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A Financial Stability Index for Israel

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Abstract

An integral financial stability index is constructed using Israel macroeconomic data. Approaches relying on the use of dependent variable as well as principal component method and its modifications are examined. Obtained indexes are compared in terms of their forecast quality. In the case of no dependent variable the influence of structural shift is analyzed.

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Keywords: financial stability; principal components method; multiple regression; integral index; Israel

1. Introduction

The global financial crisis of 2008 had a significant impact on the countries' economies and revealed a problem of integral index construction that would reflect the country's financial stability level evolution in time. In this paper the examples of integral financial stability index (IFSI) constructing using both methods involving dependent variable and methods based on principal components are presented.

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2. Literature overview

In 2003 International Monetary Fund (IMF) has proposed a list of 39 individual financial stability parameters (Financial Soundness Indicators — FSI) in order to monitor the level of financial soundness[1,2]. However simultaneous multidirectional movements of these indicators make their set of trends difficult to interpret. The unique integral index based on these parameters should potentially solve the problem.

The problem of integral index construction have already been solved for some countries[3,4,5] as well as for the global world economy[6]. For individual countries' indexes construction weighted average[3,4]/blocked weighted average[5,7] or principal components[4,8] methods were often used. Columbia's index was also build using the dependent variable — number of bankruptcies[4].

However there is generally no forecasting power analysis in these studies. The comparison of different methods in terms of their forecasting power also was not made.

3. Data

Quarterly data ranging from 1Q2003 to 3Q2013 (42 periods) for Israel is employed. The (dependent) variables used to build the index are 16 (out of 39) Financial Soundness Indicators being collected by IMF on regular basis. The dependent variable is Economic Resilience (ER) indicator collected by International Institute for Management Development (IMD). This index ranges from 2002 to 2013 on a yearly basis; its values are scores from 0 to 10 where 0 corresponds to the lowest financial soundness and 10 — to the highest. The quarterly values of ER were obtained through the linear (Yl) or spline (Ys) interpolation procedure. Table 1 presents a summary of the data.

Table 1. Summary of the dataset

ID	Variable	UoM	Max	Min	Mean	Std. err.
X1	Assets to Gross Domestic Product (GDP)	Ratio	140.97	90.35	122.42	12.79
X2	Assets to Total Financial System Assets	Ratio	30.47	22.20	26.66	1.88
X3	Commercial Real Estate Loans to Total Loans	Ratio	18.23	14.57	16.30	0.99
X4	Customer Deposits to Total (Non-interbank) Loans	Ratio	118.34	102.89	112.20	4.40
X5	Earnings to Interest and Principal Expenses	Ratio	377.53	143.59	283.63	60.67
X6	Foreign-Currency-Denominated Liabilities to Total Liabilities	Ratio	43.41	27.73	36.11	5.36
X7	Foreign-Currency-Denominated Loans to Total Loans	Ratio	37.09	14.88	26.31	7.09
X8	Household Debt to GDP	Ratio	41.89	36.29	39.64	1.33
X9	Interest Margin to Gross Income	Ratio	66.21	39.95	61.23	4.14
X10	Non-interest Expenses to Gross Income	Ratio	120.21	58.87	67.66	10.14
X11	Personnel Expenses to Non-interest Expenses	Ratio	64.88	56.24	60.13	1.96
X12	Residential Real Estate Loans to Total Loans	Ratio	32.09	19.17	24.58	3.73
X13	Residential Real Estate Prices	%	19.87	–8.55	4.88	7.59
X14	Return on Assets	Ratio	1.40	–0.61	0.84	0.36
X15	Return on Equity	Ratio	42.09	12.83	32.24	7.17
X16	Total Debt to Equity	Ratio	256.96	208.16	226.90	12.12
Y		Score	7.28	4.14	6.03	1.13
Yl		Score	7.13	4.14	6.02	1.00
Ys		Score	7.23	4.11	6.01	1.05

The correlation matrix for independent variables' time series presented in Table 2, where red indicates significance at 1% level, blue — at 5% level.

Table 2. Independent variables' correlation matrix

ID	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15
X1	1														
X2	0,93	1													
X3	–0,83	–0,82	1												
X4	–0,58	–0,58	0,33	1											
X5	0,2	0,11	–0,23	0,13	1										
X6	–0,75	–0,8	0,68	0,73	0,15	1									
X7	–0,88	–0,88	0,84	0,69	0,05	0,94	1								
X8	0,26	0,3	–0,12	–0,53	–0,12	–0,62	–0,4	1							
X9	–0,24	–0,31	0,17	0,18	0,07	0,05	0,18	0,36	1						
X10	0,29	0,35	–0,24	–0,46	–0,01	–0,22	–0,33	–0,09	–0,84	1					
X11	–0,46	–0,46	0,18	0,54	0,36	0,57	0,53	–0,34	–0,02	0,05	1				
X12	0,82	0,88	–0,85	–0,52	–0,03	–0,93	–0,93	0,5	–0,05	0,15	–0,44	1			
X13	0,77	0,75	–0,47	–0,76	–0,15	–0,65	–0,71	0,37	–0,18	0,3	–0,61	0,61	1		
X14	0,05	–0,09	–0,15	0,41	0,34	0,09	0,08	–0,03	0,7	–0,84	0,09	0,08	–0,17	1	
X15	–0,04	–0,17	–0,1	0,48	0,68	0,3	0,25	–0,16	0,55	–0,63	0,4	–0,11	–0,35	0,86	1
X16	–0,06	0,11	–0,08	–0,28	–0,62	–0,33	–0,28	0,12	–0,32	0,43	–0,14	0,21	0,03	–0,59	–0,7

4. Methodology

As indicators selected measured in different units and their values are of different order of magnitude preliminary transforming procedure is used. New standardized values of dependent variables obtained with following formulas[9]:

$$\widetilde{X}_{it} = 10\frac{X_{it} - X_i^{\min}}{X_i^{\max} - X_i^{\min}} \tag{1}$$

$$\widetilde{X}_{it} = 10\frac{X_i^{\max} - X_{it}}{X_i^{\max} - X_i^{\min}} \tag{2}$$

where $X_i^{\min}$ — minimum value of indicator, $X_i^{\max}$— minimum value of indicator.

Equation 1 is applied to the indicators which associated with greater financial stability. For remaining indicators formula 2 is used.

The methods proposed can be divided into three groups:

- The principal components (PC) method and its modifications. These methods don't need the dependent variable. The IFSI for this group is simply the first principal component. Besides the PC method itself two its modifications — the modified principal components method (MPC) and the principal components method with positive weights (PCPW) are used
- Regression models
- Hybrid methods. These methods also based on (multiple) regression but only variables having a great contribution to the IFSIs in the first group are used

4.1. The principal components (PC) method and its modifications

The principal components (PC) method[10] uses the following constraints on the variables' weights:

$$\vec{c}_j^{\,T}\vec{c}_j = 1, \tag{3}$$

Here $\vec{c}_j$ — the vector of the initial factors' weights in the j-th principal component (generally speaking, of different signs). To make possible the comparisons of IFSIs obtained by different methods the normalization formula is used:

$$\tilde{c}_{ij} = \frac{c_{ij}}{\sum_{i=1}^{k} |c_{ij}|} \tag{4}$$

where i — the factor's index number, c_{ij} — i-th factor's weight in the j-th principal component.

The modified principal components method[11] **(MPC)** differs from the previous one only in weights modification formula:

$$\tilde{c}_{ij} = \begin{cases} \dfrac{c_{ij}}{\sum_{i=1}^{k} c_{ij}}, & if\ \forall c_{ij} \geq 0\ for\ given\ i; \\ c_{ij}^2, & otherwise. \end{cases} \tag{5}$$

The principal components method with positive weights (PCPW). The method expands the constraints with the following expression:

$$c_{ij} \geq 0, \forall j \tag{6}$$

Weights modification formula for this method is:

$$\tilde{c}_{ij} = \frac{c_{ij}}{\sum_{i=1}^{k} c_{ij}} \tag{7}$$

As can be seen the PC procedure seeks a point(s) on an n-dimensional hypersphere of radius equals to one. The coordinates of this (these) point(s) when used as factors' weights maximize the total variance of initial standardized factors. The MPC then shifts the obtained point(s) to the "positive" side of the hypersphere and PCPW restricts the searching aria allowing coordinates only be non-negative.

At least 2 IFSIs can be constructed with PC: if $\vec{a}$ is principal component then $-\vec{a}$ is principal component too. The choice between $\vec{a}$ and $-\vec{a}$ will be made in favor of that vector which have a positive correlation with Yl (Ys).

4.2. Regression models

Firstly the number of independent variables (except intercept) and the significance level are set. Then given these restrictions all possible regressions are evaluated. Finally the regression having maximum value of R-squared and all parameters significant at given level is selected. Hereinafter the significance level will be set at 5% and the results of this method will be denoted as “Reg(*)” where * in brackets will be replaced by the number of independent variables in regression.

4.3. Hybrid method

For each of methods in the first group the set of factors having the cumulative weight not less than 50% is defined. Only these sets are then used in multiple regression model. If some factor is not significant (at 5% level) it is removed from the model (backward elimination). The results of this method will be marked as “Reg(**)” where ** in brackets indicates the model from the first group which defines the “short list” of factors.

It’s clear that the IFSIs obtained with the first group of methods can reflect only the dynamics of financial stability, not the absolute values. I.e. generally speaking the IFSIs’ values not necessary coincide with the values Yl or Ys. In order to simplify comparative analysis indexes were transformed using the coefficients obtained from the regression:

$$Y_t^* = \beta \cdot IFSI_t + C + \varepsilon_t \tag{8}$$

Here Y_t^* — dependent variable Yl or Ys

For further analysis the original sample was divided into two parts: the “learning” part (1Q2003–2Q2011, 34 values for each variable) was utilized for index construction and the second part was used to verify the forecast accuracy for each index and compare different IFSIs. To measure the quality models Pearson and Spearman correlation coefficients were explored

5. Results

There was not a big difference between the results for taking Yl and Ys as dependent variable (where necessary). So only the results for Yl are presented.

One of the main result characteristics obtained with the principal component methods is the proportion (r) of baseline factors’ total variance (equal to the sum of their dispersions) explained by the first principal component. To make a comparison the initial (before normalizing procedure) coefficient vectors are used. As MPC estimates were gained implicitly i.e. not at the computational step but afterwards at the normalization step, before comparison they must be transformed:

$$\hat{c}_{i1} = \frac{\tilde{c}_{i1}}{\sqrt{\sum_{i=1}^{k} \tilde{c}_{i1}^2}} \tag{9}$$

The coefficients’ estimates are presented in Table 3. Cumulative weight is the cumulative sum of the individual factors’ weights. The negative weight indicates that the factor included in IFSI calculation with negative sign.

Table 3. Normalised weights of individual factors for the first group of methods. Factors ordered by descending of their contribution to IFSI obtained by MPC

	PC ($r = 52\%$)		MPC ($r = 2.7\%$)		PCPW ($r = 29\%$)	
	Weight	Cumulative weight, %	Weight	Cumulative weight, %	Weight	Cumulative weight, %
X7	0.116	11.6	0.150	15.0	0.222	22.2
X6	0.110	22.7	0.135	28.5	0.214	43.6
X13	–0.108	33.4	0.128	41.3	0	43.6
X4	0.107	44.1	0.127	54.0	0.211	64.7
X12	–0.102	54.3	0.116	65.6	0	64.7
X2	–0.093	63.6	0.096	75.2	0	64.7
X1	–0.092	72.8	0.094	84.6	0	64.7
X3	0.085	81.3	0.080	92.6	0.156	80.3
X11	0.056	86.9	0.035	96.1	0.107	91.0
X8	–0.033	90.2	0.012	97.3	0	91.0
X15	–0.033	93.5	0.012	98.5	0	91.0
X10	0.030	96.5	0.010	99.5	0.059	96.8
X14	–0.015	98.0	0.003	99.7	0	96.8
X9	0.015	99.5	0.003	100.0	0.029	99.7
X16	–0.003	99.8	0.000	100.0	0	99.7
X5	–0.002	100.0	0.000	100.0	0.003	100.0

Thus, the best in terms of maintaining maximum information from the initial factors is PC. However, this method gives a negative weight to many factors that complicates the interpretation of the IFSI as the initial factors' standardization procedure implies positive weights to all factors. MPC solves this problem, but it uses only a small part of the information contained in the individual indicators' series (2.7 %). Above-mentioned problems can be avoided by using PCWC.

Table 4 presents the results of applying the second group of methods to the "learning" sample and their main characteristics. Regression were estimated for one, two or three indicators.

Table 4. The results of applying the second group of methods to the "learning" sample

		X3	X7	X13	X16	intercept	R-Squared	Adj R-Sq
Reg(1)	Coeff. estimate	0.2987				4.0287	0.8651	0.8609
	Std. error	0.0209				0.13998		
	T-statistics	14.33				28.78		
	p-value	<.0001				<.0001		
Reg(2)	Coeff. estimate	0.3136			–0.0813	4.48013	0.9033	0.897
	Std. error	0.0184			0.02325	0.17655		
	T-statistics	17.01			–3.5	25.38		
	p-value	<.0001			0.0014	<.0001		
Reg(3)	Coeff. estimate	0.2194	0.2197	0.1614		2.71471	0.9348	0.9283
	Std. error	0.024	0.0395	0.0317		0.27858		
	T-statistics	9.14	5.56	5.09		9.74		
	p-value	<.0001	<.0001	<.0001		<.0001		

Table 5 presents the results of applying the third group of methods to the “learning” sample and their main characteristics

Table 5. The results of applying the third group of methods to the “learning” sample

		X4	X6	X7	X12	X13	Intercept	R- Sq	Adj R-Sq
Reg (МГК)	Coeff. estimate	0.082	-0.425	0.611	-0.194	0.245	4.367	0.953	0.944
	Std. error	0.038	0.049	0.045	0.055	0.035	0.431		
	T-statistics	2.150	-8.750	13.530	-3.520	7.080	10.130		
	p-value	0.041	<.0001	<.0001	0.002	<.0001	<.0001		
Reg (ММГК)	Coeff. estimate		-0.338	0.709		0.176	3.170	0.932	0.925
	Std. error		0.038	0.041		0.032	0.293		
	T-statistics		-8.860	17.340		5.490	10.820		
	p-value		<.0001	<.0001		<.0001	<.0001		
Reg (ПМГК)	Coeff. estimate		-0.390	0.613			4.714	0.863	0.855
	Std. error		0.051	0.051			0.114		
	T-statistics		-7.600	11.920			41.390		
	p-value		<.0001	<.0001			<.0001		

Finally the main results of different IFSIs comparative analysis presented in Table 6. The Pearson correlation coefficient calculated separately for both “learning” sample and the sample for verification. Spearman correlation coefficients calculated only for the second sample. Also the significance levels for correlation coefficients are presented.

The dynamics of IFSIs obtained by different groups of methods in comparison with Yl dynamics shown in fig.1–3.

Table 6. The IFSIs comparative analysis (ρ — Pearson correlation coefficient, ρs — Spearman correlation coefficient)

	PC	MPC	PCPW	Reg(1)	Reg(2)	Reg(3)	Reg (PC)	Reg (MPC)	Reg (PCPW)
ρ (learning)	0.66	0.40	0.68	0.93	0.95	0.97	0.98	0.97	0.93
ρ (verifying)	0.75	–0.83	0.68	0.91	0.88	0.58	–0.05	–0.09	0.16
Significance ρ	>0,05	0.01	>0,05	0.01	0.01	>0,05	>0,05	>0,05	>0,05
ρs (verifying)	0.76	–0.83	0.67	0.90	0.79	0.52	0.21	–0.10	–0.02
Significance ρs	0.05	0.05	>0,05	0.01	0.05	>0,05	>0,05	>0,05	>0,05

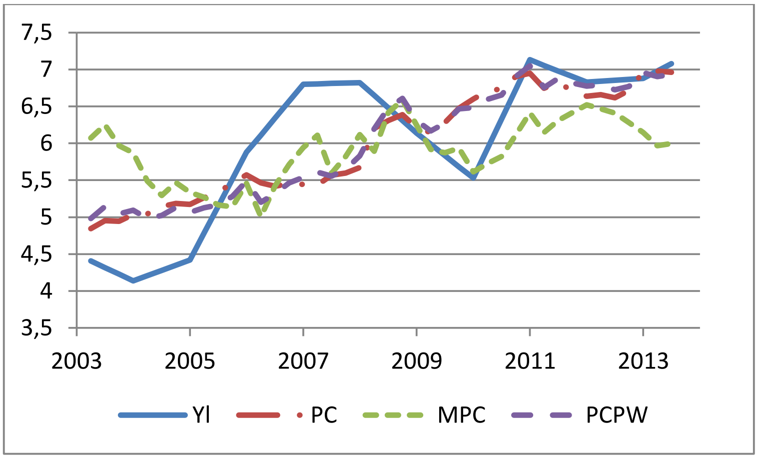

Fig. 1. IFSIs' dynamic for the first group of methods

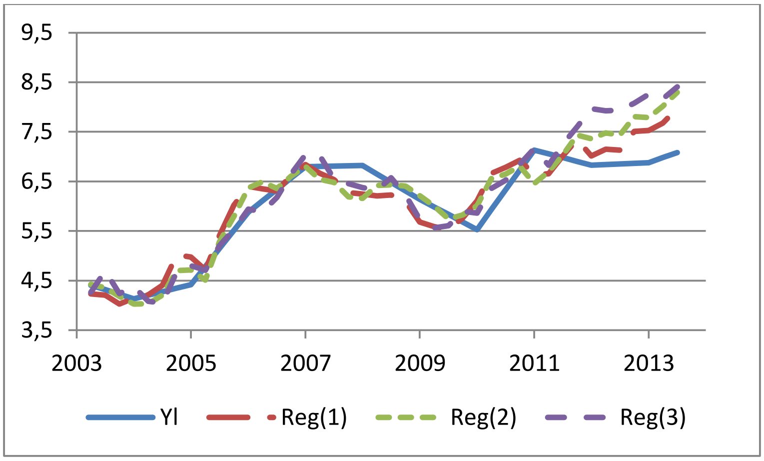

Fig. 2. IFSIs' dynamic for the second group of methods

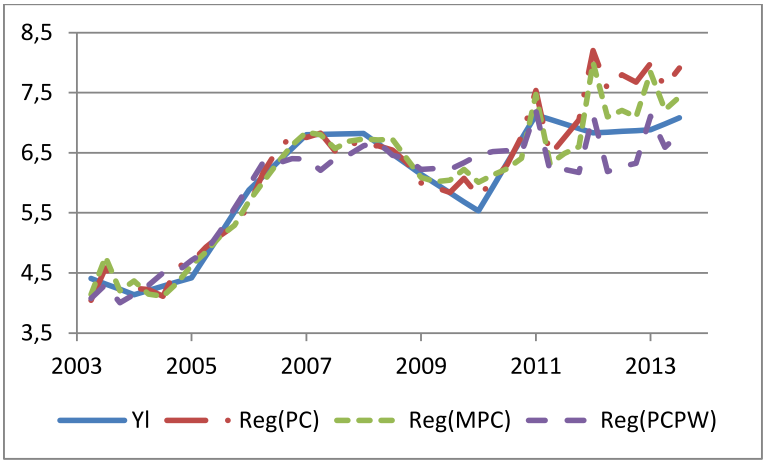

Fig. 3. IFSIs' dynamic for the third group of methods

Comparing the behavior of IFSIs on the learning and examinee samples as well as from the graphs we can conclude that the best approximation quality for Yl is achieved with the second group of methods. Namely "Commercial Real Estate Loans to Total Loans" is the best predictor for Economic Resilience index. This allows us to assume that this factor was used (explicitly or implicitly) in Economic Resilience index construction.

6. Conclusion

Different approaches to the integral financial stability index are presented. 16 macroeconomic variables collected by Bank of Israel were used as independent factors and Economic Resilience index was explored as the benchmark. The methods used can be attributed to one of three following groups: the principal components (PC) method and its modifications; regression models; hybrid methods. Before the calculation all factors transformed with the standardization procedure. IFSI constructed in such a way that its larger value corresponds to greater financial stability. Visual and statistical comparisons of IFSIs then made including Pearson and Spearman correlation.

The analysis conducted allows to make a conclusion that in first group of methods PCPW is the best in terms of its ability to retain the information containing in initial factors and their weights' interpretation.

When all 3 groups of methods are considered then the pairwise regression with "Commercial Real Estate Loans to Total Loans" as independent variable gives the best approximation. This allows us to assume that this factor was used (explicitly or implicitly) in Economic Resilience index construction.

References

1. San Jose A., Krueger R., Khay Ph. The IMF's work on financial soundness indicators // Irving Fisher Committee Bulletin No. 28 (The IFC's contribution to the 56th ISI Session, Lisbon, August 2007). 2008. P. 33–40.
2. Gadanecz B., Jayaram K. Measures of financial stability — a review // Irving Fisher Committee Bulletin No. 31 (Proceedings of the IFC Conference on "Measuring financial innovation and its impact", Basel, 26–27 August 2008). 2009. P. 365–383.
3. Central Bank of the Republic of Turkey. Financial Stability Report. 2009. P. 74.
4. Morales M., Estrada D. A financial stability index for Colombia // Annals of Finance. 2010. Vol. 6. P. 555–581.
5. Geršl A., Hermánek J. Indicators of Financial System Stability: Towards an Aggregate Financial Stability Indicator? // Prague Economic Papers. 2008. Vol. 3. P. 127–142.
6. Dattels P., McCaughrin R., Miyajima K., Puig J. Can You Map Global Financial Stability? IMF WP/10/145.
7. Cheang N., Choy I. Aggregate Financial Stability Index for an Early Warning System. 2011. P. 27–51
8. Brave S., Butters A. Monitoring Financial Stability: A Financial Conditions Index Approach // Economic Perspectives. 2011. Vol. 35, No. 1. P. 22–43.

9. Айвазян С.А., Степанов В.С., Козлова М.А. Измерение синтетических категорий качества жизни населения региона и выявление ключевых направлений совершенствования социально-экономической политики (на примере Самарской области и ее муниципальных образований) // Прикладная эконометрика. 2006. № 2. С. 18–84.
10. Айвазян С.А., Мхитарян В.С. Прикладная статистика и основы эконометрики. М.: ЮНИТИ, 1998.
11. Айвазян С.А. Анализ качества и образа жизни населения. М.: Наука, 2012, 432 с.