Forecasting with Principal Components Analysis: an application to Financial Stability Indices for Jamaica

Filippo Mingione[1]

Financial Stability Department
Research and Economic Programming Division
Bank of Jamaica

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Abstract

This paper experiments with the use of the Principal Components Analysis (PCA) in order to forecast two indices of financial vulnerability. One index is derived from a nonparametric model based on a "signaling approach". The other is built by means of aggregating microeconomic, macroeconomic and international indicators into a single measure, using parametric techniques. Once principal component factors are estimated through PCA, they are used as regressors in an Autoregressive Distributed Lag (ADL) model. The out-of-sample prediction power of this technique is tested against benchmark models. Findings are that PCA fails in overperforming benchmarks when the nonparametric "signal approach" model is forecasted. On the other hand, the PCA model leads to more accurate predictions over the out-of-sample period, when the object of the forecasting exercise is the aggregate single index.

[1] Filippo Mingione is a graduate student in the Department of Economics, Università degli Studi di Roma Tor Vergata, Rome, Italy. This paper was written while Filippo Mingione served as an intern in the Financial Stability Department of the Research and Economic Programming Division at the Bank of Jamaica. The views expressed are those of the author and does not necessarily reflect the position of the Bank of Jamaica.

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1. Introduction

The economy as a whole and not only the financial system can be dramatically affected by systemic banking crises. Such crises are not specific to the recent past or specific countries. Indeed, almost no country has avoided the experience of a distress within the banking sector at one time or another and some have had multiple banking crises.[2] Even if banking crises of the past have differed in terms of underlying causes and economic impact, they have much in common. Banking crises are often preceded by periods of high credit growth and persistent increases in asset prices, often followed by rapid reversals. Imbalances in firms' balance sheets, such as maturity mismatches or large exchange rate and interest rate risk exposures, when the macroeconomic context changes, ultimately translate into credit risk for the banking sector (Kindleberger and Aliber, 2005).

In Jamaica, the performance of banking institutions during the early 1990s was influenced by high levels of inflation following the process of liberalization and a credit boom in which many loans and investments were made without proper risk assessment or adequate level of collateral. A tighter monetary policy aimed at reducing inflation led to high real interest rates and a contraction in the aggregate demand. The fall in output coincided with notable growth in the ratio of non-performing loans to total loans in the banking system.

In addition, evidence of weak management was manifested in high operating costs within some institutions, while the absence of appropriate internal controls led to incidents of fraud. Eventually, commercial banks experienced liquidity problems, as the maturity mismatch of the assets-liabilities structure became unsustainable when public concerns led to runs on deposits in some institutions. Hence, by December 1996, these events culminated in the financial system distress within the domestic banking sector.[3]

Central banks and supervisory authorities are required to provide timely assessment of the situation in the banking sector, from where most financial and economic crises originate. Consequently several Early Warning Systems (EWS) for banking sector distress have been proposed as a surveillance tool by regulators. There are two main methods used in the EWS literature to predict financial sector turbulence. One method relies on the signal approach proposed by Kaminsky et al. (1998) and the other one relies on the construction of a financial stability index, a single quantitative measure built on the aggregation of a set of different predictors (see the studies of Illing and Liu, 2006, and Hanschel and Monnin, 2005, among the others). Langrin (2002) developed an Early Warning System Index for Jamaica, which involved the bi-variate monitoring of a comprehensive set of aggregate macroeconomic and microeconomic indicators in order to determine the future state of vulnerability of the banking sector. The index is currently one of the main surveillance tools used by the Bank in monitoring and assessing the stability of the overall banking system.

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[2] Laeven and Valencia (2010) present a comprehensive database of systemic banking crises for the period 1970-2009.

[3] For further information on the 1996-1998 crisis, BOJ (2004).

The aim of this paper is to test a forecasting model for the aggregate micro-prudential EWS score, ensuing from the approach adopted by Langrin (2002). The model to be validated is an autoregressive distributed lag (ADL) one where the dependent variable is regressed on its lags and on factors (and lags) extracted from a Principal Component Analysis (PCA) run on a set of indicators, drawn from Jamaican commercial bank balance sheets. To our knowledge, it is the first time that a non parametric Early Warning System (EWS) index has been forecasted through a regression on factors extracted from a PCA. The same technique will then be used in order to forecast a financial stability index built using the approach of Illing and Liu (2006). The Aggregate Financial Stability Index proposed by Morris (2010) for Jamaica will be employed.

The remainder of the paper is organized as follows: Section 2 presents an overview of the literature. Section 3 discusses in detail the data used. In Section 4 we describe the methodology employed for forecasting, through a Principal Component Analysis (PCA), both the Early Warning System (EWS) and the Aggregate Financial Stability Index (AFSI). Section 5 tests the principal component model against naïve models, and an investigation on both in-sample and out-of-sample behaviours is conducted. Finally, Section 6 concludes and highlights open issues for future research.

2. Literature Review

Many empirical studies of financial stability focus on selecting early warning indicators of crises. Two different approaches to the subject have been developed in literature: the "qualitative method" or "signals approach", and the aggregate financial stress index approach.

The "signals" approach recognizes a systemic banking crisis after the occurrence of certain events like bank runs, closures, mergers, recapitalization and a large increase in non-performing assets (Demirguc Kunt and Detragiache, 1998a; Kaminsky et al., 1998; Goldstein, Kaminsky & Reinhart, 2000). It is based on the idea that these chosen set of indicators will behave, before a crisis bursts, in a different way from their behaviour during a "tranquil" period. Whenever the value of an indicator crosses a predetermined threshold within a signaling window, this is identified as a warning signal.

The method, however, has its limitations. Von Hagen and Ho (2007) demonstrate that identification of crisis only when it becomes severe enough to trigger certain events can lead to delayed recognition of a crisis. On the other hand, it works effectively when there are sharp changes between crises episodes and periods of tranquility.

Langrin (2002) proposes a specific EWS based on the nonparametric "signals approach". The proposed approach is then applied to the 1996-98 Jamaican banking crisis. Findings are that the EWS would have warned policy makers of an impending crisis with a reasonable lead-time. The prediction power of this index would be improved by a forecasting exercise on the index itself. This would allow for an overcoming of the critics advanced by Von Hagen and Ho (2007).

Others (Illing Liu, 2006; Hanschel and Monnin, 2005) look at financial stress as a continuum of states, where extreme values represent episodes of financial crisis. Therefore they build an aggregate financial stability index (FSI), an index representing a single quantitative measure which can be used to describe a country's financial stability situation. Morris (2010) builds a FSI for Jamaica by aggregating microeconomic, macroeconomic and international factors indicative of banking sector performance. The results underscore the sensitivity of the index to variations in the macroeconomic environment.

Hanschel and Monnin (2005) focus on the banking sector and propose an index that can be used to measure stress in the Swiss banking sector. The paper then investigates whether the values of the index can be predicted by a set of macro variables. In assessing the latter, the authors follow Borio and Lowe (2002) focus on imbalances rather than levels of variables. Illing and Liu (2006) constructed a weighted average of various indicators of expected loss, risk, and uncertainty in the financial sector. The resulting financial stress index (FSI) is a measure that includes the indicators from equity, bond and foreign exchange markets, as well as indicators of banking-sector performance. In order to aggregate this large set of variables into a single index, among other techniques, PCA is used as a weighting method.

Our paper shares with Hanschel and Monnin (2005), the focus on the banking sector and the use of balance-sheet data, while it has in common with Illing and Liu (2006) the use of a PCA on a large set of variables. Although Illing and Liu (2006) use PCA for building up their FSI, this paper uses the estimated factors for prediction on a time series created from the EWS resulting scores over the period 1996-2011. In doing that we follow Stock and Watson (2002) and Gosselin and Tkacz (2001). Stock and Watson (2002) forecast eight macroeconomic US time series, by the terms of summarizing 215 predictors in a small number of factors, estimated by PCA. Gosselin and Tkacz (2001) apply a similar forecasting method for the prediction of Canadian inflation. Findings are that PCA forecasts outperform various benchmark models.

3. Data

In order to forecast the EWS, quarterly data from 1996Q1 to 2011Q1 were used, corresponding to 61 observations. The range size was chosen to find a balance between the variables on which data were available and the need to obtain a significant number of observations. Furthermore, we decided to use data as far as 1996 in order to consider the extreme values detected throughout the Jamaican banking crisis.

In order to obtain the parameters and factors related to the in-sample estimation, the period 1996Q1 to 2009Q3 was considered. The period 2009Q4 to 2011Q1 is instead used to conduct the out-of-sample forecasting exercise. The dependant variable in our model is the BOJ aggregate Early Warning System score, computed on asset-weighted microeconomic indicators. The set of these 21 microeconomic indicators are the basis of our PCA. The BOJ Early Warning System (EWS) monitors macro- and microeconomic indicators of the banking sector via a non-parametric approach to signal banking sector vulnerability. The signal is based on EWS scores for each indicator, which is computed based on the number of standard deviations of each indicator from its 'tranquil period' mean value. The tranquil period refers to an eight quarter period of relative stability that precedes the beginning of a signalling window. The scores range from 0 to 5 with a score of 5 representing the most severe signal. Banking sector vulnerability at a point in time is determined by the trend in the aggregate EWS score (or index) over the previous eight quarters (signalling window).

Data for the specific EWS series was readily available for the periods 1996Q1 to 1997Q4 and 2002Q1 to 2011Q1. The missing period was computed taking 1991-1994 as its related tranquil period.[4] Information regarding the micro indicators was gathered from the balance sheets of the Jamaican commercial banks. Also data about the banks that went bankrupt or passed through restructuring during the 1996-1998 banking crisis have been included in our study.[5]

Table 1 presents the 21 micro indicators employed. The first column shows the indicator names. The second column accounts for whether the signal will occur in the lower or upper tail of the distribution. The third columns provide with a brief explanation of the indicator.

The results of the tests which look for the stationarity of the variables are shown in Table 2. Three different tests are employed: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). We require the null hypothesis to be rejected at the 5 per cent level of significance. The EWS is stationary in differences – the ADF test indicates a unit root, an inference which is also confirmed by the PP test. Seven of our 21 micro variables were stationary in levels, while the other ones were found to be stationary in first differences.

Finally all the series, some of them already differenced to obtain stationarity, have been standardized to have sample mean zero and sample variance one. This standardization is conventional in PCA and matters mainly for that application, in which different forecasts would be produced if the predictors were scaled using a different method, or were they left in their native units.

[4] Langrin (2002) points out as an important limitation the fact that a signalling window is set as far as seven years after the selected tranquil period.

[5] Since the banking crisis the number of banks fell from nine to six. One bank had exited the sector, while three others were merged to form one bank.

Table 1. EWS Micro Indicators

Indicators	*Explanation*	*Tail*
Capital (% of assets)	Robustness to shocks	lower
Loans to capital	Financial leverage	upper
Deposits to loans	Liquidity risk in terms ability to expand loan base	lower
Deposits (% of assets)	Liquidity risk in terms ability to expand total assets	lower
Deposit and Repos (% of assets)	Liquidity risk	lower
Liquid assets to assets	Liquidity risk in terms of ability to withstand runs	lower
Loan loss reserves (% of assets)	Asset quality in terms of adequacy of provisions (or increased risk-taking)	lower/upper
Loan & security loss prov. (% of assets)	Asset quality in terms of adequacy of provisions (or increased risk-taking)	lower/upper
Non-performing loans (% of loans)	Asset quality in terms of quality of loan portfolio	upper
Non-performing loans (% of assets)	Asset quality in terms of overall credit risk	upper
Financial institution loans (% of loans)	Vulnerability of overall financial sector	upper
Public sector loans (% of assets)	Financial leverage in terms of public sector debt	upper
Net income (% of assets)	Overall profitability	lower
Interest income (% of assets)	Profitability in terms of interest earning assets	lower
Non-interest income (% of assets)	Profitability in terms of non-interest earning assets	lower
Employee salaries (% of assets)	Management soundness and efficiency	upper
Implicit deposit interest rate	The existence of a risk premium (market discipline/asset size)	upper
12-month growth in deposits	Deposit substitution (market discipline/asset size)	lower
Investments (% of assets)	GOJ Concentration Risk	upper
FX liabilities (% of FX assets)	FX Rate Depreciation Vulnerability	upper
FX deposits (% of FX assets)	FX Rate Liquidity Risk	upper

Table 2. EWS. Unit Root and Stationarity Tests.

Notes: *, ** indicates the rejection of the null hypothesis at 5 and 1 per cent level of significance respectively (t-statistics)

	ADF		PP	KPSS
	Level	*Difference*	*Level*	*Level*
Null Hypothesis	Unit root		Unit root	Stationarity
EWS	-2.8540	-7.0807**	-2.8996	0.1049
Capital (% of assets)	-1.5787	-7.8654**	-1.8299	0.5998*
Loans to capital	-2.8959	-11.5300**	-3.4831*	0.2149
Deposits to loans	-1.9712	-2.7943*	-1.4005	0.3677
Deposits (% of assets)	-3.5276*	-	-3.4403*	0.9297**
Deposit and Repos (% of assets)	-2.3807	-11.2393**	-2.1347	0.6793*
Liquid assets to assets	-3.5093*	-	-3.5333*	0.8699**
Loan loss reserves (% of assets)	-2.5993	-3.7719**	-2.0727	0.5127*
Loan & security loss prov. (% of assets)	-2.4192	-4.6548**	-7.3837**	0.2666
Non-performing loans (% of loans)	-1.4605	-6.8510**	-1.6843	0.5776*
Non-performing loans (% of assets)	-1.3045	-6.4923**	-1.6233	0.5229*
Financial institution loans (% of loans)	-4.0233*	-	-4.0155*	0.7090*
Public sector loans (% of assets)	-1.7272	-10.5696**	-1.7835	0.3314
Net income (% of assets)	-6.8512**	-	-5.2628**	0.7292*
Interest income (% of assets)	-2.4257	-8.3853**	-2.5021	0.6332*
Non-interest income (% of assets)	-4.5819**	-	-4.5594**	0.8784**
Employee salaries (% of assets)	-0.7516	-11.8853**	0.3154	0.8497**
Implicit deposit interest rate	-0.8957	-7.2457**	-1.0682	1.0377**
12-month growth in deposits	-4.0764**	-	-4.0764**	0.5351*
Investments (% of assets)	-0.6908	-10.0783**	-0.9404	0.6073*
FX liabilities (% of FX assets)	-1.7729	-7.9934**	-1.4854	0.8314**
FX deposits (% of FX assets)	-3.5835*		-3.6091*	0.6119*

Morris (2010) includes 19 indicators in the AFSI. These indicators embrace different dimensions of financial stability, including financial development, financial vulnerability, financial soundness as well as the world's economic climate. Data are quarterly and span from 2000:Q1 to 2010:Q4. See Table 3 for the indicators. Table 4 summarizes the results from stationarity tests on these time series.

Table 3. AFSI Indicators

Indicators	*Explanation*	*Tail*
Market Capitalization/GDP	Development of the capital markets	Lower
Total Credit/GDP	The ability of credit institutions in carrying out their intermediation functions	Lower
Interest Spread	Efficiency levels in the banking system	Upper
Herfindahl – Hirschmann Index (HHI)	Degree of concentration in the banking sector	Lower
Inflation Rate	Signal of investor confidence in the economy	Upper
General Budget Deficit/Surplus (%GDP)	Signal of investor confidence in the economy	Lower
Current Account Deficit/Surplus (%GDP)	Susceptibility to external shocks	Lower
REER (change)	Adjustments in the exchange rates	Lower
Non Governmental Credit/Total Credit	Bank funding of private sector credit	Lower
Loans (%deposits)	Liquidity risk	Upper
Deposits/M2 ("moving ratio")	Savings and consumption preferences, Inflation	Lower
(Reserves/Deposits) / (Note & Coins/M2)	Vulnerability of the banking sector	Lower
Non Performing Loans/Total Loans	Loan portfolio quality	Upper
Capital/Assets	Level of capitalization of banks	Lower
Z-Score	Risk of insolvency	Lower
Liquidity Ratio	Liquidity risk	Lower
World Economic Growth	Investors' confidence level in the financial system	Lower
World Inflation Rate	Investors' confidence level in the financial system	Upper
Economic Climate Index	Investors' confidence level in the financial system	Upper

Notes: The HHI is the sum of the squares of all bank's percentage share of deposits. The Z-Score is calculated by BoJ as: $Z = \frac{ROA + \frac{C}{A}}{STDDEV(ROA)}$. The economic climate index was sourced from the Centre for Economic Studies & Institute for Economic Research (CESifo).

Table 4. AFSI. Unit Root and Stationarity Tests.

	ADF		PP	KPSS
	Level	*Difference*	*Level*	*Level*
Null Hypothesis	Unit root		Unit root	Stationarity
AFSI	-2.3584	-11.7997**	-3.9980**	0.2703
Market Capitalization/GDP	-1.2679	-5.6432**	-1.5041	0.2104
Total Credit/GDP	-1.8528	-2.6689	-1.4355	0.7852*
Interest Spread	-0.7330	-6.6813**	-0.6714	0.4233
Herfindahl – Hirschmann Index (HHI)	-0.36080	-10.1505**	-0.6101	0.7212*
Inflation Rate	-1.7215	-4.0200**	-2.6087	0.3290
General Budget Deficit/Surplus (%GDP)	-3.2273*	-	-8.2122**	0.3702
Current Account Deficit/Surplus (%GDP)	-5.2989**	-	-5.1629**	0.3578
REER (change)	-5.8660**	-	-6.4311**	0.1197
Non Governmental Credit/Total Credit	-0.9172	-6.4085**	-1.15678	0.3617
Loans (%deposits)	-1.0300	-2.7136	-1.0016	0.7958**
Deposits/M2 (“moving ratio”)	-7.1617**	-	-7.2341**	0.3710
(Reserves/Deposits) / (Note & Coins/M2)	-1.8875	-12.8146**	-5.2855**	0.2451
Non Performing Loans/Total Loans	-1.0781	-8.3526**	-3.1814*	0.4484
Capital/Assets	-0.21176	-8.2669**	0.0159	0.8155**
Z-Score	-2.6806	-7.6744**	-2.5752	0.4947*
Liquidity Ratio	-1.6047	-6.6113**	-1.4838	0.5933*
World Economic Growth	-1.3506	-3.0000*	-0.9694	0.7936**
World Inflation Rate	-3.9314**	-	-2.9168	0.1129
Economic Climate Index	-3.4514*	-3.9846**	-2.4344	0.1477

Notes: *, ** indicates the rejection of the null hypothesis at 5 and 1 per cent level of significance respectively (t-statistics)

Five of our 20 variables were found to be stationary in levels. Other variables were stationary in differences. The ones which featured a deterministic trend were regressed on it and the residuals of this regression were utilized for the analysis

4. Methodology

Principal component analysis is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. Its general objectives are (1) data reduction and (2) interpretation. Although p components are required to reproduce the total system variability, often much of this variability can be accounted for by a small number k of the principal components as there is (almost) as much information in the k components as there is in the original p variables. The k principal components can then replace the initial p variables, and the original data set, consisting of n measurements on p variables, is reduced to a data set consisting of n measurements on k principal components. Principal components may then be used as inputs to a multiple regression.

In this paper, the principal component technique is used in order to reduce the p variables into a number k of components, where $k<p$. Afterwards they are employed as regressors for a multiple regression model with the EWS and the AFSI series as dependent variables. Finally, the regression is used for an out-of-sample forecasting and results are compared with naïve models.

The principal components of a set of variables are obtained by computing the eigenvalue decomposition of the observed variance matrix.

Let the random vector X' = [X_1, X_2, ..., X_p] have the covariance matrix $\sum$ with eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0$.
Consider the linear combinations

$$\begin{aligned} F_1 &= \mathbf{a}'_1\mathbf{X} = a_{11}X_1 + a_{12}X_2 + \ldots + a_{1p}X_p \\ F_2 &= \mathbf{a}'_2\mathbf{X} = a_{21}X_1 + a_{22}X_2 + \ldots + a_{2p}X_p \\ &\vdots \qquad\qquad\qquad \vdots \\ F_p &= \mathbf{a}'_p\mathbf{X} = a_{p1}X_1 + a_{p2}X_2 + \ldots + a_{pp}X_p \end{aligned} \tag{1}$$

F_i variance and covariance are as follows

$$Var(F_1) = a_i' \sum a_i \qquad i = 1,2,..., p \tag{2}$$

$$Cov(F_i, F_k) = a_i' \sum a_k \qquad i,k = 1,2,..., p \tag{3}$$

The principal components are those uncorrelated linear combinations $F_1, F_2, ..., F_p$ whose variances are as large as possible.
The first principal component is the linear combination with maximum variance. That is, it maximizes $Var(Y_1) = a_i' \sum a_i$. It is clear that $Var(Y_1) = a_i' \sum a_i$ can be increased by multiplying any $\mathbf{a}_1$ by some constant. To eliminate this indeterminacy, it is convenient to restrict attention to coefficient vectors of unit length.

At the *i*th step, it is therefore defined

$$
\begin{aligned}
i\text{th principal component} = \text{linear combination } \mathbf{a}_i'\mathbf{X} \text{ that maximizes} \\
\text{Var}(\mathbf{a}_i'\mathbf{X}) \text{ subject to } \mathbf{a}_i'\,\mathbf{a}_i = 1 \text{ and} \\
\text{Cov}(\mathbf{a}_i'\mathbf{X}, \mathbf{a}_k'\mathbf{X}) = 0 \text{ for } k < i
\end{aligned}
$$

The proportion of total variance due to (explained by) the *k*th principal component is

$$\text{Proportion} = \frac{\lambda_k}{\lambda_1 + \lambda_2 + \ldots + \lambda_p} \qquad k = 1, 2, \ldots, p \tag{4}$$

Principal components may also be obtained for the standardized variables

$$
\begin{aligned}
Z_1 &= \frac{(X_1 - \mu_1)}{\sqrt{\sigma_{11}}} \\
Z_2 &= \frac{(X_2 - \mu_2)}{\sqrt{\sigma_{22}}} \\
&\vdots \\
Z_p &= \frac{(X_p - \mu_p)}{\sqrt{\sigma_{pp}}}
\end{aligned} \tag{5}
$$

In matrix notation,

$$\mathbf{Z} = (\mathbf{V}^{1/2})^{-1}(\mathbf{X} - \mu) \tag{6}$$

where $\mathbf{V}^{1/2}$ is the diagonal standard deviation matrix. Clearly, E($\mathbf{Z}$) = 0 and

$$\text{Cov}(\mathbf{Z}) = (\mathbf{V}^{1/2})^{-1} \sum (\mathrm{V}^{1/2})^{-1} = \rho \tag{7}$$

The principal components of $\mathbf{Z}$ may be obtained from the eigenvectors of the correlation matrix $\boldsymbol{\rho}$ of $\mathbf{X}$.

The proportion of total variance explained by the *k*th principal component of $\mathbf{Z}$ is

$$\text{Proportion} = \frac{\lambda_k}{p} \qquad k = 1, 2, \ldots, p \tag{8}$$

where the λ_k's are the eigenvalues of $\boldsymbol{\rho}$.

The eigenvalues and eigenvectors pairs (λ_i, e_i) derived from $\sum$ are, in general, not the same as the ones derived from $\boldsymbol{\rho}$. This suggests that the standardization is not inconsequential. Variables should be standardized if they are measured on scales with differing ranges. As this is the case of our micro indicators ratios, these series, already transformed to obtain stationarity, are further modified for null mean and unit variance. Subsequently, principal components analysis is run through ordinary correlations.

The number of components extracted in PCA is equal to the number of observed variables being analyzed. However, only the first components account for meaningful amounts of variance, so only these first components are retained, interpreted, and used in subsequent analysis.[6] Five criteria are used in order to determine the number of components to retain: (1) the eigenvalue-one criterion, (2) the scree test, (3) the proportion of variance for each component, (4) the cumulative proportion of variance explained, and (5) the interpretability criterion.

One of the most commonly used criteria is the eigenvalue-one criterion, also known as the Kaiser criterion (Kaiser, 1960). With this approach one retains and interprets any component with an eigenvalue greater than one. The rationale is as follows. Each observed variable contributes one unit of variance to the total variance in the data set. Any component that displays an eigenvalue greater than one is accounting for a greater amount of variance than had been contributed by one of the observed variables. This criterion very often results in retaining the correct number of components, particularly when a small to moderate number of variables are being analyzed. Stevens (1986) recommends its use when less than 30 variables are included in the analysis. However, the mindless application of this criterion needs to be avoided, especially when the actual difference in the eigenvalues of successive components is only trivial.

A useful aid to determine an appropriate number of principal components is a scree plot. With the eigenvalues ordered from largest to smallest, a scree plot is a plot of the magnitude of an eigenvalue versus its number. To determine the appropriate number of components one should look at a break or elbow in the scree plot (Cattel, 1966). The components that appear before the break are assumed to be meaningful, those appearing after are not retained. Stevens (1986) showed that the scree test can be expected to provide reasonably accurate results, if the sample is large (over 200 observations). Otherwise, the criterion has its weakness in the fact that it is often difficult to determine where a break exists, or if a break exists at all. As our subsample includes only 54 observations we looked at this criterion judiciously.

The proportion of variance for each component is a third criterion that involves retaining a component if it accounts for a specified proportion of variance in the data set. The decidion was to retain any component that accounts for at least 5 per cent of the total variance.

[6] There is no definitive answer about the number of components to retain. Things to consider include the amount of total sample variance explained, the relative sizes of the eigenvalues, and the subjective interpretations of the components.

For a standardized variable

Proportion = $\dfrac{\lambda_k}{p} > 5\%$.

The cumulative proportion of variance explained consists of retaining enough components so that the cumulative percent of variance accounted for is equal to some minimal value. In this paper we choose a minimal value of 75.0 per cent of the total variance.

Interpreting the substantive meaning of the retained components is crucial. Three rules are considered for this criterion.
Firstly, at least three variables with significant loadings on each retained component need to be present. Secondly, variables that load on different components seem to constitute different constructs. Thirdly, the variables that load on a given component move accordingly to theory.

Once the choice on the appropriate number of principal components is made it is necessary to compute the principal component scores. A component score is a linear composite of the optimally-weighted observed variables. It is calculated as the sum of products of the eigenvectors times the values observed for the original variable each period. With this done, these component scores can then be used as predictor variables in a multiple regression model.

The regression model adopted is based on former studies by Stock and Watson (2002) and Gosselin and Tkacz (2001). The multiple regression model used for forecasting the dependent variable is an autoregressive distributed lag model, with the retained factors as regressors. Let Y_{t+1} denote the scalar series to be forecasted and let X_t be an N-dimensional multiple time series of predictor variables, our micro indicators series. Both Y_{t+1} and X_t are observed for t=1,…,T, and are taken to have zero mean and unit variance. Finally, let q denote the maximum number of lags and *r* the number of components retained.

Our model is therefore defined as

$$Y_{t+1} = \alpha + \sum_{i=0}^{q} \beta_{t-i} F_{t-i} + \gamma Y_t + \varepsilon_{t+1} \qquad (9)$$
$$F_t = X_t \Lambda$$

where $F_t = (f_1,..., f_k)'$ is $r \times 1$, and $\beta = (\beta_1,...,\beta_k)'$, where $k = 1,...,r$. Λ is $(e_1,...,e_k)$, the eigenvectors of the $N \times N$ matrix $X'X$ corresponding to its $\bar{r}$ eigenvalues.[7]

[7] Gosselin and Tkacz (2001) used different loading weights. Our decision to use normalized loadings is meant to have scores with variances equal to the corresponding eigenvalues.

Our paper focuses on *h*-step-ahead forecasts. Two approaches can be used. The first approach uses "pseudo-out-of-sample" calculations that rely on the same regression specification used above, but estimated recursively through the forecast period. Specifically, forecasts at time period *t* are constructed by estimating the regression coefficients using data from the beginning of the sample through period *t*; these estimated regression coefficients are then used to forecast Y_{t+h}. The process is repeated to construct forecasts at time *t*+1, and so on through the end of the sample.[8] However, this approach involves estimating a large number of parameters that could erode forecast performance. Thus the approach used still involves a recursive method in order to compute the multistep ahead forecast of the dependent variable, but the original regression coefficients are hold along the out-of-sample period.[9]

To pick the best model among all possible combinations of variables and lags, two types of criteria are employed. First, the model has to fulfill the following plausibility criteria: (1) the regression coefficients must be significant at at least the 10.0 per cent level; (2) no lag greater than four quarters should appear; and (3) the model must contain at least three explanatory variables. Second, among the survived models the one that minimize the Schwarz criterion (SC) is chosen, since Ng and Perron (1995) noted that the SC is usually preferred to other competing information criteria. The model selected therefore minimizes the SC, but does not necessary yields the minimal forecasted root-mean-squared error (RMSE). In order to have out-of-sample values for the factors, they are forecasted by using the best ARIMA models according to a SC. Autoregressive (AR) and Moving Averages (MA) terms are chosen up to four quarters back and we allow for the dependant variable to be differenced up to twice.

As suggested by many (see for instance Allen and Fildes, 2001), a comparison between the out-of-sample forecast performance of the proposed model with that of naïve models is made. Our model with principal components is tested against two different naïve models. We opted for a simple random walk model and a deterministic trend model. The naïve method is based on a random walk — all forecasts are equal to the last observation

$$Y_{t+h} = A_t + \varepsilon_{t+h} \tag{11}$$

[8] Hatzius et al. (2010) use this methodology in order to forecast their Financial Condition Index (FCI).

[9] An alternative approach is used by Stock and Watson (2002). It is admited that the multistep forecast would be linear F_t and Y_t (and lags) and an *h*-step-ahead dynamic projection is used to construct the forecasts directly. The latter approach was chosen, and the resulting multistep ahead version of our model is

$$Y_{t+h}^{h} = \alpha_h + \sum \beta_h F_t + \gamma_h Y_t + \varepsilon_{t+h}^{h} \tag{10}$$

where Y_{t+h}^{h} is the *h*-step-ahead variable to be forecasted, and the subscripts reflect the dependence of the projection on the horizon.

where A_t is the actual value of the last in-sample observation and $Var(\varepsilon_{t+h}) = 0$. This is often referred to as no-change model as it simply assumes that future values will be equal to the last observation at all times.

The proposed model is also compared with the Seasonal Autoregressive Integrated Moving Average (SARIMA) model with the best combination of AR and MA and seasonal autoregressive (SAR) and seasonal moving average (SMA) terms according to a SC. The model could be written as

$$\Phi(\mathrm{B}^h)\phi(\mathrm{B})\nabla_h^D \nabla^d Y_t = \alpha + \Theta(\mathrm{B}^h)\theta(\mathrm{B})\mu_t \quad (12)$$

where $\nabla_h^D \mathrm{Y}_t = (1-\mathrm{B}^h)^D \mathrm{Y}_t$ is a seasonal difference of order D; $\{\mu_t\} \sim WN(0,\sigma^2)$. $\Phi(\mathrm{B}^h) = 1 - \Phi_1 \mathrm{B}^h - \Phi_2 \mathrm{B}^{2h} - ... - \Phi_P \mathrm{B}^{Ph}$ and $\Theta(\mathrm{B}^h) = 1 + \Theta_1 \mathrm{B}^h \Theta_2 \mathrm{B}^{2h} + ... + \Theta_Q \mathrm{B}^{Qh}$ are, respectively, the seasonal AR operator and the seasonal MA operator, with seasonal period of length h. We allow for AR and MA terms up to order four and Y_t is allowed to be differenced up to two times. The seasonal period is of length four, to account for quarterly data.

If the proposed model fails in outperforming the trivial models, we conclude that it is not a valid predictor model over the used sample.[10]

5. Estimation and Forecasting

The first variable we forecast is the EWS series. 14 out of our 21 micro indicators are transformed in order to work only with stationary series. The series then are standardized to have null mean and unit variance. Principal Components Analysis is run on these variables on the subsample 1996Q2 to 2009Q3 (see Table 5 and 6). Accordingly to the required criteria, seven principal components are retained. The cumulative proportion they account for is the 77.86 per cent of the total variance.

Looking at the eigenvectors matrix it is possible to interpret each principal component depending on which are the original variables that much load on it. It is now possible to compute the principal component scores for the retained components. Graph 1 shows the seven new variables over the in-sample period. Notably extreme values appear until the second quarter of 1999.

[10] Still it can be somewhat helpful in understanding the underlying relationships among variables.

Table 5. Micro EWS. PCA Eigenvalues.

Principal Components Analysis
Sample: 1996Q2 2009Q3
Included observations: 54
Computed using: Ordinary correlations
Extracting 21 of 21 possible components
Eigenvalues: (Sum=21, Average=1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	4.7126	1.2099	0.2244	4.7126	0.2244
2	3.5026	1.0816	0.1668	8.2152	0.3912
3	2.4210	0.4895	0.1153	10.6363	0.5065
4	1.9315	0.4695	0.0920	12.5678	0.5985
5	1.4620	0.2190	0.0696	14.0298	0.6681
6	1.2431	0.1662	0.0592	15.2728	0.7273
7	1.0768	0.1707	0.0513	16.3497	0.7786
8	0.9062	0.0108	0.0432	17.2559	0.8217
9	0.8953	0.1708	0.0426	18.1512	0.8643
10	0.7246	0.2218	0.0345	18.8758	0.8988
11	0.5028	0.0661	0.0239	19.3785	0.9228
12	0.4367	0.0231	0.0208	19.8152	0.9436
13	0.4136	0.2139	0.0197	20.2288	0.9633
14	0.1997	0.0169	0.0095	20.4285	0.9728
15	0.1828	0.0497	0.0087	20.6113	0.9815
16	0.1331	0.0483	0.0063	20.7444	0.9878
17	0.0848	0.0060	0.0040	20.8292	0.9919
18	0.0788	0.0321	0.0038	20.9079	0.9956
19	0.0467	0.0151	0.0022	20.9546	0.9978
20	0.0316	0.0178	0.0015	20.9862	0.9993
21	0.0138	---	0.0007	21.0000	1

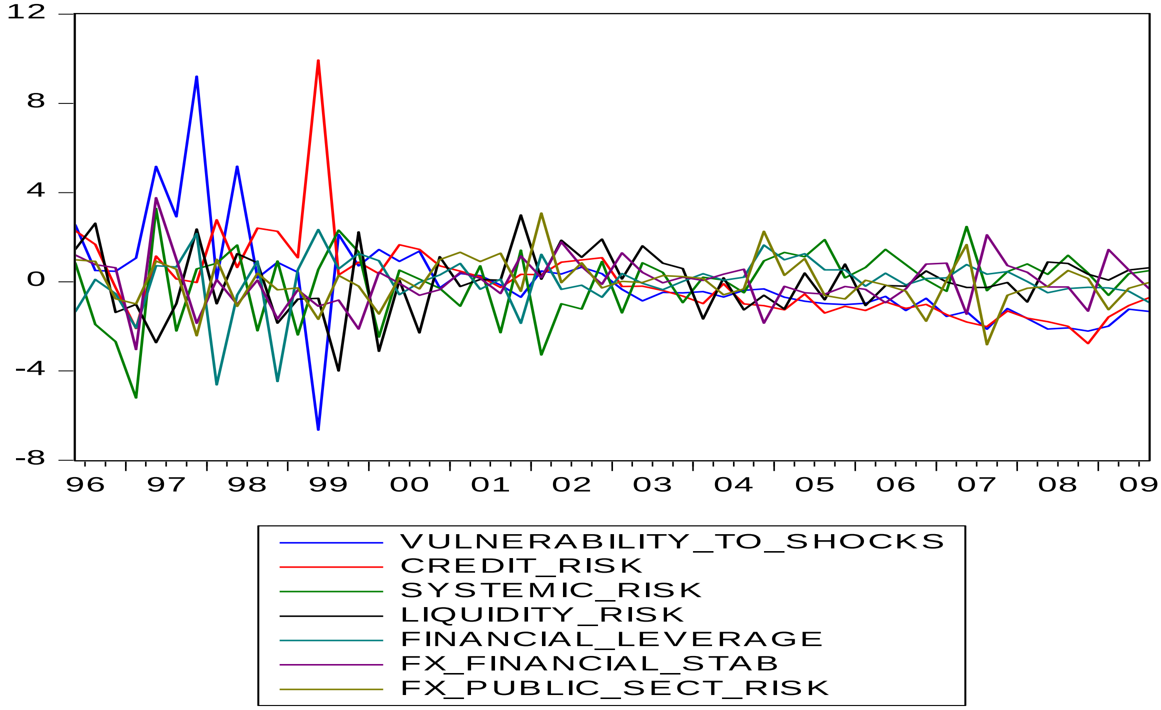
Table 6. Micro EWS. PCA Eigenvectors (Loadings).

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7
12M GROWTH DEP	0.141	0.060	0.092	-0.322*	0.394*	0.146	-0.101
DIF (CAP/AS)	-0.314*	0.335*	0.110	-0.122	-0.006	0.107	0.049
DIF (DEP/LOA)	0.100	0.136	0.178	-0.453*	0.025	-0.244	-0.204
DIF(DEP REPO/AS)	0.195	0.056	0.353*	-0.098	0.243	0.426*	0.043
DEP/AS	0.289	0.295	0.066	-0.003	0.102	0.167	0.110
DIF(FX LIAB/FX AS)	0.073	-0.101	0.210	-0.114	0.047	-0.404*	0.660*
DIF(IMP DEP RT)	-0.107	0.152	0.317*	0.412*	-0.153	-0.031	-0.044
DIF(INT INC/AS)	-0.054	0.178	0.270	0.385*	0.089	0.015	0.028
DIF(INVESTMENTS/AS)	0.152	0.179	0.468*	-0.083	-0.130	0.201	0.002
DIF(LOAN LOSS RES/AS)	0.356*	-0.288	0.053	0.132	-0.067	-0.040	-0.092
DIF(LOAN SEC P/AS)	0.186	-0.079	0.007	0.223	0.493*	-0.162	-0.321*
DIF(LOANS/CAP)	-0.113	-0.022	-0.190	0.195	0.429*	0.122	0.090
DIF(NPL/AS)	0.290	-0.359*	0.013	0.031	-0.048	0.218	0.146
DIF(NPL/LOA)	0.316*	-0.333*	0.056	0.001	-0.206	0.070	0.086
DIF(PUBLIC SECT L/AS)	0.057	0.144	-0.281	0.111	0.347*	-0.017	0.381*
DIF(SALARIES/AS)	0.016	0.036	0.266	0.373*	-0.039	-0.222	-0.033
FIN INST L LOA	0.259	0.266	-0.161	-0.110	-0.114	-0.324*	-0.268
FX DEP/FX AS	-0.137	-0.160	0.339*	-0.167	0.260	-0.349*	0.111
LIQUID AS/AS	0.277	0.307*	-0.178	0.075	-0.124	0.169	0.182
NET INC/AS	-0.359*	-0.150	0.013	-0.158	-0.110	0.269	0.146
NON INT INC/AS	-0.232	-0.338*	0.133	0.006	0.133	0.148	-0.245

Notes: * indicates loading values greater than 0.30.

In order to obtain out-of-sample values of the principal components series, the best ARIMA model according to a SC is fitted to each series. A dynamic forecasting method is applied, where at each *h*-ahead step the residuals employed in the forecasting function are formed using the forecasted value of the dependent variable and not its actual value at that time.

Graph 1. Micro EWS, Retained Principal Components.



Once all the explanatory variables have been forecasted throughout the 2009Q4 to 2011Q1 period, we are ready to fit a multiple regression of the differenced EWS series on the current and lagged values of the principal components and its lags. According to the criteria mentioned before, one final model has emerged (see Table 7).

Table 7. EWS. ADL Model with PCA factors

Dependent Variable: DIF(EWS)

Method: Least Squares

Sample (adjusted): 1997Q2 2009Q3

Included observations: 50 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CR(-2)	-0.175	0.075	-2.350	0.024
FX FIN	-0.338	0.119	-2.835	0.007
FX FIN(-4)	0.220	0.124	1.780	0.082
LEV	-0.369	0.121	-3.039	0.004
SYST(-3)	-0.264	0.084	-3.131	0.003
FX PUB(-3)	-0.384	0.120	-3.206	0.003
DIF(EWS)(-2)	-0.335	0.133	-2.509	0.016
DIF(EWS)(-4)	-0.223	0.121	-1.840	0.073

R-squared	0.424	Mean dependent var	-0.021
Adjusted R-squared	0.328	S.D. dependent var	0.994
S.E. of regression	0.815	Akaike info criterion	2.573
Sum squared resid	27.872	Schwarz criterion	2.879
Log likelihood	-56.337	Hannan-Quinn criter.	2.690
Durbin-Watson stat	2.341		

As shown in Table 7, the coefficients are significant at the 10 per cent level. The Adjusted R-squared with 0.328 is relatively low. Moreover, a 2.341 value for Durbin-Watson statistics indicates negative autocorrelation in the residuals. Findings show a low performance of the principal components when they are used as regressors on the EWS series. Relaxing our predetermined restraints, for example allowing for a larger number of lags, would improve the model in-sample performance, but it would lead to even worse out-of-sample results.

Subsequently our technique is tested against the forecasting of the AFSI time series. A PCA is run on the 18 variables composing the index, over the subsample from 2000Q2 to 2009Q2. (see Table 8 and 9).

Table 8. AFSI Variables. PCA Eigenvalues.

Principal Components Analysis
Sample: 2000Q2 2009Q2
Included observations: 37
Computed using: Ordinary correlations
Extracting 18 of 18 possible components
Eigenvalues: (Sum = 18, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.9781	0.3873	0.1655	2.9781	0.1655
2	2.5909	0.6243	0.1439	5.5690	0.3094
3	1.9666	0.1261	0.1093	7.5356	0.4186
4	1.8405	0.1234	0.1023	9.3762	0.5209
5	1.7171	0.5401	0.0954	11.0933	0.6163
6	1.1770	0.0760	0.0654	12.2703	0.6817
7	1.1010	0.0623	0.0612	13.3713	0.7429
8	1.0387	0.1359	0.0577	14.4101	0.8006
9	0.9028	0.3346	0.0502	15.3129	0.8507
10	0.5683	0.0503	0.0316	15.8811	0.8823
11	0.5179	0.0950	0.0288	16.3991	0.9111
12	0.4230	0.0536	0.0235	16.8220	0.9346
13	0.3694	0.0968	0.0205	17.1914	0.9551
14	0.2726	0.0466	0.0151	17.4640	0.9702
15	0.2260	0.1013	0.0126	17.6899	0.9828
16	0.1247	0.0148	0.0069	17.8147	0.9897
17	0.1099	0.0344	0.0061	17.9246	0.9958
18	0.0755	---	0.0042	18	1

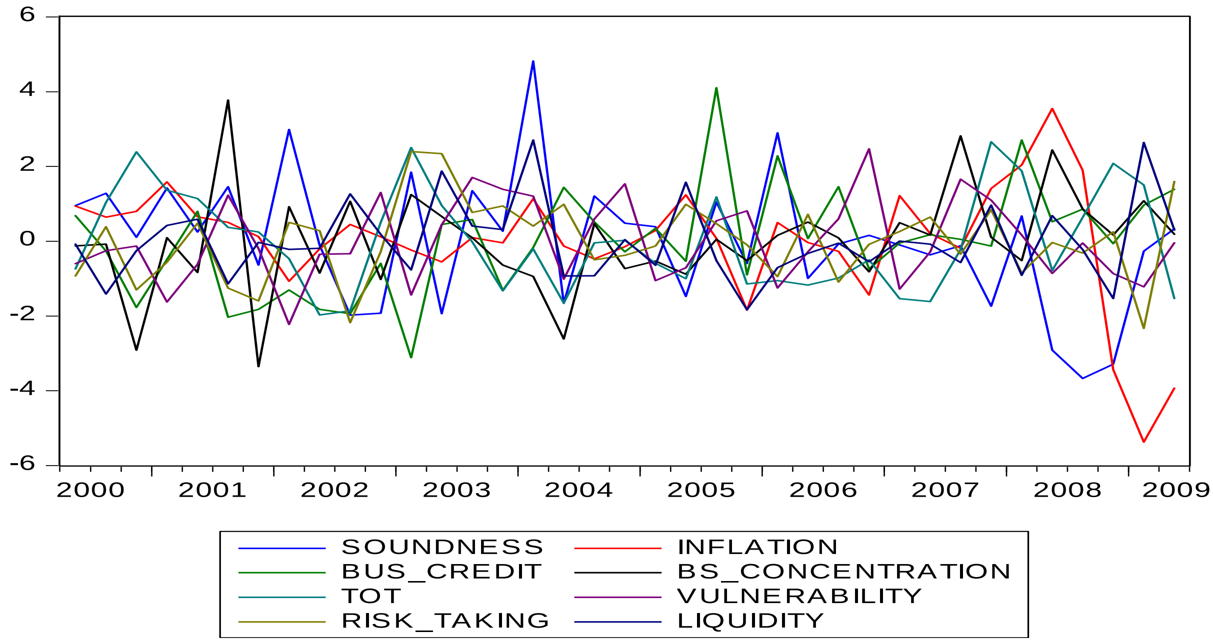
Table 9. AFSI Variables. PCA Eigenvectors (Loadings).

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
CURR ACC DEF/GDP	0.294	-0.264	-0.164	-0.359*	0.075	-0.058	0.035*	-0.060
DEP/M2	0.285	0.038	-0.192	0.133	0.423*	-0.092	0.316*	-0.208
DIF(CAP/AS)	0.012	0.202	0.378*	-0.405*	0.125	0.119	-0.193	0.077
DIF(EC CLIMATE)	0.321*	-0.178	0.002	0.059	-0.384*	-0.009	0.371*	-0.011
DIF(HHI)	0.201	0.039	-0.234	0.416*	0.007	0.252	-0.405*	0.107
DIF(INT SPREAD)	-0.029	-0.344*	0.212	0.049	0.184	-0.030	-0.278	0.509*
DIF(LIQ RATIO)	0.107	-0.323*	0.035	0.178	0.169	0.087	-0.185	-0.399*
DIF(MKT CAP/GDP)	0.259	0.022	-0.265	-0.126	0.065	0.425*	0.149	0.424*
DIF(NONGOV CR/CRED)	0.092	-0.013	0.408*	0.253	0.055	0.463*	0.069	-0.218
DIF(NPL/LOA)	-0.139	-0.159	0.424*	0.288	-0.120	0.123	0.315*	0.028
DIF(RES INFL)	0.078	0.432*	0.054	0.098	0.169	0.225	0.165	0.332*
DIF(RES LOA/DEP)	-0.455*	0.135	-0.191	-0.051	-0.168	-0.089	0.159	0.054
DIF(RES TOTCR/GDP)	-0.256	-0.027	-0.405*	0.405*	-0.061	0.066	0.025	0.077
DIF(RES WORLD GROWTH)	0.203	0.348*	-0.020	-0.124	-0.344*	0.209	0.111	-0.178
DIF(RESDEP/CASHM2)	0.222	0.107	0.261	0.303*	-0.170	-0.500*	0.105	0.291
GEN BUDGET DEF/GDP	0.407*	0.261	0.002	0.130	0.095	-0.355	-0.172	-0.023
REER	-0.108	-0.112	0.000	-0.017	0.516*	-0.062	0.459*	0.096
WORLD INFLATION	-0.186	0.433*	0.069	0.122	0.293	-0.070	-0.081	-0.211

Notes: * indicates loading values greater than 0.30.

Accordingly to the predetermined criteria 8 out of 18 principal components were retained. Graph 2 shows their behaviour over time.

Graph 2. AFSI Variables. Retained Principal Components.



See Table 10 for the regression model used to forecast the AFSI.

Table 10. AFSI. ADL model with PCA factors.
Dependent Variable: DIF_AFSI
Method: Least Squares
Sample (adjusted): 2000Q3 2009Q2
Included observations: 36 after adjustments

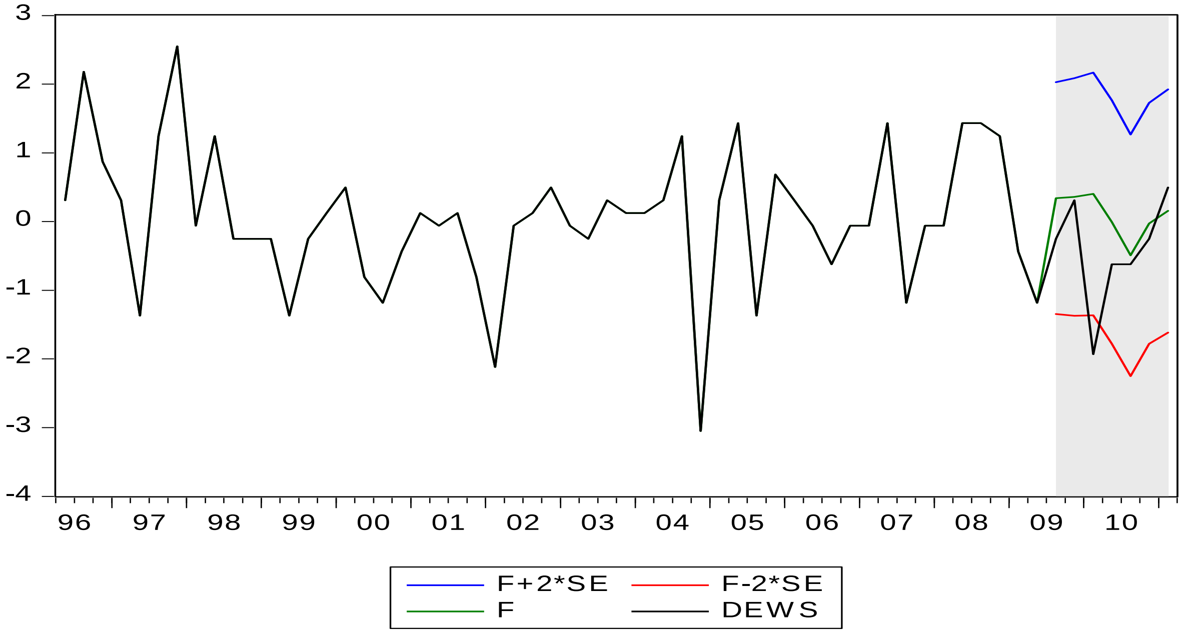
Variable	Coefficient	Std. Error	t-Statistic	Prob.
SOUNDNESSF	0.399	0.050	7.985	0.000
INFLATIONF	-0.140	0.052	-2.688	0.011
DIF_AFSI(-1)	-0.368	0.086	-4.254	0.000

R-squared	0.772	Mean dependent var	0.014
Adjusted R-squared	0.758	S.D. dependent var	1.028
S.E. of regression	0.506	Akaike info criterion	1.554
Sum squared resid	8.441	Schwarz criterion	1.686
Log likelihood	-24.975	Hannan-Quinn criter.	1.600
Durbin-Watson stat	1.885		

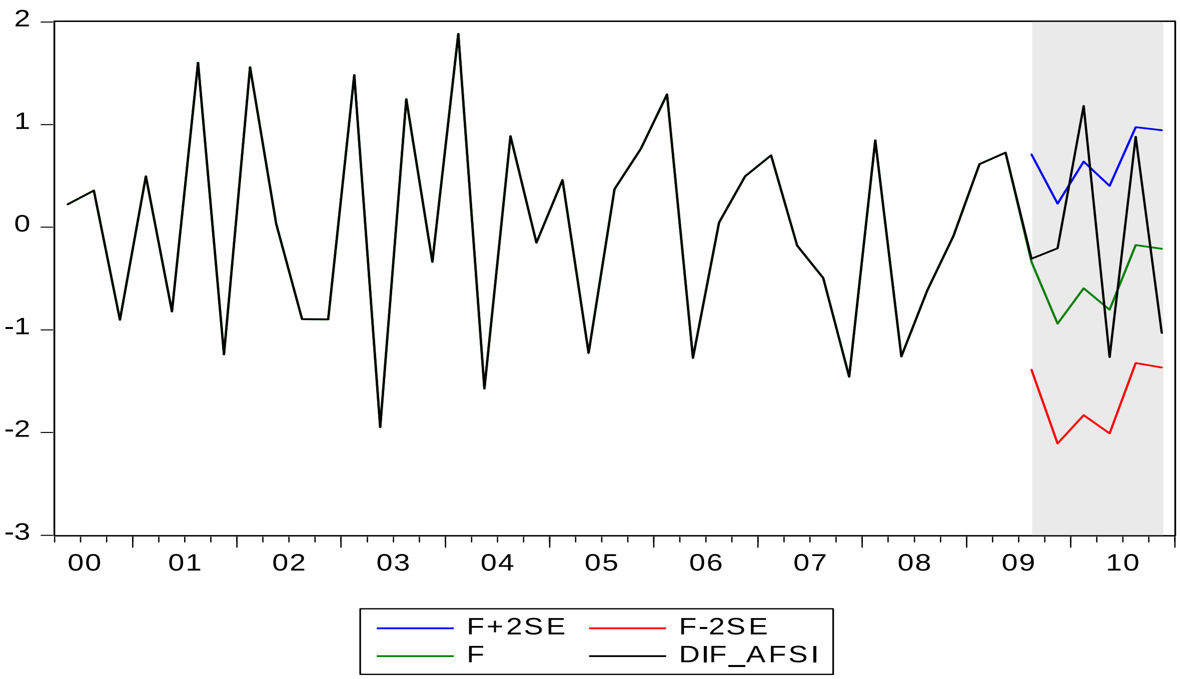
Now the regression coefficients are significant at the 5% level. High values for the Adjusted R-squared (0.758) and the SC (1.686) point out a good fit on the dependent variable. Just the first two principal components together with a one period lagged AFSI can explain much of the changes in the AFSI. An increase in the AFSI is positively related to an increase in an indicator of soundness of the financial system, and negatively related to an indicator of price sensitivity. Furthermore a decrease of the AFSI occurred in the last quarter negatively affects the current value of the AFSI.

Graphs 3 and 4 display in grey the out-of-sample forecasts for the changes in EWS and AFSI respectively.

Graph 3. Changes in EWS Out-of-Sample Forecast.



Graph 4 Changes in AFSI Out-of Sample Forecast



At this point we illustrate in Table 11 the forecasting performances of the EWS and AFSI against the benchmark models. These models are evaluated relying on two different forecasting performance measures: the relative Root Mean Square Error (RMSE) and the Theil inequality coefficient. The Mean Absolute Percentage Error (MAPE) will not be employed as it is not reliable if the series can take on absolute values less than one (Brooks, 2001).

Table 11. Out-of Sample Forecasts Performance

	EWS		AFSI	
Model	Rel RMSE	Theil Coefficient	Rel RMSE	Theil Coefficient
Naïve	1.000	0.785	1.000	0.757
ARIMA	0.988	0.708	1.029	0.878
ADL with PC	1.190	0.873	0.786	0.651

In the case of the EWS prediction the best model resulted the ARIMA, which slightly improved its out-of-sample performance against the Naïve model (Rel RMSE=0.988). This is also confirmed by the lower level of the Theil Coefficient in the panel. On the other hand, the ADL model with principal components fails in providing more accurate forecasts as it is witnessed by its higher values of Relative RMSE and Theil Coefficient.

The proposed ADL model with principal components is instead the best model in the panel when the AFSI is forecasted. Not only it leads to a significant improvement in its RMSE relatively to that of the Naïve model (Rel RMSE=0.786), but it also features a quite low level of Theil Inequality Coefficient (Theil=0.651).

6. Conclusions

This paper summarizes the two different approaches to the construction of early warning indicators for the prevention of financial crises: the nonparametric “signaling approach” and the aggregate single index. A specific forecasting technique using Principal Component Analysis (PCA) is tested against a naïve and a standard model for two examples of such approaches, the Early Warning System (EWS) developed by Langrin (2002) and the Aggregate Financial Stability Index (AFSI) constructed by Morris (2010). Findings are that the proposed forecasting method does not provide with a good out-of-sample performance when it is used to predict the EWS. Instead it significantly improved its prediction power in the case of the AFSI. Indeed, the ADL model with PCA factors resulted to be superior to benchmark models when forecasting a financial aggregate single index.

The main drawback of our model is hence that its predictive power with respect to the EWS is low. We believe that this may arise from the definition itself of the dependent variable, which it is constructed by putting together observations that rely on tranquil periods which change over time. This implies the variable definition to be constantly changing over time. The problem increases when the period after the 96-98 crisis in comparison with the former period is considered. The choice of opting for the period 1991-1994 as a signalling period may have lead to non-robust EWS values for the period immediately after the 1996-1998 crises, as already remarked by Langrin (2002). An alternative forecasting method is left to future research. This would be to forecast each micro- and macroeconomic indicator composing the EWS and then use these forecasted values to compute the new EWS scores. Another limitation in our EWS forecast is that only data from Jamaican commercial banks balance-sheets was employed. Thus an analysis that would relie on a set of data including information from both building societies and merchant banks as well as macro indicators may increase our knowledge on the EWS series behaviour. Nonetheless we reckon that most significant improvements would derive by using an alternative method when the EWS is forecasted.

In the case of the AFSI, further refinements to our study are left to future research. Among these it is to be considered the following. In our ADL model with principal components the Durbin-Watson statistic alerted the presence of positive autocorrelation in the residuals. Principal component analysis is a large-sample procedure. Our research relied to a number of observations as small as 36 after adjustments and this may have lead such a problem. Two options appear to be available to enlarge our data set. First, one can employ as regressors only higher frequency variables. Another option is to increase the frequency of some variables by estimating the values that are not directly available. This would allow incorporating the information on high-frequency variables without discarding the low-frequency ones.[11]

Furthermore, our method might be checked for robustness to changes in the model specification. Particularly, factor variables could be allowed to have a number of lags greater than four quarters.[12] As it was already discussed in Section 4 there is no definitive answer about the number of components to retain. Thus, a different number of components retained would lead to different model specifications, affecting the forecast performances. For instance, Stock and Watson (2002) also choose the number of components to retain by a SC.

Different scaling options determine the weights to be applied to eigenvalues in the calculation of factor scores. In our study we opted for normalizing loadings as to have scores with variances equal to the corresponding eigenvalues. Stock and Watson (2002) and Gosselin and Tkacz (2001) instead propose a different scaling. In their study Λ is obtained by setting it equal to $\mathrm{N}^{1/2}$ times the eigenvectors of the $N \times N$ matrix $X'X$

[11] Brave and Butters (2011) suggest a framework that allows them to make use of weekly, monthly and quarterly financial indicators with histories that potentially begin and end at different times.

[12] Hanshel and Monnin (2005) employ a number of lags up to four years in their forecasting model. However preliminary attempts in this way were not promising and this option was finally discarded from our analysis.

corresponding to its $\bar{r}$ eigenvalues, so that the scores are proportional to the square roots of the eigenvalues. PCA is heavily reliable on scaling, hence this may have deeply affected the performance of our forecast model.

Finally, the linear forecasting technique proposed by Stock and Watson (2002) could also be experimented and tested against the method used in this paper. Also, in order to have data for the exogenous variables be available for every observation in the forecast sample, a Monte Carlo Simulation using the fitted distributions, the correlation between the variables and the coefficients from the OLS model may be computed.

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