delta \hat{F}_4$, which is more closely related with nominal variables, performs consistently poorly. We note that the *DMW* test rejects the null of equal predictability for 8 out of 12 1-period ahead forecasts, while *RRMSPE* is greater than one for 10 out of 12 cases. This is a good property because out-of-sample forecast exercises are more useful when it demonstrates superior predictability for short forecast horizon, as financial turmoils often occur suddenly without systematic warnings.

Table 4 reports out-of-sample forecast exercise results for FSTI-Bond. Even though its poor in-sample forecast performances shown in previous section, our factor model beats the RW model again for most cases by *RRMSPE* criteria. The *DMW* test rejects the null of equal predictability for most cases when $j = 3, 6, 9, 12$ at the 10% significance level. With the AR model as the benchmark, our factor models overall perform well especially when $j = 3, 6, 9, 12$. Recall that $\Delta \hat{F}_4$ explains the most of variations in FSTI-Bond as can be seen in Table 2. We note that $\Delta \hat{F}_4$ exhibit the best out-of-sample predictability even when all other models perform poorly in comparison with the AR model.

Table 3: j -Period Ahead Out-of-Sample Forecast: FSTI

Recursive Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.040	1.097 [†]	1.251 [†]	1.344 [†]	1.398 [†]
$\Delta F4$	1.031	1.084 [†]	1.217 [†]	1.296 [†]	1.415 [†]
$\Delta F5$	1.049 [†]	1.128 [†]	1.246 [†]	1.331 [†]	1.392 [†]
$\Delta F1, \Delta F4$	1.039	1.076*	1.235 [†]	1.302 [†]	1.416 [†]
$\Delta F1, \Delta F5$	1.049	1.100*	1.279 [†]	1.357 [†]	1.397 [†]
$\Delta F1, \Delta F4, \Delta F5$	1.047	1.079	1.270 [†]	1.315 [†]	1.413 [†]

Rolling Window Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.050	1.106 [†]	1.280 [†]	1.378 [†]	1.438 [†]
$\Delta F4$	1.021	1.085*	1.219 [†]	1.354 [†]	1.432 [†]
$\Delta F5$	1.039*	1.111 [†]	1.279 [†]	1.348 [†]	1.442 [†]
$\Delta F1, \Delta F4$	1.036	1.084 [†]	1.244 [†]	1.371 [†]	1.437 [†]
$\Delta F1, \Delta F5$	1.057	1.090*	1.331 [†]	1.374 [†]	1.437 [†]
$\Delta F1, \Delta F4, \Delta F5$	1.043	1.071	1.295 [†]	1.377 [†]	1.435 [†]

Recursive Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.008	0.975	1.015 [†]	1.014 [†]	1.003
$\Delta F4$	0.999	0.963	0.987	0.977	1.015 [†]
$\Delta F5$	1.017 [†]	1.003	1.010	1.004	0.999
$\Delta F1, \Delta F4$	1.007	0.956	1.001	0.982	1.016 [†]
$\Delta F1, \Delta F5$	1.017*	0.977	1.037 [†]	1.023 [†]	1.002
$\Delta F1, \Delta F4, \Delta F5$	1.015*	0.959	1.030 [†]	0.992	1.014 [†]

Rolling Window Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.020*	0.981	1.028 [†]	1.015 [†]	0.998
$\Delta F4$	0.992*	0.962	0.979	0.997	0.994
$\Delta F5$	1.009 [†]	0.986	1.027 [†]	0.993	1.001
$\Delta F1, \Delta F4$	1.007*	0.962	0.999	1.009*	0.998
$\Delta F1, \Delta F5$	1.027*	0.967	1.069 [†]	1.012 [†]	0.998
$\Delta F1, \Delta F4, \Delta F5$	1.013	0.950 [†]	1.040 [†]	1.014 [†]	0.997

Note: *RRMSPE* denotes the mean square error from the random walk model relative to the mean square error from our factor model. Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Our factor models perform overall the best for FSTI-FX, especially when the rolling window method is employed. *RRMSPE* is greater than one for all cases with the random walk benchmark model. The *DMW* test rejects the null for all

Table 4: j -Period Ahead Out-of-Sample Forecast: FSTI-Bond

Recursive Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F4$	1.025	1.154 [†]	1.204 [†]	1.365 [†]	1.547 [†]
$\Delta F5$	0.998	1.084 [†]	1.154 [†]	1.243 [†]	1.392 [†]
$\Delta F1$	1.000	1.047	1.141 [†]	1.239 [†]	1.400 [†]
$\Delta F4, \Delta F5$	1.008	1.164 [†]	1.218 [†]	1.375 [†]	1.549 [†]
$\Delta F4, \Delta F1$	1.005	1.114 [*]	1.207 [†]	1.368 [†]	1.537 [†]
$\Delta F1, \Delta F4, \Delta F5$	0.987	1.117 [*]	1.218 [†]	1.374 [†]	1.543 [†]

Rolling Window Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F4$	1.033	1.158 [†]	1.264 [†]	1.402 [†]	1.639 [†]
$\Delta F5$	1.011	1.120 [†]	1.257 [†]	1.360 [†]	1.594 [†]
$\Delta F1$	1.005	1.085 [†]	1.245 [†]	1.335 [†]	1.599 [†]
$\Delta F4, \Delta F5$	1.021	1.170 [†]	1.298 [†]	1.447 [†]	1.669 [†]
$\Delta F4, \Delta F1$	1.009	1.136 [†]	1.298 [†]	1.437 [†]	1.679 [†]
$\Delta F4, \Delta F5, \Delta F1$	0.998	1.142 [†]	1.331 [†]	1.475 [†]	1.697 [†]

Recursive Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F4$	1.011 [*]	1.076 [†]	1.057 [†]	1.108 [†]	1.116 [†]
$\Delta F5$	0.984	1.011 [*]	1.013 ^t	1.009 [†]	1.003 [†]
$\Delta F1$	0.986	0.976	1.002	1.006	1.009
$\Delta F4, \Delta F5$	0.994	1.086 [†]	1.070 [†]	1.116 [†]	1.117 [†]
$\Delta F4, \Delta F1$	0.990	1.039 [†]	1.060 [†]	1.110 [†]	1.108 [†]
$\Delta F4, \Delta F5, \Delta F1$	0.973	1.042 [†]	1.069 [†]	1.115 [†]	1.113 [†]

Rolling Window Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F4$	1.011 [*]	1.050 [†]	1.036 [†]	1.067 [†]	1.052 [†]
$\Delta F5$	0.990	1.015 [†]	1.031 [†]	1.035 [†]	1.024 [†]
$\Delta F1$	0.983	0.983	1.021 [†]	1.016 [†]	1.027 [†]
$\Delta F4, \Delta F5$	0.999	1.061 [†]	1.064 [†]	1.101 [†]	1.072 [†]
$\Delta F4, \Delta F1$	0.987	1.029 [†]	1.064 [†]	1.094 [†]	1.078 [†]
$\Delta F4, \Delta F5, \Delta F1$	0.976	1.035 [†]	1.091 [†]	1.122 [†]	1.090 [†]

Note: *RRMSPE* denotes the mean square error from the random walk model relative to the mean square error from our factor model. Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

cases when the rolling window scheme is employed. Our models exhibit very good one-period ahead forecast performances with the AR benchmark whenever $\Delta \hat{F}_1$ is used.

Table 5: j -Period Ahead Out-of-Sample Forecast: FSTI-Foreign Exchange

Recursive Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.120	1.293	1.372 [†]	1.617 [†]	1.658 [†]
$\Delta F4$	1.095	1.237 [†]	1.385 [†]	1.584 [†]	1.614 [†]
$\Delta F7$	1.088	1.359 [†]	1.312 [†]	1.666 [†]	1.623 [†]
$\Delta F1, \Delta F4$	1.118	1.245 [†]	1.426 [†]	1.590 [†]	1.652 [†]
$\Delta F1, \Delta F7$	1.109	1.349	1.336	1.675	1.657
$\Delta F1, \Delta F4, \Delta F7$	1.107	1.299 [†]	1.402 [†]	1.662 [†]	1.651 [†]

Rolling Window Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.126*	1.296 [†]	1.392 [†]	1.611 [†]	1.612 [†]
$\Delta F4$	1.088*	1.222 [†]	1.372 [†]	1.611 [†]	1.566 [†]
$\Delta F7$	1.095 [†]	1.285 [†]	1.305 [†]	1.688 [†]	1.560 [†]
$\Delta F1, \Delta F4$	1.120*	1.232 [†]	1.395 [†]	1.618 [†]	1.598 [†]
$\Delta F1, \Delta F7$	1.124 [†]	1.289 [†]	1.337 [†]	1.673 [†]	1.585 [†]
$\Delta F1, \Delta F4, \Delta F7$	1.117*	1.222 [†]	1.377 [†]	1.679 [†]	1.571 [†]

Recursive Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.020 [†]	0.994	1.028 [†]	1.003*	1.017 [†]
$\Delta F4$	0.997	0.951	1.038 [†]	0.982	0.990
$\Delta F7$	0.991	1.044 [†]	0.983	1.033 [†]	0.995
$\Delta F1, \Delta F4$	1.018 [†]	0.957	1.069 [†]	0.986	1.014 [†]
$\Delta F1, \Delta F7$	1.010*	1.037	1.001	1.038	1.016
$\Delta F1, \Delta F4, \Delta F7$	1.008*	0.998	1.051*	1.031*	1.013 [†]

Rolling Window Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.029 [†]	0.999	1.037 [†]	0.992	1.014 [†]
$\Delta F4$	0.994	0.942	1.022 [†]	0.992	0.985
$\Delta F7$	1.000	0.991	0.973	1.040 [†]	0.981
$\Delta F1, \Delta F4$	1.023 [†]	0.950	1.039 [†]	0.996	1.005*
$\Delta F1, \Delta F7$	1.027 [†]	0.994	0.996	1.030 [†]	0.997
$\Delta F1, \Delta F4, \Delta F7$	1.020 [†]	0.942	1.026 [†]	1.034 [†]	0.988

Note: *RRMSPE* denotes the mean square error from the random walk model relative to the mean square error from our factor model. Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Out-of-sample forecast performances for FSTI-Stock shown in Table 6 sharply contrast results in Table 5. *RRMSPE* is greater than most cases with the RW benchmark but the *DMW* test rejects the null of equal predictability only when $j = 12$,

Table 6: j -Period Ahead Out-of-Sample Forecast: FSTI-Stock

Recursive Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.016	0.999	1.062	1.090	1.238 [†]
$\Delta F4$	1.022	1.055	1.082	1.088	1.253 [†]
$\Delta F8$	1.033	1.056	1.114	1.103	1.239*
$\Delta F1, \Delta F4$	1.028	1.000	1.063	1.075	1.261 [†]
$\Delta F1, \Delta F8$	1.008	0.995	1.087	1.106	1.268 [†]
$\Delta F1, \Delta F4, \Delta F8$	1.013	0.995	1.086	1.093	1.298 [†]

Rolling Window Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.051	1.022	1.070	1.104	1.300 [†]
$\Delta F4$	1.010	1.076	1.129	1.143	1.340 [†]
$\Delta F8$	1.038	1.074	1.161	1.152	1.302 [†]
$\Delta F1, \Delta F4$	1.035	1.020	1.076	1.096	1.324 [†]
$\Delta F1, \Delta F8$	1.053	1.007	1.096	1.122	1.296 [†]
$\Delta F1, \Delta F4, \Delta F8$	1.036	1.004	1.105	1.122	1.330 [†]

Recursive Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.000	0.945	0.975	1.004 [†]	1.024 [†]
$\Delta F4$	1.006 [†]	0.998	0.993	1.002	1.037 [†]
$\Delta F8$	1.016 [†]	0.999	1.022 [†]	1.016*	1.025 [†]
$\Delta F1, \Delta F4$	1.011	0.945	0.975	0.991	1.043 [†]
$\Delta F1, \Delta F8$	0.992	0.941	0.997 [†]	1.019 [†]	1.049 [†]
$\Delta F1, \Delta F4, \Delta F8$	0.997	0.941	0.996	1.007*	1.074 [†]

Rolling Window Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	1.034*	0.949	0.944	0.966	0.992
$\Delta F4$	0.993	0.999	0.996	1.001	1.023 [†]
$\Delta F8$	1.022 [†]	0.997	1.024 [†]	1.009*	0.994
$\Delta F1, \Delta F4$	1.018*	0.947	0.949	0.960	1.011*
$\Delta F1, \Delta F8$	1.036 [†]	0.935	0.967	0.982	0.989
$\Delta F1, \Delta F4, \Delta F8$	1.019*	0.933	0.975	0.983	1.015 [†]

Note: *RRMSPE* denotes the mean square error from the random walk model relative to the mean square error from our factor model. Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

which may not be very useful in practice. With the AR model, factor models performed well only in a few cases, though the *DMW* test rejects the null for 5 out of 6 cases when the rolling window scheme is used for one-period ahead forecasts.

Table 7: j -Period Ahead Out-of-Sample Forecast: FSTI-Financial Industry

Recursive Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	0.961	0.992	1.117	1.246 [†]	1.428 [†]
$\Delta F4$	1.027	1.123 [†]	1.218 [†]	1.315 [†]	1.405 [†]
$\Delta F5$	1.023	1.068	1.177*	1.267 [†]	1.409 [†]
$\Delta F1, \Delta F4$	0.946	1.015	1.172*	1.294 [†]	1.423 [†]
$\Delta F1, \Delta F5$	0.953	0.970	1.132	1.245 [†]	1.426 [†]
$\Delta F1, \Delta F4, \Delta F5$	0.937	0.996	1.213*	1.308 [†]	1.423 [†]

Rolling Window Method: RRMSPE vs. Random Walk					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	0.953	0.979	1.117	1.256 [†]	1.424 [†]
$\Delta F4$	1.017	1.130 [†]	1.193 [†]	1.386 [†]	1.400 [†]
$\Delta F5$	1.024	1.044	1.217 [†]	1.236 [†]	1.388 [†]
$\Delta F1, \Delta F4$	0.923	0.997	1.140	1.356 [†]	1.427 [†]
$\Delta F1, \Delta F5$	0.951	0.954	1.153*	1.223 [†]	1.407 [†]
$\Delta F1, \Delta F4, \Delta F5$	0.920	0.979	1.203*	1.350 [†]	1.417 [†]

Recursive Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	0.934	0.891	0.947	0.974	1.010 [†]
$\Delta F4$	0.998	1.007	1.032 [†]	1.029	0.994
$\Delta F5$	0.995	0.959	0.998	0.991	0.997
$\Delta F1, \Delta F4$	0.920	0.911	0.993	1.012	1.007 [†]
$\Delta F1, \Delta F5$	0.927	0.871	0.959	0.974	1.009 [†]
$\Delta F1, \Delta F4, \Delta F5$	0.911	0.894	1.028	1.023	1.007

Rolling Window Method: RRMSPE vs. Autoregressive					
Factors	$j = 1$	$j = 3$	$j = 6$	$j = 9$	$j = 12$
$\Delta F1$	0.926	0.875	0.931	0.975	1.014 [†]
$\Delta F4$	0.988	1.009*	0.995	1.076 [†]	0.996
$\Delta F5$	0.995	0.932	1.015*	0.960	0.987
$\Delta F1, \Delta F4$	0.896	0.891	0.950	1.053 [†]	1.015 [†]
$\Delta F1, \Delta F5$	0.923	0.852	0.961	0.950	1.001 [†]
$\Delta F1, \Delta F4, \Delta F5$	0.894	0.874	1.003*	1.048 [†]	1.008 [†]

Note: *RRMSPE* denotes the mean square error from the random walk model relative to the mean square error from our factor model. Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Finally, we report forecast exercise results for FSTI-Industry in Table 7. Our factor models performed better than the random walk model only when the forecast horizon is longer than a half year. *RRMSPE* was often less than one when

$j = 1, 3$. Forecast performances were worse when the AR model serves as the benchmark. Overall, our factor models perform the worst for FSTI-Industry.

5. Concluding Remarks

This paper proposes an out-of-sample forecast model for the financial stress index in Korea in a data rich environment. We use the financial stress index and its 4 subindices to measure the vulnerability in financial markets in Korea. We employ a parsimonious method to extract latent common factors from 198 time series macroeconomic variables that include not only nominal but also real activity variables. Following Bai and Ng (2004), we applied the method of the principal components to these variables after differencing them to estimate the common factors consistently. Our in-sample fit analyses demonstrate that estimated factors explain substantial shares of variations of all financial stress indices with an exception of FSTI-Bond.

We implement out-of-sample forecast exercises using the recursive and the fixed size rolling window schemes with the two benchmark modes, the random walk and a stationary AR (1) models. We evaluate out-of-sample predictability of our factor models using the ratio of root mean square prediction errors (*RRMSP E*) and the *DMW* test statistics. Our findings imply that there exist a tight linkage between the Korean FSTIs and macroeconomic common factors. Interestingly, we observe that not only nominal but also real activity variables, proxied especially by the first common factor estimate, seem to contain useful predictive contents for FSTIs in Korea. Especially, our factor models demonstrate superior performance over the random walk benchmark model in most cases. Our models also show fairly good performances relative to the AR model in short forecast horizons, which can be practically more useful because financial crises often occur abruptly. We also find parsimonious models that are based on a few common factors perform as well as other bigger models.

References

- Donald W. K. Andrews, and J. Christopher Monahan (1992), “An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator,” *Econometrica*, Vol. 60(4), pp. 953-966.
- Jushan Bai, and Serena Ng (2004), “A Panic Attack on Unit Roots and Cointegration,” *Econometrica*, Vol. 72, pp. 1127-1177.
- Andrew Berg, and Catherine Pattillo (1999), “Predicting Currency Crises: The Indicators Approach and an Alternative,” *Journal of International Money and Finance*, Vol. 18(4), pp. 561-586.
- Andrew Berg, Eduardo Borensztein, and Catherine Pattillo (2005), “Assessing Early Warning Systems: How Have They Worked in Practice?” IMF Working Paper 04/52, International Monetary Fund.
- Axel Brüggemann, and Thomas Linne (1999), “How Good are Leading Indicators for Currency and Banking Crises in Central and Eastern Europe? An Empirical Test,” IWH Discussion Papers, No. 95, Halle Institute for Economic Research.
- Matthieu Bussiere, and Christian Mulder (1999), “External Vulnerability in Emerging Market Economies - How High Liquidity Can Offset Weak Fundamentals and The Effects of Contagion,” IMF Working Papers 99/88.
- Emrah Ismail Cevik, Sel Diboogu, and Turalay Kenc (2013), “Measuring Financial Stress in Turkey,” *Journal of Policy Modeling*, Vol. 35, pp. 370-383.
- Ian Christensen, and Fuchun Li (2014), “Predicting Financial Stress Events: A Signal Extraction Approach,” Working Paper No. 37, Bank of Canada.
- Andrea Cipollini, and George Kapetanios (2009), “Forecasting Financial Crises and Contagion in Asia Using Dynamic Factor Analysis,” *Journal of Empirical Finance*, Vol. 16(2), pp. 188-200.
- Hali J. Edison (2003), “Do Indicators of Financial Crises Work? An Evaluation of an Early Warning System,” *International Journal of Finance and Economics*, Vol. 8(1), pp. 11-53.

- M. El-Shagi, T. Knedlik, and G. Von Schweinitz (2013), "Predicting Financial Crises: The (Statistical) Significance of the Signals Approach," *Journal of International Money and Finance*, Vol. 35, pp. 75-103.
- Barry Eichengreen, Andrew K. Rose, and Charles Wyplosz (1995), "Exchange Market Mayhem: The Antecedents and Aftermath of Speculative Attacks," *Economic Policy*, Vol. 10(21), pp. 249-312.
- Jeffrey Frankel, and George Saravelos (2012), "Can Leading Indicators Assess Country Vulnerability? Evidence from the 2008-09 Global Financial Crisis," *Journal of International Economics*, Vol. 87, pp. 216-231
- Jeffrey A. Frankel, and Andrew K. Rose (1996), "Currency Crashes in Emerging Markets: An Empirical Treatment," *Journal of International Economics*, Vol. 41(3/4), pp. 351-366.
- Lance Gorton, and Don Roper (1977), "A Monetary Model of Exchange Market Pressure Applied to the Postwar Canadian Experience," *American Economic Review*, Vol. 67, pp. 537-548.
- Marianna B. Grimaldi (2010), "Detecting and Interpreting Financial Stress in the Euro Area," ECB Working Paper Series No. 1214, European Central Bank.
- Marianna B. Grimaldi (2011), "Up For Count? Central Bank Words and Financial Stress," Sveriges Riksbank Working Paper Series 252.
- Elke Hanschel and Pierre Monnin (2005), "Measuring and Forecasting Stress in the Banking Sector: Evidence from Switzerland," BIS Paper No. 22, Bank for International Settlements.
- Jakob L. Hansen (2006), "A Risk Index for Euro-Denominated Assets," National Bank of Denmark Working Paper No. 36.
- Daniel Hollo, Manfred Kremer, and Marco Lo Duca (2012), "Ciss-A Composite Indicator of Systemic Stress in the Financial System," ECB Working Paper Series No. 1426.
- Mark Illing, and Ying Liu (2006), "Measuring Financial Stress in a Developed Country: An Application to Canada," *Journal of Financial Stability*, Vol. 2(3), pp. 243-265.

- Mevlud Islami, and Jeong-Rong Kurz-Kim (2013), “A Single Composite Financial Stress Indicator and its Real Impact in the Euro Area,” Discussion Paper No. 31, Deutsche Bundesbank.
- Graciela Kaminsky, Saul Lizondo, and Carmen Reinhart (1998), “Leading Indicators of Currency Crises,” IMF Working Paper No. 45, International Monetary Fund.
- Hyeonwoo Kim, and Wen Shi (2015), “Forecasting Financial Market Vulnerability in the U.S.: A Factor Model Approach,” Technical Report, Auburn University.
- Hyun Hak Kim (2013), “Forecasting Macroeconomic Variables Using Data Dimension Reduction Methods: The Case of Korea,” BOK Working Paper No. 26, Bank of Korea.
- Dimitrios P. Louzis, and Angelos T. Vouldis (2011), A Financial Systemic Stress Index for Greece. Presented at the First Conference of the Macro-prudential Research (MaRs) Network of the European System of Central Banks in Frankfurtam Main.
- Michael W. McCracken (2007), “Asymptotics for Out of Sample Tests of Granger Causality,” *Journal of Econometrics*, Vol. 140, pp. 719-752.
- Miroslav Misina, and Greg Tkacz (2009), “Credit, Asset Prices, and Financial Stress,” *International Journal of Central Banking*, Vol. 5, pp. 95-122.
- Miguel A. Morales, and Dairo Estrada (2010), “A Financial Stability Index for Colombia,” *Annals of Finance*, Vol. 6(4), pp. 555-581.
- Mikhail V. Oet, Ryan Eiben, Timothy Bianco, Dieter Gramlich, and Stephen J. Ong (2011), “The Financial Stress Index: Identification of System Risk Conditions,” Working Paper No. 1130, Federal Reserve Bank of Cleveland.
- Jeffrey Sachs, Aaron Tornell, and Andres Velasco (1996), “Financial Crises in Emerging Markets: The Lessons from 1995,” *Brookings Papers on Economic Activity*, Vol. 27(1), pp. 147-199.
- Johannes Sandahl, Mia Holmfeldt, Anders Rydén, and Maria Strömqvist (2011), “An Index of Financial Stress for Sweden,” *Sveriges Riksbank Economic Review*, Vol. 2, pp. 49-67.

Jan Willem Slingenberg, and Jakob De Haan (2011), “Forecasting Financial Stress,” DNB Working Paper No. 292, De Nederlandsche Bank.

James H. Stock, and Mark W. Watson (2002), “Macroeconomic Forecasting Using Diffusion Indexes,” *Journal of Business and Economic Statistics*, Vol. 20(2), pp. 147-162.

Matthew S. Yiu, Wai.-Yip Alex Ho, and Lu Jin (2010), “A Measure of Financial Stress in Hong Kong Financial Market: The Financial Stress Index,” Hong Kong Monetary Authority Research Note No. 02.

Evan Tanner (2002), “Exchange Market Pressure, Currency Crises, and Monetary Policy: Additional Evidence from Emerging Markets,” IMF Working Papers No. 02/14.

Björn Van Roye (2011), “Financial Stress and Economic Activity in Germany and the Euro Area,” Kiel Working Paper No. 1743, Kiel Institute for the World Economy.

<Abstract in Korean>

금융스트레스지수의 예측: 요인모형을 통한 접근

김형우* 김현학** Wen Shi***

금융위기 발생 여부를 예측하기 위한 노력의 일환으로 다수의 중앙은행이 Financial STress Indices (FSI)*를 작성·발표하고 있으면 한국은행 또한 지난 2007년부터 FSI*를 전체지수외에도 채권시장, 외환시장, 주식시장, 금융시장 등 시장의 부문별 지수들의 1995년 시점부터 시작하는 시계열을 발표하고 있다. 이런 FSI를 보다 정확하게 예측할 수 있으면 이는 금융위기 예측에 도움이 될 수 있으며, 조기경보시스템(Early Warning System) 구축의 기반이 된다. 본고에서는 대량의 거시경제변수로부터 주성성분분석을 통해 주요요인들을 찾고 이를 통해 FSI를 예측하는 방법을 찾고자 하였다. 실증분석 결과 거시변수들의 주요요인이 FSI에 대해 상당한 예측력을 가지는 것으로 분석되었으며, 특히 실물활동을 반영하는 주요요인들이 FSI 예측에 매우 유용한 것으로 보인다. 1~3개의 요인들만 사용한 전망모형이 단기 FSI전망에서 우수한 것으로 보여 전략적인 간결한(parsimonious) 전망모형이 금융위기 예측에 유용할 것으로 보인다.

핵심 주제어: 금융스트레스지수, 주성분분석, PANIC, 표본내 적합, 표본외 예측, Diebold-Mariano-West 검정

JEL Classification: C53, G17, C38

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