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Forecasting Financial Vulnerability in the US: A Factor Model Approach

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Abstract

This paper presents a factor-based forecasting model for the financial market vulnerability, measured by changes in the Cleveland Financial Stress Index (CFSI). We estimate latent common factors via the method of the principal components from 170 monthly frequency macroeconomic data in order to out-of-sample forecast the CFSI. Our factor models outperform both the random walk and the autoregressive benchmark models in out-of-sample predictability at least for the short-term forecast horizons, which is a desirable feature since financial crises often come to a surprise realization. Interestingly, the first common factor, which plays a key role in predicting the financial vulnerability index, seems to be more closely related with real activity variables rather than nominal variables. We also present a binary choice version factor model that estimates the probability of the high stress regime successfully.

Keywords: Financial Stress Index; Method of the Principal Component; Out-of-Sample Forecast; Relative Root Mean Square Prediction Error; Diebold-Mariano-West Statistic; Ordered Probit Model

JEL Classification: E44; E47; G01; G17

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1 Introduction

Financial market crises often occur abruptly, then quickly spread to other sectors of the economy. As Reinhart and Rogoff (2014) point out, harmful effects of financial crises on the real sectors of the economy tend to be severe because recessions that result from financial market crises are likely to persist for a long period of time.

The recent global recession that ensued from the collapse of the US financial market in 2008 provides a stark reminder of the danger of financial crises. Unfortunately, the profession has failed to anticipate it, and greatly underestimated the severity of the spillover effect of the crisis to real activity that resulted in the Great Recession. For this reason, it would be useful to have an early-warning system (EWS) that alerts financial market participants to incoming danger before it occurs (Reinhart and Rogoff (2009)).

Designing an EWS naturally requires an appropriate measure of the financial vulnerability which quantifies the potential risk that may become prevalent in financial markets. One may consider using the Exchange Market Pressure (EMP) index that has been frequently employed by researchers since the seminal work of Girton and Roper (1977).[1] The EMP index, however, may not be ideal to study the financial distress in a large economy such as the US, because it is based on changes in exchange rates and reserves. That is, it may be more suitable for small open economies.

One alternative measure that is rapidly gaining popularity is a financial stress index (FSI). Unlike the EMP index, FSI's are constructed using a broad range of key financial market variables. In the U.S., 13 financial stress indices have currently become available since the recent financial crisis[2], including the FSIs contributed by regional Federal Reserve banks, for example, Oet et al. (2011), Hakkio and Keeton (2009), Kliesen and Smith (2010), and Brave and Butters (2012), and by the Office of Financial Research (OFR) such as Monin (2019).

Empirical research on early warning systems is extensive, utilizing conventional approaches to identify leading indicators and predict financial crises. Frankel and Saravelos (2012), Eichengreen et al. (1995) , and Sachs et al. (1996) use linear regression approaches to test the statistical significance of various economic variables on the occurrence of crises. Others employ discrete choice models including parametric probit or logit models (Frankel and Rose (1996); Cipollini and Kapetanios (2009)) and non-

[1] See Tanner (2002) for a review.

[2] See Kliesen et al. (2012) for a survey of U.S. financial stress indices.

parametric signals approach (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)).

Holopainen and Sarlin (2017) point out that both signals approach and discrete choice models handle the early warnings as a classification problem. They review the innovation classification techniques and compare conventional statistical methods with recent machine learning methods such as artificial neural networks and k-nearest neighbors as early warning models. Beutel et al. (2019) also compare the out-of-sample predictive performance of a benchmark logit approach with several machine learning approaches for systemic banking crises using a sample of advanced economies covering the past 45 years.

Both papers report limited advantages of machine learning models, finding that conventional statistical approaches tend to use the available information fairly efficiently. On the other hand, Tölö (2020) and Bluwstein et al. (2020) show that machine learning models outperformed traditional logistics regression models and are successful in predicting the systemic financial crises.

FSI has been developed rapidly as a single statistic for quantification of stress level in monitoring financial stability. It brings more and more attention to the leading indicators of financial stress in the recent early warning literature. Misina and Tkacz (2009) identify business credit and real estate prices movements that could predict the FSI for Canada (Illing and Liu (2006)), using both linear and endogenous threshold models. Slingenberg and de Haan (2011) develop a multi-country FSI for 13 OECD countries and investigate the predictive contents of 28 economic variables for the FSI via linear regression models. They find only credit growth has predictive power for most countries.

Duca and Peltonen (2013) construct FSIs for 10 advanced and 18 emerging economies. They use the signal extraction approach proposed by Kaminsky et al. (1998) to identify both domestic and global variables. Their analysis shows that combining indicators of domestic and global macro-financial vulnerabilities substantially improves the discrete choice models' ability in forecast systemic financial crises.Christensen and Li (2014) monitor the evolutions of 12 leading indicators via the signal extraction approach for 13 OECD countries and propose three different composite indicators. They forecast the FSIs developed by the IMF by utilizing three composite indicators, and weighted composite indicator consistently outperforms the other two.

Duprey and Klaus (2017) predict phases of the financial stress periods for a sample of 15 EU in a Markov-switching (MS) framework. They find the debt service ratio and property market variables helpful in predicting high financial stress periods. Vašíček et al. (2017) employ Bayesian model averaging (BMA) to identify the most important leading indicators of the FSI for 25 OECD countries (Vermeulen et al. (2015)). Those indicators are used as explanatory variables in panel and country-level models. Their out-of-sample exercises results show panel and country-level models with BMA-based leading indicators can hardly explain FSI dynamics.

Our study expands the early warning literature by exploring whether big economic data can be used to identify the emerging challenges to the U.S. financial system[3] and enhance the prediction of financial instability. This paper presents factor-based out-of-sample forecasting approach for the Cleveland Financial Stress Index (CFSI) developed by the Cleveland Fed. We estimate multiple latent common factors via the method of the principal components (Stock and Watson (2002)) to a large panel of 170 time series macroeconomic data that include nominal and real activity variables from October 1991 to October 2014. To avoid potential issues that are associated with nonstationarity of the data, we apply the principle component analysis (PCA) to first-differenced data, then recover *level* factors from estimated *differenced* factors (Bai and Ng (2004)). Then, we augment an autoregressive (AR) type model with estimated common factors.

To evaluate the out-of-sample prediction performance of our models, we implement an array of forecast exercises with the random walk (RW) as well as a stationary AR-type model as the benchmark. We test the equal predictability of our models relative to these benchmark models using the relative root mean squared prediction errors ($RRMSPE$) and the Diebold-Mariano-West (DMW) test statistics.

Our major findings are as follows. First, our models outperform the RW benchmark model in out-of-sample forecasting for up to 1-year forecast horizons. Our models also perform better than the AR model for short-term ($1-$ to $6-$month) forecast horizons. It should be noted that this is a desirable feature since financial crises often occur abruptly with no prior warnings. Second, parsimonious models with just one or two factors perform as well as bigger models that use up to 8 factors. Third, the first common factor that plays a key role in our forecast exercises seems to be closely related with real sector variables rather than nominal variables. That is, real activity variables

[3] Kim et al. (2019) and Kim and Ko (2020) employ factor-based models to forecast the FSI of Korea.

provide useful predictive contents for the financial vulnerability.

The rest of the paper is organized as follows. Section 2 describes the econometric model and the out-of-sample forecasts schemes. We also explain our evaluation methods as to the out-of-sample prediction accuracy of our models. In Section 3, we provide a data description and preliminary analyses for estimated latent common factors. Section 4 reports our major findings from in-sample fit analyses and out-of-sample forecast exercises. In Section 5, we propose a binary choice version factor model to estimate the probability of a high stress regime, then discuss our findings. Section 6 concludes.

2 The Econometric Model

Let $x_{i,t}$ be a macroeconomic time series variable that is characterized by the following factor structure. Abstracting from deterministic terms, we assume the following factor structure:

$$x_{i,t} = \lambda_i^{'}\mathbf{F}_t + e_{i,t}, \;\; i = 1, 2, .., N, \;\; t = 1, 2, .., T, \tag{1}$$

where $\mathbf{F}_t = [F_{1,t} \; \cdots \; F_{r,t}]^{'}$ is not directly observable (latent) *common* factors and $\lambda_i = [\lambda_{i,1} \; \cdots \; \lambda_{i,r}]^{'}$ denotes i^{th} variable specific, time invariant factor loading coefficients. Note that $\lambda_i^{'}\mathbf{F}_t$ jointly determines the dependency of $x_{i,t}$ on the common factors, while $e_{i,t}$ is the *idiosyncratic* error term. All variables except those that are represented as percentage (e.g., interest rates and unemployment rates) 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 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.

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

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 prior to 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 recovered by re-integrating these estimates. That is,

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

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

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

After obtaining the latent factor estimates, we augment an autoregressive (AR) type model with factor estimates. Abstracting from deterministic terms, we employ the following model,

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

where α_j is the coefficient on the *current* FSI for the j-period ahead FSI. That is, we implement *direct* forecasting scheme for fsi_{t+j} on (differenced) common factor estimates ($\Delta \hat{\mathbf{F}}_t$) and fsi_t, which are assumed to belong to the econometrician's information set (Ω_t) at time t. Note that (5) is an AR(1) process for $j = 1$, augmented by exogenous common factor estimates. This formulation is based on our preliminary unit-root test results for the FSI that show strong evidence of stationarity.[4] Applying the least squares (LS) estimation for (5), we obtain the following j-period ahead forecast from our factor (F) model.

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

where $\hat{\beta}$ and $\hat{\alpha}_j$ are the LS estimates.

To statistically evaluate the out-of-sample predictability performance of our factor models, we employ the following nonstationary random walk (RW) model that serves the (no change) benchmark model.

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

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

$$\widehat{fsi}^{RW}_{t+j|t} = fsi_t,\ j \geq 1 \tag{8}$$

[4]Results are available upon request.

where fsi_t is the current value of the financial stress index.[5]

In addition, we employ the following stationary AR(1)-type forecasting model as an alternative benchmark model.

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

which yields the following j-period ahead forecast.

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

For evaluation criteria, we use the relative root mean squared prediction error ($RRMSPE$), which is defined as the root mean squared prediction error ($RMSPE$) from the benchmark model divided by $RMSPE$ from our factor model. Note that our factor model outperforms the benchmark model when $RRMSPE$ is greater than 1.

We also employ the Diebold-Mariano-West (DMW) test. For this, 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 based on forecast errors under each model. That is,

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

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 following DMW statistic can be used to test the null hypothesis of equal predictive accuracy, $H_0 : Ed_t = 0$,

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

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

[5]For $j = 3$, for example, $fsi_{t+3} = fsi_{t+2} + \varepsilon_{t+3} = fsi_{t+1} + \varepsilon_{t+2} + \varepsilon_{t+3} = fsi_t + \varepsilon_{t+1} + \varepsilon_{t+2} + \varepsilon_{t+3}$, resulting in (8).

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.[6]

Note that our factor model (5) nests the stationary benchmark model in (9). Therefore, we use critical values proposed by McCracken (2007) 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 Data Descriptions and Factor Estimations

3.1 Data Descriptions

We use the Cleveland Financial Stress Index (CFSI) to measure the financial market vulnerability. We obtained the data from the FRED. Observations are monthly and are available from October 1991. The CFSI is designed to track financial distress in the US on a continuous basis. The index integrates 11 daily financial market indicators which are grouped into four sectors: debt, equity, foreign exchange, and banking. See Oet et al. (2011) for details. Units of the CFSI are expressed as z-scores and a high value of the CFSI indicates an elevated level of systemic financial stress. For example, a score higher than 0.544 implies a moderate to significant stress period.

As we can see in Figure 1, the CFSI traces past episodes of financial distress in the US quite well. For instance, the CFSI increases rapidly during the turbulent periods such as the Long-Term Capital Management (LTCM) crisis in the late 1990's. The CFSI began picking up an elevated financial distress since late 2007. The index reached 2.42 when the Bear Stearns collapsed and sold to JPMorgan in March 2008, then peaked in December 2008 after the failure of Lehman Brothers in September of the same year. We observe a similarly sharp rise of the index during the European debt crisis in the early 2010's. Overall, the CFSI seems to be an appropriate measure of the financial vulnerability.

[6] T_0 is the number of initial observations that are used to formulate the first out-of-sample forecast. Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

Figure 1 around here

We obtained 170 monthly frequency macroeconomic time series data from the FRED and the Conference Board Indicators Database. Observations span from October 1991 to October 2014 to match the availability of the CFSI. We organized these 170 time series data into 9 small groups as summarized in Table 1. Groups #1 through #5 (Data ID #1 to #103) are variables that are closely related with real sector activity, while groups #6 to #9 (Data ID #104 to #170) are mostly nominal variables. Detailed explanations on individual time series are reported in the appendix.

Table 1 around here

3.2 Latent Factors and their Characteristics

We estimated up to 8 latent common factors via the method of the principal components for the first-differenced data. In Figure 2, we report first four (differenced) common factor estimates, $\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_4$ and their level counterparts F_1, F_2, F_3, F_4, obtained by re-integrating these differenced factors. One notable observation is that the first common factor F_1 exhibits rapid declines around 2001 and 2008, which correspond to a recession after the burst of the US IT bubble (so-called, the dot-com bubble) and the recent Great Recession, respectively. In what follows, we demonstrate that F_1 is more closely related with real sector variables, though it also represent a group of nominal variables as well.

Figure 2 around here

We report the factor loading coefficient (λ_i) estimates and marginal R^2 of each variable in Figures 3 to 6 to study how each of these factors is associated with the macroeconomic variables in groups #1 to #9. The marginal R^2 is an in-sample fit statistic obtained by regressing each of the individual time series variables onto each estimated common factor, one at a time, using the full sample data. The individual series in each group are separated by vertical lines and labeled by group ID's. The individual data ID's are on the x-axis and the descriptions are reported in the Data Appendix.

We first investigate the nature of the first common factor using the factor loading coefficients for ΔF_1. It should be noted that loading coefficients of most variables in the groups #1 (output and income) and #2 (orders) are positive. Among the group #3 variables, the loading coefficients are negative for the unemployment-related variables (ID's $41-50$), whereas they are positive for employment or labor participation variables (ID's $51-74$) and earnings related data (ID's $75-80$). Positive coefficients were also found from the group #4 (housing) and #5 (stock price) variables. And, within the group #8, interest rates have positive loading coefficients, while interest rate spreads including risk premium variables have negative signs. Price level variables in the group #9 have positive loadings, which are consistent with negative loading coefficients of foreign exchange rates measured as the price of domestic currency (US dollars) relative to the foreign currencies. Overall, these observations imply that the first common factor represent the business cycle (booms and recessions) of the US economy.

As to the marginal R^2 estimation, F_1 explains a substantial portion of variations in measures of production and the employment part in the labor market, even though it also explain non-negligible portions of variations in price variables as well. Overall, F_1 seems to better represent real activity performance.

Figure 3 around here

As we can see in Figure 4, the second common factor F_2 seems to be highly correlated with the group #9 (price variables) as well as the group #7 (exchange rates). That is, the marginal R^2 values of these variables are far greater than those of other variables. Factor loading coefficients of these variables are similar to those in Figure 3 and tend to be bigger in absolute terms than other coefficients. Therefore, F_2 seems to be more closely associated with the two groups of nominal variables, domestic prices and foreign exchange rates.

Figure 4 around here

F_3 seems to reflect mainly the information on the group #5 stock price variables. As we can see in the marginal R^2 analysis, it explains over 60% of variations in these variables. The loading coefficient estimates are mostly negative except the first one in this group, the price-earning ratio (earnings/price), which makes sense because the stock price appears in the denominator. Similar reasoning implies that the group #8 variables (interest rates) are well explained by F_4.

Figures 5 and 6 around here

4 Forecasting Exercises

4.1 In-Sample Fit Analysis

We implement an array of the LS estimations for the CFSI with various sets of explanatory variables from $\{\Delta F_1, \Delta F_2, ..., \Delta F_8\}$. Results are reported in Table 2 for the $1-, 2-, 3-, 6-$, and $12-$month ahead values of the CFSI.

We employ an R^2-based selection method considering one-factor model to the 8-factor full model to find good combinations of explanatory variables. The first common factor ΔF_1 seems to play the most important role in explaining variations in the CFSI for all forecasting time horizons we consider.

We note that adding more factors after the first common factor does not substantially increase the goodness of fit. That is, one or two factor models seem to be sufficient for a good in-sample fit. It should be also noted that factor estimates help explain CFSI's in relatively short time horizons. For example, factors explain 20 to 30% variations in $1-$month ahead CFSIs, while they explain less than 10% of variations in $1-$year ahead CFSIs even with full 8 factor models.[7]

Table 2 around here

In Table 3, we report the LS estimates of the coefficients in the regression model of the $1-$period ahead CFSI index ($cfsi_{t+1}$). We note that the first common factor is highly significant whether one period lagged CFSI ($cfsi_t$) is included in the regression or not. The second common factor also plays an important role when pure factor

[7] We also considered alternative factor selection methods. For instance, the adjusted R^2 selection method usually chose the $5-$ or $6-$factor model, while a stepwise selection method (Specific-to-General rule) selected the $4-$ or $5-$factor model for the FSI. However, added gains are still fairly small.

models without $cfsi_t$ are employed. Our models provides good in-sample fit especially when $cfsi_t$ is included, although our models still exhibit fairly good in-sample fit performance without it.[8] The 8−factor full model explains roughly 30% of variation of the one-month ahead CFSI.

Table 3 around here

4.2 Out-of-Sample Forecast Exercises and Evaluations of the Models

We evaluate the out-of-sample predictability of our factor models using the following two methods. First, we employ a recursive forecast scheme. That is, we begin with an out-of-sample forecast of the $j-$period ahead CFSI index (fsi_{T_0+j}) using the initial 50% observations ($t = 1, 2, ..., T_0,\ T_0 = \frac{T}{2}$). Then, we add one next observation to the sample ($t = 1, 2, ..., T_0, T_0 + 1$), and implement another forecast (fsi_{T_0+j+1}) using new estimates from this expanded set of observations. We repeat this until we forecast the last observations. We implement this scheme for up to 12 month forecast horizons, $j = 1, 2, 3, 6, 12$.

The second scheme is a fixed-size rolling window method that repeats forecasting by adding one next observation with the same split point (50% or $T_0 = \frac{T}{2}$), but dropping one earliest observation in order to maintain the same size of the window. That is, after the initial forecast described earlier, we forecast fsi_{T_0+j+1} using an updated (shifted to the right) data set ($t = 2, 3, ..., T_0, T_0+1$) maintaining the same number of observations.

As we described in the previous section, we employ the following two benchmark models: the nonstationary random walk (RW) model and a stationary autoregressive (AR) model. Out-of-sample forecast performance is evaluated using the relative root mean square prediction error, $RRMSPE$. Also, we implement the DMW test to statistically evaluate prediction accuracy of our models.

$RRMSPE$ estimates of our factor models relative to the random walk benchmark are reported in Table 4. We note that our factor models outperform the benchmark model for all forecast horizons from 1 month to 1 year. The $RRMSPE$ estimates are greater than one for all cases both with the recursive and the rolling window schemes.

[8] This probably is due to high degree persistence of the CFSI.

Similarly as in the in-sample fit analyses reported earlier, one factor model with the first common factor ΔF_1 performs as well as bigger models with more factor estimates.

The DMW statistics are reported in Table 5. Using the asymptotic critical values from the standard normal distribution, the test rejects the null hypothesis of equal predictive accuracy at the 10% significance level in majority cases when the forecast horizon is 3 month or longer. For shorter forecast time horizon (1 and 2 month), the test rejects the null for just one case even though the test statistic is all positive meaning that the test favors the factor models.

Tables 4 and 5 around here

Next, we report $RRMSPE$ values and the DMW statistics of our factor model with a stationary autoregressive competing model in Tables 6 and 7. We note that most $RRMSPE$ values are greater than one when the forecast horizon is between $1-$ and $6-$month. The $RRMSPE$ was all less than one for $12-$month ahead out-of-sample forecast. It should be noted, however, that short-term forecast accuracy is more desirable feature for predicting the financial market vulnerability, because financial crises often occur abruptly.

Note that our factor models nest the benchmark AR model, which results in size distortion when the asymptotic critical values are used. Based on the critical values from McCracken (2007), the DMW test rejects the null hypothesis for most cases at the 10% significance level when the forecast horizon is shorter than $12-$month, which is consistent with the results in Table 6.

Tables 6 and 7 around here

5 An Ordered Probit Model Approach

This section presents an ordered probit model version factor model by transforming fsi_t into a binary variable that takes either 1 (high financial stress: H) or 0 (low financial stress: L) values. Following the guideline from the Cleveland Fed, we assume that the US financial market is under the high financial stress regime when fsi_t is greater than 0.544, while it is under the low financial stress regime otherwise.[9]

For such a two-regime probit model, we consider the following latent equation:

$$y_t^* = \mathbf{x}_t' \beta - \varepsilon_t, \tag{15}$$

where y_t^* is unobservable latent variable with an $r \times 1$ vector of covariates $\mathbf{x}_t = [\Delta F_{1,t}, ..., \Delta F_{r,t}]'$. ε_t is assumed to obey the standard normal distribution.

Let y_t denote the observable state variable from this latent equation. When y_t^* is greater than the threshold τ, we observe the high stress regime H $(y_t = 1)$. Otherwise, the low stress regime L is realized, $y_t = 0$. That is,

$$y_t = \begin{cases} 1, & \text{if} \quad y_t^* > \tau \quad : H \\ 0, & \text{if} \quad y_t^* < \tau \quad : L \end{cases} \tag{16}$$

The log-likelihood function for a random sample of size T, $\{y_t\}_{t=1}^T$, is the following.

$$\mathcal{L} = \sum_{t=1}^{T} \left[I(y_t = 1) \ln \left(F \left(\mathbf{x}_t' \beta - \tau \right) \right) + I(y_t = 0) \ln \left(1 - F \left(\mathbf{x}_t' \beta - \tau \right) \right) \right], \tag{17}$$

where $I(\cdot)$ is the indicator function and $F(\cdot)$ is the standard normal distribution function.

We estimated (17) via the method of the maximum likelihood estimation using the two factor estimates ΔF_1 and ΔF_2.[10] We report the probability estimates of the two regimes, H and L, in Figure 7. Bar graphs indicate actual realizations of the regimes from the data using the threshold 0.544. Our factor model seems to perform well in this framework too, because estimated probabilities trace changes in the state of the financial vulnerability fairly well over time. For example, the estimated probability of the regime H rapidly increases during the recent financial crisis, whereas the low regime probability stays high in the 1990's.

Figure 7 around here

[9] The Cleveland Fed provides three threshold values for 4 regimes: low stress, normal stress, moderate stress, and significant stress. the first two regimes correspond to 0, whereas the last two regimes are associated with 1 in our model.

[10] Models with one or three factor estimates yield qualitatively similar results. All results are available upon request.

6 Concluding Remarks

This paper proposes a factor-based forecasting model for systemic risk in the U.S. financial market in a data-rich environment. We use the financial stress index developed by Federal Reserve Bank of Cleveland to measure the financial vulnerability. We employ a dimensionality reduction method that extracts multiple latent common factors from a panel of 170 monthly frequency time series macroeconomic variables from October 1991 to October 2014. In the presence of nonstationarity in the data, we apply the method of the principle components (Stock and Watson (2002)) to first-differenced data (Bai and Ng (2004)) to estimate the latent factors consistently. Our factor models augment an AR-type self-exciting process of the Cleveland Financial Stress Index with estimated common factors.

To evaluate the practical usefulness of our factor models, we implement an array of out-of-sample prediction exercises using the recursive and the fixed-size rolling window schemes for 1-month to 1-year forecast horizons. Based on the $RRMSPE$ estimates and the DMW statistics, our factor-based forecasting models overall outperform the nonstationary random walk benchmark model as well as the stationary autoregressive model especially for short-horizon predictions, which is a desirable feature because financial crises often come to a surprise realization. Parsimonious models with just one or two factors performed as well as bigger models in providing potentially useful information to policy makers and financial market participants. Interestingly, real activity variables represented by the first common factor are shown to have substantial predictive contents for the financial market vulnerability even in the short-run.

We also propose a binary choice-type factor model. That is, we employed a two-regime model, high and low financial stress regimes, and estimated the probability of each regime over time. Our factor-based ordered probit models again demonstrated a good performance in tracing realized regimes of the financial vulnerability.

In the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2009 highlights the importance of monitoring financial stability. Financial crises normally occur at a low frequency, and a spike in financial stress may appear very abruptly. Therefore, a clear and timely signal is required in risk management for policymakers and the private sector. Here we provide an approach to forecasting FSI from the broader set of information. Our empirical results report a strong link between real activities and FSI dynamics in the U.S., demonstrating good out-of-sample performance of our factor-based forecasting models. Note that our factor models perform fairly well not only under the linear but also with nonlinear probit model specification, suggesting that policymakers are able to monitor constant changes in financial vulnerability as well as sudden elevation in FSI in a data-rich environment.

7 Data Availability Statement

Most of the data that support the findings of this study are available on the federal reserve economic data websites. These data were derived from the following resources available in the public domain, https://fred.stlouisfed.org/. U.S. indicators in the Conference Board Indicators Database could be purchased via https://conference-board.org/data/datasearch.cfm?cid=1.

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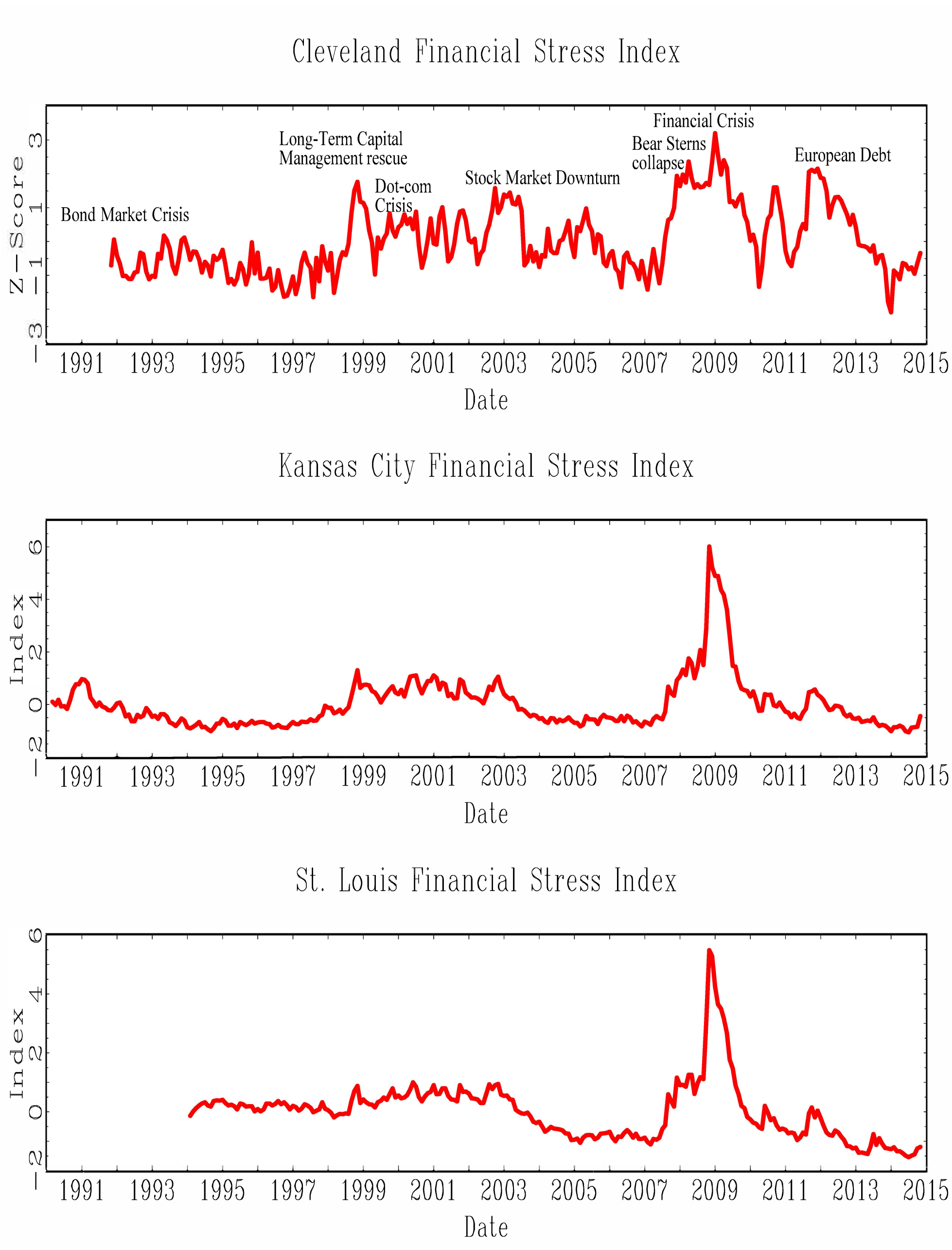
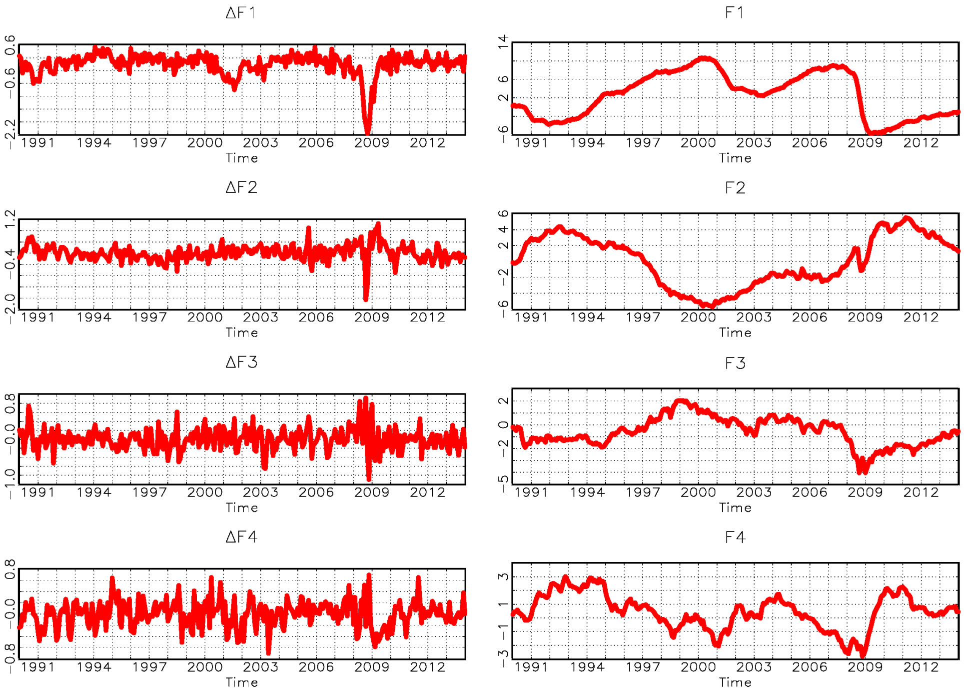
Figure 1. Financial Stress Indices



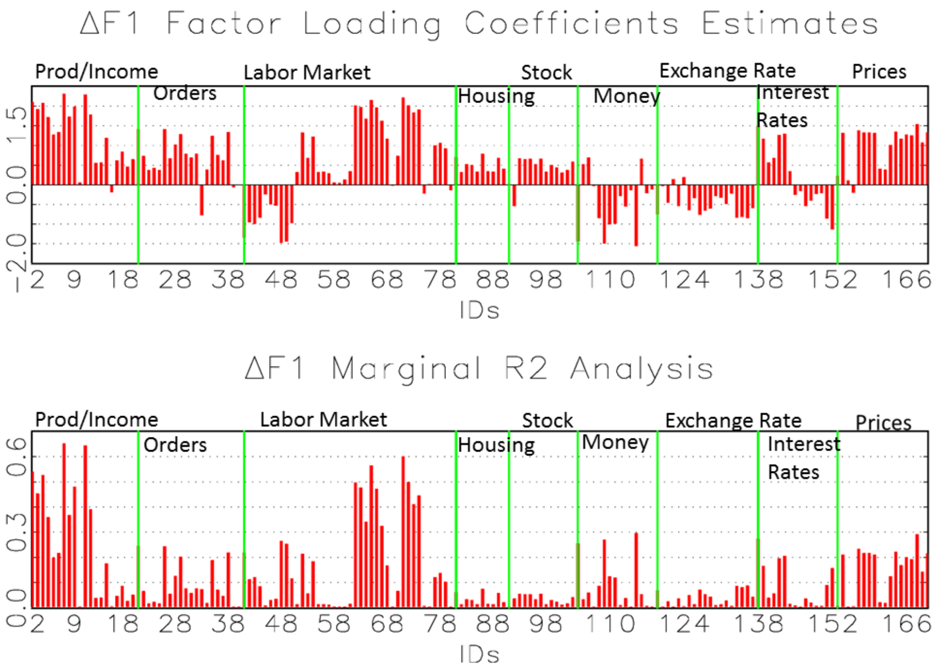
Note: The Cleveland Financial Stress Index is obtained from the FRED. The index is a z-score monthly frequency data constructed by the Cleveland Fed. The other two indices are also obtained from the FRED.

Figure 2. Factor Estimates: Differenced and Level Factors



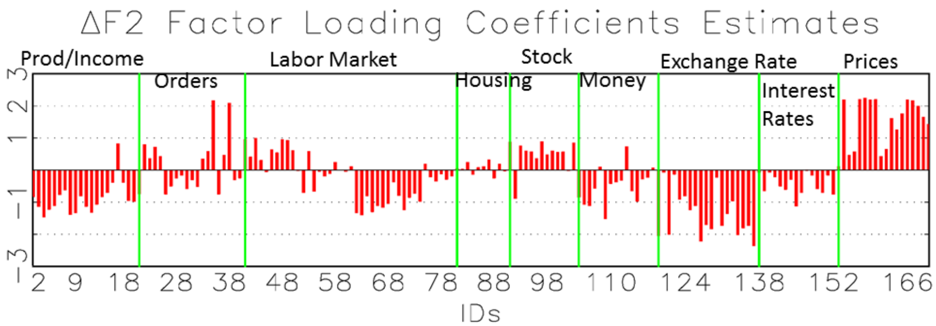
Note: We obtained up to 8 factors by applying the method of the principal components to 170 monthly frequency macroeconomic time series variables. Level factors (second column) are obtained by re-integrating estimated common factors (first column).

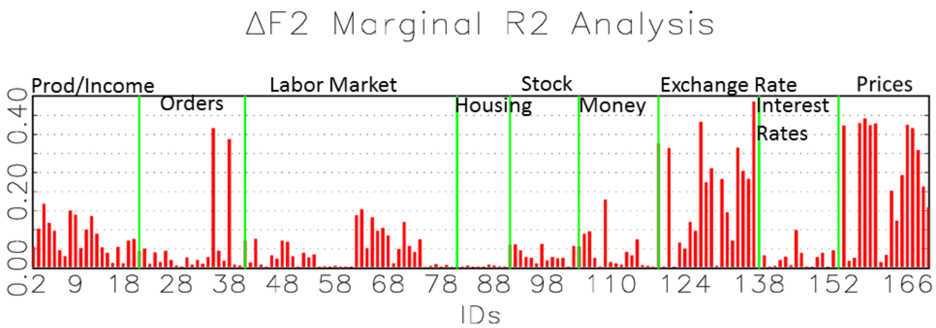
Figure 3. Common Factor #1



Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

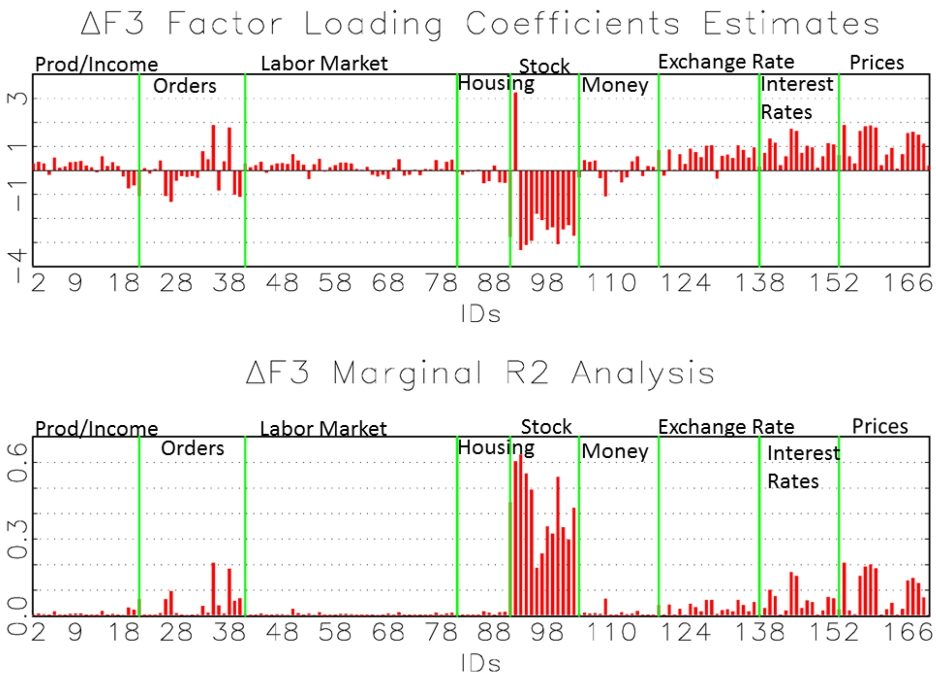
Figure 4. Common Factor #2





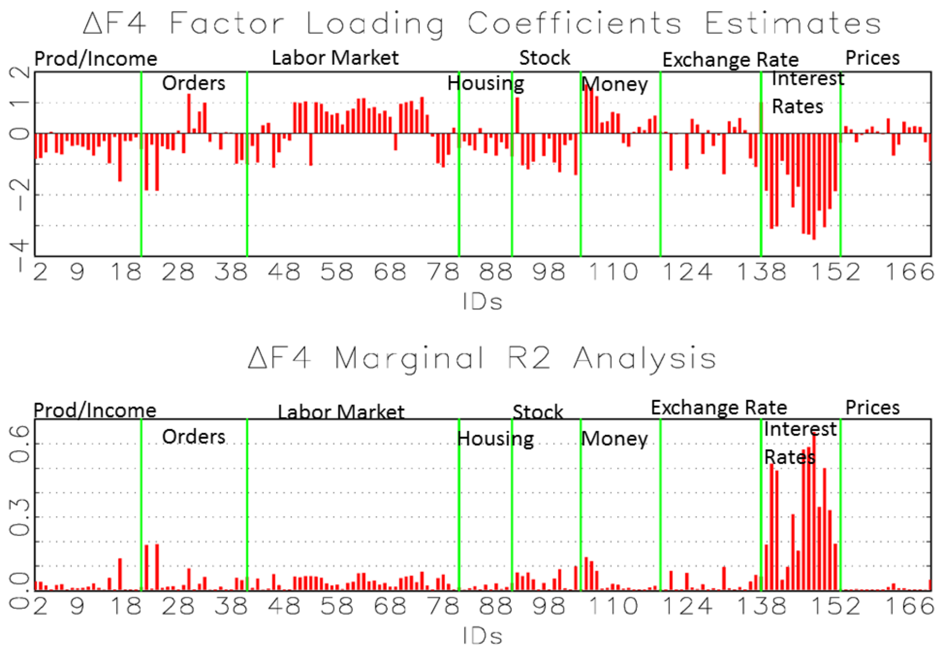
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 5. Common Factor #3



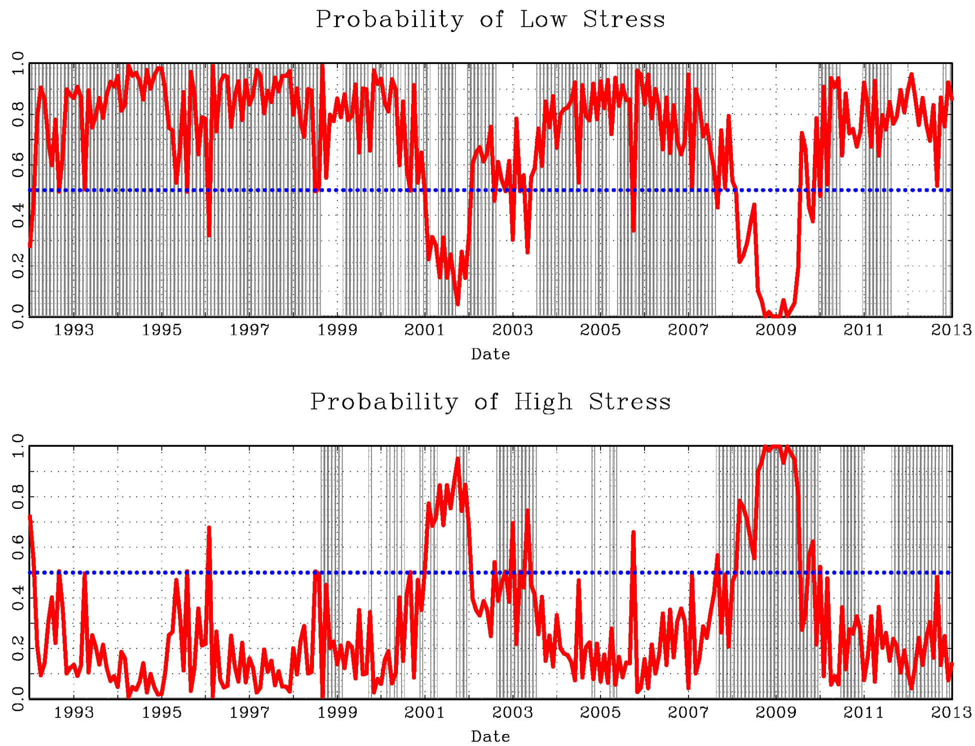
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 6. Common Factor #4



Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 7. Probability Estimation Results



Note: Solid lines are the probability estimate of each event, while bar graphs indicate the realization of each event. We employed the maximum likelihood estimator for the ordered probit model using the first two common factor estimates.

Table 1. Macroeconomic Data Descriptions

Group ID	Data ID	Data Descriptions
#1	$1 - 20$	Output and Income
#2	$21 - 40$	Consumption, Orders and Inventories
#3	$41 - 80$	Labor Market
#4	$81 - 90$	Housing
#5	$91 - 103$	Stock Market
#6	$104 - 118$	Money and Credit
#7	$119 - 137$	Exchange Rate
#8	$138 - 152$	Interest Rate
#9	$153 - 170$	Prices

Note: See the data appendix for descriptions of individual data series.

Table 2. j-Period Ahead In-Sample R^2 Fit Analysis

	Factors	R^2
$j = 1$	ΔF_1	0.211
	$\Delta F_1, \Delta F_5$	0.251
	$\Delta F_1, \Delta F_2, \Delta F_5$	0.270
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.283
$j = 2$	ΔF_1	0.194
	$\Delta F_1, \Delta F_5$	0.224
	$\Delta F_1, \Delta F_2, \Delta F_5$	0.255
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.267
$j = 3$	ΔF_1	0.183
	$\Delta F_1, \Delta F_3$	0.209
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.228
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.247
$j = 6$	ΔF_1	0.103
	$\Delta F_1, \Delta F_3$	0.124
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.137
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_7$	0.147
$j = 12$	ΔF_1	0.020
	$\Delta F_1, \Delta F_2$	0.034
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.047
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_7$	0.061

Note: We regress each set of estimated factors to j-period (month) ahead financial stress index, then report the R^2 value from each regression.

Table 3. OLS Estimations for the 1-Period Ahead Index ($cfsi_{t+1}$)

	OLS Coefficient Estimates							
$cfsi_t$	**0.848** (26.599)	$n.a.$	**0.857** (26.161)	$n.a.$	**0.855** (25.973)	$n.a.$	**0.851** (24.523)	$n.a.$
$\Delta F_{1,t}$	**−0.205** (−2.301)	**−1.288** (−8.605)	**−0.194** (−2.166)	**−1.288** (−8.703)	**−0.196** (−2.189)	**−1.288** (−8.727)	**−0.202** (−2.222)	**−1.288** (−9.014)
$\Delta F_{2,t}$	$n.a.$	$n.a.$	−0.118 (−1.143)	**0.503** (2.677)	−0.116 (−1.126)	**0.504** (2.689)	−0.112 (−1.079)	**0.507** (2.793)
$\Delta F_{3,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	0.077 (0.653)	0.349 (1.589)	0.080 (0.674)	0.352 (1.655)
$\Delta F_{4,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	−0.003 (−0.022)	0.274 (1.262)
$\Delta F_{5,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	0.042 (0.296)	**1.050** (4.282)
$\Delta F_{6,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	0.104 (0.694)	−0.108 (−0.399)
$\Delta F_{7,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	−0.289 (−1.843)	−0.452 (−1.602)
$\Delta F_{8,t}$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	$n.a.$	0.055 (0.328)	0.187 (0.616)
c	0.003 (0.109)	0.028 (0.532)	0.003 (0.104)	0.028 (0.528)	0.003 (0.104)	0.027 (0.525)	0.003 (0.096)	0.027 (0.526)
R^2	0.782	0.213	0.783	0.234	0.783	0.241	0.786	0.301
$\tilde{R}^2$	0.779	0.208	0.779	0.225	0.779	0.229	0.778	0.277

Note: We regress 1-period (month) ahead financial stress index onto a set of explanatory variables that include factor estimates and lagged financial stress index. Coefficient estimates that are significant at the 5% are in bold. R^2 and adjusted R^2 ($\tilde{R}^2$) are also reported. t-statistics are reported in the brackets.

Table 4. j-Period Ahead Out-of-Sample Forecast: ARF vs. RW

RRMSPE: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	1.021	1.040	1.057	1.099	1.120
$\Delta F_1, \Delta F_2$	1.019	1.030	1.039	1.082	1.098
$\Delta F_1, \Delta F_3$	1.018	1.059	1.064	1.112	1.126
$\Delta F_1, \Delta F_4$	1.018	1.039	1.060	1.091	1.113
$\Delta F_1, \Delta F_2, \Delta F_3$	1.015	1.048	1.045	1.094	1.108

RRMSPE: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	1.025	1.044	1.060	1.102	1.129
$\Delta F_1, \Delta F_2$	1.023	1.032	1.036	1.085	1.113
$\Delta F_1, \Delta F_3$	1.033	1.072	1.068	1.110	1.126
$\Delta F_1, \Delta F_4$	1.012	1.042	1.067	1.092	1.126
$\Delta F_1, \Delta F_2, \Delta F_3$	1.029	1.059	1.043	1.091	1.114

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

Table 5. j-Period Ahead Out-of-Sample Forecast: ARF vs. RW

DMW: Recursive Method					
Factors/j	1	2	3	6	12
ΔF_1	0.735	1.262	1.847^*	$2.892^\ddagger$	$3.502^\ddagger$
$\Delta F_1, \Delta F_2$	0.667	0.974	1.235	$2.397^\dagger$	$2.651^\ddagger$
$\Delta F_1, \Delta F_3$	0.639	1.572	1.844^*	$3.006^\ddagger$	$3.268^\ddagger$
$\Delta F_1, \Delta F_4$	0.661	1.228	1.899^*	$2.693^\ddagger$	$3.412^\ddagger$
$\Delta F_1, \Delta F_2, \Delta F_3$	0.552	1.291	1.293	$2.527^\dagger$	$2.679^\ddagger$

DMW: Rolling Window Method					
Factors/j	1	2	3	6	12
ΔF_1	0.833	1.271	1.835^*	$2.519^\ddagger$	$2.905^\ddagger$
$\Delta F_1, \Delta F_2$	0.783	0.978	1.078	$2.176^\dagger$	$2.545^\dagger$
$\Delta F_1, \Delta F_3$	1.110	1.721^*	1.829^*	$2.501^\dagger$	$2.753^\ddagger$
$\Delta F_1, \Delta F_4$	0.429	1.181	$1.995^\dagger$	$2.259^\dagger$	$2.791^\ddagger$
$\Delta F_1, \Delta F_2, \Delta F_3$	0.988	1.485	1.148	$2.100^\dagger$	$2.467^\dagger$

Note: DMW denotes the Diebold-Mariano-West statistic. $\ddagger$, $\dagger$, and $*$ indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively. Critical values were obtained from the standard normal distribution, which is the asymptotic distribution of the DMW test statistic.

Table 6. j-Period Ahead Out-of-Sample Forecast: ARF vs. AR

RRMSPE: Recursive Method					
Factors/j	1	2	3	6	12
ΔF_1	1.013	1.013	1.019	1.008	0.973
$\Delta F_1, \Delta F_2$	1.011	1.004	1.001	0.992	0.953
$\Delta F_1, \Delta F_3$	1.010	1.032	1.025	1.020	0.978
$\Delta F_1, \Delta F_4$	1.010	1.013	1.021	1.001	0.967
$\Delta F_1, \Delta F_2, \Delta F_3$	1.008	1.021	1.006	1.003	0.962

RRMSPE: Rolling Window Method					
Factors/j	1	2	3	6	12
ΔF_1	1.016	1.018	1.023	1.023	0.996
$\Delta F_1, \Delta F_2$	1.014	1.006	1.000	1.007	0.981
$\Delta F_1, \Delta F_3$	1.024	1.045	1.030	1.030	0.993
$\Delta F_1, \Delta F_4$	1.004	1.016	1.030	1.013	0.993
$\Delta F_1, \Delta F_2, \Delta F_3$	1.020	1.033	1.006	1.012	0.983

Note: *RRMSPE* denotes the mean square error from the autoregressive (AR) model relative to the mean square error from our factor model (ARF). Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Table 7. j-Period Ahead Out-of-Sample Forecast: ARF vs. AR

DMW: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	0.550^*	0.531^*	$1.067^\dagger$	0.594^*	-1.947
$\Delta F_1, \Delta F_2$	0.484^*	0.181	0.060	-0.581	-2.586
$\Delta F_1, \Delta F_3$	0.436^*	$1.079^\dagger$	$1.219^\dagger$	$1.215^\dagger$	-1.672
$\Delta F_1, \Delta F_4$	0.450^*	0.512^*	$1.363^\ddagger$	0.053	-2.246
$\Delta F_1, \Delta F_2, \Delta F_3$	0.351^*	$0.803^\dagger$	0.313^*	0.194^*	-2.071

DMW: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	$0.571^\dagger$	$0.611^\dagger$	$1.296^\ddagger$	$1.766^\ddagger$	-0.344
$\Delta F_1, \Delta F_2$	$0.543^\dagger$	0.246^*	0.010	$0.583^\dagger$	-1.209
$\Delta F_1, \Delta F_3$	$0.861^\dagger$	$1.335^\ddagger$	$1.430^\ddagger$	$1.859^\ddagger$	-0.558
$\Delta F_1, \Delta F_4$	0.133^*	$0.527^\dagger$	$1.618^\ddagger$	$1.031^\ddagger$	-0.576
$\Delta F_1, \Delta F_2, \Delta F_3$	$0.757^\dagger$	$1.080^\ddagger$	$0.295^\dagger$	$0.770^\dagger$	-1.134

Note: *DMW* denotes the Diebold-Mariano-West statistic. ‡, †, and ∗ indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively. Critical values were obtained from McCracken (2008) since the factor model nests the benchmark AR model.

Data Appnnedix

Data ID	Series ID	Descriptions
1 (Group #1)	CUMFNS	Capacity Utilization: Manufacturing (SIC), Percent of Capacity, Monthly, S.A.
2	TCU	Capacity Utilization: Total Industry, Percent of Capacity, Monthly, S.A.
3	INDPRO	Industrial Production Index, Index 2007=100, Monthly, S.A.
4	IPBUSEQ	Industrial Production: Business Equipment, Index 2007=100, Monthly, S.A.
5	IPCONGD	Industrial Production: Consumer Goods, Index 2007=100, Monthly, S.A.
6	IPDCONGD	Industrial Production: Durable Consumer Goods, Index 2007=100, Monthly, S.A.
7	IPDMAT	Industrial Production: Durable Materials
8	IPFINAL	Industrial Production: Final Products (Market Group), Index 2007=100, Monthly, S.A.
9	IPFPNSS	Industrial Production: Final Products and Nonindustrial Supplies
10	IPFUELS	Industrial Production: Fuels
11	IPMANSICS	Industrial Production: Manufacturing (SIC), Index 2007=100, Monthly, S.A.
12	IPMAT	Industrial Production: Materials
13	IPMINE	Industrial Production: Mining, Index 2007=100, Monthly, S.A.
14	IPNCONGD	Industrial Production: Nondurable Consumer Goods
15	IPNMAT	Industrial Production: nondurable Materials
16	IPUTIL	Industrial Production: Electric and Gas Utilities, Index 2007=100, Monthly, S.A.
17	NAPMPI	ISM Manufacturing: Production Index
18	PI	Personal Income
19	RPI	Real Personal Income,S.A. Annual Rate,Billions of Chained 2009 Dollars
20	W875RX1	Real personal income excluding current transfer receipts
21 (Group #2)	CMRMTSPL	Real Manufacturing and Trade Industries Sales
22	NAPM	ISM Manufacturing: PMI Composite Index,S.A.
23	NAPMII	ISM Manufacturing: Inventories Index
24	NAPMNOI	ISM Manufacturing: New Orders Index;S.A.
25	NAPMSDI	ISM Manufacturing: Supplier Deliveries Index, S.A.
26	A0M057	Manufacturing and trade sales (mil. chain 2009 $)
27	A0M059	Sales of retail stores (mil. Chain 2000$)
28	A0M007	Mfrs' new orders durable goods industries (bil. chain 2000 $)
29	A0M008	Mfrs' new orders consumer goods and materials (mil. 1982 $)
30	A1M092	Mfrs' unfilled orders durable goods indus. (bil. chain 2000 $)
31	A0M027	Mfrs' new orders nondefense capital goods (mil. 1982 $)
32	A0M070	Manufacturing and trade invertories(bil.Chain 2009$)
33	A0M077	Ratio mfg. and trade inventories to sales (based on chain 2009 $)
34	DDURRG3M086SBEA	Personal consumption expenditures: Durable goods (chain-type price index)
35	DNDGRG3M086SBEA	Personal consumption expenditures: Nondurable goods (chain-type price index)

36	DPCERA3M086SBEA	Real personal consumption expenditures (chain-type quantity index)
37	DSERRG3M086SBEA	Personal consumption expenditures: Services (chain-type price index)
38	PCEPI	Personal Consumption Expenditures: Chain-type Price Index
39	U0M083	Consumer expectations NSA (Copyright, University of Michigan)
40	UMCSENT	University of Michigan: Consumer Sentiment
41 (Group #3)	UEMP15OV	Number of Civilians Unemployed for 15 Weeks Over (Thousands of Persons)
42	UEMP15T26	Number of Civilians Unemployed for 15 to 26 Weeks
43	UEMP27OV	Number of Civilians Unemployed for 27 Weeks and Over
44	UEMP5TO14	Number of Civilians Unemployed for 5 to 14 Weeks
45	UEMPLT5	Number of Civilians Unemployed - Less Than 5 Weeks
46	UEMPMEAN	Average (Mean) Duration of Unemployment, S.A.
47	UEMPMED	Median Duration of Unemployment
48	UNEMPLOY	Civilian Unemployment Thousands of Persons, Monthly, S.A.,
49	UNRATE	Civilian Unemployment Rate, Percent, Monthly, S.A.
50	A0M005	Average weekly initial claims unemploy
51	A0M441	Civilian Labor Force
52	CE16OV	Civilian Employment, Thousands of Persons, Monthly, S.A.
53	NAPMEI	ISM Manufacturing: Employment Index©
54	A0M090	Ratio civilian employment to working-age population (pct.)
55	CIVPART	Civilian Labor Force Participation Rate, Percent, Monthly, S.A.
56	LNS11300012	Civilian Labor Force Participation Rate - 16 to 19 years
57	LNS11300036	Civilian Labor Force Participation Rate - 20 to 24 years
58	LNS11300060	Civilian Labor Force Participation Rate - 25 to 54 years, Percent, Monthly, S.A.
59	LNS11324230	Civilian Labor Force Participation Rate - 55 years and over, Percent, Monthly, S.A.
60	LNS11300002	Civilian Labor Force Participation Rate - Women, Percent, Monthly, S.A.
61	LNU01300001	Civilian Labor Force Participation Rate - Men, Percent, Monthly, Not S.A.
62	MANEMP	All Employees: Manufacturing
63	DMANEMP	All Employees: Durable goods
64	NDMANEMP	All Employees: Nondurable goods
65	PAYEMS	All Employees: Total nonfarm
66	SRVPRD	All Employees: Service-Providing Industries
67	USCONS	All Employees: Construction
68	USFIRE	All Employees: Financial Activities
69	USGOVT	All Employees: Government
70	USMINE	All Employees: Mining and logging

71	USPRIV	All Employees: Total Private Industries
72	USTPU	All Employees: Trade, Transportation Utilities
73	USTRADE	All Employees: Retail Trade
74	USWTRADE	All Employees: Wholesale Trade
75	AHECONS	Average Hourly Earnings Of Production And Nonsupervisory Employees:Construction
76	AHEMAN	Average Hourly Earnings Of Production And Nonsupervisory Employees:Manufacturing
77	A0M001	Average Weekly Hours: Manufacturing
78	AWOTMAN	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing
79	CES0600000007	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing
80	CES0600000008	Average Hourly Earnings Of Production And Nonsupervisory Employees:Goods-Producing
81 (Group #4)	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
82	HOUSTMW	Housing Starts in Midwest Census Region
83	HOUSTNE	Housing Starts in Northeast Census Region
84	HOUSTS	Housing Starts in South Census Region
85	HOUSTW	Housing Starts in West Census Region
86	PERMIT	New Private Housing Units Authorized by Building Permits
87	PERMITMW	New Private Housing Units Authorized by Building Permits in the Midwest
88	PERMITNE	New Private Housing Units Authorized by Building Permits in the North
89	PERMITS	New Private Housing Units Authorized by Building Permits in the South
90	PERMITW	New Private Housing Units Authorized by Building Permits in the West
91 (Group #5)	P/E	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)
92	Dvd 12M Yld - Gross	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
93	SP500	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE
94	S5INDU	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS
95	SPF	S&P'S COMMON STOCK PRICE INDEX: Financials
96	S5UTIL	S&P'S COMMON STOCK PRICE INDEX:Utilities
97	S5ENRS	S&P'S COMMON STOCK PRICE INDEX: Energy
98	S5HLTH	S&P'S COMMON STOCK PRICE INDEX: Health Care
99	S5INFT	S&P'S COMMON STOCK PRICE INDEX: Information Technology
100	S5COND	S&P'S COMMON STOCK PRICE INDEX: Consumer Discretionary
101	S5CONS	S&P'S COMMON STOCK PRICE INDEX: Consumer Staples
102	S5TELS	S&P'S COMMON STOCK PRICE INDEX: Telecommunicaiton Services
103	S5MART	S&P'S COMMON STOCK PRICE INDEX: Materials
104 (Group #6)	AMBSL	St. Louis Adjusted Monetary Base
105	BUSLOANS	Commercial and Industrial Loans, All Commercial Banks

106	CILDCBM027SBOG	Commercial and Industrial Loans, Domestically Chartered Commercial Banks
107	CILFRIM027SBOG	Commercial and Industrial Loans, Foreign-Related Institutions
108	M1SL	M1 Money Stock
109	M2REAL	Real M2 Money Stock(Billions of 1982-83 Dollars)
110	M2SL	M2 Money Stock
111	MABMM301USM189S	M3 for the United States©
112	MBCURRCIR	Monetary Base; Currency In Circulation
113	NONBORRES	Reserves Of Depository Institutions, Nonborrowed
114	REALLNNSA	Real Estate Loans, All Commercial Banks
115	TOTRESNS	Total Reserves of Depository Institutions
116	NONREVSL	Total Nonrevolving Credit Owned and Securitized, Outstanding
117	NREVNSEC	Securitized Consumer Nonrevolving Credit, Outstanding(Billions of Dollars);Not S.A.
118	A0M095	Ratio consumer installment credit to personal income (pct.)
119 (Group #7)	EXCAUS	Canada / U.S. Foreign Exchange Rate
120	EXCHUS	China / U.S. Foreign Exchange Rate
121	EXDNUS	Denmark / U.S. Foreign Exchange Rate
122	EXHKUS	Hong Kong / U.S. Foreign Exchange Rate
123	EXINUS	India / U.S. Foreign Exchange Rate
124	EXJPUS	Japan / U.S. Foreign Exchange Rate
125	EXKOUS	South Korea / U.S. Foreign Exchange Rate
126	EXMAUS	Malaysia / U.S. Foreign Exchange Rate
127	EXNOUS	Norway / U.S. Foreign Exchange Rate
128	EXSFUS	South Africa / U.S. Foreign Exchange Rate
129	EXSIUS	Singapore / U.S. Foreign Exchange Rate
130	EXSLUS	Sri Lanka / U.S. Foreign Exchange Rate
131	EXSZUS	Switzerland / U.S. Foreign Exchange Rate
132	EXTAUS	Taiwan / U.S. Foreign Exchange Rate
133	EXTHUS	Thailand / U.S. Foreign Exchange Rate
134	EXALUS	Australia/U.S. Foreign Exchange Rate
135	EXNZUS	New Zealand/U.S. Foreign Exchange Rate
136	EXUKUS	U.K./U.S. Foreign Exchange Rate
137	TWEXMMTH	Trade Weighted U.S. Dollar Index: Major Currencies
138 (Group #8)	FEDFUNDS	Effective Federal Funds Rate
139	GS1	1-Year Treasury Constant Maturity Rate
140	GS10	10-Year Treasury Constant Maturity Rate

141	GS5	5-Year Treasury Constant Maturity Rate
142	TB3MS	3-Month Treasury Bill: Secondary Market Rate
143	TB6MS	6-Month Treasury Bill: Secondary Market Rate
144	AAA	Bond Yield: Moody's Aaa Corporate(% Per Annum)
145	BAA	Bond Yield: Moody's Baa Corporate(% Per Annum)
146	sfyGS1	GS1-FEDFUNDS
147	sfyGS10	GS10-FEDFUNDS
148	sfyGS5	GS5-FEDFUNDS
149	sfy3mo	TB3MS-FEDFUNDS
150	sfy6mo	TB6MS-FEDFUNDS
151	sfyAAA	BAA-FEDFUNDS
152	sfyBAA	AAA-FEDFUNDS
153 (Group #9)	CPIAPPSL	Consumer Price Index for All Urban Consumers: Apparel(Index 1982-84=100)
154	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items
155	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
156	CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care
157	CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation
158	CUSR0000SA0L2	Consumer Price Index for All Urban Consumers: All items less shelter
159	CUSR0000SA0L5	Consumer Price Index for All Urban Consumers: All items less medical
160	CUSR0000SAC	Consumer Price Index for All Urban Consumers: Commodities
161	CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables
162	CUSR0000SAS	Consumer Price Index for All Urban Consumers: Services
163	NAPMPRI	ISM Manufacturing: Prices Index©
164	PPICMM	Producer Price Index: Commodities: Metals and metal products: Primary nonferrous metals
165	PPICRM	Producer Price Index: Crude Materials for Further Processing
166	PPIFCG	Producer Price Index: Finished Consumer Goods
167	PPIFGS	Producer Price Index: Finished Goods
168	PPIITM	Producer Price Index: Intermediate Materials: Supplies Components
169	DCOILWTICO	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma
170	PINDU_Index	Industrial Inputs Price Index, 2005 = 100, includes Agri Raw Materials and Metals Price Indices not S.A.