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Measuring Stress and Risks to the Financial System in Israel on a Radar Chart

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מדידה של לחץ וסיכונים למערכת הפיננסית בישראל באמצעות דיאגרמת רדאר

חנן זלקינדר

תקציר

המשבר הפיננסי של 2008 הדגיש את החשיבות ואת הצורך במדדים ואינדיקטורים טובים יותר ללחץ פיננסי אשר יכולים לסייע לזהות נקודות תורפה וחוסר איזון במערכת הפיננסית.

במאמר זה אנו מפתחים דרך אינטואיטיבית ואינפורמטיבית להציג את מסת הנתונים הקשורים ללחץ פיננסי בישראל. בשלב הראשון, אנו מציגים שיטה לבניית מדדים המשקפים סיכונים אשר מקורם במערכת הפיננסית בישראל וכן סיכונים חיצוניים אשר עלולים להשפיע עליה. בשלב שני, אנו מציגים שיטה גרפית להצגת המדדים הללו המוכרת כדיאגרמת רדאר. אנו מאמינים שההצגה מהווה נקודת התחלה אינטואיטיבית לדיונים שעוסקים במערכת הפיננסית ויכולה לסייע לקובעי מדיניות להעריך טוב יותר את מצבה של המערכת הפיננסית בישראל.

הממצאים שלנו תופסים בהצלחה את הדינאמיקה ואת התפתחות הלחץ הפיננסי בישראל מ 1998-ואילך. על מנת לחזק את הממצאים, אנו מראים שהם אינם תלויים בתצפיות אחרונות על ידי מבחני out-of-sample.

Measuring Stress and Risks to the Financial System in Israel on a Radar Chart

Hanan Zalkinder

Abstract

The recent financial crisis has focused attention on the need for better measures and conceptual indicators of financial stress that can help identify vulnerabilities and imbalances that may threaten the stability of the financial system.

This paper develops for Israel an intuitive and informative way to summarize and display the large amount of data relating to financial stress in Israel. The methodology, known as a Radar Chart, is used widely in the financial stability literature. It consists of a method for constructing indices of internal and external risks to the financial system and a graphic approach for displaying these key indices. Our contention is that our approach provides an intuitive starting point for policymaking discussions, and allows policymakers to better assess the current condition of the financial system.

Our findings successfully capture the dynamics and developments of stress in the financial system in Israel from 1998 onward. We reinforce our results by performing an out-of-sample test showing that our results do not depend on ex post observations.

1. Introduction

The 2008 financial crisis brought to the center of attention the need for better measures and conceptual indicators of financial stress that can help identify vulnerabilities and imbalances that may threaten the stability of the financial system.

Financial stress is defined as the force exerted on economic agents by uncertainty and changing expectations of loss in financial markets and institutions (Illing and Liu, 2003). Since uncertainty and expectations are difficult to measure, the question, "What is the level of stress in the financial system?" is not easy to answer. Nevertheless, data on variables relating to financial stress are available and can be used to learn about this unobservable variable.

Current tools for understanding financial stress in Israel are limited and usually involve the analysis of masses of data and time series. This poses difficulties in the assessment of the state of the financial system and the identification of various sources of potential threat. Our goal is to develop an intuitive and informative way to summarize and display the copious data relating to financial stress. This paper is an initial stepping stone in its area for Israel and should be regarded as a basis for future research.

Gauging financial stress may be an ambiguous endeavor when one looks solely at an aggregated composite indicator. Consequently, a display of several key indices that reflect different parts of the economy may be both informative and easier to grasp, improving policymakers' assessment capabilities. In this paper, we use a Kalman filter to construct key indices of financial stress in Israel and illustrate them via a multivariate graphic approach that, is recently used widely in financial stability analysis and we believe, addresses these needs.[1]

It is difficult to define when an economy is in a financial crisis. A financial crisis is a situation in which the risk of a financial system breakdown is high, whether this risk is realized or not. Dovman (2010) investigates business cycles and elaborates on recent financial and non-financial crises in Israel. Table 1.1 shows the financial crises:

Table 1.1. Periods of Financial Crisis in Israel

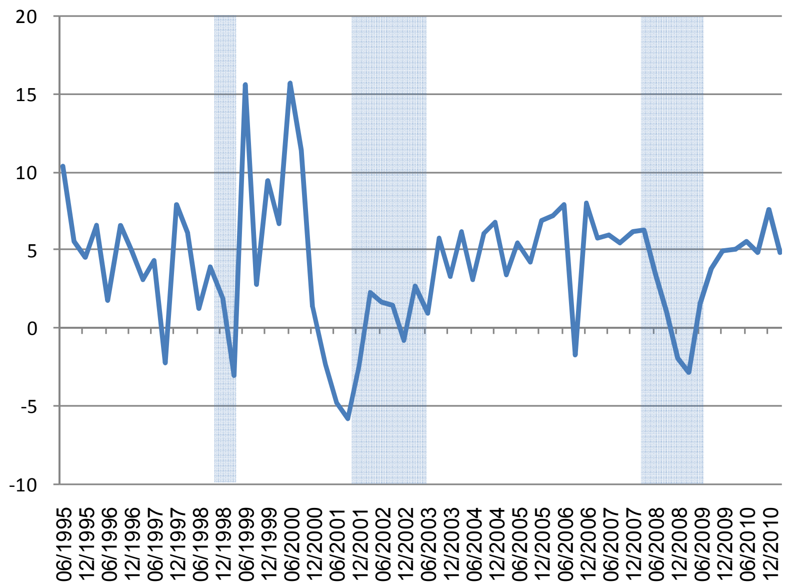
Name	Span	Cause
Russian/LTCM crisis	1998Q4-1999Q1	Russia defaults on its debts; fall of LTCM
High-tech crisis	2001Q4-2003Q2	Dotcom bubble and second intifada
Subprime crisis	2008Q3-2009Q2	Bursting of housing bubble ;Increase in subprime mortgage lending coupled with high LTV ratios

[1] The general structure of the indices constructed in this paper is shown in Appendix C (Figure C.1).

Figure 1.1 shows periods of real GDP growth and periods of financial crises in Israel (shown in blue). Dovman (2010) identifies three financial crises since 1996.

Although the literature on financial stress is extensive, it devotes much of its attention to early warning composite indicators of mixed predictive ability (Berg, Bozensztein, and Patillo, 2004). Coincident indicators, in contrast, are contemporaneous and therefore less prone to errors and false projections. Examples of the use of such indicators are Stock and Watson (1989), who constructed a state of the economy index for the United States; van der End (2006), who constructed a financial stability index for the Dutch financial system; Yiu, Ho, and Jon (2010), who constructed a financial stress index for Hong Kong; Illing and Liu (2003), who constructed an index for financial stress in Canada, and Y. Saadon (2005), who constructed a composite index for stress in financial markets in Israel. The Federal Reserve Banks of St. Louis (Kliesen and Smith, 2009) and Kansas City (Kliesen and Smith, 2010) constructed a stress index for the U.S. as well. Despite the evident advantages of these types of indicators, the complexity of the concept of financial stress means that aggregation may lead to the loss of important information; therefore, to obtain a more complete picture of the condition of the financial system, the examination of several key indices is vital (Lo Duca and Peltonen, 2011). The IMF uses a radar chart as part of its assesment of the global financial stability.

Figure 1.1. QoQ Real GDP Growth (Seasonally Adjusted, Annualized)



We apply a graphic approach to the display of several key indices related to financial stress and potential risks that may induce financial stress in Israel, such as the deterioration of the global or domestic real economy. Our goal is to illustrate potential risks and stress levels in the financial system on several dimensions, allowing us to examine specific indices and their development over time.

The diagram that we construct below is called a radar chart,[2] a method of displaying multivariate data via the two-dimensional display of several composite indices based on groups of the underlying variables; the composite indices are represented on axes that originate in the same point. This method allows us to identify outlier variables and simplifies the comparison of the data in different periods.

Radar charts are found in the literature on multivariate data visualization. The IMF uses a radar chart to measure global financial stability. Dattels et al. (2010) use indices such as emerging market risk and credit risk in the construction of their global financial stability map. The Reserve Bank of New Zealand uses a radar chart to illustrate financial stability in New Zealand (Bloor and Bedford, 2009). Radar charts are used for other purposes, too, e.g., to examine labor markets in different countries (Mosely and Mayer, 1999) and to examine athletes' strengths and weaknesses.

In the literature, indices for the construction of radar charts use relatively basic statistical methods. In an economic analysis where serial correlation is evident, however, some of these methods may yield inaccurate results. Disregarding serial correlation and avoiding a structural econometric model may lead to invalid conclusions. Indeed, serial correlation couldn't be confidently ruled out in most time series used in this paper,[3] implying the need for a proper structural autoregressive model. Other issues include the categorization of variables and rescaling methods. To mitigate these problems, we use methods from time series analysis and estimation theory, which are more appropriate for these types of indices.

Our radar chart consists of six main unobserved indices (time series), chosen to capture developments in different areas of the economy and the financial system. Three indices measure risks to the financial system: global and domestic macroeconomic risks and global financial risk. The three other indices measure domestic financial stress: market risk, credit risk, and instability of financial institutions. We outline seven steps for the construction of each index. We start by selecting and scaling component variables. Next, we aggregate these variables to form the index using a Kalman filter,[4] which we use to solve a set of dynamic equations, namely a state space representation. In the final stage, we perform a transformation that allows us to compare the different indices.

The rest of the paper is organized as follows: Section 2.1 outlines the seven steps in which the indices used for the radar chart are constructed, Section 2.2 describes the construction of the radar chart, Section 3 examines the results, and Section 4 concludes.

[2] Alternately known as spider charts, star plots, cobweb, charts and kiviat diagrams.
[3] The Durbin Watson Test and LM Test were used to determine the existence of serial correlation.
[4] The Kalman filter was introduced by Kalman (1960) and applied to economic coincident indicators by Stock and Watson (1989). Examples of its use in Israel are Melnick and Golan (1992) and Marom, Menashe, and Suchoy (2003), who constructed a state of the economy index for Israel.

2. Methodology

2.1 Construction of the indices

In this section we present the seven-step methodology for the construction of the indices that we later plot onto the radar chart. Six of the indices capture the key risks that may trigger a financial downturn in Israel; together, they purport to draw a complete picture of the condition of the country's financial system. Three indices capture risks that are external to the domestic financial system; the other three, which are essentially financial stress indices, capture risks within the financial system (Table 2.1).

Table 2.1

Index	Starting date
External risk indices	
Global macroeconomic risk	1999Q1
Domestic macroeconomic risk	1990Q1
Global financial risk	1992Q2
Financial stress indices	
Market risk	1996Q2
Credit risk	1997Q1
Financial institutions	2001Q1

The indices are latent time series ("Index"), each one constructed on the basis of a number of observable time series ("Component Indices"). We use a macroeconomic index previously constructed in Israel to capture the domestic macroeconomic risk (Marom, Menashe, and Suchoy (2003).

The method used for the construction of the indices is the autoregressive dynamic model pioneered by Stock and Watson (1989), which explains the relationship between the indices and the component indices. This set of equations, known as a state space representation, is solved using the Kalman filter. In the final stage of construction, the resulting indices are transformed into a common scale, by which we may compare them and subsequently plot them on the radar chart.

The following notations are used throughout this section:

x_t^i —Index i time series

$y_t^{i,j}$ —Component index j of indicator i time series

T —Length of the shortest component index time series of index i

J —Number of component indices

μ —Expectation

σ —Standard Deviation

1. Data Retrieval

Data for the component indices were collected at quarterly frequency.[5] To best reflect the risk associated with each specific index, the data for each index were chosen using conventions in the literature and measures commonly used in Israel. Although we could have used statistical methods to select the series, we considered judgment to be critically important in this case, believing that statistical significance should not compromise presumed relevance as some variables may not be statistically significant within sample but may still capture future events. Specifications for all time series are found in Appendix A.

2. Stationarity

This step addresses the notion of non-stationary time series. To make the data comparable over time, series must be stationary. Since non-stationary time series have an expectation, $E_t(y_t^{i,j})$, that changes over time, no benchmark can be set and the relative level of the series becomes meaningless. A prevalent solution that works in most cases is to use differences; in some cases, however, this transformation may adversly affect the significance of the results. When this happens, de-trending may be performed using the Hodrick-Prescott filter, which decomposes the time series to cyclical and trend components.

Some series were found to be non-stationary even though theory strongly defines them as stationary. This may happen if sample sizes are relatively small and may not capture periods in which the series behaved differently. In these cases, we decided to use the original series and maintaining the assumption that the series are indeed stationary.[6] This approach, supported by Canova,[7] is advised when time series are short and capture a subsample of a long-term time series. Canova notes that treating data as non-stationary when we are confident that they are in fact stationary may vitiate the results. Most component indices were in fact found to be stationary ($I(0)$) (some series were taken initially as differences). Consequently, the indices, which as we will see are a linear function of the component series, are also stationary, allowing us to set a benchmark and compare observations over time.

3. Direction of the time series

The level of each observation of an index must reflect the condition of the feature of the economy that it represents. We decided that high levels of an index would reflect poor (below-average) conditions in the relevant area and that low levels would reflect good

[5] Our main constraints pertained to the historical availability of data. We will strive to increase the frequency of the data in the future.

[6] An example is the average unemployment rate in the G7 countries.

[7] Prof. Fabio Canova (University of Minnesota), class notes.

(above-average) conditions. Consequently, several component series had to be inverted. To obtain the desired result without distorting the features of the series, we simply multiplied these series by (-1).[8] A specification for series inversion is found in Appendix A.

4. Normalization

As component indices often have different measurement units, normalization was required. Popular normalization methods include rescaling, which compares observations against the extreme observation values, and ranking of observations using normal ranks or percentiles. The shortcoming of these methods lies in the fact that outliers/extreme values may heavily affect scaling and lead to distortion of the transformed component index. Moreover, expectations and standard deviations of component indices may not be equal, thus affecting the efficiency of distribution estimation at later stages.

The method used in this paper is $z-score$ normalization, used extensively in the literature (e.g., Bloor and Bedford, 2009); this method allows us to derive statistical expectations and standard deviations and is less susceptible to outliers.

Normalization is performed as follows: $z_t^{i,j} = \frac{y_t^{i,j} - \mu^{i,j}}{\sigma^{i,j}}$ where $\mu^{i,j} = \frac{1}{T}\sum_{t=1}^{T} y_t^{i,j}$ and $\sigma = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(y_t - \mu)^2}$.

5. Constructing the indices

The next step is the construction of each of the indices x_t^i . To accomplish this, we must aggregate the components of the index by what is called dimension reduction, a technique used extensively in the literature. Examples are the General Indicator of Science and Technology, the Index of Financial Stress in Canada, and the Kansas City Financial Stress Index. Common methods for dimension reduction include equal weighting, credit aggregate weighting, Principal Component Analysis (PCA), and Factor Analysis (FA).[9] These methods are suited for cross-sectional analysis because they do not take into account the possibility of serial correlation, as is often the case in economic and financial time series. Consequently, their use may lead to biased coefficients and, in turn, unreliable indicators. For this reason, we use a dynamic factor analysis model, first introduced by Stock and Watson (1989).[10] Examples of its use in Israel are Melnick and Golan (1992) and Marom, Menashe, and Suchoy (2003), who constructed a state-of-the-economy index for Israel.

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[8] An example of a series that had to be inverted is GDP growth, as high levels of GDP growth are associated with good economic conditions. Unemployment, in contrast, did not have to be inverted because higher unemployment is associated with worse economic conditions.

[9] For additional techniques, see OECD, *Toolbox for the Construction of Composite Indicators.* PCA and FA are the most frequently used methods in economics and finance.

[10] Stock and Watson (1989) constructed a coincident state-of-the-economy index for the United States.

The general model is defined as follows (for simplicity, we drop the i index and notate a generic index x_t and component indices $y_t^{\,j}$ $1 \le j \le J$):

Measurement equation: $\vec{y}_t = Z\vec{x}_t + \vec{\varepsilon}_t$

$\vec{y}_t$— $J \times 1$ vector of component indices time series $\vec{y}_t = (y_t^1, y_t^2, ..., y_t^J)'$

$\vec{x}_t$— $p \times 1$ vector of lags of unobservable index $\vec{x}_t = (x_t, x_{t-1}, ..., x_{t-p-1})'$

$\vec{\varepsilon}_t$— $J \times 1$ vector of error terms in measurement equation $\vec{\varepsilon}_t \sim N(0_J, H)$

Z — $J \times p$ coefficient matrix

p —Number of lags of unobservable variable in measurement equation plus 1.

The measurement matrix shows the relationship between the unobservable index and the observable component indices and is assumed to be linear. Every component index $y_t^{\,j}$ is assumed to have some common trend with $\vec{x}_t$ and Gaussian idiosyncratic noise $\varepsilon_t^{\,j}$. The unobservable variable $\vec{x}_t$ is assumed to behave as an autoregressive equation with 0 mean:

Transition equation: $\vec{x}_t = A\vec{x}_{t-1} + \vec{u}_t$

$\vec{x}_t$— $m \times 1$ vector of lags of unobservable index $\vec{x}_t = (x_t, x_{t-1}, ..., x_{t-m+1})'$

A — $m \times m$ coefficient matrix

m —dimension of state space (number of lags in transition equation)

$\vec{u}_t$— $m \times 1$ vector of error terms in transition equation $\vec{u}_t \sim N(0_J, Q)$

The transition equation defines the relationship between different observations of $\vec{x}_t$ and is assumed, like the measurement equation, to be linear.

The following assumptions are made on the errors:

I. $E(\varepsilon_t u_{t-s}) = 0$ for all s,t.

II. The idiosyncratic errors $\vec{u}_t$ and $\vec{\varepsilon}_t$ follow Gaussian distributions.

III. H is a constant diagonal matrices.

Under these assumptions and given component indices $\vec{y}_t = (y_t^1, y_t^2, ..., y_t^J)'$ and parameters Z, A, H, Q , (x_0, x_{-1}, x_{-2}) , P_0 (which will be explained shortly) the Kalman filter finds the optimal solution for x_t and, hence, for the dynamic equations defined above. (Harvey, 1989, and Kim and Nelson, 1998, developed an analytical framework to obtain a solution.) The Kalman filter is a recursive process that allows the efficient estimation of unobservable time series using autoregressive equations of observable and unobservable data. The filter derives the level of the latent variable at time t using information obtained in previous periods.

Since *Z, A, H,* and *Q* are unknown, we use maximum likelihood estimation to obtain local optimal coefficients. The maximum likelihood function accounts for the error terms between the fitted and the actual results for the observed variables.

Formally, if the Kalman filter estimation is $\hat{\vec{x}}_t$, then $\hat{\vec{y}}_t = Z\hat{\vec{x}}_t$, the error between the predicted observable data and the actual observable data is defined by $\vec{v}_t = \vec{y}_t - \hat{\vec{y}}_t = \vec{y}_t - Z\hat{\vec{x}}_t$. Given *Z, A, H,* and *Q,* we can obtain a series of these errors, $\vec{v}_t$. The likelihood function is defined by:

$$\ln(L) = \sum_{t=1}^{T} \ln(L_t) = \sum_{t=1}^{T} \left[-\frac{\mathrm{T}}{2}\ln(2\pi) - \frac{1}{2}\ln(\det(E(v_t v_t'))) - \frac{1}{2} v_t' E(v_t v_t')^{-1} v_t \right]$$

Given the complex character of the likelihood function, we used the interior-point algorithm[11] to obtain a numerical solution.[12] To ensure that we maintained economic relevance, we maximized the likelihood function under the constraints that Z, A are non-negative. The solution yields optimal estimates for *Z, A, H,* and *Q* and an optimal solution for x_t. As in any iteration algorithm, an initial guess must be made; when we tested out different starting points, however, we found that the results did not change. The Kalman filter requires initial guesses for $(x_0, x_{-1}, ..., x_{-(m-1)})$ and P_0, which is the covariance matrix of $\vec{x}_t - \hat{\vec{x}}_{t|t-1}$ in the algorithm. A conventional guess is $(x_0, x_{-1}, ..., x_{-(m-1)}) = 0_m$, which is suitable because x_t is linearly constructed from normalized variables. P_0 was chosen to be I_m to avoid situations that may involve singular matrices.

An additional issue that had to be appropriately addressed was the selection of the model to use, as different models may yield different results. Selecting a model means selecting optimal lags *m* and *p*. To select the best model, we used the Akaike information criterion, which measures the goodness of fit of a statistical model. The criterion seeks the model with the highest likelihood function value and penalizing for the use of more parameters. The general case is defined as $AIC = 2k - 2\ln(L)$. We found that $m = 1, p = 0$ was sufficient for all indices, allowing us to use the standard one-lag model.

Ultimately, we obtained optimal estimates for all unobserved variables.[13]

As for assumptions about the error terms in the model, testing the results showed that some idiosyncratic errors do not follow a Gaussian distribution due to outliers. Considering the contribution of the recent financial crisis to outliers and the relatively small sample sizes, several outlier observations may exaggeratedly lengthen the tails. Indeed, testing normality without these outliers showed that the distributions are in fact normal. We believe that larger samples would reinforce this statement.

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[11] Trust Region methods were found to yield the same results.

[12] The likelihood function is optimized by iteration; therefore, it is local and initial guesses must be made. We chose average weighting as an initial guess because we expect logical solutions to be found in that area.

[13] Importantly, other sophisticated methods exist for dealing with various problems that may arise in the modeling of financial data, e.g., ARCH, GARCH, unscented Kalman filter, and ensemble Kalman filter. Given the drawbacks of most of these methods, however, we decided to use the standard Kalman filter model.

The purpose of the last two steps (6 and 7) is to transform the indices into a common scale.

6. Construction of density function for each index

Since the radar chart consists of identically scaled axes, plotting the indices onto it requires one common scale. There are numerous ways of doing this. Dattels et al. (2010) use percentiles for the IMF's global financial stability index. This method is simple and avoids estimation theory but is highly sensitive to outliers and does not incorporate tail events that are more extreme than those described above. Bloor and Bedford (2009) use a parametric estimation to estimate the distribution of each index. They check normality using the Jarque-Berra test and use t distributions when the kurtosis is large. This method solves the problem of tail events but may lead to inaccurate results when a high degree of skewness is evident.[14] Indeed, financial markets empirically exhibit non-symmetry as a result of bubbles. This argument is backed by our findings; we found with over 95% confidence[15] that all indices are not normally distributed (Table B.3 in Appendix B).

Consequently, we decided to use a method called kernel density estimation, a non-parametric method for estimating the probability density function (pdf) of a random variable— $f(x_t)$ in our case. In our view, this method yields more accurate results than parametric estimation because no assumptions are made on the underlying data. Moreover, it is less sensitive to outliers and allows future tail events that are more extreme than hitherto.

Kernel density estimation resembles a histogram in the sense that a bandwidth h is chosen and the pdf is constructed according to the number of observations in a given interval. However, the method improves on the histogram because it entails the use of continuous pdf's instead of bi-value step functions and allows the estimation of an optimal bandwidth h.[16]

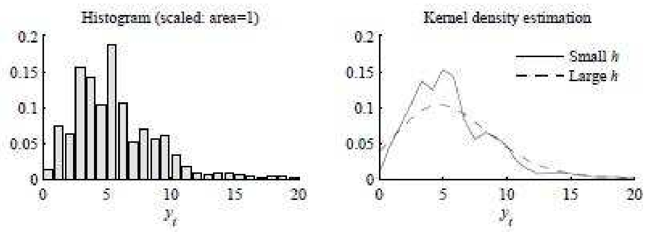
The kernel density estimator of $f(x)$ for $x \in R$ is defined as:

$$f(x) = \frac{1}{Th}\sum_{i=1}^{T} K(\frac{x_i - x}{h}) \text{ where } K(u) = \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}}$$

The resulting estimator is:

$$f(x) = \frac{1}{Th}\sum_{i=1}^{T} \frac{1}{\sqrt{2\pi}} e^{-\frac{(\frac{x_i}{h}-\frac{x}{h})^2}{2}}$$

Figure 2.1



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[14] x_t having a normal distribution, may be very useful because it allows us to make inferences on the data. (Note that it is enough for x_0 to be normally distributed for all x_t to be normally distributed because of the normality assumption of the errors.)

[15] We used the Jarque-Berra test and the Lilliefors test to test the hypothesis that the indicators are normally distributed.

[16] Optimal by mean integrated square errors, minimizing the risk function.

We can easily see that:

i. $f(x) \geq 0 \ \forall x \in R$

ii. $$\int_{-\infty}^{\infty} f(x)dx = \int_{-\infty}^{\infty} \frac{1}{Th} \sum_{i=1}^{T} \frac{1}{\sqrt{2\pi}} e^{-\frac{(\frac{x_i}{h}-\frac{x}{h})^2}{2}} dx = \frac{1}{Th} \int_{-\infty}^{\infty} \sum_{i=1}^{T} \frac{Th}{\sqrt{2\pi}} e^{-\frac{(t-\frac{x}{h})^2}{2}} dt = 1$$

Hence $f(x)$ is a probability density function. The resulting distribution is dependent on the bandwidth selection (Figure 2.1). As mentioned above, however, we may choose an optimal bandwidth that minimizes the mean integrated squared errors.

We estimated probability density functions for each of the indices. The final step is the transformation of the indices to one common scale.

7. Scaling of the unobservable indices

In Step 6, we derived the probability function of x_t. Now we transform the indices to one common scale so that they may be plotted onto the radar chart. We define the cumulative probability function (cdf) to measure the level of the index relative to its specific distribution. Formally, $F(x_t) = \int_{-\infty}^{x_t} f(t)dt$ defines the final scaled index. Hence, levels close to 1 are associated with very high index values.

Extreme high stress observations receive values close to 1 (the recent financial crisis for several indices). If we experience a more drastic crisis in the future, the revised estimation of the pdf will value it as close to 1 while lowering the value given to the recent financial crisis. Thus, the approach must be that pdf values for each index are relative to the most extreme event in the sample and not to the most extreme events theoretically possible. Nevertheless, the recent financial crisis was indeed a rare event and is therefore a reasonable point of reference.

An additional advantage is the continuity of our method, which avoids discrete categorizing that may lead to distortion of the data. The reason is that the interpretation of the chart is somewhat reliant on the barriers of each level. The continuous method is easier to interpret because the values simply explain where the observation is situated along the distribution function.

Having completed the construction of the indices, we now construct the radar chart.

2.2 Construction of the Radar Chart

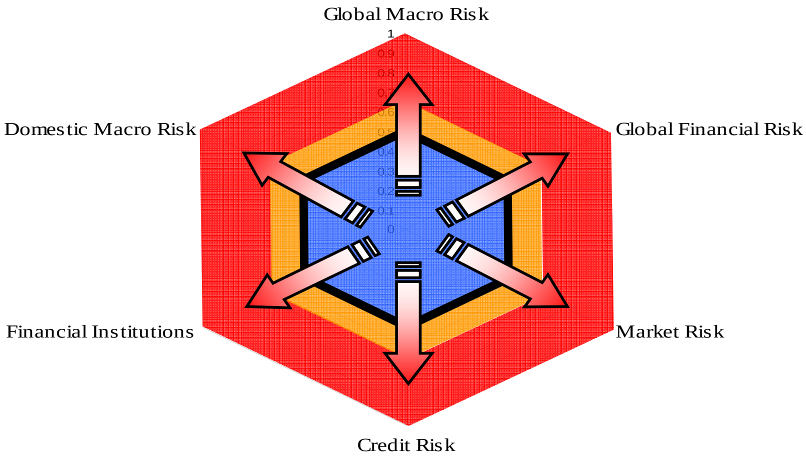
In this section, we elaborate on the construction of the radar chart. Radar charts make it easier to present several indices at once. We positioned the vertices in a way that links the different indices. The following indices were placed side-by-side:

I. domestic and global macroeconomic;
II. domestic market risk and global market risk;
III. global macroeconomic risk and global financial risk;
IV. financial stress indices and domestic macroeconomic risks;
V. external risks.

This positioning allows us to identify stress and risks in specific areas easily. If the source of a given risk is global, for example, the polygon will expand in the direction of the global indices. If the sources of the risk are only internal, the polygon will expand in the direction of the indices of internal risks while remaining constant for the global indices.

Understanding how to interpret the chart is vital. Each vertex illustrates the value of a specific index according to the construction set forth in Section 2.1. Possible values fall between 0 and 1, 1 illustrating extreme values associated with high levels of stress and 0 illustrating extremely low levels. The median value, 0.5, is the reference point for the scale, meaning that values above it are considered higher than normal. Importantly, while high levels are interpreted as “bad,” low levels should not necessarily be interpreted as “good.” Levels of unemployment lower than the natural unemployment rate are considered good. Large positive changes in the domestic stock market, however, may be interpreted as a bubble that results in a quick downturn if it bursts. While the levels shown on the radar chart yield absolute values, the chart has the additional useful feature of time factor dynamics. By examining changes between periods, we may better understand the direction of general stress levels and risks to the financial system. For example, if a low index , say 0.2, climbs to 0.5 in two quarters, the correct interpretation should be that even though the index is now at a normal level, the rapid increase in the last two periods suggests a sharp increase in stress related to this index, possibly pointing to a trend that will lead to higher levels in subsequent periods. An interpretation that disregards this information may be misleading. In sum, the index should be interpreted carefully, with both absolute values and time factor changes taken into account. Figure 2.2.1 illustrates the radar chart and shows the direction of increasing stress and risks to the financial system. The red area is historically associated with high stress levels (over 0.65). The orange area indicates above-normal levels, an area that should raise awareness, particularly if levels are close to the red area or posted increases in previous periods. The blue areas indicate levels that are normal and below normal.

Figure 2.2.1. Interpretation of the Radar Chart



The six indices are elaborated below:

External risks to the financial system:

These indices reflect risks that are external to the financial system. Deterioration of these indices may lead to a downturn in the financial system.

i. Global macroeconomic risk

Global macroeconomic risk captures the risk of real external shocks. The Israeli economy, being small and open, is heavily reliant on exports—at 36.6 percent of GDP in 2009 and 38.8 percent in 2010.[17] A global slowdown may have a detrimental effect on the Israeli economy; such was the case in the recent financial crisis, which reduced Israel's exports by 38 percent in only three months.[18] This was the main cause of the slowdown in the Israeli economy in 2009, when GDP grew by only 0.8 percent and companies inevitably suffered losses that induced an increase in insolvencies.[19] This exemplifies the impact that changes in the global economy can have on the financial system in Israel. Since many additional transmission processes may tie the domestic financial system to the global real economy, global macroeconomic risk is a crucial factor.

The component indices of the index include the G7 countries, which are Israel's main trading partners. The data include confidence survey indicators, unemployment, GDP growth rates, and imports.[20] We considered using the OECD leading indicator but decided to use our own construction despite some disadvantages.[21]

ii. Domestic macroeconomic risk

The domestic economy index captures the risk of internal macroeconomic shocks. The index used, derived from the state-of-the-economy index (Marom, Menashe, and Suchoy, 2003), effectively measures the probability that the economy will be in recession. The inclusion of this index is important considering the interconnectedness of the real economy and the financial system. BIS (2005) discusses this relation, arguing that business cycles have an important effect on the incomes, profits, and hence the balance sheets and creditworthiness of economic agents. The component indices for the domestic economy index include manufacturing production, exports of goods, and employee posts in the business sector.

iii. Global financial risk

Global financial risk captures the risk of a global financial market downturn. The interconnectedness of financial markets means that downturns in global financial markets more often than not lead to downturns in Israel's financial markets. The recent financial crisis clearly demonstrated the strong correlation between the domestic and global markets. The

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[17] Excluding diamonds.

[18] 9/2008–12/2008.

[19] Fifty-six companies entered debt settlement arrangements (6.7 percent of the outstanding value of the bond market).

[20] Imports provide a better indicator than exports, because Israel is reliant on external demand from trade partners.

[21] The main disadvantages are the use of the latest revisions for G7 GDP growth. However, using initial GDP estimates should not change the results substantially.

component indices include volatility measures of bond, equity, and FX markets as well as stock market performance in key global markets.

Financial stress indices:

Financial stress indices measure stress in different areas of the domestic financial system, namely market risk, credit risk, and instability of financial institutions. Their aim is to provide a direct measure of financial stress.

iv. Market risk

Market risk captures the risk to the financial system in Israel that may arise from expected losses and uncertainty in various markets. Market risk factors generally include equity risk, interest rate risk, and currency risk. Component indices include option implied volatilities in equity and FX markets. In addition, we included domestic stock market performance.[22]

v. Credit risk

Credit risk captures the expected risk of domestic borrower default. The index includes the three non-financial borrowers[23] by sectors: business, households, and government. An increase in credit risk reflects an increase in concern about default, possibly narrowing credit channels and toughening the conditions under which debt and capital can be raised. In the recent financial crisis, the nonbank credit market evaporated as risk premiums skyrocketed. This was one of the main catalysts (in addition to exports) of the economic downturn in Israel in 2009.

The component indices of this index are the risk premiums of the household, business, and government sectors.

vi. Financial institutions

The financial institutions index captures risks to the financial system that may arise from the instability of financial institutions. As these institutions are a key component of the financial system, their stability is vital for a well-functioning financial system. Component indices include measures regularly published by the Supervisor of Banks[24] at the Bank of Israel.[25] To reflect market expectations regarding financial institutions, credit risk and stock performance are also included.

Due to the limited availability of historical data, some data (e.g., liquidity risk, clearinghouse counterparty risk, and CDS spreads) were excluded. In some cases, we used various data series as proxies for the measurement of Israel's risk premium, such as ten-year government bond spreads instead of credit default swaps. In the future, larger sample sizes will allow these additional variables to be included.

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[22] We used the TA25 index to represent the domestic stock market.
[23] Financials are captured in the financial institutions index.
[24] The calculations accord with the Basel II requirements and will be revised in the future to accord with Basel III.
[25] http://www.boi.org.il/he/BankingSupervision/Data/Pages/Default.aspx.

3. Results

3.1 The six indices

Figures 3.1.1–3.1.6 plot the results for the six cumulative functions of the indices from the different starting dates.[26] The results show that the levels of index stress are generally high at times associated with high financial stress (Dovman, 2010). Moreover, despite varying levels of stress for different indices, most indices rise sharply in buildups to financial crises. The multivariate approach illustrates possible precursors of episodes of financial stress and allows us to compare the levels of different indices. The performance of the model is hard to examine due to lack of clear-cut data on conditions in the different areas of the economy. Thus, to check our results, we will qualitatively and chronologically review the global financial crisis that began in 2007 and see if the results are consistent with global and domestic economic developments that occurred as the crisis unfolded.

The first signs of the crisis surfaced in February 2007, when a number of large financial institutions that had extended subprime loans began to report losses. The crisis erupted at around July–August 2007 when three hedge funds managed by the French bank BNP-Paribas collapsed. Since this development triggered a dramatic increase in the markets' risk assessments, we would expect external risk factors—specifically, the global financial risk index—to increase. Indeed, the level of this index climbed from an extremely low 0.02 in the first half of 2007 to 0.25 in 2007Q3. The concerns precipitated into domestic financial markets as well; market risk increased steadily from 2007Q1 and reached 0.58 in 2007Q3. Because the levels of most of the component indices were initially far below their long-term benchmarks, the absolute level of the index remained relatively low.[27] The intensity of the crisis continued to increase: in September 2007, the British bank Northern Rock, asked the Bank of England for a bailout and in March 2008 the Bear Stearns investment bank collapsed and was subsequently acquired by JPMorgan Chase. Global financial risk skyrocketed in 2008Q1 to 0.92. The domestic financial indices also increased sharply: market risk to 0.82, credit risk to 0.51 (as against 0.19 in the previous period), and financial institutions to 0.94 as major banks' profitability changed direction, raising concerns over their future. In 2008Q1, as the real economy began to slow and the outlook turned bleak, global macroeconomic risk increased from low levels (below 0.25) in 2007 to 0.43 in 2008Q1 and domestic macroeconomic risk did the same: from below 0.5 to 0.58 in the respective periods.

The financial crisis peaked in 2008Q4 as the Lehmann Brothers investment bank collapsed and the U.S. Government had to bail out Fannie Mae and Freddie Mac, in only three examples of the many financial institutions that had fallen into difficulties. The fright prevailing in the markets due to the increase in risk made it impossible to raise capital and triggered an increase in insolvencies. Global financial risk crested at 0.99 in 2008Q4 and the market risk and financial institutions indices rose to 0.99 and 0.98, respectively. Credit risk

[26] Estimations for the coefficients are shown in Table B.3 of Appendix B.

[27] Implied volatility in U.S. government bonds, FX markets, and the MSCI Emerging Markets and World Bank indices were still below their long-term benchmarks.

ascended to 0.76 as concerns over Israeli corporate insolvencies intensified.

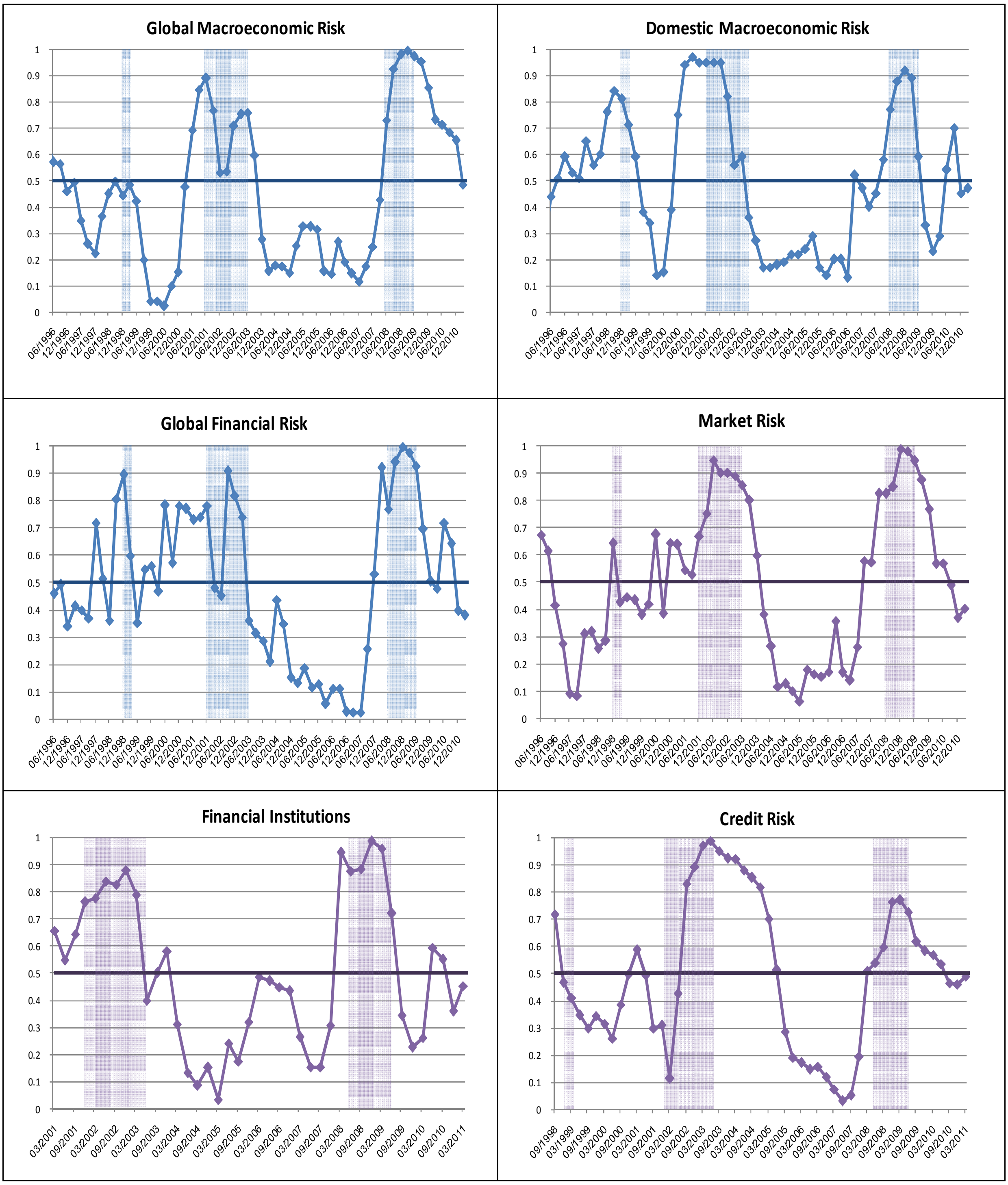
The macroeconomic situation, domestic and abroad, was grim: major economies shrank, trade dried up, unemployment rose, and outlooks were dire. Reflecting this, global macroeconomic risk was 0.98 and domestic macroeconomic risk was 0.92 in 2008Q4. As a result of these extraordinary events, central banks and governments around the world took unprecedented measures to ease the uncertainty and systemic risk in the financial system and restore the public's confidence. Partly due to the authorities' unprecedented intervention, the financial system achieved a rapid and impressive return to stability. Although the sustainability of the recovery was unknown, the lower stress levels in the financial system were reflected in the 2009Q4 indices as global financial risk fell to 0.5 market risk to 0.77, and credit risk to 0.58. Concerns about the solvency of most corporations diminished after peaking at 0.77 mostly due to crisis in the domestic bond market crisis. Financial institutions fell to 0.23 as confidence in the condition of Israeli financial institutions improved.

The global economy shifted from acute contraction of activity to slow recovery. Global macroeconomic risk decreased to 0.85 in 2009Q4 after exceeding 0.92 for five quarters, nevertheless a high level as the outlook remained uncertain and high unemployment persisted. The real economy was much less intensively and protractedly harmed in Israel than elsewhere and did not need massive fiscal injections of the sort that were essential in other economies. Hence, its recovery was quicker; indeed, domestic macroeconomic risk gradually decreased throughout 2009 and dropped to 0.23 in 2009Q4.

The next year, 2010, saw more positive trends in the global and domestic financial markets. The index levels were generally around the long-term benchmark. Although the recovery continued, the stabilization of the global financial system was hampered somewhat in 2010Q2 due to the PIIGS sovereign debt crisis and fear that the intensification of the crisis, if any, would affect the stability of European and American banks. These fears waned somewhat in the last two quarters of 2010. The indices reflected these developments: the domestic indices were relatively low (below 0.6) and both global indices exceeded 0.7 in 2010Q2. In the last two quarters of 2010, the levels of all indices except global macroeconomic risk returned to normal. Global macroeconomic risk remained relatively high due to concerns about economic slowdown; even this index, however, decreased to 0.65 by 2010Q4. The resilience of the Israeli economy in 2010 was reflected in the domestic macroeconomic risk index, which stayed below the benchmark.

Other periods, such as the bursting of the dotcom bubble and Russian crisis/LTCM collapse, were checked, as were "quiet periods" such as 2005. We found that our model successfully captured developments in the different areas of the global and domestic economies in these periods as well. In the next section, we present the radar diagram.

Figures 3.1.1–3.1.6. Cumulative Functions of the Six Indices*



* External risks are in blue; domestic risks are in purple. All graphs are calculated up to 03/2011.

3.2 Results—the radar chart

In this section we show the results for the radar chart in different periods. The six indices are plotted on the chart after density estimation. Figures 3.2.1–3.2.2 show the results at six-month intervals from 2007Q4 to 2008Q4 and from 2009Q2 to 2009Q4, covering the financial crisis and the recovery. Despite relatively low levels in 2007Q4, most of the indices did increase over several periods. The unfolding of the crisis between 2007Q4 and 2008Q4 is visible in Figure 3.2.1. The worsening began in the global and domestic financial markets and quickly spread to other areas. In 2008Q4, the peak of the global financial crisis, all indices show very high levels, signifying extreme stress in the global and domestic financial systems and real economies.

Figure 3.2.2 illustrates the recovery period in 2009. The quick recovery in Israel is evident as the domestic indices remained below the benchmark and far below the global indices at the end of 2009. The healthy condition of Israel's financial institutions is also evident as the relevant index levels returned to below-normal.

Next, we examine the results for the dotcom/Second Intifada crisis. Figures 3.2.3–3.2.4 show radar charts for the periods between 2001 (beginning of the crisis) and 2003 (post crisis). We began with 2001Q1 because the stability of financial institutions index was not available earlier. (2000Q3 signifies the peak of the bubble.) The following periods effectively coincided with the beginning of the crisis in the U.S. By the end of 2001, the downslide turned into a full-blown crisis, of which Israel was a part. Moreover, the Second Intifada, the events of 9/11, and the default in Argentina exacerbated uncertainty in the financial markets and amplified the crisis. As we would expect, the radar chart shows high levels in most indices in 2001Q3 (with the exception of credit risk, which, however, increased sharply in subsequent periods). Throughout 2002, the Israeli economy was mired in difficulty[28] and domestic financial stress was high. External risks, high inflation, rising unemployment, a strong dollar, and a large government deficit contributed to increasing pressure on the financial system. Risk premiums in bond markets increased as the crisis unfolded. Consequently, credit risk increased substantially in the latter stages of the crisis. In the first half of 2002, global financial markets showed signs of recovery as volatility measures decreased and stock markets rose. This recovery however, was short-lived as panic returned to the markets in 2002Q3 when WorldCom filed for bankruptcy, in what was the largest such filing in the United States at the time.[29]

[28] Contracting by 1% .
[29] It was since overtaken by Lehmann Brothers and Washington Mutual in 2008.

Figure 3.2.1. Radar Chart 2007Q4–2008Q4—Buildup to the Global Financial Crisis

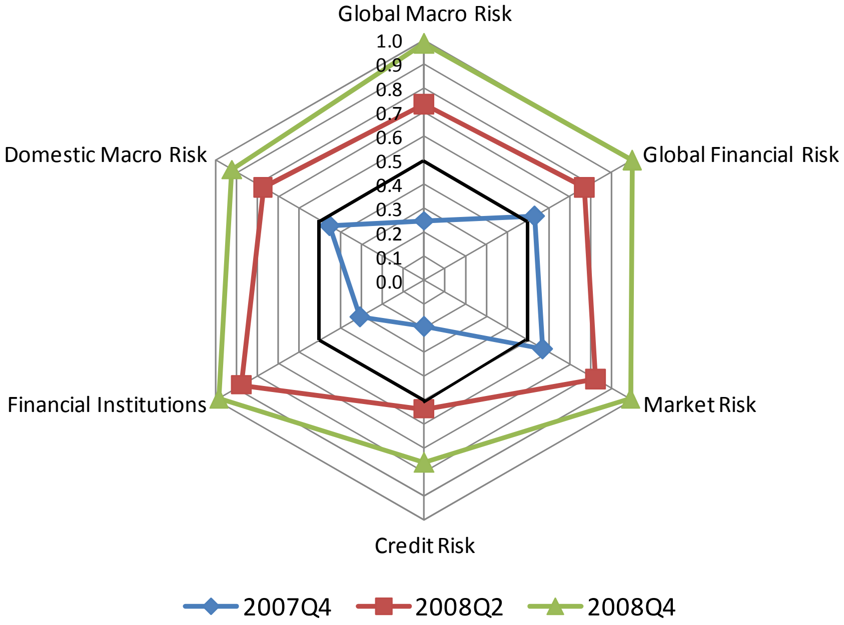
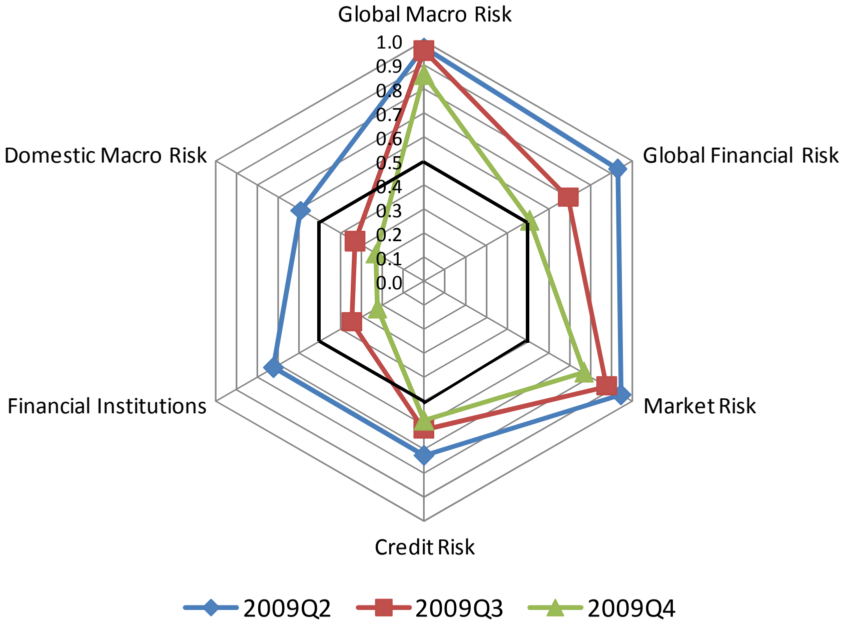


Figure 3.2.2. Radar Chart 2009Q2–2009Q4—Recovery from the Global Financial Crisis



The chart illustrates that indices were indeed above their benchmarks throughout most of 2002. Signs of recovery in the financial system first became visible in 2003 as all indices (except credit risk, which remained high due to high risk premiums following the crisis, started to decline. By the end of 2003, all indices apart from credit risk returned to normal levels.

**Figure 3.2.3. Radar Chart 2001Q1–2002Q1—
Dotcom Crisis/Second Intifada**

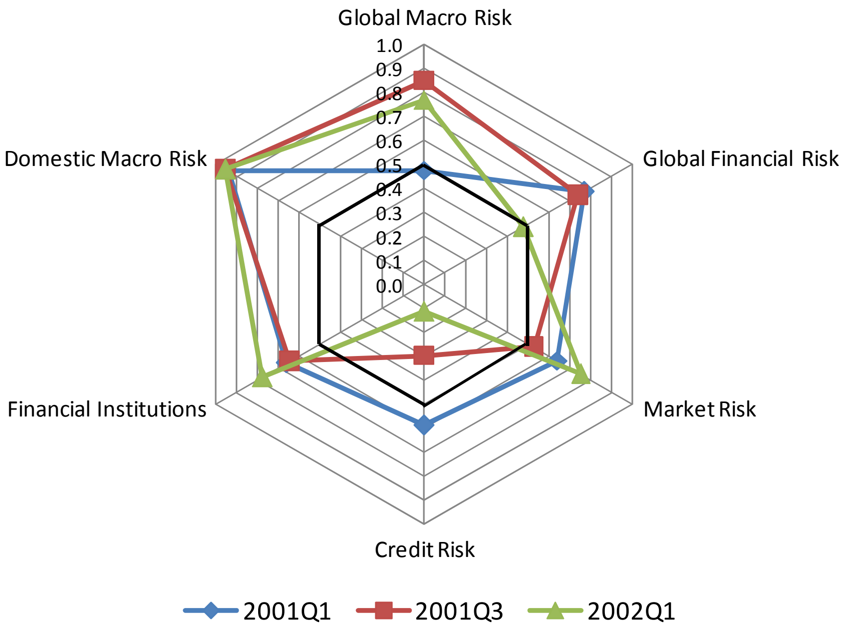
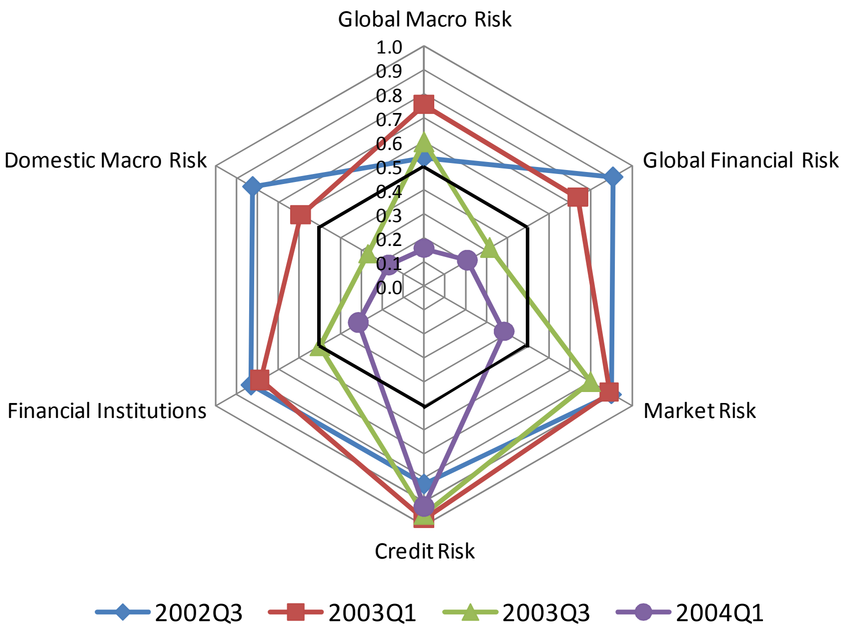


Figure 3.2.4. Radar Chart 06/2002–12/2003—End of Dotcom Crisis/Second Intifada, Large Government Deficit, and Strong Dollar



Figures 3.2.6 and 3.2.7 show radar charts for additional periods; the Russian/LTCM crisis and 2005, a relatively quite period after the final stages of recovery from Israel’s government debt problems. Figure 3.2.6 has five vertices due to lack of data on financial institutions before 2001.

Figure 3.2.6. Radar Chart 1998Q4–1999Q2–Russian/LTCM Crisis

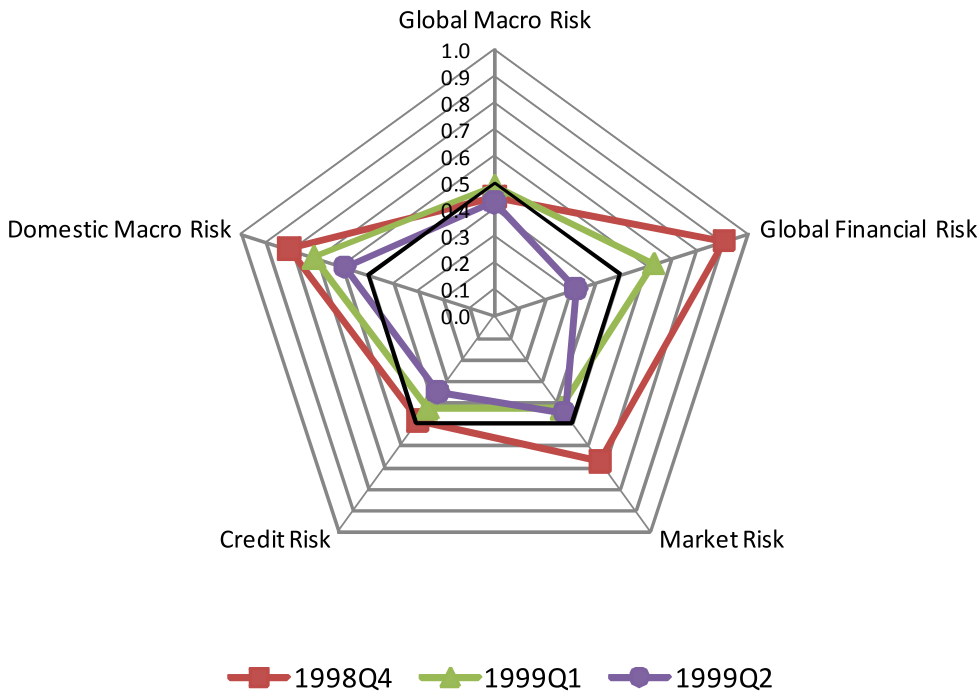


Figure 3.2.7. Radar Chart 2005Q3–2006Q3

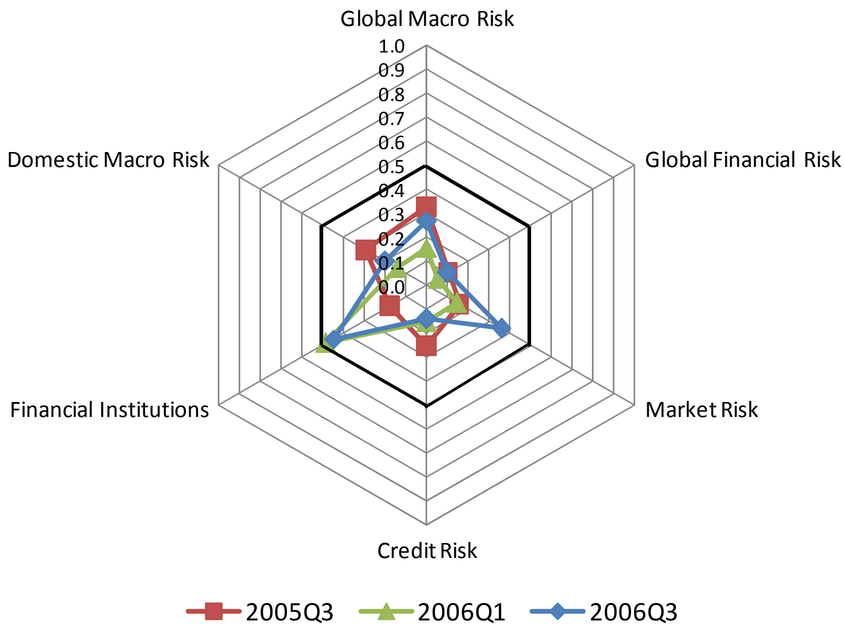
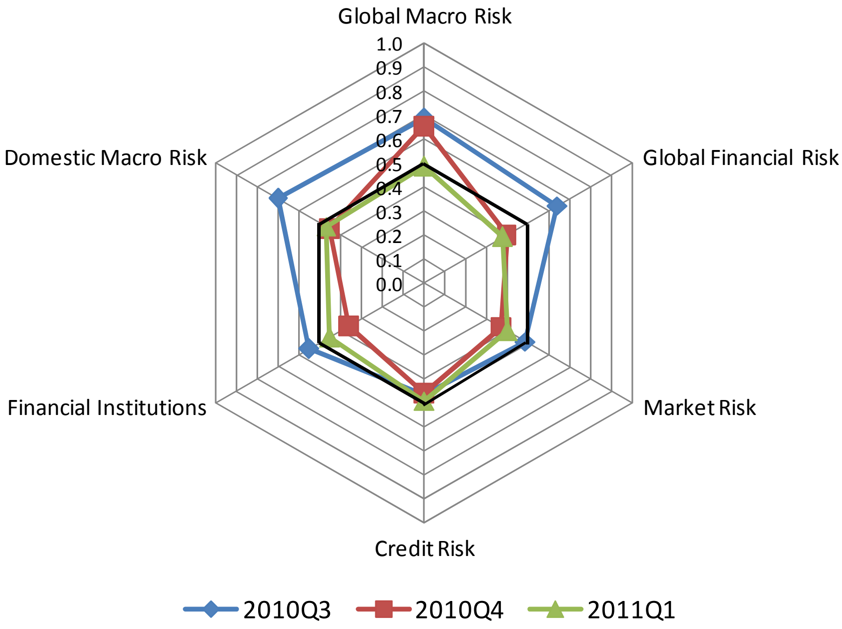


Figure 3.2.8, covering the most recent periods available at the present writing, shows that all indices were around their long-term benchmarks in 2011Q1.

Figure 3.2.8. Radar Chart, 2010Q3–2011Q1—Most Recent Periods



3.3.1 Out-of-Sample-Test

To reinforce our findings, we must check if we can identify increases in stress levels when post crisis observations are not taken into account. To check whether the developments related to the crisis were identified successfully, we performed an out-of-sample test for the periods between 2007Q2 and 2011Q1. Essentially, an out-of-sample test is a calculation for a number of periods according to data that were available up to those periods.[30] Such a test allows us to determine whether our results captured previous changes in stress levels in actual time or due to data that became available after the fact.

Figures 3.3.1–3.3.5 show the out-of-the-sample results for five indices. (For an analysis of the sixth index, domestic macroeconomic risk, see Marom, Menashe, and Suchoy, 2003.) The solid lines indicate in-sample results; the dotted lines indicate out-of-sample results.[31]

The similarity between the out-of-sample test and the ex post results is striking. This suggests that our conclusions would not have been substantially different at the time of measurement. For example, we would have seen sharp increases in most indices in 2007Q3 after obtaining all the data, as an indication of things to come.

Figures 3.3.6 and 3.3.7 show the in-sample and out-of-sample results for the periods between 2007Q4 and 2008Q4. Despite minor differences in the global financial risk index, the charts are strikingly similar and illustrate the same dynamics and high levels of stress in the periods leading to the peak of the crisis in 2008Q4. Hence, the results derived from the model do not depend on ex post observations.

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[30] Some of the data became available after the stated period. In this case, we calculated the period level once all data for that period became available.

[31] The out-of-sample test for global macroeconomic risk uses the last revision of G7 GDP growth.

Figures 3.3.1–3.3.5. Cumulative Functions of the Six Indices—Out of Sample

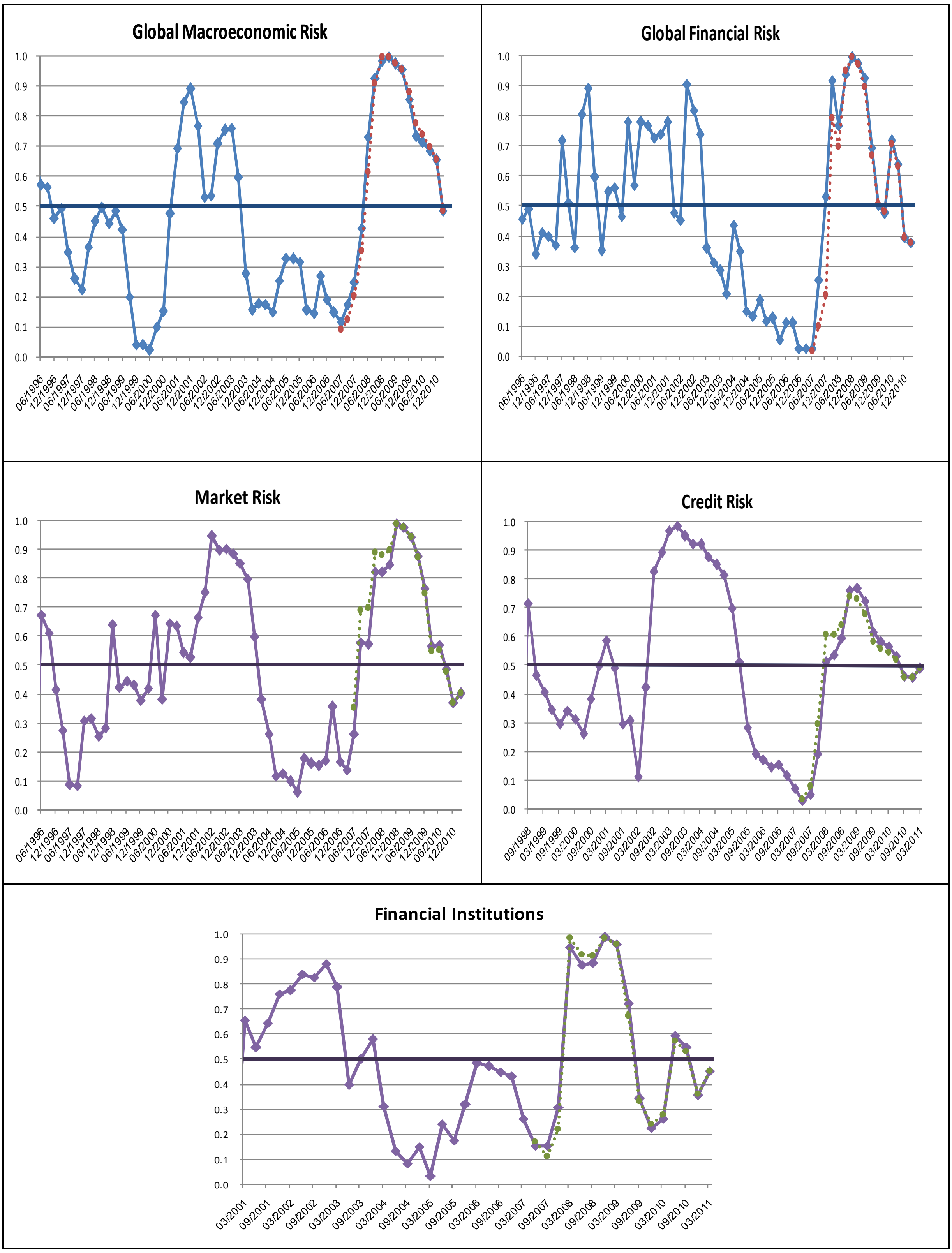


Figure 3.3.6. Radar Chart 06/2007–12/2008—In-Sample

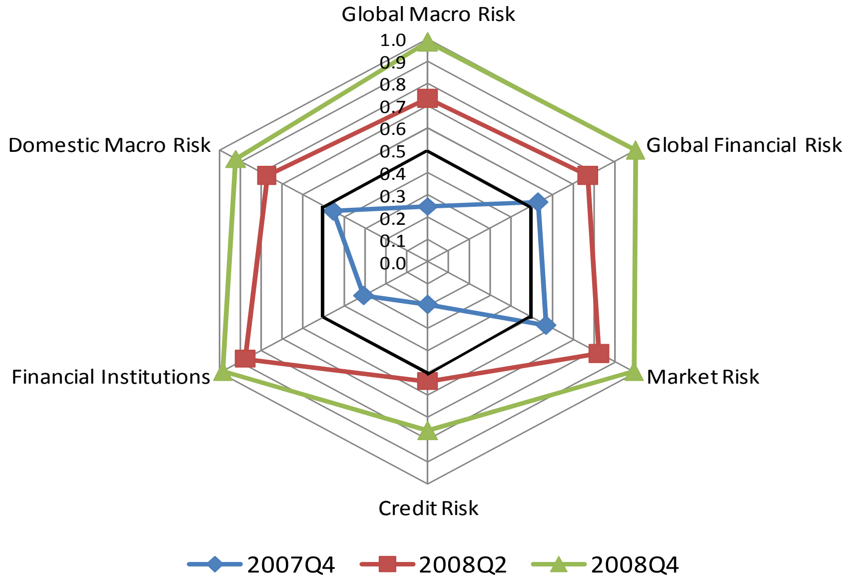
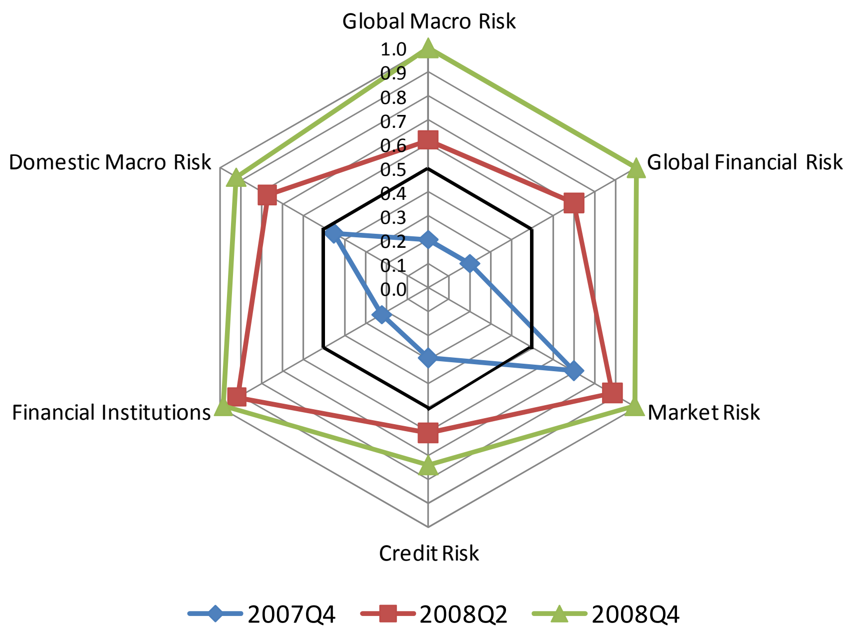


Figure 3.3.7. Radar Chart 06/2007–12/2008—Out-of-Sample



5. Conclusion

We presented a method for the construction of indices that measure internal risks (financial stress) and external risks (real economy risks and global financial risk) to the financial system. The main theme was the presentation of a multivariate graphic approach that allows the intuitive visualization of six main indices on one graph. We showed how the radar chart can contribute to intuition and facilitate preliminary analysis of the financial system. We think that our approach provides policymakers with an intuitive starting point for discussions and may help them make a better assessment of the condition of the financial system.

Our findings successfully capture the dynamics and developments of stress in the financial system. Moreover, successive increases in stress over a number of periods are usually a good indication of very high stress in the future. For robustness, we performed an out-of-sample test to check whether our findings would have captured changes in stress levels ex ante. The test showed that our results do not depend on ex ante observations.

We are constantly striving to improve the methodology, quality, and availability of the data and better capture the changes and levels of stress in the financial system.[32]

[32] An index of risk tolerance may serve as another indicator of financial stress as economic agents can radically change their risk appetite, which in turn increases or decreases the level of risk taking in the economy. Due to measurement problems, however, we decided to exclude this index at this stage.

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Appendix A: Data Specification

Index			Component Index	Mean	Median	ADF p-value*	Inverted	Source	Frequency availability	Starting date	Calculation
External Risks to the Financial System	Macroeconomic risk	Global macro risk	G7 GDP growth	0.48	0.55	0.011	No	OECD	Quarterly	1990Q1	QoQ change, seasonally adjusted
			G7 unemployment rate	6.47	6.39	0.003	Yes	OECD	Monthly	1990Q1	QoQ change, seasonally adjusted
			G7 consumer confidence index	99.88	100.30	0.024	Yes	OECD	Monthly	1990Q1	QoQ change, seasonally adjusted
			G7 business confidence index	99.44	99.60	0.008	Yes	OECD	Monthly	1990Q1	QoQ change, seasonally adjusted
			G7 imports	1.72	2.20	0.000	No	OECD	Monthly	1990Q1	QoQ change, seasonally adjusted
		Domestic macro risk	Probability of recession	0.44	0.36		No	BOI	Monthly	1990Q1	seasonally adjusted
	Global financial risk		VIX Index	20.34	19.32	0.012	No	Bloomberg	Daily	1990Q1	quarterly average
			MSCI Emerging Markets	2.70	3.15	0.000	Yes	Bloomberg	Daily	1990Q1	QoQ change (quarterly average)
			MSCI World Index	1.34	2.11	0.000	Yes	Bloomberg	Daily	1990Q1	QoQ change (quarterly average)
			MOVE Index	102.53	102.26	0.004	No	Bloomberg	Daily	1990Q1	quarterly average
			Option implied volatility in G7 FX market	10.65	10.61	0.027	No	Bloomberg	Daily	1992Q2	quarterly average
			Ted spread	0.47	0.38	0.007	No	Bloomberg	Daily	1990Q1	quarterly average
			MSCI World Bank Index	101.12	97.43	0.169	Yes	Bloomberg	Daily	1996Q1	QoQ change (quarterly average)
Financial Stress Indices	Market risk		TA25 Index	3.49	2.77	0.000	Yes	BOI	Daily	1996Q1	QoQ change (quarterly average)
			Option implied volatility of TA25	24.70	23.48	0.002	No	BOI	Monthly	1996Q1	quarterly average
			Un-indexed government bonds volatility	2.14	1.67	0.062	No	BOI	Monthly	1994Q1	quarterly average
			Option implied volatility of NIS/USD	8.29	7.63	0.123	No	BOI	Monthly	1996Q1	quarterly average
	Credit risk		Corporate bond spread	2.83	1.89	0.060	No	BOI	Daily	1998Q3	quarterly average, 4y-7y duration
			Average spread on household mortgages	0.96	0.97	0.000	No	BOI	Monthly	1997Q1	quarterly average
			Spread between indexed Israeli government bonds and US TIPS	1.70	1.53	0.066	No	BOI	Daily	1997Q4	quarterly average, 10y
	Financial institutions		TASE Banks and Insurance Index	2.85	1.31	0.000	Yes	BOI	Daily	2000Q3	QoQ change (quarterly average)
			Spread on bonds issued by banks	1.23	0.86	0.260	No	BOI	Daily	1998Q3	quarterly average
			Return on equity	14.72	16.32	0.006	Yes	BOI	Quarterly	1997Q1	net profit to equity
			Regulatory Tier 1 capital to risk-weighted assets	-0.15	0.47	0.008	Yes	BOI	Quarterly	2000Q4	de-trended series (HP filter)
			Problematic loans to total loans	9.23	9.44	0.928	No	BOI	Quarterly	2001Q1	

*Augmented Dicky Fuller test for stationary series. The test was performed using intercept and no trend. The number of lags was selected according to the Schwarz Info Criterion.

Appendix B: Tables

Table B.1. Results for the Six Indices

Index	Russian crisis/LTCM				Dotcom crisis				Subprime crisis			
	2 quarters before crisis	1 quarter before crisis	Start of crisis	Average during crisis	2 quarters before crisis	1 quarter before crisis	Start of crisis	Average during crisis	2 quarters before crisis	1 quarter before crisis	Start of crisis	Average during crisis
	1998Q2	1998Q3	1998Q4	1998Q4-1999Q1	2001Q2	2001Q3	2001Q4	2001Q4-2003Q2	2008Q1	2008Q2	2008Q3	2008Q3-2009Q2
Global macroeconomic risk	0.45	0.50	0.44	0.46	0.69	0.85	0.89	0.71	0.43	0.73	0.92	0.97
Domestic macroeconomic risk	0.76	0.84	0.81	0.76	0.97	0.95	0.95	0.74	0.58	0.77	0.88	0.82
Global financial risk	0.36	0.80	0.89	0.74	0.73	0.74	0.78	0.65	0.92	0.77	0.94	0.96
Market risk	0.25	0.28	0.64	0.53	0.54	0.53	0.67	0.84	0.82	0.82	0.85	0.94
Credit risk	0.00	0.72	0.47	0.44	0.49	0.30	0.31	0.65	0.51	0.54	0.60	0.71
Financial institutions					0.55	0.55	0.76	0.75	0.94	0.88	0.88	0.89
Min	**0.00**	**0.28**	**0.47**	**0.44**	**0.49**	**0.30**	**0.31**	**0.65**	**0.51**	**0.54**	**0.60**	**0.71**
Max	**0.25**	**0.72**	**0.64**	**0.53**	**0.55**	**0.55**	**0.76**	**0.84**	**0.94**	**0.88**	**0.88**	**0.94**
Average	**0.13**	**0.50**	**0.55**	**0.49**	**0.53**	**0.46**	**0.58**	**0.75**	**0.76**	**0.75**	**0.78**	**0.85**
Median	**0.13**	**0.50**	**0.55**	**0.49**	**0.54**	**0.53**	**0.67**	**0.75**	**0.82**	**0.82**	**0.85**	**0.89**

* Calculations are taken over financial stress indices: market risk, credit risk, and financial institutions.

Table B.3. Numerical Results for the Six Indices

Parameters	J	Global macroeconomic risk	Global financial risk	Market risk	Credit risk	Financial institutions
Z	1	0.20	0.14	0.25	0.33	0.20
	2	0.12	0.09	0.48	0.00	0.00
	3	0.24	0.11	0.46	0.32	0.29
	4	0.22	0.14	0.55		0.25
	5	0.17	0.13			0.00
	6		0.11			
	7		0.09			
	8					
A		0.83	0.73	0.84	0.88	0.74
Transition matrix variance		**3.72**	**20.20**	**0.58**	**1.26**	**3.77**
Measurement matrix variance		**0.53**	**0.58**	**0.61**	**0.62**	**0.74**
Number of observation		**85**	**61**	**60**	**51**	**41**
Maximum likelihood function value		**513.2**	**536.2**	**304.1**	**195.5**	**277.2**
Maximum likelihood function value/number of positive component series		**102.6**	**76.6**	**76.0**	**97.7**	**92.4**
Jarque Bera Statistic p-value		**0.00**	**0.00**	**0.00**	**0.00**	**0.02**

1) The zero hypothesis of the Jarque Bera test is that the observations are sampled from a normal distribution.
2) The zero hypothesis of the Lilliefors test is that the observations are sampled from a normal distribution. This Lilliefors test is an extension of the Kolmogorov Smirnov test and is better suited to small samples.
3) *10 percent significant ** 5 percent significant ***1 percent significant. Augmented Dicky Fuller Test, optimal number of lags selected by Schwartz Info Criterion.

Appendix C. Figures and Graphs

C.1 Illustration of Stages in Construction of Radar Chart