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Forecasting Financial Market Vulnerability in the U.S.: A Factor Model Approach

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Forecasting Financial Market Vulnerability in the U.S.: A Factor Model Approach

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Abstract

This paper presents a factor-based forecasting model for the financial market vulnerability in the U.S. We estimate latent common factors via the method of the principal components from 170 monthly frequency macroeconomic data to out-of-sample forecast the Cleveland Financial Stress Index. Our factor models outperform both the random walk and the autoregressive benchmark models in out-of-sample predictability for 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. The recursive and the rolling window approaches with a 50% split point perform similarly well.

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

JEL Classification: E44; E47; G01; G17

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1 Introduction

Financial market crises often occur abruptly and quickly spread to other sectors of the economy, which often results in prolonged economic downturns. The recent global financial crisis triggered by the collapse of Lehman Brothers in September 2008 provides one of the most recent and relevant examples. The economics profession has failed to anticipate this financial crisis, and greatly underestimated severity of the spillover of the crisis to real activity that resulted in the Great Recession. Since these crises often come to a surprise realization with no systemic warnings, and because they create long-lasting harmful effects on real sectors even when turbulent periods are over, it would be useful to have an instrument that predicts the vulnerability of financial markets in the near future.

For this purpose, it is crucially important to find appropriate measures of the financial market vulnerability, which quantifies the potential risk that prevails in financial markets. Since the seminal work of Girton and Roper [1977], the Exchange Market Pressure (EMP) index has been frequently employed by researchers in this literature. See Tanner [2002] for a review.

One alternative measure that is rapidly gaining popularity since the recent financial crisis is the financial stress index (FSI). Unlike the EMP index that is based on exchange rate depreciation and reserves changes, the FSI index is constructed using a broad range of financial market key variables. In the case of the U.S., 12 financial stress indices has become available Oet et al. [2011] including three FSIs contributed by regional Federal Reserve banks. See, among others, Hakkio and Keep [2009], Kliesen and Smith [2010], Oet et al. [2011], and Brave and Butters [2012]. For other recent research contribution to financial stress, see also Hatzius et al. [2010] and Carlson et al. [2014].[1]

Conventional approaches to predict financial crises include the following. Frankel and

[1] There's also an array of work that provides regional financial stress indices such as Grimaldi [2010], Grimaldi [2011] Hollo et al. [2012], and Islami and Kurz-Kim [2013] for the Euro area as well as for individual countries such as Greece (Louzis and Vouldis [2011]), Sweden (Sandahl et al. [2011]), Canada (Illing and Liu [2006]), Denmark (Hansen [2006]), Switzerland (Hanschel and Monnin [2005]), Germany (van Roye [2011]), Turkey(Cevik et al. [2013]), Colombia (Morales and Estrada [2010]), and Hong Kong (S.Yiu et al. [2010]).

Saravelos [2012], Eichengreen et al. [1995], and Sachs et al. [1996] use linear regressions to test the statistical significance of various economic variables on the occurrence of crises. Other group of researches employs discrete choice model approaches, either parametric probit or logit regressions (Frankel and Rose [1996]; Cipollini and Kapetanios [2009]) or nonparametric signals approach (Kaminsky et al. [1998]; Brüggemann and Linne [1999]; Edison [2003]; Berg and Pattillo [1999]; Bussiere and Mulder [1999]; Berg et al. [2005]; EI-Shagi et al. [2013]; Christensen and Li [2014]).

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

This paper presents a factor-based prediction model in a data-rich environment to out-of-sample forecast the Financial Stress Index (FSI) developed by the Federal Reserve Bank of Cleveland. We extract multiple latent common factors using the method of the principal components (Stock and Watson [2002]) for a large panel of 170 time series macroeconomic data that include nominal and real activity variables from October 1991 to October 2014. To avoid complications from nonstationarity issues, we apply the principle component analysis (PCA) to differenced data then recover *level* factors from estimated factors (Bai and Ng [2004]). We implement an array of out-of-sample forecast exercises with the random walk as well as a stationary autoregressive model as the benchmark model. We evaluate the predictive accuracy of our models relative to these benchmark models using the ratio of the 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 benchmark models in out-of-sample predictability 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 more closely related with real sector variables rather than nominal sector variables. Lastly, we employ the recursive scheme as well as the fixed rolling window approach with the 50% split point. Our factor models perform similarly well under these two schemes.

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. Section 5 concludes.

2 The Econometric Model

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

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

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. All variables other than those that are represented as a percentage term (interest rates, unemployment rates, etc.) are log-transformed.

Estimation is carried out via the method of the principal components for the first-differenced data. As Bai and Ng [2004] show, the principal component 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 before the estimations, since the method of the principal components is not scale invariant. Taking the principal components method for $\Delta \mathbf{x} \Delta \mathbf{x}^{'}$ yields factor estimates $\Delta \hat{\mathbf{F}}_t$ along with their associated factor loading coefficients $\hat{\lambda}_i$. Estimates for the idiosyncratic components are naturally given by the residuals $\Delta \hat{e}_{i,t} = \Delta x_{i,t} - \hat{\lambda}_i^{'} \Delta \hat{\mathbf{F}}_t$. Level variables are 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 employ the following regression model. Abstracting from deterministic terms,

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

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. Note that (5) is an AR(1) process for $j = 1$ extended by exogenous common factors. This formulation is based on our preliminary unit-root test results for the FSI that show strong evidence of stationarity.[2] Applying the ordinary least squares (OLS) estimator for (5) yields the following j-period ahead forecast for the financial stress index.

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

To statistically evaluate our factor models, we employ the following nonstationary random walk model as the (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.

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

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

We also employ the following stationary AR(1)-*type* model as an alternative 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, which yields the following j-period ahead forecast.

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

For evaluation of the prediction accuracy, we use the ratio of the root mean square prediction error ($RRMSPE$), $RMSPE$ from the benchmark model divided by $RMSPE$ from the factor model. Note that our factor model performs better than the benchmark model when $RRMSPE$ is greater than 1.

[2] Results are available upon request.

Also, we employ the Diebold-Mariano-West (DMW) test in order to statistically evaluate the out-of-sample predictability of our factor model. For the DMW test, we define the following 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,

$$\varepsilon^A_{t+j|t} = fsi_{t+j} - \widehat{fsi}^A_{t+j|t} \ (A = R, AR), \ \varepsilon^F_{t+j|t} = fsi_{t+j} - \widehat{fsi}^F_{t+j|t} \tag{12}$$

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 DMW statistic can be used to test the null 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, $\bar{d} = \frac{1}{T-T_0}\sum_{t=T_0+1}^{T} d_t$, 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.[3] 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] Following Andrews and Monahan [1992], we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

3 Data Descriptions and Factor Estimations

3.1 Data Descriptions

We use the Cleveland Financial Stress Index (CFSI), obtained from the FRED, to measure the financial market vulnerability. 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. As we can see in Figure 1, the CFSI tracks recent financial crises reasonably well. For example, the index shows elevated level of risk during the recent major crises such as the U.S. subprime mortgage crisis that started around 2006, global financial market meltdown triggered by the failure of Lehman Brothers in September 2008, and the European sovereign debt crisis that started at the end of 2009. That is, the CFSI seems to be an appropriate measure of the financial market vulnerability. The data is monthly frequency and is traced back to October 1991.

Figure 1 around here

We obtained 170 monthly frequency macroeconomic time series data from the FRED and the Conference Boards 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 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 estimated first four (differenced) common factors, $\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_4$ 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 U.S. IT bubble (a.k.a. the dot-com bubble) and the Great Recession, respectively. In what follows, we demonstrate that F_1 is more closely related with real activity 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 7 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 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 and the descriptions are reported in the Data Appendix.

We investigate the nature of the first common factor using the factor loading coefficients for F_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 (IDs $41 - 50$), whereas they are positive for employment or labor participation variables (IDs $51 - 74$) and earnings related data (IDs $75 - 80$). Positive coefficients were also found from the group #3 (housing) and #4 (stock price) variables. Also 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 of the US economy.

When it comes 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 loads heavily on the group #9 (price variables) as well as the group #5 (exchange rates). The marginal R^2 estimates 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 captures 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 should be the case. Note that the sign itself does not matter because the method of the principle components estimates the loadings and factors jointly.[4] 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 least squares estimations for the CFSI with alternative 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 for 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 fit. That is, it seems that one or two factor models are sufficient for a good in-sample fit. It should be also noted that factor estimates help explain CFSIs for 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.[5]

Table 2 around here

[4] One may multiply both the loadings and the factor by -1 without affecting any stastistical inferences.

[5] 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.

In Table 3, we also report the least squares 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 models without $cfsi_t$ are employed. Our models are good as to the In-sample fit especially when $cfsi_t$ is included, which should be the case because the CFSI is highly persistent. Our factor models without lagged CFSI index still exhibit fairly high in-sample fit. 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 Models

We implement out-of-sample forecast exercises using two methods. First, we use a recursive forecast scheme. That is, we begin with an out-of-sample forecast of the $j-$period ahead CFSI index ($fsi_{\frac{T}{2}+j}$) using the 50% initial observations ($t = 1, 2, ..., \frac{T}{2}$). Then, we add one additional observation to the sample ($t = 1, 2, ..., \frac{T}{2}, \frac{T}{2} + 1$) and implement another forecast ($fsi_{\frac{T}{2}+j+1}$) using 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 rolling window method that repeats forecasting by adding one additional observation with the same split point but dropping one earliest observation in order to maintain the identical sample size. That is, after the initial forecast described earlier, we forecast $fsi_{\frac{T}{2}+j+1}$ using an updated (shifted to the right) data set ($t = 2, 3, ..., \frac{T}{2}, \frac{T}{2} + 1$) maintaining the same number of observations.

We employ two benchmark models for the evaluations of our factor-based forecast models: the nonstationary random walk model and a stationary autoregressive model.

Out-of-sample forecast performance is evaluated using the ratio of the root mean square prediction error, $RRMSPE$, of the benchmark model to that of the factor model. When the $RRMSPE$ is greater than one, the factor model outperforms the benchmark model. 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. 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

We report $RRMSPE$ estimates and the DMW statistics of our factor model with a stationary autoregressive competing model in Tables 6 and 7. We note that most $RRMSPE$ estimates are greater than one when the forecast horizon is between $1-$ and $6-$month. The $RRMSPE$ estimates were 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. Therefore, we use the critical values from McCracken (2008). 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 Concluding Remarks

This paper proposes a forecast model for systemic risk in the U.S. financial market in a data-rich environment. We use the latest financial stress index developed by Federal Reserve Bank of Cleveland as a proxy variable of the financial market vulnerability. We employ a parsimonious method to extract latent common factors from a panel of 170 monthly frequency time series macroeconomic variables from October 1991 to October 2014. In presence of nonstationarity in the data, we apply the method of the principle components (Stock and Watson [2002]) to differenced data (Bai and Ng [2004]) to estimate the latent factors consistently.

We implement an array of out-of-sample prediction exercises using the recursive and the fixed rolling window schemes for 1-month to 1-year forecast horizons. Based on the $RRMSPE$ estimates and the DMW statistics, our factor-based forecast 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. The parsimonious models with one or two factors perform 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.

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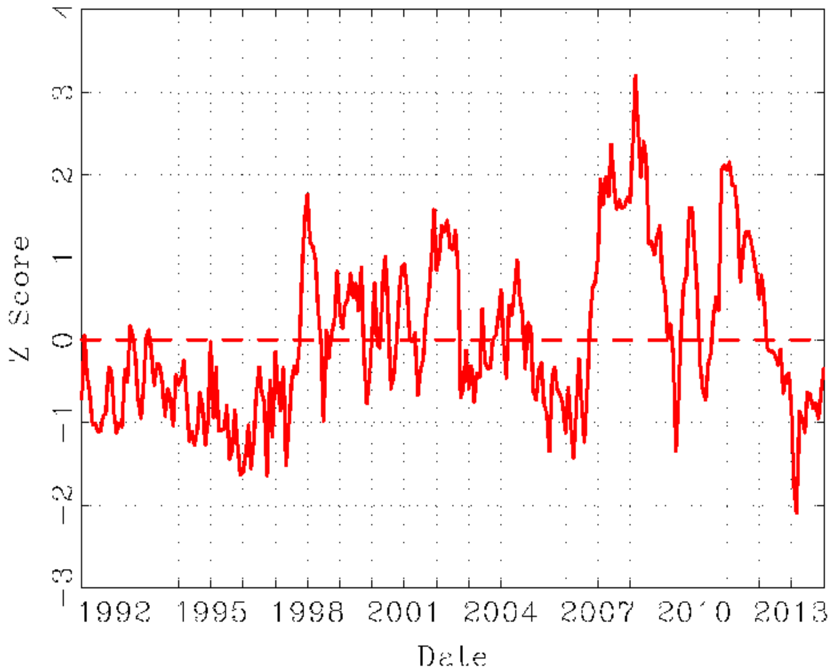
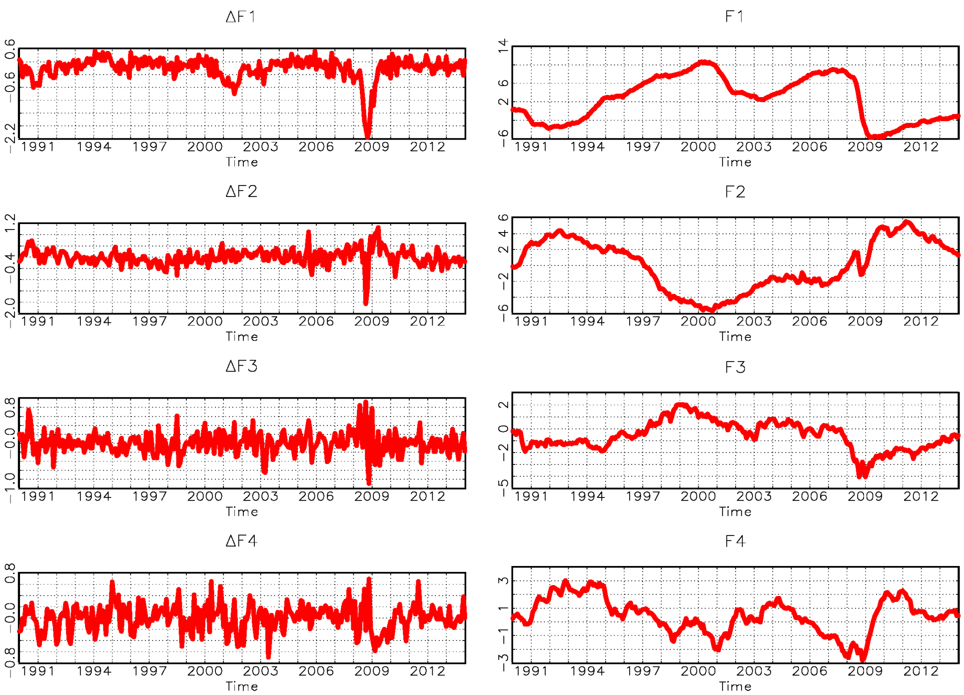
Björn van Roye. Financial stress and economic activity in germany and the euro area. Kiel Working Paper No. 1743, Kiel Institute for the World Economy, November 2011.

Figure 1. Cleveland Financial Stress Index



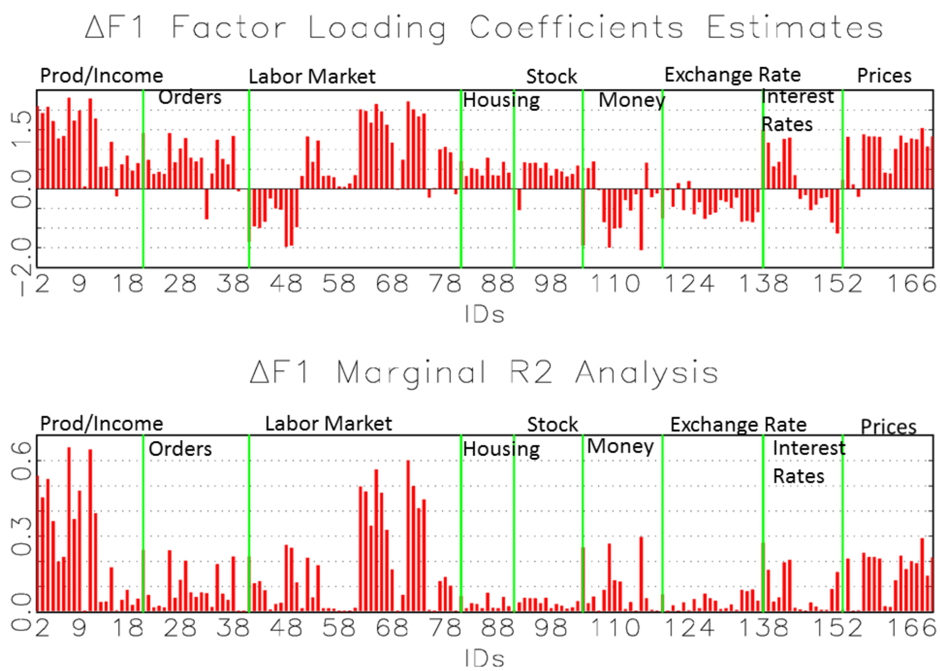
Note: The Cleveland Financial Stress Index is obtained from the FRED. The index is a z-score monthly frequency data constructed by the Cleveland Fed.

Figure 2. Factor Estimates: Differenced and Level Factors



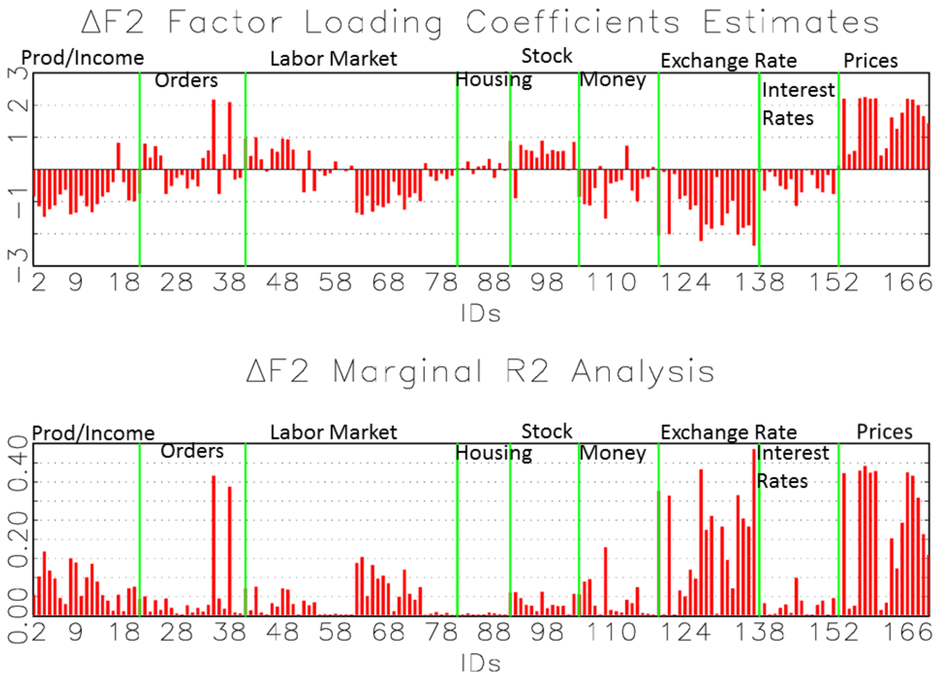
Note: We obtained up to 8 factors by applying the method of the principal components to 170 monthly frequency macroeconomic time series variables. Level factors (second column) are obtained by re-integrating estimated common factors (first column).

Figure 3. Common Factor #1



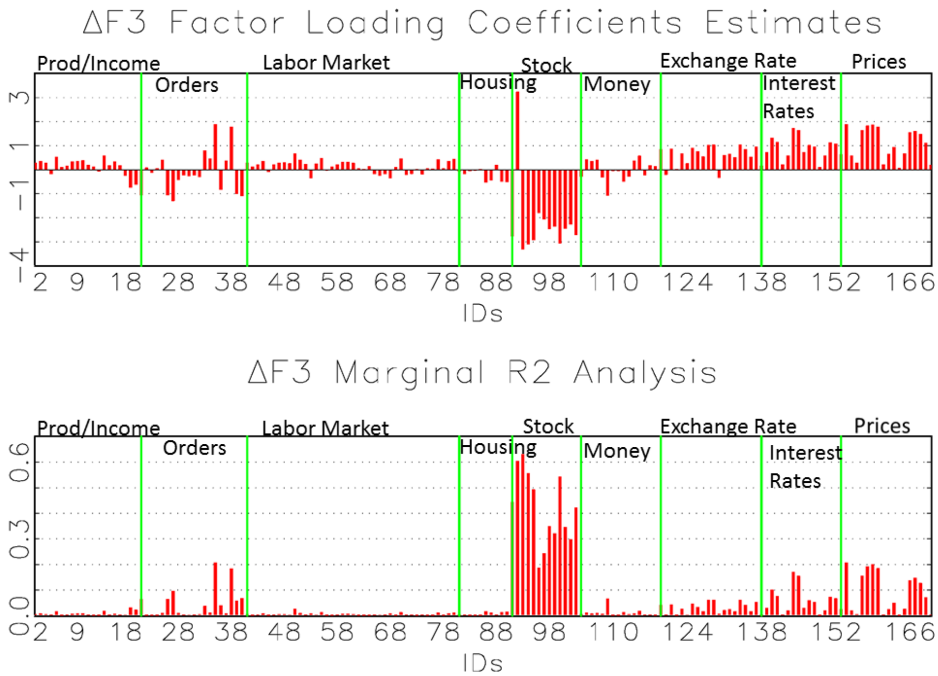
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by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

Figure 4. Common Factor #2



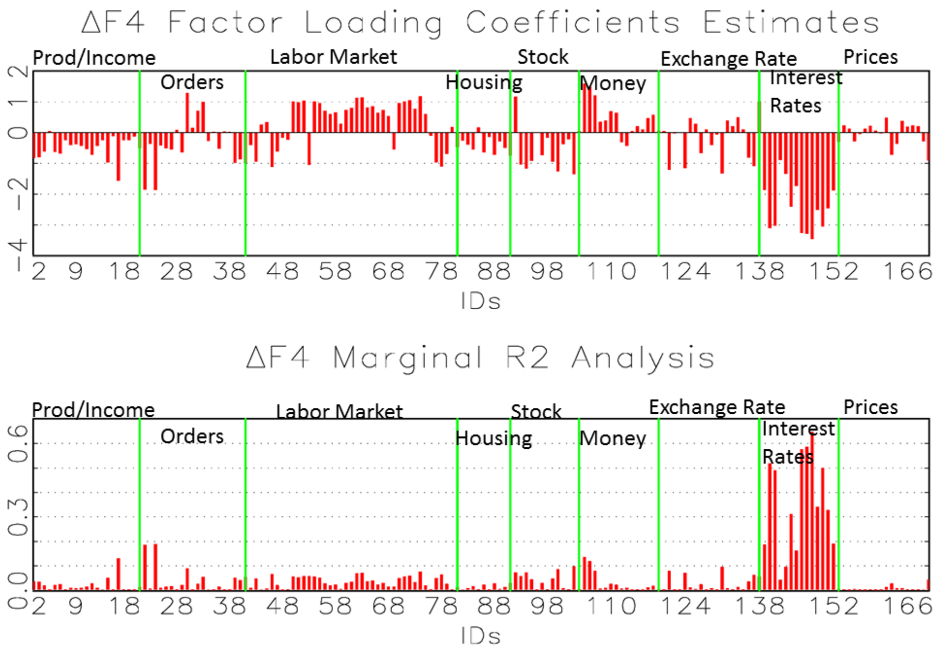
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by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

Table 1. Macroeconomic Data Descriptions

Group ID	Data ID	Data Descriptions
#1	$1 - 21$	Output and Income
#2	$22 - 40$	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. ‡, †, 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. $\ddagger$, $\dagger$, 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.