Forecasting Financial Stress Indices in Korea: A Factor Model Approach

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Abstract

We propose factor-based out-of-sample forecast models for Korea's financial stress index and its 4 sub-indices that are developed by the Bank of Korea. We extract latent common factors by employing the method of the principal components for a panel of 198 monthly frequency macroeconomic data after differencing them. We augment an autoregressive-type model of the financial stress index with estimated common factors to formulate out-of-sample forecasts of the index. Our models overall outperform both the stationary and the nonstationary benchmark models in forecasting the financial stress indices for up to 12-month forecast horizons. The first common factor that represents not only financial market but also real activity variables seems to play a dominantly important role in predicting the vulnerability in the financial markets in Korea.

Keywords: Financial Stress Index; Principal Component Analysis; PANIC; In-Sample Fit; Out-of-Sample Forecast; Diebold-Mariano-West Statistic

JEL Classification: E44; E47; G01; G17

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1 Introduction

The bankruptcy of Lehman Brothers on September 15, 2008 has triggered the collapse of financial markets not only in the US but also in other countries including Korea. Since then, the Korean Won has depreciated against the US dollar by 18.2% in mere one quarter as global risk aversion spurred the demand for safe assets, leading to strong deteriorating spillover effects on real sectors. Share prices fell by 15.3% and 25.4% in the last two quarters of 2008.[1]

As we can see in this episode, financial market crises often occur abruptly, and quickly spread to other sectors of the economy, even to other countries. That is, financial market crises tend to come to a surprise realization with no systemic warnings. Since financial crises have harmful long-lasting spillover effects on real activities even after the financial system becomes stabilized, it would be useful to have forecasting algorithms such as an Early Warning Signal (EWS), which can provide timely information on the vulnerability in financial markets that might be materialized in the near future.

There's an array of research works that attempt to predict financial crises in the current literature. For instance, Frankel and Saravelos [2012], Eichengreen et al. [1995], and Sachs et al. [1996] used linear regressions to test the statistical significance of various economic variables on the occurrence of crises. Some others employed discrete choice model approaches, either parametric probit or logit regressions (Frankel and Rose [1996]; Cipollini and Kapetanios [2009]) or nonparametric signal detection approaches (Kaminsky et al. [1998]; Brüggemann and Linne [1999]; Edison [2003]; Berg and Pattillo [1999]; Bussiere and Mulder [1999]; Berg et al. [2005]; EI-Shagi et al. [2013]; Christensen and Li [2014]).

It is crucial to find a proper measure of financial market vulnerability, which quantifies the potential risk that prevails in financial markets. One popularly used measure in the current literature is the Exchange Market Pressure (EMP) index. Since the seminal work of Girton and Roper [1977], many researchers have used the EMP index to develop EWS mechanisms in order to detect the turbulence in the money market across countries. See Tanner [2002] for a review.

One alternative measure that is rapidly gaining popularity is financial stress index (FSI). Unlike the EMP index that is primarily based on changes in exchange rates and international reserves, FSI's are typically constructed using a broad range of financial market variables. As of 2015, there are 12 FSIs available for the US financial market (Oet et al. [2011]) including 4 indices that are reported by the US Federal Reserve system.[2]

[1] Source: Organization for Economic Co-operation and Development, Total Share Prices for All Shares for the Republic of Korea [SPASTT01KRQ657N]

[2] For some of FSI's in the Euro, see Grimaldi [2010], Grimaldi [2011], Hollo et al. [2012], and Islami

Some recent studies investigate what economic variables help predict financial market vulnerability using FSI's. For instance, Christensen and Li [2014] propose a model to forecast the FSIs developed by the IMF for 13 OECD countries, utilizing 12 economic 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 FSIs for 13 OECD countries and investigated what economic variables have predictive contents for the FSIs via linear regression models. Unfortunately, they fail to find any clear linkages between economic variables and those FSI's.[3]

The present paper proposes a new forecasting model for the financial market vulnerability in Korea using a broad range of time series macroeconomic data. We use the financial stress index and its four sub-indices developed by the Bank of Korea.[4,5] We estimate multiple latent common factors by employing the method of the principal components (Stock and Watson [2002]) for a panel of 198 monthly frequency time series data from October 2000 to December 2013.[6] We augment an autoregressive-type model of the financial stress index with estimated common factors, then formulate out-of-sample forecasts of the index for up to 12-month forecast horizons. 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) model using the ratio of the root mean square prediction errors ($RRMSPE$) and the Diebold-Mariano-West (DMW) test statistics.

Note that these statistics are primarily based on the least squares (LS) principles, meaning that our major focus is to develop a good model that out-of-sample forecasts FSIs well on average. Alternatively, one may employ a tail-based performance metrics to find forecasting models that perform well in capturing a tail event, which occurs rarely by construction. Although this type of models provide very useful information, we are more interested in developing simple prediction models in a data rich enviroment that are designed for constant monitoring to detect unusually high elevations in FSIs that ultimately can lead to a systemic financial crisis.

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and Kurz-Kim [2013]. There are FSI's for individual countries: 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]).

[3] 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 FSI in the US using a similar methodologies used in this paper.

[4] The 4 sub-indices are for the foreign exchange market, the stock market, the bond market, and the financial industry in Korea.

[5] The data is not publicly available and is for internal use only. We express our gratitude to give permission to use the data.

[6] We categorized these 198 variables into 13 groups that include an array of nominal and real activity variables.

Our major findings are as follows. First, our factor models overall outperform the benchmark models. For example, in our exercise for the foreign exchange market sub-index, $RRMSPE$ 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 from 1 to 12-month forecast horizons. Second, parsimonious models with just one single factor perform as well as bigger models that include up to 8 common factors. Augmenting the AR-type model of the FSI with the first common factor seems to be sufficient to beat the benchmark models. Third, fixed-size rolling window methods performed overall similarly well as the recursive approach, which implies the stability of our models over time. We note that the first common factor, which plays a dominantly important role in predicting the FSIs, represents not only financial market but also real activity variables. That is, our findings suggest that real sector variables also contain substantial predictive contents for the financial market vulnerability in Korea.

We further investigate more specific channels of shocks by estimating macroeconomic factors separately from those from the monetary/finance variables. Our out-of-sample forecast exercises reveal overall stronger performance of the full factor models especically for the total FSI, meaning that a wide range of macro-finance variables contain useful predictive contents for the vulnerability in Korea's financial market system. On the other hand, for FSI-bond and FSI-Stock, we show that our monetary/finance factor models outperform not only the AR benchmark model but also the total factor model, which implies that the predictability for these indices can be improved by excluding the macroeconomic factors.

The rest of the paper is organized as follows. Section 2 describes the baseline econometric model and the out-of-sample forecasts schemes used in the present paper. We also explain our evaluation methods for our models. 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. In Section 5, we report forecast performances of our sub-factor models relative to the total factor model, and discuss the implications of the findings. Section 6 concludes.

2 The Econometric Model

Let $x_{i,t}$ be a macroeconomic variable $i \in \{1, 2, .., N\}$ at time $t \in \{1, 2, .., T\}$. Assume that $x_{i,t}$ has the following factor structure.

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

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.

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 after differencing the data. Lag (1) by one period then subtract it from (1) to get,

$$\Delta x_{i,t} = \lambda_i^{'} \Delta \mathbf{F}_t + \Delta e_{i,t} \tag{2}$$

for $t = 2, \cdots, T$. Let $\Delta \mathbf{x}_i = [\Delta x_{i,1} \ \cdots \ \Delta x_{i,T}]^{'}$ and $\Delta \mathbf{x} = [\Delta \mathbf{x}_1 \ \cdots \ \Delta \mathbf{x}_N]$. We first normalize the data before the estimations, since the method of the principal components is not scale invariant. Employing 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 coefficient estimates $\hat{\lambda}_i$. 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,

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

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

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

After obtaining latent factor estimates, we augment an AR-type model for the financial stress index (fsi_t) with $\Delta \hat{\mathbf{F}}_t$. Abstracting from deterministic terms,

$$fsi_{t+j} = \beta_j^{'} \Delta \hat{\mathbf{F}}_t + \alpha_j fsi_t + u_{t+j}, \ j = 1, 2, .., k \tag{5}$$

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.[7] Note that (5) is an AR(1) process for $j = 1$, extended by exogenous common factor estimates $\Delta \hat{\mathbf{F}}_t$. This formulation is based on our preliminary unit-root test results for the FSI's that show strong evidence of

[7] Alternatively, one may use a *recursive* forecasting regression model that replaces α_j with α^j, where α is the coefficient from an AR(1) model.

stationarity.[8] Applying the ordinary least squares (OLS) estimation for (5), we obtain the following j-period ahead forecast for the financial stress index.

$$\widehat{fsi}^{F}_{t+j|t} = \hat{\beta}'_j \Delta \hat{\mathbf{F}}_t + \hat{\alpha}_j fsi_t \tag{6}$$

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

$$fsi_{t+1} = fsi_t + \varepsilon_{t+1} \tag{7}$$

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

$$\widehat{fsi}^{RW}_{t+j|t} = fsi_t, \tag{8}$$

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 the second benchmark model.

$$fsi_{t+j} = \alpha_j fsi_t + \varepsilon_{t+1}, \tag{9}$$

where α_j is the coefficient on the current FSI in the direct regression for the j-period ahead FSI variable. This model specification yields the following j-period ahead forecast.

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

where $\hat{\alpha}_j$ is the least squares estimate for α_j.

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 outperforms the benchmark model when $RRMSPE$ is 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 loss differential function.

$$d_t = L(\varepsilon^{A}_{t+j|t}) - L(\varepsilon^{F}_{t+j|t}), \tag{11}$$

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

$$\varepsilon^{A}_{t+j|t} = fsi_{t+j} - \widehat{fsi}^{A}_{t+j|t} \ (A = RW, AR), \ \varepsilon^{F}_{t+j|t} = fsi_{t+j} - \widehat{fsi}^{F}_{t+j|t} \tag{12}$$

[8] ADF test results are available upon request.

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

The DMW test statistic tests the null of equal predictive accuracy, $H_0 : Ed_t = 0$, and is defined as follows.

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

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 $\bar{d}$,

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

$k(\cdot)$ 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.[9] Note that our factor model (5) nests the stationary benchmark model in (9) with $\beta_j = \mathbf{0}$. Therefore, we use critical values obtained with re-centered distributions of the test statistic for nested models (McCracken [2007]). 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 Data Descriptions and Factor Estimations

3.1 Data Descriptions

We use the financial stress index (FSI) data to assess the degree of the vulnerability in financial markets in Korea to potential risk of having possible financial crises. Financial Condition Indices (FCI) share similar information as FSI's in the sense that they all measure the current financial conditions in the economy, though FCI's focus more on how financial variables react to changes in the market conditions.

There were earlier attempts to develop an FSI 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 began using FSIs since 2008. In Korea, the Bank of Korea developed FSIs in 2007 and started to report the indices on a yearly basis in their Financial Stability Report. We obtained monthly frequency data which have been transformed from daily frequency raw data. The data are in principle for internal use only.[10]

The Korea's FSI data is based on 4 sub-indices for the bond market (FSI-Bond), the

[9] Following Andrews and Monahan [1992], we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

[10] We obtained permission from the Bank of Korea to use the data for this research.

foreign exchange market (FSI-FX), the stock market (FSI-Stock), and the financial industry (FSI-Industry). Each sub-index is constructed as follows. FSI-Bond is based on a variety of credit spreads, long-short interest rate spreads, and covered interest rate differentials (CID). FSI-FX is obtained by utilizing the volatility and the growth rate of the Korean Won-US Dollar exchange rate as well as the growth rate of Korea's foreign exchange reserves. FSI-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, FSI-Industry is based on the volatility and the βs 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 total FSI index. FSI-Bond exhibits much lower volatility than FSI, while FSI-Stock shows the highest volatility. All indices imply extremely high degree vulnerability during the recent financial crisis that began in 2008.

Note that these indices keep track of actual historic events of financial crises, including the burst of the dot com bubble and the recent financial crisis, which confirms that the Bank of Korea's FSIs may provide useful timely signals of rising tensions in Korea's financial market system. Given that, developing a good forecasting model for these FSIs would provide useful information to the policy makers.

Figure 1 around here

We obtained all macroeconomic time series data from Kim [2013], which are used to extract latent common factors for our out-of-sample forecast exercises. Observations are monthly frequency and span from October 2000 to December 2013. All variables other than those in percent (e.g., interest rates and unemployment rates) are log-transformed prior to estimations. 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 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 monetary/finance 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.

Table 1 around here

3.2 Latent Factors and their Characteristics

We estimate up to 8 latent common factors by applying the method of the principal components (PCA) to 198 macroeconomic data series after differencing and normalizing them. Estimated (differenced) common factors, $\Delta\hat{F}_1, \Delta\hat{F}_2, ..., \Delta\hat{F}_8$, as well as their associated *level* common factor estimates $\hat{F}_1, \hat{F}_2, ..., \hat{F}_8$, obtained by re-integrating differenced common factors, in the Appendix.

We note a dramatic decline in the first common factor estimate $\hat{F}_1$ around the beginning of the Great Recession in 2008. Similarly, the second common factor estimates $\hat{F}_2$ exhibits an abrupt downward movement about the same time. All estimated common factors in *levels* exhibit highly persistent dynamics, indicating a nonstationary stochastic process. Therefore, it seems to be appropriate to employ PCA to the data after differencing them to ensure the stationarity of the data (see Bai and Ng [2004]) to consistently estimate the factors.

To understand the source of each latent factor more closely, we estimate the factor loading coefficients ($\hat{\lambda}_i$). In addition, we provide the marginal R^2 analysis by regressing each predictor variable $x_{i,t}$ on each common factor estimate $\Delta\hat{F}_i$ to get R^2 values. All results are reported in the Appendix.

In what follows, we investigate the properties of the three key common factors to understnad the nature of those factors. First, we plot $\Delta\hat{F}_1$ and $\hat{F}_1$ as well as its associated factor loading coefficients ($\hat{\lambda}_{i,1}$) and the marginal R^2 values in Figure 2.

We note that the factor loading coefficients for the first four groups (groups #1 through #4) and the last three groups (groups #11 through #13) are positively associated with $\Delta\hat{F}_1$, while variables in groups #5, #6, and #8 are mostly negatively associated with it. Overall, $\Delta\hat{F}_1$ represents not only the monetary variables (e.g., interest rates, prices, monetary aggregates, and nominal exchange rates) but also real activity macroeconomic variables (e.g., new orders, industrial production, and industrial production).

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), because domestic inflation is likely to be associated with depreciation of the home currrency. Marginal R^2 analysis results are overall consistent with the factor loading coefficients. To put it differently, $\Delta\hat{F}_1$ seems to be representing both the monetary variables (#1, #2, #3, #5) and the macroeconomic variables (#11, #12, #13).

Figure 2 around here

As we can see in Figure 3, the second common factor seems to closely represent variables in groups #5, #6, and #9 through #12, which are real sector variables with an exception of group #5. $\Delta\hat{F}_2$ is overall positively related with the majority of the variables in these groups. For instance, the factor loading coefficients ($\hat{\lambda}_{i,2}$) for nominal exchange rates (group #5) are positive, which implies that a depreciation of Korean wons ($\Delta x_{i,t} > 0$) are associated with an increase in real activities ($\Delta\hat{F}_2 > 0$) in Korea, that is, $\hat{\lambda}_{i,2}\Delta\hat{F}_2 > 0$. Similarly, new orders, sales, industrial production, and business condition index variables have positive coefficients. Among the variables in group #10, unemployment variables have negative coefficients, while employment variables tend to exhibit positive ones, which are consistent with each other. Putting all together, $\Delta\hat{F}_2$ seems to represent overall real sector variables.

Figure 3 around here

In what follows, our in-sample-fit analysis demonstrates a substantially important role of the fourth common factor estimate $\Delta\hat{F}_4$ in explaining FSIs. So we investigate the properties of $\Delta\hat{F}_4$ more closely in Figure 4. Estimates of $\lambda_{i,4}$ imply that $\Delta\hat{F}_4$ is more closely related with monetary/finance variables in groups #1 through #5, while some variables among macroeconomic variable groups #7 and #8 (inventory indices) are also somewhat closely related with $\Delta\hat{F}_4$. The marginal R^2 analysis also confirms these findings. Therefore, we may conclude $\Delta\hat{F}_4$ primarily represents the nominal/monetary variables.

Figure 4 around here

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 $\left\{\Delta\hat{F}_1, \Delta\hat{F}_2, ..., \Delta\hat{F}_8\right\}$ as predictor variables.

$$fsi_{t+j} = \beta_j^{'}\Delta\hat{\mathbf{F}}_t + u_{t+j},\ j = 0, 1, 2, .., k \tag{15}$$

We report our in-sample fit analyses in Table 2 for the contemporaneous case ($j = 0$).[11]

We employed an R^2-based selection method from a one-factor model to an eight-factor full model to find the best combination of explanatory variables. It turns out that the first

[11] Regressions for the 1-, 3-, and 6-month ahead FSI indices yield similar patterns, although R^2 values overall decline as the time horizon becomes larger.

common factor estimate $\Delta\hat{F}_1$ plays the most important role in explaining variations in all FSI indices with an exception of FSI-Bond. The second common factor estimate $\Delta\hat{F}_2$ explains a negligibly small portion of variations in FSI indices.

Since R^2 increases as more variables are included, this R^2-based selection method always picks 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) picked a 6-factor model for FSI and a 5-factor model for FSI-FX. It should be noted, however, that maginal gains from adding more factors are often small, which implies that small dimension models with just one or two factors are sufficient to obtain a good in-sample fit for each financial stress index. In what follows, we demonstrate that parsimonious models perform well in out-of-sample forecast exercises as well.

Table 2 around here

We also implement similar in-sample analysis based on (15) for the time horizon $j = 0, 1, ..., 12$ months. R^2 values for FSIs are reported in Figure 5. We note that the first common factor ($\Delta\hat{F}_1$) explains the most variations not just in contemporaneous FSIs (over 20%) but also in up to a half-year ($h = 0, 1, 2, ..., 6$) ahead FSIs with an exception of FSI-bond. It is interesting to see that $\Delta\hat{F}_4$ overall plays a non-negligible role especially in the short-run. For example, its R^2 values for contemporaneous FSI and FSI-Stock exceeded 0.10. Recall that $\Delta\hat{F}_4$ represents mainly monetary variables that include interest rates and exchange rates. That is, these fast-moving variables provide more predictive contents through $\Delta\hat{F}_4$ in addition to those in $\Delta\hat{F}_1$ that represents both the monetary and the slow-moving macroeconomic variables. Other than these two factors, none explains much of the variations in FSIs, although $\Delta\hat{F}_7$ contains some predictive contents in the medium-run.

Figure 5 around here

4.2 Out-of-Sample Forecast Exercises and Model Evaluations

We implement out-of-sample forecast exercises using the following two schemes. First, we employ a recursive forecast method. We start formulating $k-$period ahead out-of-sample forecasts of FSI's (fsi_{T_0+k}) using the initial T_0 observations.[12] That is, we extract common

[12] We used 70% initial observations.

factors from $\{x_{i,t}\}_{i=1,..,N}^{t=1,...,T_0}$ after differencing. Then, we formulate our factor model forecast via (6). Next, we add one new set of observations to the sample and implement next forecast for fsi_{T_0+1+k} using this expanded set of observations $\{x_{i,t}\}_{i=1,..,N}^{t=1,...,T_0+1}$. We repeat this procedure until we forecast the last observation fsi_T. 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 (T_0/T) but dropping one earliest observation, maintaining the same sample size.

For statistical evaluations of our factor model, we employ the two benchmark models, the random walk (RW, no change) model and a stationary AR(1) model, and formulate forecasts via the equations (8) and (10), respectively. We evaluate our factor model forecasting 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 relative 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 the total FSI 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 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, denoted in bold. Our factor models outperform the benchmark model with the DMW test for majority 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. We find especially 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 monetary variables, performs consistently poorly. We note that the DMW test rejects the null of equal predictability for 7 out of 12 one-period ahead forecasts, while $RRMSPE$ is greater than 1 (in bold) 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 3 around here

Table 4 reports out-of-sample forecast exercise results for FSI-Bond. Irrespective of its poor in-sample fit as seen 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 least 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, although small, in FSI-Bond as can be seen in Table 2. It is interesting to see 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. In what follows, we show that forecast models that utilize factors only from the monetary/finance variables outperform the AR benchmark by both the $RRMSPE$ and the DMW statistics criteria, indicating that the predictability can be enhanced by excluding the macroeconomic variables.

Table 4 around here

Our factor models perform overall extememly well for FSI-FX, especially when the rolling window method is employed. $RRMSPE$ is greater than one for all cases with the random walk benchmark model, while the DMW test rejects the null for all cases when the rolling window scheme is employed. Our models exhibit failry good one-period ahead forecast performances with the AR benchmark whenever $\Delta\hat{F}_1$ is used.

Table 5 around here

Out-of-sample forecast performances for FSI-Stock are reported in Table 6. $RRMSPE$ is greater than 1 in most cases with the RW benchmark model, while the DMW test rejects the null of equal predictability only when $j = 12$. With the AR model, factor models demonstrated limited success 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. Similar to the case of FSI-Bond, we show that the predictability can be enhanced when factors are extracted only from the monetary/finance variables in the next section.

Table 6 around here

Finally, we report forecast exercise results for FSI-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 especially when the AR model serves as the benchmark. Overall, our factor models perform the worst for FSI-Industry, although $\Delta\hat{F}_4$ seems to perform relatively better than other factors.

Table 7 around here

5 Discussions

5.1 Macroeconomic vs. Monetary Variables

This section extracts common factors from two groups of predictor variables: monetary/finance variables (groups #1 through #5) and macroeconomic variables (groups #6 through #13). Since the latent factors are estimated from a large panel of time series, they contain not only fast-moving monetary variables but also slow-moving macro variables. The idea is to evaluate the individual roles of the macroeconomic and finance factors by estimating common factors from these groups of variables separately.

We first investigate how common factors from the entire predictor variables ($\Delta\hat{F}_i$) are associated with common factors from the monetary variables ($\Delta Mn\hat{F}_i$) and those from the macroeconomic variables ($\Delta Mc\hat{F}_i$). Scatter plot diagrams in Figure 6 confirm our earlier conjectures about the source of each common factor ($\Delta\hat{F}_i$). $\Delta\hat{F}_1$ is closely associated with the first factor from the monetary variables ΔMnF_1 as well as the two factors from the macroeconomic variables, ΔMcF_1 and ΔMcF_2 in the sense that the slope coefficient estimates (β) were highly significant at the 5% significance level. $\Delta\hat{F}_2$ seems to be mainly extracted from macroeconomic variables. On the other hand, the major source of $\Delta\hat{F}_4$ seems to be the monetary/finance variables because it is strongly correlated with ΔMnF_1 and ΔMnF_2, while the β estimate for $\Delta\hat{F}_4$ and ΔMcF_2 is only marginally significant.

Figure 6 around here

We report out-of-sample predictability test results for the macro and financial factors in Tables 8 through 12. For the total FSI, it seems that the full factor models perform better than the sub-factor models, the macro and the finance factors, in terms of significance of the DMW test. See Tables 3 and 8. For both the rolling window and recursive schemes and for the both benchmark models, $\Delta\hat{F}_i$ exhbited superior performances to ΔMnF_i and ΔMcF_i, although ΔMnF_1 peformed overall better than the macro factors.

Table 8 around here

The full factor model for FSI-Bond again perform better than the sub-factor models in terms of significance of the DMW test. See Tables 4 and 9. Interestingly, the finance factors outperform the macro factors in the tests with the AR benchmark model. ΔMnF_i exhibited a superior predictability both in terms of the $RRMSPE$ and the DMW statistics, while the AR benchmark model performed better than ΔMcF_i. Recall that the total factor model did not beat the AR benchmark (Table 4). These findings imply that major gains in out-of-sample predictability of the full factor model are obtained from the monetary/finance predictor variables, and its predictability can be improved by excluding the macroeconomic variables.

Table 9 around here

These findings for FSI-Bond contrast sharply with those for FSI-FX. See Tables 5 and 10. The full factor model again outperforms the sub-factor models. However, unlike the previous results for FSI-Bond, the macro factors perform better than monetary factors in the tests with the AR benchmark model, although ΔMcF_i contained good prediction contents only for 1-month ($j = 1$) and 1-year ($j = 12$) ahead FSI-FX. That is, it seems that the predictability of the full factor model mainly comes from the macro predictor variables, which sharply contrasts with the case of FSI-Bond.

Table 10 around here

Our forecasting exercises for FSI-Stock with the sub-factor models exhibit intriguing results that the finance factor models outperform the full factor models in terms of $RRMSPE$ and the DMW test statistics. See Table 11. The DMW test mostly failed to reject the equal predictability null hypothesis for the full factor models (see Table 6), while the test rejected the null hypothesis for the monetary/finance factor models whichever benchmark models were employed. That is, as in the case of FSI-Bond, our factor models perform better when we extract common factors only from the monetary variables.

Table 11 around here

Lastly, the total factor models perform similarly well for FSI-Industry in comparison with the sub-factor models in the tests with the RW benchmark. However, the macro and finance factor models barely outperform the AR benchmark, while ΔMnF_1 has a limited success in outperforming the AR model. We note that the full factor model performed relatively well against the AR model only when it contains ΔF_4 which extracts the predictive contents mostly from the monetary/finance variables, which are consistent with the findings in Table 12.

Table 12 around here

Since Korea is a small open economy, its financial system may be vulnerable to spillover effecfts of external shocks that originate from foreign large economies. This implies that common factors that are estimated from open economy variables may have useful predictive contents for the vulnerability of Korea's financial system.

To assess this possibility, we estimate latent factors utilizing the following 50 open economy variables: 22 Morgan Stanley Capital International (MSCI) stock indices in the developed market category; 12 Korean stock market indices; 16 monentary variables including the VIX, 12 Korean won exchange rates, and 3 international interest rates.[13] To save space, we report out-of-sample forecast exercises using only the one-factor model for all 5 FSIs in Table 13.

Results imply that this open economy sub-factor model performs as good as the total factor model only for FSI-FX when the RW model serves the benchmark. With the AR benchmark, the total factor model outperformed the open economy sub-factor model for all FSIs, implying that open economy factors have some useful but limited predictive contents for the stability in Korea's financial system.

Table 13 around here

[13] Note that some variables such as Korean stock indices and bilateral exchange rates were included in our baseline study.

5.2 Predictability of Sub-Indices

We compare the out-of-sample predictability of our factor model (5) against the following model with the four sub-indices. Abstracting from deterministic terms,

$$fsi_{t+j} = \beta_j^{'}\mathbf{sfsi}_t + u_{t+j},\ j = 1, 2, .., k, \tag{16}$$

where fsi_{t+j} is the total financial stress index at time $t+j$ and $\mathbf{sfsi}_t$ is a 4×1 vector of four sub-indices at time t. The idea is to check whether these sub-indices contain good out-of-sample predictive contents for the total FSI index, because it is a weighted average of the four sub-indices. Note that the lagged total index fsi_t cannot be included in the regression because it is not independent of $\mathbf{sfsi}_t$. We report results in Table 14.

Our factor model completely outperforms this sub-indices benchmark model. All $RRMSPE$ values are greater than one, and the DMW test rejects the null of equal predictability at least at the 5% significance level, meaning that our factor-based forecasting models extract additional important predictive contents for fsi_{t+j} that are not contained in the four sub-indices.

Table 14 around here

5.3 Time-Varying Coefficient?

Our out-of-sample forecast exercises require repeated estimations of common factors using either a recursive or a fixed-size rolling window scheme. One related question is whether we estimate the same underlying factors consistently from these repeated estimations because of the "latent nature" of common factors. Therefore, it might be an interesting exercise to see how factor estimates are formulated from the data over time, and whether the pattern of the dependency of factor estimates on each variabel remains stable over time.

For this purpose, we repeatedly estimate common factors using the following two methods. First method begins with estimating the common factors $\Delta\mathbf{F}_{T_0}$ using the first T_0 observations $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=1,\ldots,T_0}$. Then, we implement the marginal R^2 analysis by regressing each variable in $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=1,\ldots,T_0}$ on $\Delta\mathbf{F}_{T_0}$, which generates N marginal R^2 values. Then, we move the sample window to the right by one set of observations, $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=2,\ldots,T_0+1}$, and estimate the next set of the common factors $\Delta\mathbf{F}_{T_0+1}$. Then, we obtain another N marginal R^2 values by the same regression method. We repeat until we obtain $(T - T_0 + 1)$ sets of N marginal R^2 values.

The second method estimates the common factors $\Delta\mathbf{F}_T$ using the entire T observations $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=1,\ldots,T}$. Then, we implement the marginal R^2 analysis by regressing each of $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=1,\ldots,T_0}$ on $\{\Delta\mathbf{F}_{T,s}\}_{s=1,\ldots,T_0}$. We shift the sample window by one and implement the same analysis utilizing $\{\Delta x_{i,s}\}_{i=1,\ldots,N}^{s=2,\ldots,T_0+1}$ and $\{\Delta\mathbf{F}_{T,s}\}_{s=2,\ldots,T_0+1}$ to get the next set of marginal R^2 values. We repeat until we obtain $(T - T_0 + 1)$ sets of N marginal R^2 values.

We report results for the first common factor in Figure 7. We note that marginal R^2 values from the both methods are similar with each other, although those from the rolling window scheme tend to be noisier. This implies that the data generating process of the first latent common factor remains stable. $\Delta\hat{F}_1$ has been closely associated with both the macroeconomic and the monetary/finance variables. It is interesting to see marginal R^2 values have increased for some monetary variables, especially for bilateral exchange rates over time.

Figure 7 around here

6 Concluding Remarks

This paper proposes an out-of-sample forecast model for the financial stress index developed by the Bank of Korea (BOK). We use the BOK's highly confidential financial stress index and its 4 sub-indices to measure the vulnerability in financial markets in Korea. To deal with issues on high data dimensionality, we employ a parsimonious method to extract latent common factors from a panel of 198 time series macroeconomic variables that includes not only nominal but also real activity variables. Following Bai and Ng [2004], we apply 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 FSI-Bond.

We implement out-of-sample forecast exercises using the recursive and the fixed size rolling window schemes with the two benchmark models, 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 ($RRMSPE$) and the DMW test statistics.

Our findings imply that there exists a tight linkage between the Korean FSI's and estimated 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 FSIs 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 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.

We further delve into this matter by estimating common factors from the two sub-groups separately, the monetary/finance variables and the macroeconomic variables. Although these sub-factor models overall perform well relative to the two benchmark models, the full factor models still outperform the sub-factor models for the total FSI. However, we note that the predictability for FSI-Bond and FSI-Stock can be enhanced greatly against the AR model when we utilize only the monetary/finance factors excluding macroeconomic factors. That is, a broad range of variables seems to be useful to capture the vulnerability of Korea's entire financial system, but bond and stock markets seem to be more greatly influenced by fast-moving monetary/financial variables.

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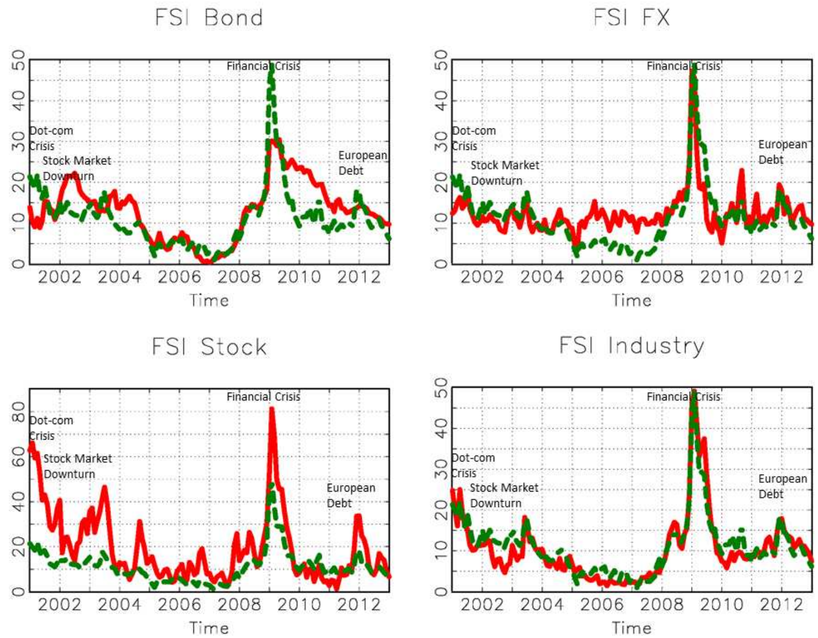
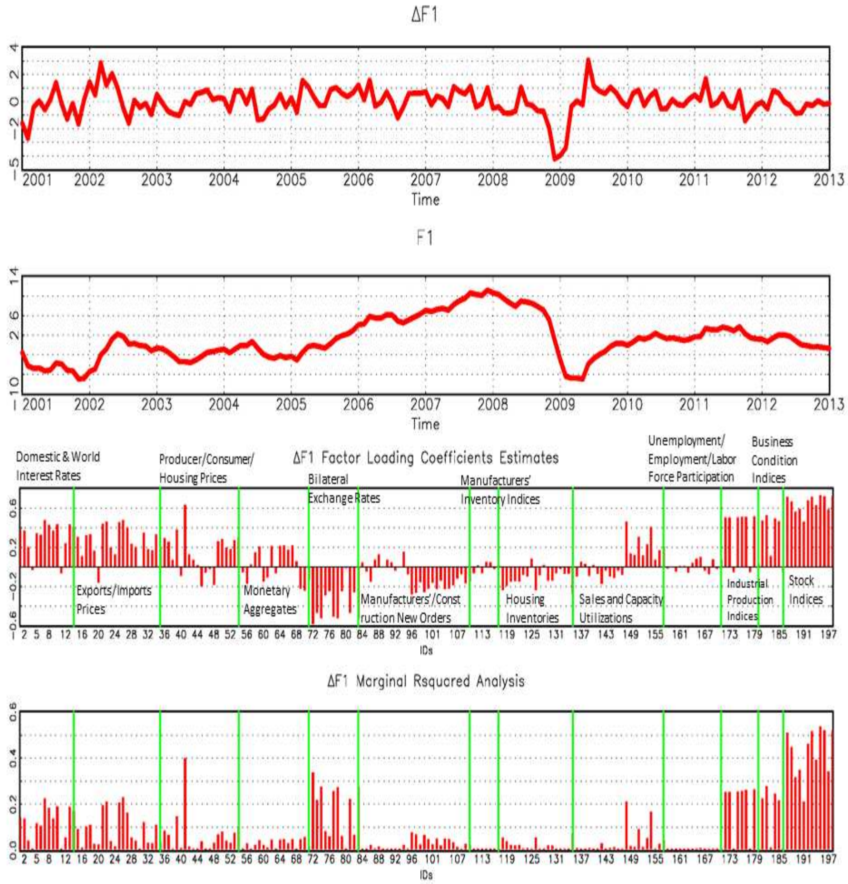
Figure 1. Financial Stress Index (Dashed) and 4 Sub-Indices



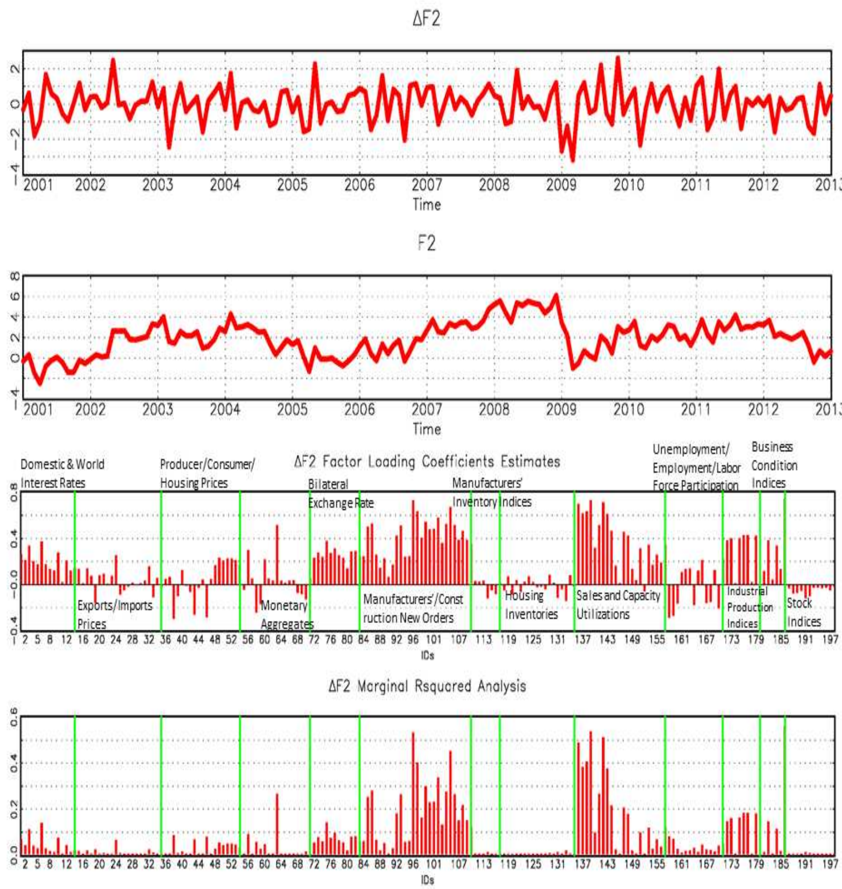
Note: The total financial stress index and its four sub-indices are obtained from the Bank of Korea. The data is not publicly available but we obtained a permission to use them.

Figure 2. Common Factor #1 and its Factor Loading Coefficients



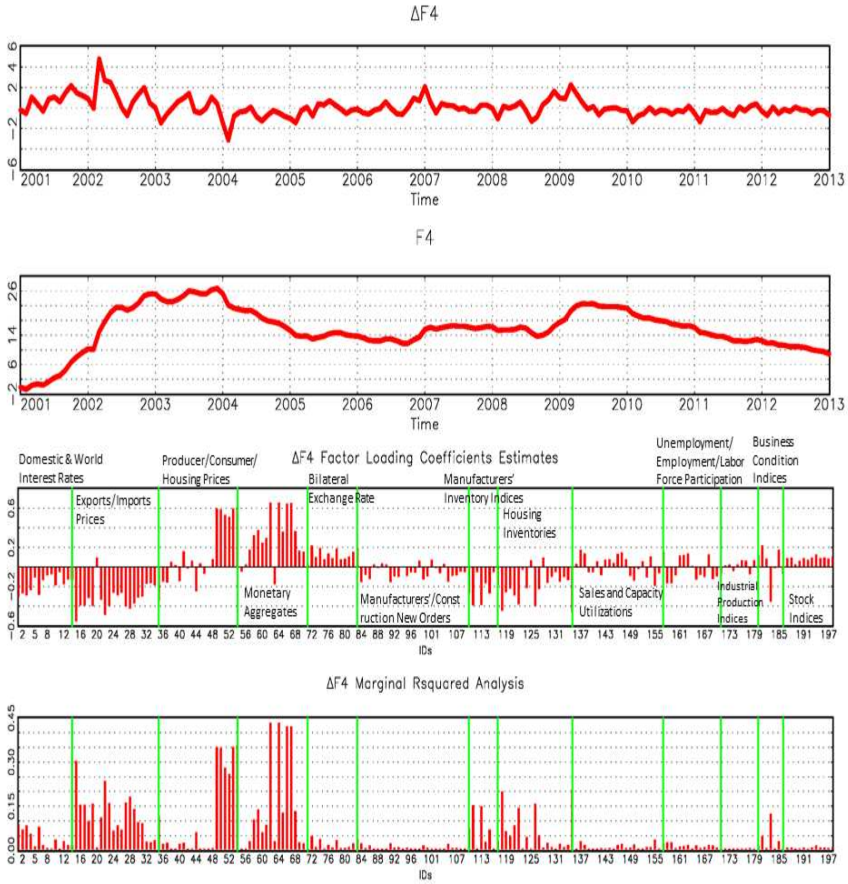
Note: We estimate the latent common factors by employing the method of the principal components for a panel of 198 monthly frequency time series data after differencing the data to consistently estimate the factors given nonstationarity of the data. Level factors are recovered by re-integrating the differenced factor estimates. Marginal R^2 values were obtained via a regression of each predictor variable $x_{i,t}$ onto the common factor.

Figure 3. Common Factor #2 and its Factor Loading Coefficients



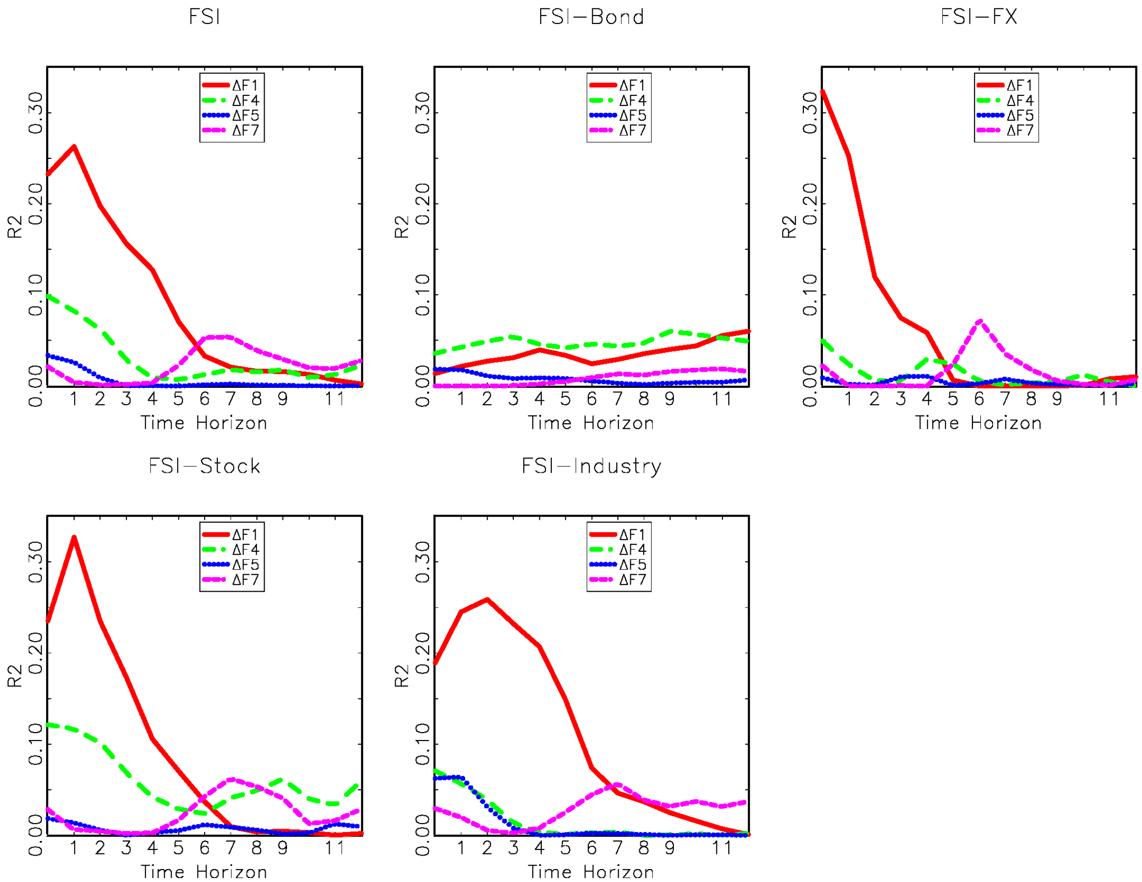
Note: We estimate the latent common factors by employing the method of the principal components for a panel of 198 monthly frequency time series data after differencing the data to consistently estimate the factors given nonstationarity of the data. Level factors are recovered by re-integrating the differenced factor estimates. Marginal R^2 values were obtained via a regression of each predictor variable $x_{i,t}$ onto the common factor.

Figure 4. Common Factor #4 and its Factor Loading Coefficients



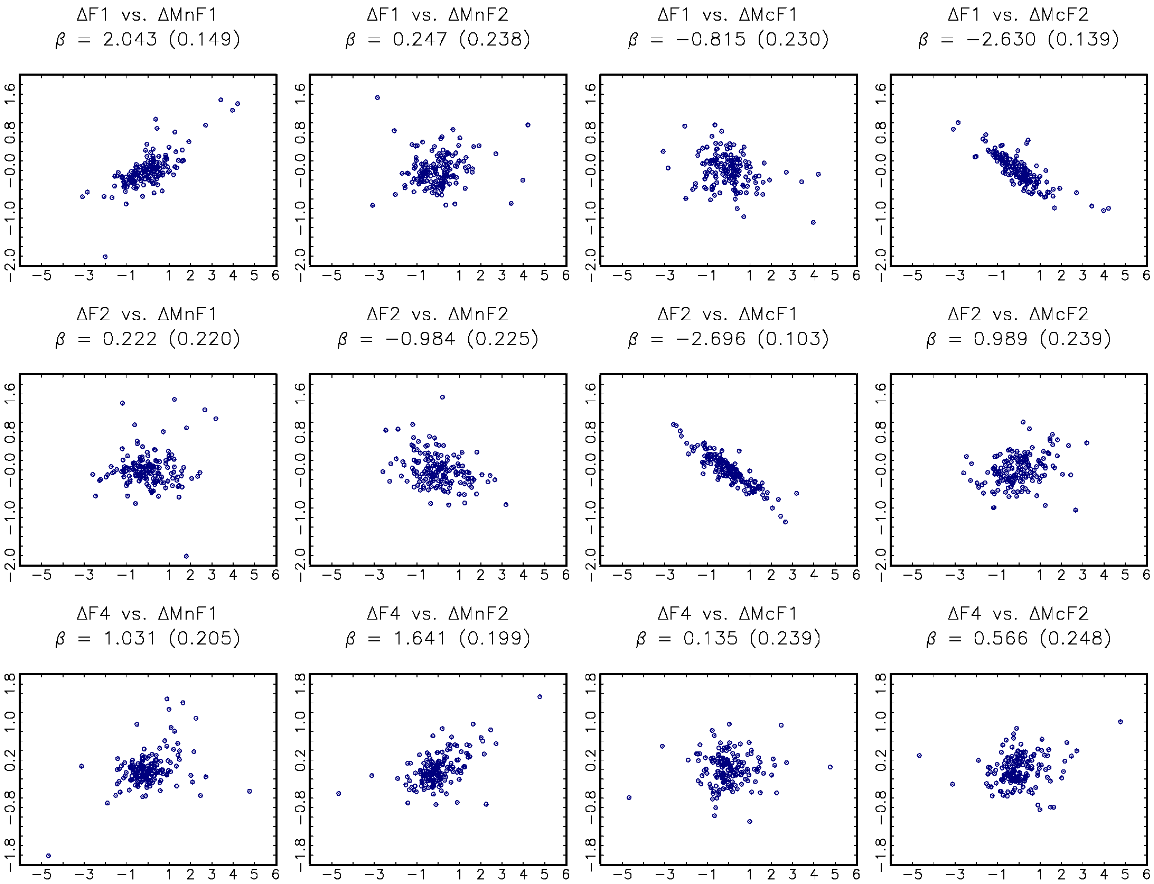
Note: We estimate the latent common factors by employing the method of the principal components for a panel of 198 monthly frequency time series data after differencing the data to consistently estimate the factors given nonstationarity of the data. Level factors are recovered by re-integrating the differenced factor estimates. Marginal R^2 values were obtained via a regression of each predictor variable $x_{i,t}$ onto the common factor.

Figure 5. Marginal R^2 for h-Period Ahead FSIs



Note: Marginal R^2 values were obtained via a regression of each common factor onto the j-period ahead financial stress index. We considered up to one year ($j = 12$) time hirozon.

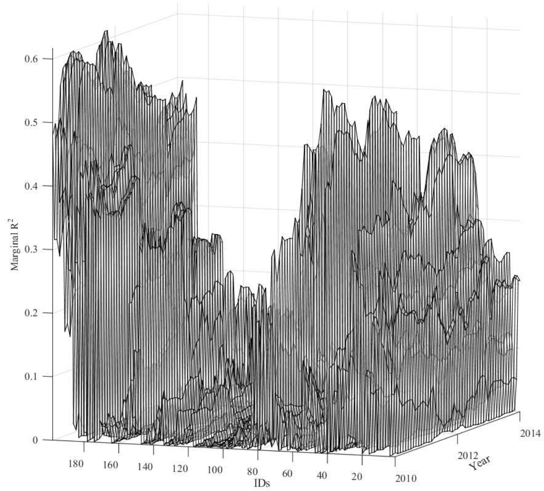
Figure 6. Macro and Monetary Common Factors



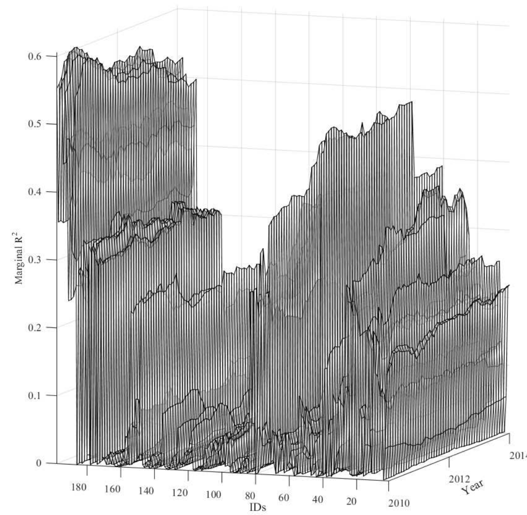
Note: ΔF_i, ΔMnF_i, and ΔMcF_i denote the common factor estimates from the entire variables, the monetary/finance variables (#1~#5), and the macroeconomic variables (#6~#13), respectively. β is the slope coefficient estimate and the standard errors are in the brackets.

Figure 7. Robustness of Factor Estimates

(a) $\Delta\hat{F}_1$ from the Rolling Window Scheme



(b) $\Delta\hat{F}_1$ from the Entire Observations



Note: Panel (a) reports marginal R^2 values utilizing the predictor variables and the first common factor estimate with a fixed-size rolling window. For this, we repeatedly re-estimate the first common factor. Panel (b) reports marginal R^2 values that are obtained the *pre*-estimated common factor and predictor variables with a fixed-size rolling window. That is, we first estimate the common factor using the entire observations, then apply the least squares regression with a rolling window scheme to obtain the R^2 values.

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	118-135	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

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

	Financial Stress Index	
#Factors	Factors	R^2
1	$\Delta\hat{F}1$	0.233
2	$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.331
3	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.365
4	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}8$	0.388
5	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.409
$6^{\dagger}$	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.421
7^{*}	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.426
8	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.429

	Financial Stress Index - Bond	
#Factors	Factors	R^2
1	$\Delta\hat{F}4$	0.036
2	$\Delta\hat{F}4$, $\Delta\hat{F}5$	0.054
$3^{\dagger}$	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.068
4^{*}	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}8$	0.079
5	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}8$	0.083
6	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}8$	0.084
7	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}8$	0.085
8	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.085

	Financial Stress Index: Foreign Exchange	
#Factors	Factors	R^2
1	$\Delta\hat{F}1$	0.324
2	$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.373
3	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$	0.395
4	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}6$, $\Delta\hat{F}7$	0.405
$5^{*\dagger}$	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$	0.414
6	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$	0.417
7	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.419
8	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.419

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

Table 2. Continued

	Financial Stress Index: Stock	
#Factors	Factors	R^2
1	$\Delta\hat{F}1$	0.235
2	$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.357
3	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}8$	0.388
4	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.417
5	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.438
6	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.456
7	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.471
$8^{*\dagger}$	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.479

	Financial Stress Index: Financial Industry	
#Factors	Factors	R^2
1	$\Delta\hat{F}1$	0.189
2	$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.260
3	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.322
4	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$	0.352
5	$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.378
6	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.395
7	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.410
$8^{*\dagger}$	$\Delta\hat{F}1$, $\Delta\hat{F}2$, $\Delta\hat{F}3$, $\Delta\hat{F}4$, $\Delta\hat{F}5$, $\Delta\hat{F}6$, $\Delta\hat{F}7$, $\Delta\hat{F}8$	0.421

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

Table 3. j-Period Ahead Out-of-Sample Forecast: FSI

Recursive Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.040**	**1.097**†	**1.251**‡	**1.344**‡	**1.398**‡
$\Delta\hat{F}4$	**1.031**	**1.084**†	**1.217**†	**1.296**‡	**1.415**‡
$\Delta\hat{F}5$	**1.049**†	**1.128**†	**1.246**†	**1.331**‡	**1.392**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.039**	**1.076***	**1.235**†	**1.302**‡	**1.416**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.049**	**1.100***	**1.279**‡	**1.357**‡	**1.397**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.047**	**1.079**	**1.270**†	**1.315**‡	**1.413**‡
Rolling Window Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.050**	**1.106**†	**1.280**‡	**1.378**‡	**1.438**‡
$\Delta\hat{F}4$	**1.021**	**1.085***	**1.219**†	**1.354**‡	**1.432**‡
$\Delta\hat{F}5$	**1.039***	**1.111**†	**1.279**†	**1.348**‡	**1.442**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.036**	**1.084**†	**1.244**‡	**1.371**‡	**1.437**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.057**	**1.090***	**1.331**‡	**1.374**‡	**1.437**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.043**	**1.071**	**1.295**‡	**1.377**‡	**1.435**‡

Recursive Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.008**	0.975	**1.015**‡	**1.014**‡	**1.003**
$\Delta\hat{F}4$	0.999	0.963	0.987	0.977	**1.015**†
$\Delta\hat{F}5$	**1.017**‡	**1.003**	**1.010**	**1.004**	0.999
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.007**	0.956	**1.001**	0.982	**1.016**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.017***	0.977	**1.037**†	**1.023**‡	**1.002**
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.015***	0.959	**1.030***	0.992	**1.014**†
Rolling Window Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.020***	0.981	**1.028**‡	**1.015**†	0.998
$\Delta\hat{F}4$	0.992	0.962	0.979	0.997	0.994
$\Delta\hat{F}5$	**1.009**‡	0.986	**1.027**†	0.993	**1.001**
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.007**	0.962	0.999	**1.009***	0.998
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.027**†	0.967	**1.069**‡	**1.012**†	0.998
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.013***	0.950†	**1.040**†	**1.014**†	0.997

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

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

Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Recursive Method: Random Walk Benchmark					
$\Delta\hat{F}4$	**1.025**	**1.154**‡	**1.204**‡	**1.365**‡	**1.547**‡
$\Delta\hat{F}5$	0.998	**1.084**†	**1.154**‡	**1.243**‡	**1.392**‡
$\Delta\hat{F}1$	1.000	**1.047**	**1.141**‡	**1.239**‡	**1.400**‡
$\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.008**	**1.164**‡	**1.218**‡	**1.375**‡	**1.549**‡
$\Delta\hat{F}4$, $\Delta\hat{F}1$	**1.005**	**1.114***	**1.207**‡	**1.368**‡	**1.537**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.987	**1.117***	**1.218**‡	**1.374**‡	**1.543**‡
Rolling Window Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}4$	**1.033**	**1.158**‡	**1.264**‡	**1.402**‡	**1.639**‡
$\Delta\hat{F}5$	**1.011**	**1.120**‡	**1.257**‡	**1.360**‡	**1.594**‡
$\Delta\hat{F}1$	**1.005**	**1.085**†	**1.245**‡	**1.335**‡	**1.599**‡
$\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.021**	**1.170**‡	**1.298**‡	**1.447**	**1.669**‡
$\Delta\hat{F}4$, $\Delta\hat{F}1$	**1.009**	**1.136**†	**1.298**‡	**1.437**‡	**1.679**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.998	**1.142**†	**1.331**‡	**1.475**‡	**1.697**‡
Recursive Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}4$	**1.011**	**1.076**‡	**1.057**‡	**1.108**‡	**1.116**‡
$\Delta\hat{F}5$	0.984	**1.011***	**1.013**†	**1.009**‡	**1.003**†
$\Delta\hat{F}1$	0.986	0.976	**1.002**	**1.006**	**1.009**
$\Delta\hat{F}4$, $\Delta\hat{F}5$	0.994	**1.086**‡	**1.070**‡	**1.116**‡	**1.117**‡
$\Delta\hat{F}4$, $\Delta\hat{F}1$	0.990	**1.039**†	**1.060**‡	**1.110**‡	**1.108**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.973	**1.042**†	**1.069**‡	**1.115**‡	**1.113**‡
Rolling Window Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}4$	**1.011***	**1.050**‡	**1.036**‡	**1.067**‡	**1.052**‡
$\Delta\hat{F}5$	0.990	**1.015**†	**1.031**‡	**1.035**‡	**1.024**†
$\Delta\hat{F}1$	0.983	0.983	**1.021**‡	**1.016***	**1.027***
$\Delta\hat{F}4$, $\Delta\hat{F}5$	0.999	**1.061**‡	**1.064**‡	**1.101**‡	**1.072**‡
$\Delta\hat{F}4$, $\Delta\hat{F}1$	0.987	**1.029**†	**1.064**‡	**1.094**‡	**1.078**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.976	**1.035**†	**1.091**‡	**1.122**‡	**1.090**‡

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

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

Recursive Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.120**	**1.293**	**1.372**‡	**1.617**†	**1.658**†
$\Delta\hat{F}4$	**1.095**	**1.237**†	**1.385**‡	**1.584**†	**1.614**‡
$\Delta\hat{F}7$	**1.088**	**1.359**†	**1.312**†	**1.666**†	**1.623**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.118**	**1.245**†	**1.426**‡	**1.590**†	**1.652**†
$\Delta\hat{F}1$, $\Delta\hat{F}7$	**1.109**	**1.349**	**1.336**	**1.675**	**1.657**
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$	**1.107**	**1.299**†	**1.402**‡	**1.662**†	**1.651**‡
Rolling Window Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.126***	**1.296**†	**1.392**‡	**1.611**†	**1.612**†
$\Delta\hat{F}4$	**1.088***	**1.222**†	**1.372**‡	**1.611**†	**1.566**†
$\Delta\hat{F}7$	**1.095**†	**1.285**†	**1.305**‡	**1.688**†	**1.560**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.120***	**1.232**†	**1.395**‡	**1.618**†	**1.598**†
$\Delta\hat{F}1$, $\Delta\hat{F}7$	**1.124**†	**1.289**†	**1.337**†	**1.673**†	**1.585**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$	**1.117***	**1.222**†	**1.377**†	**1.679**†	**1.571**†
Recursive Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.020**†	0.994	**1.028**‡	**1.003**	**1.017**†
$\Delta\hat{F}4$	0.997	0.951	**1.038**‡	0.982	0.990
$\Delta\hat{F}7$	0.991	**1.044**†	0.983	**1.033**‡	0.995
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.018**†	0.957	**1.069**‡	0.986	**1.014**†
$\Delta\hat{F}1$, $\Delta\hat{F}7$	**1.010***	**1.037**	**1.001**	**1.038**‡	**1.016***
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$	**1.008***	0.998	**1.051***	**1.031***	**1.013***
Rolling Window Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.029**†	0.999	**1.037**‡	0.992	**1.014**†
$\Delta\hat{F}4$	0.994	0.942	**1.022**‡	0.992	0.985
$\Delta\hat{F}7$	**1.000**	0.991	0.973	**1.040**‡	0.981
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.023**†	0.950	**1.039**†	0.996	**1.005***
$\Delta\hat{F}1$, $\Delta\hat{F}7$	**1.027**†	0.994	0.996	**1.030**†	0.997
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}7$	**1.020**†	0.942	**1.026***	**1.034**†	0.988

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

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

Recursive Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.016**	0.999	**1.062**	**1.090**	**1.238**†
$\Delta\hat{F}4$	**1.022**	**1.055**	**1.082**	**1.088**	**1.253**†
$\Delta\hat{F}8$	**1.033**	**1.056**	**1.114**	**1.103**	**1.239***
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.028**	1.000	**1.063**	**1.075**	**1.261**†
$\Delta\hat{F}1$, $\Delta\hat{F}8$	**1.008**	0.995	**1.087**	**1.106**	**1.268**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}8$	**1.013**	0.995	**1.086**	**1.093**	**1.298**†

Rolling Window Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.051**	**1.022**	**1.070**	**1.104**	**1.300**†
$\Delta\hat{F}4$	**1.010**	**1.076**	**1.129**	**1.143**	**1.340**†
$\Delta\hat{F}8$	**1.038**	**1.074**	**1.161**	**1.152**	**1.302**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.035**	**1.020**	**1.076**	**1.096**	**1.324**†
$\Delta\hat{F}1$, $\Delta\hat{F}8$	**1.053**	**1.007**	**1.096**	**1.122**	**1.296**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}8$	**1.036**	**1.004**	**1.105**	**1.122**	**1.330**‡

Recursive Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	1.000	0.945	0.975	**1.004**‡	**1.024**‡
$\Delta\hat{F}4$	**1.006**†	0.998	0.993	**1.002**	**1.037**‡
$\Delta\hat{F}8$	**1.016**†	0.999	**1.022**†	**1.016***	**1.025**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.011**	0.945	0.975	0.991	**1.043**‡
$\Delta\hat{F}1$, $\Delta\hat{F}8$	0.992	0.941	0.997‡	**1.019***	**1.049**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}8$	0.997	0.941	0.996	**1.007**	**1.074**‡

Rolling Window Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.034***	0.949	0.944	0.966	0.992
$\Delta\hat{F}4$	0.993	0.999	0.996	**1.001**	**1.023**‡
$\Delta\hat{F}8$	**1.022**†	0.997	**1.024**‡	**1.009**	0.994
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.018***	0.947	0.949	0.960	**1.011***
$\Delta\hat{F}1$, $\Delta\hat{F}8$	**1.036***	0.935	0.967	0.982	0.989
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}8$	**1.019***	0.933	0.975	0.983	**1.015**†

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 7. j**-Period Ahead Out-of-Sample Forecast: FSI-Financial Industry**

Recursive Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	0.961	0.992	**1.117**	**1.246**‡	**1.428**‡
$\Delta\hat{F}4$	**1.027**	**1.123**‡	**1.218**†	**1.315**‡	**1.405**‡
$\Delta\hat{F}5$	**1.023**	**1.068**	**1.177***	**1.267**‡	**1.409**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.946	**1.015**	**1.172***	**1.294**‡	**1.423**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	0.953	0.970	**1.132**	**1.245**‡	**1.426**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.937	0.996	**1.213***	**1.308**‡	**1.423**‡
Rolling Window Method: Random Walk Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	0.953	0.979	**1.117**	**1.256**‡	**1.424**‡
$\Delta\hat{F}4$	**1.017**	**1.130**†	**1.193**†	**1.386**‡	**1.400**‡
$\Delta\hat{F}5$	**1.024**	**1.044**	**1.217**†	**1.236**‡	**1.388**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.923	0.997	**1.140**	**1.356**‡	**1.427**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	0.951	0.954	**1.153***	**1.223**‡	**1.407**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.920	0.979	1.203*	1.350‡	1.417‡
Recursive Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	0.934	0.891	0.947	0.974	**1.010**†
$\Delta\hat{F}4$	0.998	**1.007**	**1.032**†	**1.029***	0.994
$\Delta\hat{F}5$	0.995	0.959	0.998	0.991	0.997
$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.920	0.911	0.993	**1.012**	**1.007***
$\Delta\hat{F}1$, $\Delta\hat{F}5$	0.927	0.871	0.959	0.974	**1.009***
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.911	0.894	**1.028***	**1.023***	**1.007***
Rolling Window Method: Autoregressive Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	0.926	0.875	0.931	0.975	**1.014**‡
$\Delta\hat{F}4$	0.988	**1.009***	0.995	**1.076** ‡	0.996
$\Delta\hat{F}5$	0.995	0.932	**1.015***	0.960	0.987
$\Delta\hat{F}1$, $\Delta\hat{F}4$	0.896	0.891	0.950	**1.053**‡	**1.015**†
$\Delta\hat{F}1$, $\Delta\hat{F}5$	0.923	0.852	0.961	0.950	**1.001**
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	0.894	0.874	**1.003**	**1.048**‡	**1.008***

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 8. Macro vs. Financial Factors: FSI

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
		Recursive Method: Random Walk Benchmark				
Macro	$\Delta Mc\hat{F}1$	**1.057**	**1.068**	**1.209**	**1.300**‡	**1.394**‡
	$\Delta Mc\hat{F}2$	**1.020**	**1.110**	**1.225**	**1.320**‡	**1.393**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.056**	**1.084**	**1.210**	**1.295**‡	**1.394**‡
Finance	$\Delta Mn\hat{F}1$	**1.023**	**1.144**‡	**1.361**‡	**1.452**‡	**1.398**‡
	$\Delta Mn\hat{F}2$	0.996	**1.114**†	**1.233**	**1.429**‡	**1.395**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.976	**1.133**†	**1.337**‡	**1.530**‡	**1.404**‡
		Rolling Window Method: Random Walk Benchmark				
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.064**	**1.078**	**1.222**	**1.326**‡	**1.437**‡
	$\Delta Mc\hat{F}2$	**1.021**	**1.102**	**1.232**	**1.348**‡	**1.436**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.066**	**1.086**	**1.219**	**1.321**‡	**1.431**‡
Finance	$\Delta Mn\hat{F}1$	**1.033**	**1.134**†	**1.304**†	**1.412**‡	**1.395**‡
	$\Delta Mn\hat{F}2$	0.979	**1.124**‡	**1.195**†	**1.359**‡	**1.375**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.968	**1.130**†	**1.239**†	**1.418**‡	**1.370**‡
		Recursive Method: Autoregressive Benchmark				
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.024**‡	0.949	0.980	0.980	1.000
	$\Delta Mc\hat{F}2$	0.989	0.987	0.993	0.995	1.000
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.024**†	0.963	0.981	0.976	1.000
Finance	$\Delta Mn\hat{F}1$	0.991	**1.016**†	**1.104**†	**1.095**†	**1.003**
	$\Delta Mn\hat{F}2$	0.966	0.990†	1.000	**1.077**†	**1.001**
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.946	**1.006***	**1.084**†	**1.153**‡	**1.007**
		Rolling Window Method: Autoregressive Benchmark				
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.033**‡	0.956	0.982	0.977	0.998
	$\Delta Mc\hat{F}2$	0.992	0.978	0.990	0.992	0.997
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.035**‡	0.963	0.979	0.972	0.994
Finance	$\Delta Mn\hat{F}1$	**1.003***	**1.006**	**1.048***	**1.040***	0.969
	$\Delta Mn\hat{F}2$	0.951	0.997	0.960	**1.001**	0.955
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.940	**1.002**	0.995	**1.044***	0.951

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 9. Macro vs. Financial Factors: FSI-Bond

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
	Recursive Method: Random Walk Benchmark					
Macro	$\Delta Mc\hat{F}1$	**1.035**	**1.041**	**1.122**‡	**1.203**‡	**1.366**‡
	$\Delta Mc\hat{F}2$	**1.002**	**1.077**	**1.134**‡	**1.233**‡	**1.354**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.007**	**1.057**	**1.132**‡	**1.224**‡	**1.379**‡
Finance	$\Delta Mn\hat{F}1$	**1.027**	**1.070**†	**1.141**‡	**1.239**‡	**1.425**‡
	$\Delta Mn\hat{F}2$	**1.034**	**1.132**†	**1.300**‡	**1.534**‡	**1.622**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.047**	**1.127**†	**1.302**‡	**1.535**‡	**1.607**‡
	Rolling Window Method: Random Walk Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.026**	**1.068**‡	**1.205**‡	**1.277**‡	**1.528**‡
	$\Delta Mc\hat{F}2$	**1.014**	**1.098**	**1.217**‡	**1.304**‡	**1.510**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.013**	**1.078**	**1.215**‡	**1.295**‡	**1.545**‡
Finance	$\Delta Mn\hat{F}1$	**1.023**	**1.124**‡	**1.245**‡	**1.361**‡	**1.624**‡
	$\Delta Mn\hat{F}2$	**1.059**	**1.172**‡	**1.395**‡	**1.570**‡	**1.673**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.059**	**1.176**†	**1.370**‡	**1.567**‡	**1.629**‡
	Recursive Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.020**†	0.971	0.985	0.976	0.985
	$\Delta Mc\hat{F}2$	0.988	**1.004**	0.996	1.000	0.976
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	0.993	0.986	0.994	0.993	0.995
Finance	$\Delta Mn\hat{F}1$	**1.013***	0.998	**1.002**	**1.006**†	**1.028**†
	$\Delta Mn\hat{F}2$	**1.019***	**1.056**†	**1.142**‡	**1.245**‡	**1.170**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.032**†	**1.051**†	**1.144**‡	**1.246**‡	**1.159**‡
	Rolling Window Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.004***	0.968	0.988	0.972	0.981
	$\Delta Mc\hat{F}2$	0.992	0.995	0.998	0.992	0.970
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	0.991	0.977	0.997	0.985	0.992
Finance	$\Delta Mn\hat{F}1$	**1.001**	**1.019**‡	**1.021**†	**1.036**‡	**1.043**‡
	$\Delta Mn\hat{F}2$	**1.036**†	**1.062**†	**1.144**‡	**1.195**‡	**1.074**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.036**†	**1.066**‡	**1.124**‡	**1.192**‡	**1.046***

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 10. Macro vs. Financial Factors: FSI-Foreign Exchange

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
	Recursive Method: Random Walk Benchmark					
Macro	$\Delta Mc\hat{F}1$	**1.113***	**1.225**	**1.310**	**1.548**†	**1.694**
	$\Delta Mc\hat{F}2$	**1.105***	**1.307**†	**1.338**	**1.601**	**1.630**†
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.126**	**1.257***	**1.314**	**1.536***	**1.703**
Finance	$\Delta Mn\hat{F}1$	**1.096**†	**1.271**†	**1.367**‡	**1.621**†	**1.636**†
	$\Delta Mn\hat{F}2$	**1.083**	**1.293**†	**1.204***	**1.497***	**1.546**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.079**	**1.271**†	**1.266**†	**1.508***	**1.552**†
	Rolling Window Method: Random Walk Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.116***	**1.232**	**1.320**	**1.540***	**1.661**
	$\Delta Mc\hat{F}2$	**1.100***	**1.284**	**1.339**	**1.613**	**1.591**
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.127**†	**1.248***	**1.318**	**1.529***	**1.668**
Finance	$\Delta Mn\hat{F}1$	**1.092***	**1.261**†	**1.343**†	**1.593**†	**1.601**†
	$\Delta Mn\hat{F}2$	**1.077**	**1.308**†	**1.211**†	**1.475***	**1.511**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.076**	**1.243**†	**1.246***	**1.481***	**1.510**†
	Recursive Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.014**‡	0.942	0.982	0.960	**1.039**†
	$\Delta Mc\hat{F}2$	**1.006***	**1.005**	**1.003***	0.993	1.000
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.025**‡	0.966	0.985	0.953	**1.045**†
Finance	$\Delta Mn\hat{F}1$	0.999	0.977	**1.025**	**1.005**	**1.004**
	$\Delta Mn\hat{F}2$	0.987	0.994	0.902	0.928	0.949
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.983	0.977	0.949	0.935	0.952
	Rolling Window Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.019**‡	0.949	0.984	0.948	**1.045**†
	$\Delta Mc\hat{F}2$	**1.005***	0.990	0.998	0.993	**1.001**
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.029**‡	0.962	0.982	0.941	**1.049**†
Finance	$\Delta Mn\hat{F}1$	0.997	0.972	**1.001**	0.981	**1.007**
	$\Delta Mn\hat{F}2$	0.984	**1.008***	0.902	0.908	0.951
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.983	0.958	0.929	0.912	0.950

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 11. Macro vs. Financial Factors: FSI-Stock

Recursive Method: Random Walk Benchmark

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.072**	**1.011**	**1.069**	**1.075**	**1.225***
	$\Delta Mc\hat{F}2$	0.987	**1.051**	**1.068**	**1.078**	**1.208***
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.081**	**1.022**	**1.055**	**1.068**	**1.227***
Finance	$\Delta Mn\hat{F}1$	0.977	**1.060**	**1.301**‡	**1.275**†	**1.281**†
	$\Delta Mn\hat{F}2$	**1.035**	**1.086***	**1.214**†	**1.306**†	**1.324**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.998	**1.078***	**1.370**‡	**1.445**‡	**1.353**‡

Rolling Window Method: Random Walk Benchmark

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.086***	**1.032**	**1.108**	**1.129**	**1.325**†
	$\Delta Mc\hat{F}2$	0.997	**1.077**	**1.092**	**1.104**	**1.284**†
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.106***	**1.050**	**1.080**	**1.097**	**1.299**†
Finance	$\Delta Mn\hat{F}1$	**1.018**	**1.077**	**1.367**‡	**1.406**‡	**1.361**‡
	$\Delta Mn\hat{F}2$	**1.015**	**1.101**†	**1.200***	**1.291**†	**1.409**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	**1.001**	**1.085***	**1.362**‡	**1.479**‡	**1.424**‡

Recursive Method: Autoregressive Benchmark

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.054**†	0.956	0.981	0.990	**1.013***
	$\Delta Mc\hat{F}2$	0.971	0.994	0.979	0.993	0.999
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.064**†	0.966	0.968	0.984	**1.015**†
Finance	$\Delta Mn\hat{F}1$	0.961	**1.003**†	**1.194**‡	**1.175**‡	**1.060**‡
	$\Delta Mn\hat{F}2$	**1.018**	**1.027**‡	**1.113**‡	**1.203**‡	**1.095**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.982	**1.020**†	**1.257**‡	**1.331**‡	**1.119**‡

Rolling Window Method: Autoregressive Benchmark

	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.069**‡	0.958	0.978	0.989	**1.011***
	$\Delta Mc\hat{F}2$	0.981	1.000	0.963	0.967	0.980
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.089**‡	0.975	0.953	0.960	0.991
Finance	$\Delta Mn\hat{F}1$	**1.002**	1.000	**1.206**‡	**1.231**‡	**1.039**‡
	$\Delta Mn\hat{F}2$	0.999	**1.022**†	**1.059**‡	**1.131**‡	**1.075**‡
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.985	**1.007***	**1.202**‡	**1.295**‡	**1.086**‡

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 12. Macro vs. Financial Factors: FSI-Financial Industry

	Recursive Method: Random Walk Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.015**	0.995	**1.078**	**1.194***	**1.408**‡
	$\Delta Mc\hat{F}2$	**1.001**	0.983	**1.121**	**1.238**‡	**1.405**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.023**	**1.003**	**1.107**	**1.204**†	**1.396**‡
Finance	$\Delta Mn\hat{F}1$	0.940	**1.097**†	**1.354**†	**1.438**‡	**1.488**‡
	$\Delta Mn\hat{F}2$	0.965	**1.091***	**1.050**	**1.158**	**1.218**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.874	**1.069**	**1.158***	**1.264**†	**1.278**‡
	Rolling Window Method: Random Walk Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	**1.016**	**1.003**	**1.085**	**1.193***	**1.399**‡
	$\Delta Mc\hat{F}2$	**1.006**	0.953	**1.108**	**1.238**‡	**1.392**‡
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	**1.027**	0.975	**1.095**	**1.199**†	**1.381**‡
Finance	$\Delta Mn\hat{F}1$	**1.004**	**1.121**‡	**1.285***	**1.334**†	**1.393**‡
	$\Delta Mn\hat{F}2$	0.937	**1.083***	0.988	**1.102**	**1.166**†
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.884	**1.070**	**1.058**	**1.167**	**1.219**‡
	Recursive Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	0.987	0.893	0.914	0.934	0.996
	$\Delta Mc\hat{F}2$	0.973	0.882	0.950	0.969	0.994
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	0.995	0.900	0.938	0.942	0.988
Finance	$\Delta Mn\hat{F}1$	0.914	0.984	**1.148**†	**1.125**†	**1.053**†
	$\Delta Mn\hat{F}2$	0.938	0.979	0.890	0.906	0.862
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.850	0.959	0.981	0.988	0.904
	Rolling Window Method: Autoregressive Benchmark					
	Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Macro	$\Delta Mc\hat{F}1$	0.987	0.896	0.905	0.926	0.995
	$\Delta Mc\hat{F}2$	0.977	0.851	0.924	0.961	0.990
	$\Delta Mc\hat{F}1$, $\Delta Mc\hat{F}2$	0.997	0.871	0.913	0.931	0.982
Finance	$\Delta Mn\hat{F}1$	0.975	**1.001***	**1.072***	**1.035***	0.991
	$\Delta Mn\hat{F}2$	0.910	0.967	0.824	0.855	0.830
	$\Delta Mn\hat{F}1$, $\Delta Mn\hat{F}2$	0.858	0.956	0.882	0.906	0.868

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 13. Open Economy Variables

	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
Recursive Method: Random Walk Benchmark					
FSI	**1.205**	**1.050**	**1.136**	**1.225**†	**1.353**‡
FSI-Bond	0.997	**1.066**	**1.102**	**1.203**†	**1.242**†
FSI-FX	**1.400**‡	**1.235***	**1.299**‡	**1.524***	**1.644**†
FSI-Stock	**1.169**	**1.024**	**1.002**	**1.013**	**1.197***
FSI-Industry	0.840	0.923	0.925	**1.114**	**1.372**‡
Rolling Window Method: Random Walk Benchmark					
FSI	**1.188**	**1.045**	**1.133**	**1.229**†	**1.378**‡
FSI-Bond	**1.013**	**1.094**	**1.183**‡	**1.282**‡	**1.372**‡
FSI-FX	**1.370**†	**1.222***	**1.289**‡	**1.487***	**1.592**†
FSI-Stock	**1.163**	**1.035**	**1.024**	**1.039**	**1.287**†
FSI-Industry	0.821	0.907	0.897	**1.098**	**1.337**‡
Recursive Method: Autoregressive Benchmark					
FSI	**1.168**†	0.933	0.921	0.924	0.970
FSI-Bond	0.983	0.994	0.968	0.976	0.896
FSI-FX	**1.276**‡	0.949	0.973	0.945	**1.009**†
FSI-Stock	**1.150**†	0.968	0.919	0.933	0.990
FSI-Industry	0.817	0.828	0.784	0.872	0.971
Rolling Window Method: Autoregressive Benchmark					
FSI	**1.154**†	0.927	0.910	0.905	0.957
FSI-Bond	0.991	0.991	0.970	0.976	0.881
FSI-FX	**1.251**‡	0.941	0.961	0.916	**1.001***
FSI-Stock	**1.144**†	0.961	0.903	0.910	0.982
FSI-Industry	0.798	0.810	0.748	0.853	0.951

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Table 14. Predictability of Sub-Indices

Recursive Method: Sub-Indices Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.087**	**1.078**	**1.309**‡	**1.184**†	**1.105**†
$\Delta\hat{F}4$	**1.077**	**1.065**	**1.272**‡	**1.141**†	**1.119**‡
$\Delta\hat{F}5$	**1.096**	**1.109**	**1.303**‡	**1.173**†	**1.101**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.086**	**1.057**	**1.291**‡	**1.147**‡	**1.119**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.097**	**1.081**	**1.338**‡	**1.195**‡	**1.104**†
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.094**	**1.060**	**1.328**‡	**1.158**‡	**1.117**‡
Rolling Window Method: Sub-Indices Benchmark					
Factors	$j=1$	$j=3$	$j=6$	$j=9$	$j=12$
$\Delta\hat{F}1$	**1.128**	**1.139**	**1.521**‡	**1.346**‡	**1.161**‡
$\Delta\hat{F}4$	**1.097**	**1.117**	**1.449**‡	**1.323**‡	**1.157**‡
$\Delta\hat{F}5$	**1.116**	**1.144**	**1.519**‡	**1.317**‡	**1.165**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$	**1.113**	**1.116**	**1.478**‡	**1.339**‡	**1.161**‡
$\Delta\hat{F}1$, $\Delta\hat{F}5$	**1.136**	**1.122**	**1.581**‡	**1.343**‡	**1.161**‡
$\Delta\hat{F}1$, $\Delta\hat{F}4$, $\Delta\hat{F}5$	**1.120**	**1.103**	**1.539**‡	**1.345**‡	**1.159**‡

Note: We report the *RRMSPE*, the root mean squared prediction error from the benchmark model relative to that of our factor model. The *RRMSPE* in bold indicates that it is greater than one, which implies that our factor model performs better than the benchmark model. *, †, and ‡ denote a rejection of the equal predictability of the DMW test statistics at the 10%, 5%, and 1%, respectively. We use the asymptotic critical values for the test with the random walk benchmark, whereas critical values from McCracken (2007) were used for the test with the AR benchmark. The DMW statistics are omitted to save space, but are available upon request from authors.

Appendix

Figure A1. Factor Estimates: Differenced Factors

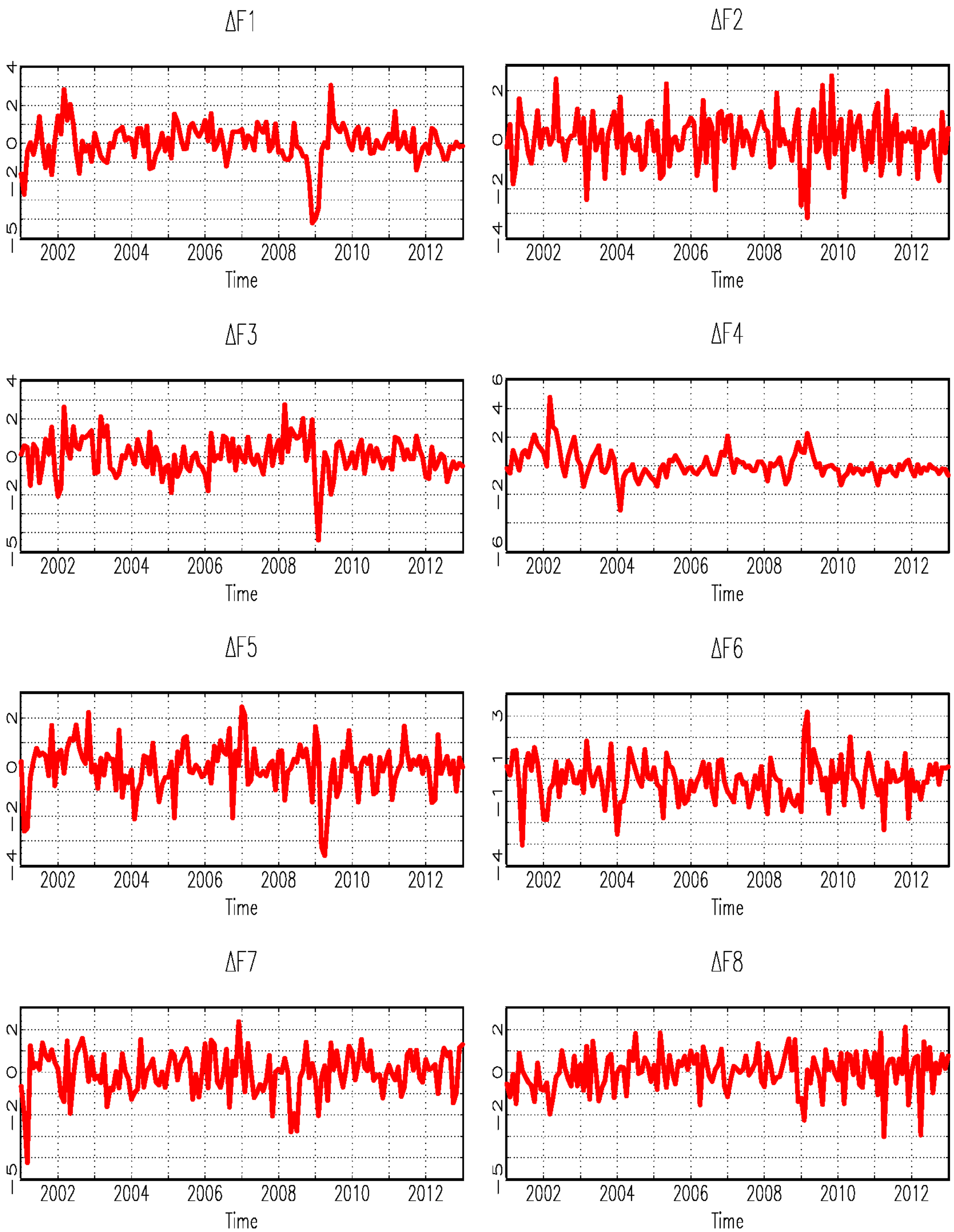


Figure A2. Factor Estimates: Level Factors

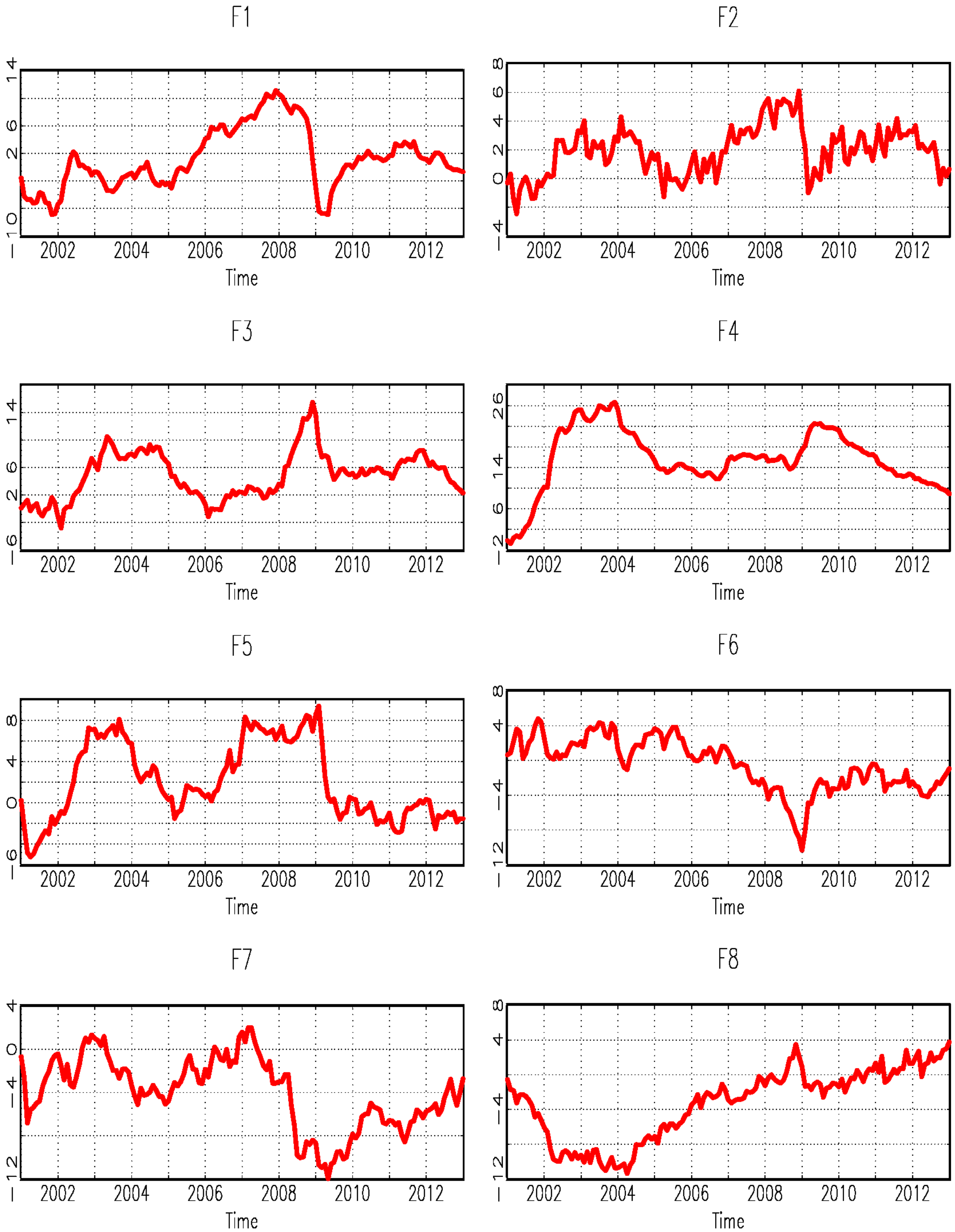


Figure A3. Factor Loading Coefficients Estimates

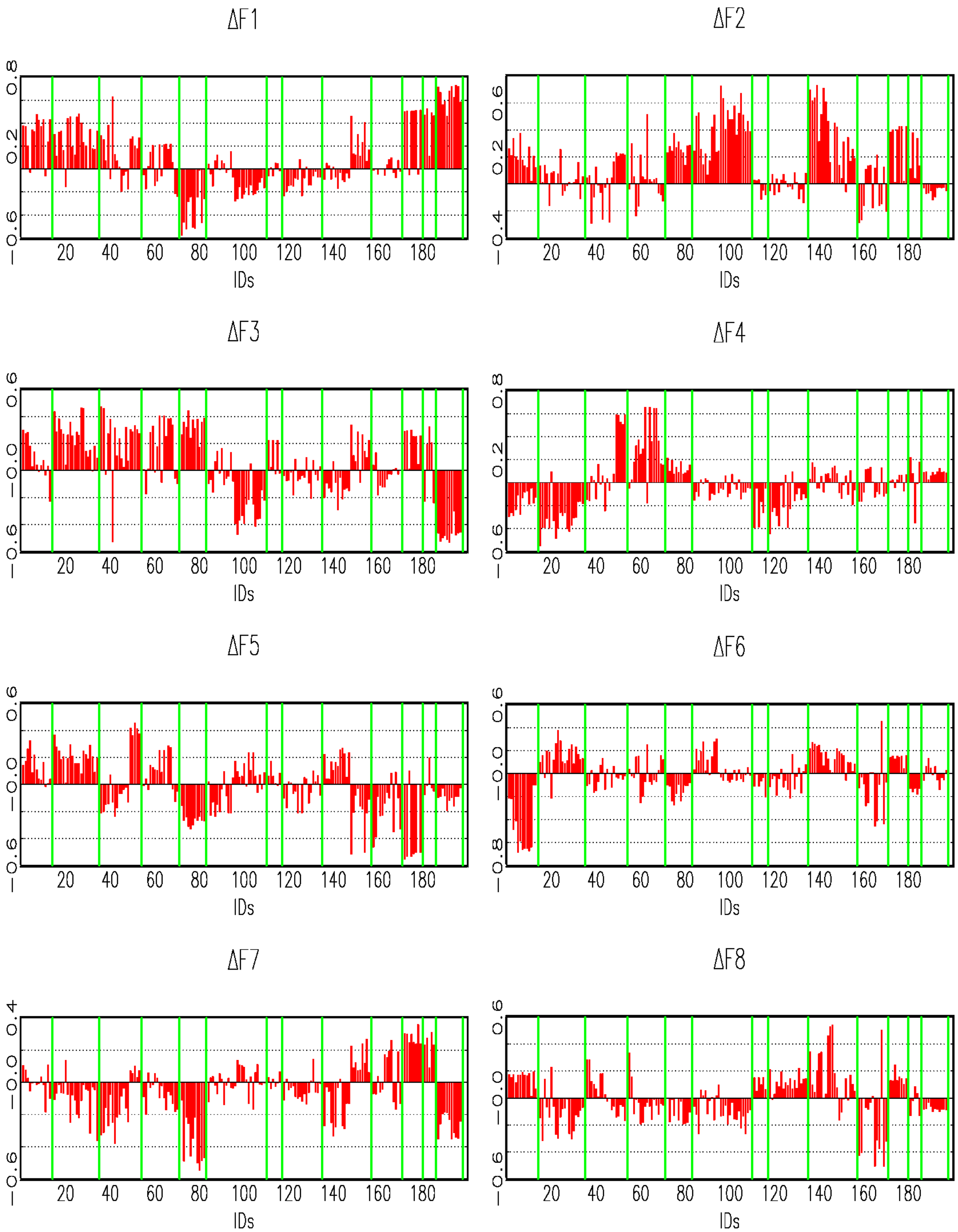


Figure A4. Marginal R^2 Analysis