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# An Analytic Network Process model for financial-crisis forecasting

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**Abstract**

We discuss and develop an imbalance-crisis turning point model to forecast the likelihood of a financial crisis based on an Analytic Network Process framework. The Analytic Network Process (ANP) is a general theory of relative measurement used to derive composite-priority-ratio scales from individual-ratio scales that represent relative influence of factors that interact with respect to control criteria. Through its supermatrix, which is composed of matrices of column priorities, the ANP framework captures the outcome of dependence and feedback within and between clusters of explanatory factors. We argue that our framework is more flexible and is more comprehensive than traditional methods and previous models. We illustrate how the ANP model would be implemented for forecasting the probability of crises.


*Keywords:* Financial crises; Modeling; Analytic Network Process (ANP); 1991 U.S. banking crisis

## 1. Introduction

William Stanley Jevons (1835–1882) was a highly respected and influential economist and statistician of his time. Jevons argued in his book, *Investigations in Currency and Finance*, the economy underwent a series of "commercial crises," which he traced back to the 18th century. Jevons' view of the trade or business cycle as a *sequence of crises* was embraced broadly throughout the economics profession until the 1920s. Then as more economic and financial data were compiled and newer statistical techniques were crafted to analyze them, Wesley Mitchell's "statistical cycles" replaced the event-driven concept of the business cycle. *Statistical time-series cycles* continue to underlie modern business cycle research. Today, cyclical composite index models, probit models, hidden Markov models (HMM), and threshold autoregressive (TAR) models are some typical methodologies used to forecast turning points in statistical cycles.

However, over the last 10 years, the literature on financial crises rediscovered the traditional Jevons view of the cycle, where a turning point is triggered by some economic and/or political event. Financial crises are *sudden events* that may and often do occur after a growth cycle slowdown begins or classical business cycle recession ensues. Crises are predicated on some development, such as a collapse of a financial or nonfinancial institution or the recognition of a major imbalance in the financial sector, such as heavy debt holdings or too much dependence on foreign capital.

In modern crisis theory of the business cycle, three types of financial crises are identified: *fiscal,*

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*banking*, and *currency* (Sachs, 1998). A *fiscal crisis* occurs when a government cannot roll over foreign debt and/or attract new loans. A *currency crisis* occurs when investors shift demand to foreign-denominated assets and away from domestic assets. A *banking crisis* occurs when a bank cannot attract enough new deposits to meet sudden withdrawal of reserves. Each of these crises can exist independently or in conjunction with one or more other crisis.

Statistical data needed to track and to forecast a potential financial-crisis point can be somewhat illusive from country to country. Data limitations exist especially in some emerging market economies that have undergone major structural change. In those countries, historical data are no longer consistent with the present institutions and, as such, are insufficient to signal a financial crisis before it occurs. Even when data exist, judgmental variables play a role in statistical models, as witnessed by the "freedom from corruption" qualitative variable in the probit model by Radelet and Sachs (1998).

For these reasons, we propose a flexible and comprehensive framework to simultaneously model and forecast the three types of financial crisis using an Analytic Hierarchy Process (AHP) with feedback, which is known as the Analytic Network Process (ANP) as developed and implemented by Saaty (1996). The Analytic Network Process also provides a structure that potentially can reduce judgmental forecast error through improved "reliability of information processing."[1]

The modeling application in this paper extends the ANP recession forecasting model by Blair, Nachtmann, Saaty, and Whitaker (2002) to capture key economic concepts specified in the financial-crisis econometric model by Kaminsky and Reinhart (1999), the contagion econometric model by Lowell, Neu, and Tong (1998), as well as the studies by Aziz, Caramazza, and Salgado (2000), Burns (1969), Glick and Moreno (1999), International Monetary Fund (1998), Kindleberger (1996), and Wolfson (1994). Our ANP financial crisis model's determinants are directly specified using quantitative and qualitative variables and empirically tested using an "expert system" approach instead of a true "expert opinion" approach—as the Blair study did—to allow for an historical back-test.

## 2. The ANP financial crisis model structure

The Analytic Network Process provides the mathematical framework for our model to forecast a financial-crisis probability using heuristics. Conceptually, the financial-crisis model can be described as a system of $N$ components (which may be part of a cluster of components) that forms a network where every component ($C_{\mathrm{n}}$) can interact or have an influence on itself or some or all of the other components of the system. The network, $N$, equals $\{C_a, C_b, C_c, \ldots, C_n\}$ where $L=\{\{C_a, C_a\}, \{C_a, C_b\}, \{C_a, C_c\}, \ldots, \{C_n, C_n\}\}$ and represents the set of pairwise linkage within or between components of the network. The ANP-based crisis-forecasting model provides a formal

[1] Judgmental forecasting accuracy is difficult to establish ex ante since it is impossible to go back in time and evaluate how a person or group would have forecasted a situation. However, one insight from Stewart and Lusk (1994) is worth considering. The authors proposed a seven-part decomposition of Murphy's skill score for measuring judgmental forecast accuracy, which is defined as:

$$\mathrm{ss} = (r_{fa})^2 - \left[r_{fa} - \left(\frac{s_f}{s_a}\right)\right]^2 - \left[\frac{[\bar{F} - \bar{A}]}{s_a}\right]^2$$

where $r_{fa}$ is the correlation between the forecast ($f$) and the observed or actual event ($a$); $s_f$ and $s_a$ are the standard deviations of the forecast and the actual values, and the notation $F$ and $A$ with the bars over the letters designate the means of the forecast and the actual values. The first term—the square of the correlation coefficient—represents the "potential" skill of the forecaster or judgmental forecast. The second term is "conditional bias" and will be equal to zero when the regression slope between the forecast and actual values is one. The third term is "unconditional bias"; as the difference between the forecast and actual means increases, the intercept of the regression line between the forecast and actual departs from zero. The Stewart and Lusk version of the Murphy skill score divides the first term into five additional segments, which represent: (1) environmental predictability, (2) fidelity of the information, (3) match between the environment and the forecaster, (4) reliability of information acquisition, and (5) reliability of the information processing. The last two components of the skill score are retained by Stewart and Lusk. The authors observed that their decomposition of the skill score into seven subcriteria for evaluation was to emphasize the conceptual and theoretical issues, but the skill score, while useful for empirical analysis of forecast performance, faced a major limitation that "the data necessary to estimate all the parameters of the full decomposition will rarely be available." So what is the point? The authors argued that decomposition provides a sense of where judgmental forecasts can go wrong. Hence, one of their proposed methods to improve judgmental forecasts was to decompose the forecast task. In essence, this provides another reason to use the Analytic Network Process for judgmental forecasting since it structures the forecast decision-making process based on key determinants or criteria.

scheme for mapping the component evaluations to an aggregate judgmental probability of a crisis (Saaty, 1990, 1994, 1996, 2001a). This multicriteria decision-making/forecasting model derives priorities or weights for each of the "$n$" criteria or components, $C_n$, of the model based on their judged (by the forecaster or a consensus of forecaster opinion) relative importance to the overall goal—which in this application is the likelihood that it will contribute to a financial crisis in a given period of time for a given forecast horizon. Not surprisingly, this process shares a common conceptual foundation with the derivation of component contributions from regression-based, time series, and/or cyclical-indicator composite index methodologies (Zarnowitz & Boschan, 1975). However, the derivation of the ANP priority weights, which use pairwise assessment based on statistical or judgmental relevance, is quite different from those more traditional methods (Frei & Harker, 1999; Niemira, 2001).

The Analytic Network Process framework is based on the following basic definitions and axioms: (a) a priority or weight, which is an absolute number, belongs to the closed interval [0,1] and is a measure of relative dominance; (b) a reciprocal condition exists that posits the ratio comparison between components is possible such that an evaluation of the pairwise couplet ($C_A$,$C_B$) equals 1/($C_B$,$C_A$); (c) homogeneity exists, which is the motivation for the 1–9 evaluation scale whereby the upper limit of 9 on that scale is due to the requirement of homogeneity to maintain the stability of the eigenvector to perturbation from consistency, and also to the requirement that only a small number of elements that are of close importance should be compared (an eigenvector with a small number of components considered.); and (d) a dependence condition is assumed that the system can be decomposed into component parts. Both the scale and the number of elements compared can be extended indefinitely. This is done by creating clusters with a small number of homogeneous elements in each and using a pivot element from cluster to the next (the largest in one as the smallest in the other) and applying the scale 1–9 to compare the elements in each, dividing by the priority of the pivot in the second cluster and multiplying the resulting priorities by the priority of the pivot in the first cluster and then combining the two clusters.

Moreover, the Analytic Network Process extends the AHP method to incorporate component dependence and feedback by using a *supermatrix* approach (Saaty, 1996, 2001a). A supermatrix, $\mathbf{W}$, is a complete system matrix of components, $\{C_a, C_b, C_c, \ldots, C_n\}$, and their linkages or system weights, $\mathbf{W}_{ij}$, where $\mathbf{C}_i=\{e_{i1}, e_{i2}, \ldots, e_{in}\}$ is the subcomponent elements of the criterion component "$i$." ANP allows interaction and feedback

$$\mathbf{W} = \begin{array}{c} \\ C_a \\ C_b \\ \\ \vdots \\ \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_a & C_b & \ldots & C_n \end{array} \\ \begin{bmatrix} \mathbf{W}_{aa} & \mathbf{W}_{ab} & \ldots & \mathbf{W}_{an} \\ \mathbf{W}_{ba} & \mathbf{W}_{bb} & \ldots & \mathbf{W}_{bn} \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{W}_{na} & \mathbf{W}_{nb} & \ldots & \mathbf{W}_{nn} \end{bmatrix} \end{array}$$

within clusters, $C_i$, which is known as *inner dependence*, and between clusters, which is known as *outer dependence*. To make this more concrete, if there is no linkage between, say component $C_b$ and $C_c$, then $\mathbf{W}_{bc}$ would be 0. However, if there is some relationship, then the entry would be nonzero, suggesting an outer dependence. An inner dependence would exist if there is a linkage within the components of a cluster, $\{e_{i1}, e_{i2}, \ldots, e_{in}\}$.

The supermatrix represents the impact of *all* model elements relative to the complete element set. The actual elements that make up the columns ($\mathbf{W}_{ij}$) of the supermatrix are the eigenvector solutions within the components (such that each column sums to one). However, each column of the supermatrix itself may include several subcolumns with its own priority element, which must be normalized and synthesized to account for the overall components' influence by column. This process makes the supermatrix column stochastic. The final priority weights—which account for element interactions—are derived by multiplying the supermatrix by itself until the columns stabilize, which occurs when the supermatrix entries become identical across each row or cycles in blocks in which case one uses what is known as Cesaro summability, and the result is known as the limiting matrix. The final priority weights are extracted from this limiting matrix.

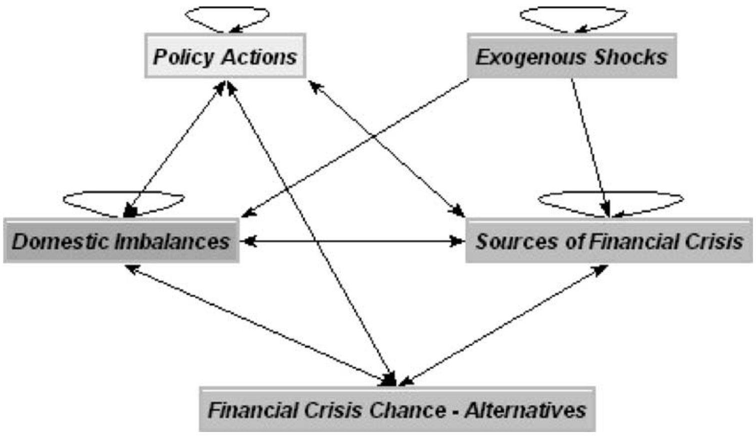


Fig. 1. Overview: the ANP-network financial crisis model's control hierarchy.

In essence, this solution algorithm derives weights that account for component interaction, which is a clear benefit of the dynamic ANP model over static models.

## 3. Building the ANP financial crisis model

Our objective is to demonstrate that an ANP model structure incorporating a majority of variables from prior studies can be used to predict the likelihood that an economy would be in "financial crisis," of any form, within 6 months. Explicitly, the model must account for banking, currency, and fiscal crises as well as contagion effects on the domestic economy from other countries experiencing one of more of those crises. Moreover, it would be useful to include a conceptual range of "all possible" indicators of financial crisis into this model, even if some rarely occur and might not show up as statistically significant in econometric models. One of the advantages of the ANP framework is that it is not constrained by some statistical problems, such as multicollinearity, which might be encountered in econometric modeling of the same process. In this way, the ANP model shares a common conceptual foundation with traditional composite indicator methods, which also attempt to select indicators across a wide spectrum of economic processes. Diversification of the criteria used to trigger a forecast decision is important, but one should not give too much weight to trivial indicators, even if the variable is included for completeness.

Arguably, the greatest advantage of the ANP model is that it can handle data limitations and intangibles (or qualitative variables—such as political or war risk) based on individual or collective judgment of the situation. As such, the measurement of intangibles is the main concern of the mathematics of the AHP/ANP approach. Often, even if there are no recent statistical data or no time series at all for such intangibles, there may be a qualitative sense of the importance of the factor (that might be gleaned through news reports, for example), which can be accounted for and incorporated into the ANP forecasting model.

Our model, which is dubbed the *imbalance-crisis turning point model*, incorporates the following features: (1) contagion effects, (2) fiscal crises, (3) banking crises, (4) currency crises, (5) the role of real-sector changes, (6) monetary policy, (7) fiscal or tax policy, and (8) external shocks, which include oil prices, food prices, and technological or productivity changes (this block also might include other exogenous influences, including legal restrictions on capital flows, political instability, social unrest, etc.).[2] The imbalance-crisis turning point ANP model is specified by clusters of criteria, their elements and the

[2] Although the selection of variables included in our model was based on econometric and other analytical studies, it is possible to search judgmentally for the relevant factors using a decision-making factor search technique, such as "rough set analysis" (Pawlak, 1991). Additionally, other decision-making schemes, such as "flags" or thresholds, could be built into the ANP framework (Medda & Nijkamp, in press; Vreeker, Nijkamp, & Ter Welle, 2001), but that is beyond the scope of this paper.

connection between them, and judgmental evaluations are made with a forecast horizon of up to 6 months.

The control cluster, in our model, is diagramed in Fig. 1. The arrows indicate direction of causal impact with the looped arrow indicating feedback effects. For example, in the exogenous-shocks block, it is assumed that an impact from oil prices will impact productivity shocks. The domestic imbalance criteria incorporate typical theoretical concepts and empirical evidence, but can be customized for a specific country's economy. As we have modeled the process, the domestic imbalance block includes evaluations of capacity utilization rates (too low or too high could be problems), the ratio of cash flow-to-investment (ability to afford the investment), the consumer debt burden (an over-leveraged consumer could pose problems for the economy), foreign debt reliance (capital or current account deficit problem), labor shortages (implications for wages or immigration policy), and profit margins (ability to sustain business). The policy-actions block includes evaluations of tax policy and monetary policy. The sources-of-financial-crisis block includes evaluations on banking, currency, fiscal deficits, and crisis contagion. The exogenous block includes evaluations on oil price shocks, food price shocks, and productivity shocks (which encompass numerous factors from strikes to technological impacts). Finally, the financial crisis chance block includes two elements—crisis or no crisis.

Although these elements are generic enough to cover most economies, there would be a need to customize the subcriteria for a specific type of economy. For example, the consumer debt burden subcriterion, which is a component of domestic imbalance in some developed countries, would not apply to every economy since some local customs or banking system infrastructures would not result in heavy consumer borrowing. Similarly, labor shortages may be a problem in developed countries, but not in emerging markets.

Once the characteristics of the model have been specified, then the forecaster must provide judgments on the relative importance of those various factors in the model as they relate to the system's alternatives (in this case, financial crisis or not). The process to solve the ANP forecasting model is as follows.

### *3.1. Step 1: determine the main cluster weights*

The main or control cluster weights for $\{C_a, C_b, C_c, \ldots, C_n\}$ are determined based on: (1) whether there is feedback in the cluster (if not, the matrix entry is zero), and (2) the intensity of the relationship between the cluster and other clusters using the nine-point scale (see Table 1). Instead of assigning two numbers $w_i$ and $w_j$ and forming the ratio $w_i/w_j$, we assign a single number drawn from the fundamental 1–9 scale of absolute numbers to represent the ratio $(w_i/w_j)/1$. It is a nearest integer approximation to the

Table 1
The fundamental scale: numerical ratings associated with pairwise comparisons

| intensity of importance | Definition | Explanation |
|---|---|---|
| 1 | equal importance | two activities contribute equally to the objective |
| 2 | weak | |
| 3 | moderate importance | experience and judgment slightly favor one activity over another |
| 4 | moderate plus | |
| 5 | strong importance | experience and judgment strongly favor one activity over another |
| 6 | strong plus | |
| 7 | very strong or demonstrated importance | an activity is favored very strongly over another; its dominance demonstrated in practice |
| 8 | very, very strong | |
| 9 | extreme importance | the evidence favoring one activity over another is of the highest possible order of affirmation |
| Reciprocals of above | if activity *i* has one of the above nonzero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *I* | a reasonable assumption |

Table 2
Formulating the control matrix

With respect to domestic imbalance

| | Domestic imbalances | Financial crisis chance | Policy actions | Source of crisis | Weights |
|---|---|---|---|---|---|
| Domestic imbalances | 1 | 7 | 3 | 1 | 0.425 |
| Financial crisis chance | 1/7 | 1 | 1/2 | 1/8 | 0.061 |
| Policy actions | 1/3 | 2 | 1 | 1 | 0.180 |
| Source of crisis | 1 | 8 | 1 | 1 | 0.334 |

Inconsistency index = 0.061
(desirable value to be less than 0.10)

With respect to financial crisis chance

| | Domestic imbalances | Policy actions | Source of crisis | Weights |
|---|---|---|---|---|
| Domestic imbalances | 1 | 1 | 1 | 0.333 |
| Policy actions | 1 | 1 | 1 | 0.333 |
| Source of crisis | 1 | 1 | 1 | 0.333 |

Inconsistency index = 0.000
(desirable value to be less than 0.10)

With respect to policy actions

| | Domestic imbalances | Financial crisis chance | Policy actions | Source of crisis | Weights |
|---|---|---|---|---|---|
| Domestic imbalances | 1 | 1 | 3 | 3 | 0.377 |
| Financial crisis chance | 1 | 1 | 4 | 2 | 0.367 |
| Policy actions | 1/3 | 1/4 | 1 | 2 | 0.139 |
| Source of crisis | 1/3 | 1/2 | 1/2 | 1 | 0.117 |

Inconsistency index = 0.051
(desirable value to be less than 0.10)

With respect to policy actions

| | Domestic imbalances | Financial crisis chance | Policy actions | Source of crisis | Weights |
|---|---|---|---|---|---|
| Domestic imbalances | 1 | 2 | 2 | 2 | 0.400 |
| Financial crisis chance | 1/2 | 1 | 1 | 1 | 0.200 |
| Policy actions | 1/2 | 1 | 1 | 1 | 0.200 |
| Source of crisis | 1/2 | 1 | 1 | 1 | 0.200 |

Inconsistency index = 0.000
(desirable value to be less than 0.10)

With respect to exogenous shocks

| | Domestic imbalances | Policy actions | Source of crisis | Weights |
|---|---|---|---|---|
| Domestic imbalances | 1 | 1 | 1 | 0.333 |
| Policy actions | 1 | 1 | 1 | 0.333 |
| Source of crisis | 1 | 1 | 1 | 0.333 |

Inconsistency index = 0.000
(desirable value to be less than 0.10)

Table 2 (*continued*)

| Control matrix node | Domestic imbalances | Financial crisis chance | Policy actions | Sources of crisis | Exogenous shocks |
|---|---|---|---|---|---|
| Domestic imbalances | 0.425 | 0.333 | 0.377 | 0.400 | 0.333 |
| Financial crisis chance | 0.061 | 0.000 | 0.367 | 0.200 | 0.000 |
| Policy actions | 0.180 | 0.333 | 0.139 | 0.200 | 0.000 |
| Sources of crisis | 0.334 | 0.333 | 0.117 | 0.200 | 0.333 |
| Exogenous shocks | 0.000 | 0.000 | 0.000 | 0.000 | 0.333 |

ratio $w_i/w_j$. The derived scale will reveal what the $w_i$ and $w_j$ are. This is a central fact about the relative measurement approach used within ANP and the need for a fundamental scale. However, it should be noted that the $1-9$ evaluation scale, in principle, has an unlimited range given the homogeneity and clustering that are used to extend the fundamental scale gradually from cluster to adjacent cluster, eventually enlarging the scale from $1-9$ to $1-\infty$.

To illustrate the development of the main cluster weights in our model, first observe that the exogenous-shock and financial-crisis-risk clusters do not include feedback (Fig. 1). Consequently, the entries for both clusters in the control matrix are zero. On the other hand, the policy actions, imbalances, and sources of financial crisis clusters are modeled with feedback given that those actions, events, or activities can spiral upon themselves. This means a full forecast period effect must be assessed/forecasted akin to using the "dynamic multiplier" in stochastic modeling and cutting off the cumulative effect at the end of the forecast horizon. The crisis model's forecast horizon is specified as 6 months.

The pairwise comparisons and normalized weights for the five components of the main cluster are derived as paired comparisons of intensities, based on the nine-point scale. The development of the main-cluster priority weights is shown in Table 2 for a hypothetical developed economy.

With respect to domestic imbalances, for example, a pairwise comparison of the sources-of-crisis criterion compared with the financial-crisis chance might be assigned a score in the control matrix of "8," which would mean that the sources-of-crisis component has a very high likelihood of impacting domestic imbalances relative to the financial-crisis chance. These ratings—demonstrated here as judgmental scores—incorporate "existing knowledge" about the economic landscape from various informational sources. Each score encompasses two aspects of the forecasting process into one evaluation measure: (a) the significance of the cluster or economic process relative to the overall stated objective, and (b) the current importance of that factor. Although the former aspect may be relatively invariant over time, the latter evaluation criterion will clearly change.

Table 3

Comparison for domestic imbalances with respect to banking crisis

| | Capacity utilization | Cash flow-to-investment | Consumer debt burden | Foreign debt reliance | Inventory-to-sales ratio | Labor shortage | Profit margins | Normalized weights |
|---|---|---|---|---|---|---|---|---|
| Capacity utilization | 1.000 | 0.200 | 1.000 | 0.333 | 1.000 | 1.000 | 0.333 | 0.06975 |
| Cash flow-to-investment | 5.000 | 1.000 | 3.000 | 1.000 | 3.000 | 3.000 | 3.000 | 0.29725 |
| Consumer debt burden | 1.000 | 0.333 | 1.000 | 0.333 | 1.000 | 1.000 | 0.333 | 0.07511 |
| Foreign debt reliance | 3.000 | 1.000 | 3.000 | 1.000 | 1.000 | 2.000 | 0.500 | 0.17439 |
| Inventory-to-sales ratio | 1.000 | 0.333 | 1.000 | 1.000 | 1.000 | 1.000 | 0.333 | 0.09085 |
| Labor shortage | 1.000 | 0.333 | 1.000 | 0.500 | 1.000 | 1.000 | 1.000 | 0.09672 |
| Profit margins | 3.000 | 0.333 | 3.000 | 2.000 | 3.000 | 1.000 | 1.000 | 0.19593 |
| Inconsistency index = 0.047 (desirable value to be less than 0.10) | | | | | | | | |

Table 4
ANP supermatrices and limit matrix

| | Capacity | Cash flow | Consumer | Foreign ~ | Invento ~ | Labor S ~ | Profit ~ | Food Pr ~ | Oil Pri ~ | Product ~ | Financi ~ | No Fina ~ | Monetar ~ | Tax Pol ~ | Banking | Contagi ~ | Currency | Fiscal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Unweighted supermatrix* | | | | | | | | | | | | | | | | | | |
| Capacity | 0.06610 | 0.05744 | 0.10546 | 0.09744 | 0.06157 | 0.06777 | 0.06721 | 0.09233 | 0.05828 | 0.32589 | 0.06211 | 0.10321 | 0.11808 | 0.00000 | 0.06975 | 0.13310 | 0.05320 | 0.13968 |
| Cash flow | 0.20587 | 0.17473 | 0.25809 | 0.19666 | 0.13073 | 0.14182 | 0.26506 | 0.10049 | 0.19610 | 0.10863 | 0.12684 | 0.13354 | 0.13872 | 0.00000 | 0.29725 | 0.14879 | 0.21086 | 0.20503 |
| Consumer | 0.15973 | 0.11506 | 0.15762 | 0.10777 | 0.09742 | 0.11603 | 0.10636 | 0.43324 | 0.27882 | 0.08421 | 0.12373 | 0.13056 | 0.15479 | 0.00000 | 0.07511 | 0.12875 | 0.15938 | 0.12537 |
| Foreign ~ | 0.14116 | 0.31232 | 0.10859 | 0.26877 | 0.36021 | 0.31847 | 0.16283 | 0.09233 | 0.12161 | 0.10863 | 0.33893 | 0.12799 | 0.17459 | 0.00000 | 0.17439 | 0.23837 | 0.23329 | 0.12672 |
| Invento ~ | 0.10936 | 0.05652 | 0.08147 | 0.09115 | 0.09552 | 0.05085 | 0.08732 | 0.09233 | 0.06787 | 0.10863 | 0.06501 | 0.26006 | 0.11583 | 0.00000 | 0.09085 | 0.07901 | 0.06903 | 0.11227 |
| Labor s ~ | 0.11842 | 0.13593 | 0.13625 | 0.09115 | 0.09628 | 0.14182 | 0.13190 | 0.10433 | 0.07751 | 0.13200 | 0.11499 | 0.09868 | 0.14292 | 0.00000 | 0.09672 | 0.11785 | 0.07374 | 0.10342 |
| Profit ~ | 0.19936 | 0.14800 | 0.15252 | 0.14706 | 0.15826 | 0.16324 | 0.17932 | 0.08496 | 0.19982 | 0.13200 | 0.16839 | 0.14596 | 0.15507 | 0.00000 | 0.19593 | 0.15413 | 0.20049 | 0.18752 |
| Food pr ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Oil pri ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Product ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 1.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Financi ~ | 0.16667 | 0.66667 | 0.75000 | 0.87500 | 0.50000 | 0.66667 | 0.66667 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.16667 | 0.16667 | 0.66667 | 0.66667 | 0.83333 | 0.25000 |
| No fina ~ | 0.83333 | 0.33333 | 0.25000 | 0.12500 | 0.50000 | 0.33333 | 0.33333 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.83333 | 0.83333 | 0.33333 | 0.33333 | 0.16667 | 0.75000 |
| Monetar ~ | 0.50000 | 0.66667 | 0.75000 | 0.50000 | 0.50000 | 0.75000 | 0.75000 | 0.00000 | 0.00000 | 0.00000 | 0.50000 | 0.80000 | 1.00000 | 0.00000 | 0.80000 | 0.50000 | 0.66667 | 0.25000 |
| Tax pol ~ | 0.50000 | 0.33333 | 0.25000 | 0.50000 | 0.50000 | 0.25000 | 0.25000 | 0.00000 | 0.00000 | 0.00000 | 0.50000 | 0.20000 | 0.00000 | 1.00000 | 0.20000 | 0.50000 | 0.33333 | 0.75000 |
| Banking | 0.40000 | 0.23034 | 0.49500 | 0.09366 | 0.25000 | 0.20000 | 0.38905 | 0.20000 | 0.38905 | 0.24627 | 0.22572 | 0.46659 | 0.24626 | 0.53556 | 0.54341 | 0.29626 | 0.51704 | 0.51704 |
| Contagi ~ | 0.20000 | 0.17885 | 0.16500 | 0.36975 | 0.25000 | 0.20000 | 0.17240 | 0.40000 | 0.17240 | 0.24627 | 0.13414 | 0.17134 | 0.20360 | 0.08434 | 0.09057 | 0.10818 | 0.07097 | 0.07097 |
| Currency | 0.20000 | 0.49339 | 0.19958 | 0.40259 | 0.25000 | 0.40000 | 0.31704 | 0.20000 | 0.31704 | 0.29788 | 0.51664 | 0.17134 | 0.34654 | 0.32068 | 0.31374 | 0.53567 | 0.36497 | 0.36497 |
| Fiscal | 0.20000 | 0.09743 | 0.14042 | 0.13400 | 0.25000 | 0.20000 | 0.12151 | 0.20000 | 0.12151 | 0.20959 | 0.12350 | 0.19073 | 0.20360 | 0.05942 | 0.05229 | 0.05989 | 0.04701 | 0.04701 |
| *Weighted supermatrix* | | | | | | | | | | | | | | | | | | |
| Capacit ~ | 0.02733 | 0.02375 | 0.04360 | 0.04028 | 0.02545 | 0.02802 | 0.02779 | 0.04616 | 0.01943 | 0.16295 | 0.02070 | 0.03440 | 0.04319 | 0.00000 | 0.02790 | 0.05324 | 0.02128 | 0.05587 |
| Cash flow | 0.08511 | 0.07223 | 0.10670 | 0.08130 | 0.05405 | 0.05863 | 0.10958 | 0.05024 | 0.06537 | 0.05432 | 0.04228 | 0.04451 | 0.05074 | 0.00000 | 0.11890 | 0.05951 | 0.08435 | 0.08201 |
| Consumer | 0.06604 | 0.04757 | 0.06516 | 0.04455 | 0.04028 | 0.04797 | 0.04397 | 0.21662 | 0.09294 | 0.04210 | 0.04124 | 0.04352 | 0.05662 | 0.00000 | 0.03004 | 0.05150 | 0.06375 | 0.05015 |
| Foreign ~ | 0.05836 | 0.12912 | 0.04489 | 0.11111 | 0.14892 | 0.13166 | 0.06732 | 0.04616 | 0.04054 | 0.05432 | 0.11298 | 0.04266 | 0.06386 | 0.00000 | 0.06976 | 0.09535 | 0.09332 | 0.05069 |
| Invento ~ | 0.04521 | 0.02337 | 0.03368 | 0.03768 | 0.03949 | 0.02102 | 0.03610 | 0.04616 | 0.02262 | 0.05432 | 0.02167 | 0.08669 | 0.04237 | 0.00000 | 0.03634 | 0.03160 | 0.02761 | 0.04491 |
| Labor s ~ | 0.04896 | 0.05620 | 0.05633 | 0.03768 | 0.03981 | 0.05863 | 0.05453 | 0.05217 | 0.02584 | 0.06600 | 0.03833 | 0.03289 | 0.05228 | 0.00000 | 0.03869 | 0.04714 | 0.02950 | 0.04137 |
| Profit ~ | 0.08242 | 0.06119 | 0.06306 | 0.06080 | 0.06543 | 0.06749 | 0.07413 | 0.04248 | 0.06661 | 0.06600 | 0.05613 | 0.04865 | 0.05672 | 0.00000 | 0.07837 | 0.06165 | 0.08020 | 0.07501 |
| Food pr ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Oil pri ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Product ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.33333 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Financi ~ | 0.01013 | 0.04053 | 0.04559 | 0.05319 | 0.03040 | 0.04053 | 0.04053 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.06191 | 0.09761 | 0.13333 | 0.13333 | 0.16667 | 0.05000 |
| No fina ~ | 0.05066 | 0.02026 | 0.01520 | 0.00760 | 0.03040 | 0.02026 | 0.02026 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.30953 | 0.48804 | 0.06667 | 0.06667 | 0.03333 | 0.15000 |
| Monetar ~ | 0.09337 | 0.12450 | 0.14006 | 0.09337 | 0.09337 | 0.14006 | 0.14006 | 0.00000 | 0.00000 | 0.00000 | 0.16667 | 0.26667 | 0.14318 | 0.00000 | 0.16000 | 0.10000 | 0.13333 | 0.05000 |
| Tax pol ~ | 0.09337 | 0.06225 | 0.04669 | 0.09337 | 0.09337 | 0.04669 | 0.04669 | 0.00000 | 0.00000 | 0.00000 | 0.16667 | 0.06667 | 0.00000 | 0.22576 | 0.04000 | 0.10000 | 0.06667 | 0.15000 |
| Banking | 0.13562 | 0.07809 | 0.16783 | 0.03175 | 0.08476 | 0.06781 | 0.13191 | 0.10000 | 0.12968 | 0.12313 | 0.07524 | 0.15553 | 0.02945 | 0.10100 | 0.10868 | 0.05925 | 0.10341 | 0.10341 |
| Contagi ~ | 0.06781 | 0.06064 | 0.05594 | 0.12536 | 0.08476 | 0.06781 | 0.05845 | 0.20000 | 0.05747 | 0.12313 | 0.04471 | 0.05711 | 0.02435 | 0.01591 | 0.01811 | 0.02164 | 0.01419 | 0.01419 |
| Currency | 0.06781 | 0.16728 | 0.06767 | 0.13650 | 0.08476 | 0.13562 | 0.10749 | 0.10000 | 0.10568 | 0.14894 | 0.17221 | 0.05711 | 0.04145 | 0.06048 | 0.06275 | 0.10713 | 0.07299 | 0.07299 |
| Fiscal | 0.06781 | 0.03303 | 0.04761 | 0.04543 | 0.08476 | 0.06781 | 0.04120 | 0.10000 | 0.04050 | 0.10479 | 0.04117 | 0.06358 | 0.02435 | 0.01121 | 0.01046 | 0.01198 | 0.00940 | 0.00940 |

Table 4 (*continued*)

| | Capacity | Cash flow | Consumer | Foreign ~ | Invento ~ | Labor S ~ | Profit ~ | Food Pr ~ | Oil Pri ~ | Product ~ | Financi ~ | No Fina ~ | Monetar ~ | Tax Pol ~ | Banking | Contagi ~ | Currency | Fiscal |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Limiting supermatrix* | | | | | | | | | | | | | | | | | | |
| Capacit ~ | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 | 0.03071 |
| Cash flow | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 | 0.06755 |
| Consumer | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 | 0.04491 |
| Foreign ~ | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 | 0.07701 |
| Invento ~ | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 | 0.03672 |
| Labor s ~ | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 | 0.04045 |
| Profit ~ | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 | 0.05974 |
| Food pr ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Oil pri ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Product ~ | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Financi ~ | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 | 0.06523 |
| No fina ~ | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 | 0.10457 |
| Monetar ~ | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 | 0.13282 |
| Tax pol ~ | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 | 0.07959 |
| Banking | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 | 0.09172 |
| Contagi ~ | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 | 0.04548 |
| Currency | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 | 0.08912 |
| Fiscal | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 | 0.03439 |

### 3.2. Step 2: determine the pairwise comparisons for the model elements

The model weights *within* each cluster, $\{e_{i1}, e_{i2},\ldots, e_{in}\}$, are derived using the standard application of AHP. Again, pairwise comparisons are used to establish the element relationships within each cluster; the eigenvalue of observable pairwise-comparison matrix, $A$, from the system of homogeneous linear equations, $Aw = nw$, or:

$$\begin{bmatrix} \frac{w_1}{w_1} & \cdots & \frac{w_1}{w_n} \\ \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = n \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix}$$

provides the element weights at this level, which will be used in the supermatrix. However, the formulation of this problem shows that the scale for the weights, in the original units, can be recovered from the matrix of ratios by solving the problem $Aw = nw$ or $(A - n\mathrm{I})w = 0$, which provides further assurance that the weights are mathematically related to the unobserved vector, $w$; that is, with judicious pairwise judgment, the derived weights should closely mirror the actual weights if they are available for checking. When the 1–9 scale values are used, the matrix $A=(a_{ij})$ is simply reciprocal and one solves the corresponding principal eigenvalue problem $Aw=\lambda_{\max}w$.

To demonstrate the process, consider an evaluation of paired comparison within the domestic imbalances block of the ANP model. The matrix of paired comparisons in this example might look as demonstrated in Table 3 for an evaluation of the elements within the domestic imbalance block with respect to the likelihood of a banking crisis for a hypothetical developed economy.

The diagonal of this matrix will be all one, which implies that any component cannot be more or less likely than itself. Next, consider the entry in the cell for the comparison of the cash flow-to-investment ratio on the left and capacity utilization rates with a banking crisis at the top of the matrix. Under the current circumstances, the cash flow of businesses would greatly influence the likelihood of a banking crisis and hence the couplet is assigned the score of "5" on the 1–9 scale. By design, the comparison of capacity utilization and cash flow (row 1, column 2) will be equal to the reciprocal of the cash flow and capacity utilization evaluation (row 2, column 1), that is, 1/5 or 0.20. Similarly, paired comparison is used to build up the full matrix. Finally, the principal eigenvector provides the solution weights, which are shown in right-most column of Table 3.

The degree of logical inconsistency is also checked. The value of the inconsistency index is 0.047 or a modest 4.7% for this matrix of paired comparison, well below the 10% practical threshold above which the evaluations are reassigned. Of course, a consistent evaluation is not necessarily a correct evaluation of the risks. Priority weights are computed for the other 15 matrices, in this model, using a comparable approach and each matrix is checked for its degree of inconsistency.

### 3.3. Step 3: construct and solve the supermatrix

The weights derived from steps 1 and 2 are used to populate the columns of the supermatrix. Each column of a supermatrix is either a normalized eigenvector with possibly some zero entries or all of its block entries are zero. The unweighted supermatrix, which is illustrated in the first panel of Table 4, is then multiplied by the priority weights from the clusters (which were determined in step 1), which yields the weighted supermatrix (second panel of Table 4). This is done because a matrix must be stochastic, that is, its columns must add to one, for a limit that is not zero to exist.

Finally, the system solution is derived by multiplying the weighted supermatrix of model variables by itself, which accounts for variable interaction, until the system's row values converge to the same value for each column of the matrix. This "power method" process yields the limiting matrix, which provides the relative importance weights for every factor in the model. In our example, those weights are reported in the bottom panel of Table 4.

Now that the system weights have been determined, a financial-crisis turning point forecast could be derived using zero (0%) and one (100%) to represent no crisis or crisis (similar to the Radelet and Sachs model). This structured-judgmental forecast would be computed as Forecast Risk = 0.3841 × (Financial

Table 5
Back-testing rule for assigning risk scores using the "signaling technique for evaluating incoming information on the 1–9" scale based on histogram

| Assigned score | Threshold for lower tail of distribution | Threshold for upper tail of distribution |
|---|---|---|
| 1 | less than 75% | greater than 25% |
| 3 | equal to 75% but less than 80% | equal to 25% but greater than 20% |
| 5 | greater than 80% but less than 85% | less than 20% but greater than 15% |
| 7 | greater than 85% but less than 90% | less than 15% but greater than 10% |
| 8 | greater than 90% but less than 95% | less than 10% but greater than 5% |
| 9 | greater than 95% | less than 5% |

Crisis) + 0.6159 × (No Financial Crisis) = 0.3841 × 100% = 38.4% chance of a financial crisis within 6 months. Although the forecast probability is a "snapshot" at a point in time for a specific economy, it demonstrates the process of constructing a financial-crisis turning point forecast model using ANP.

Historical simulations based on rules for interpreting incoming information or expert-system rules could be used to back-test the model for accuracy and to construct a time-dependent supermatrix (Saaty, 1994), if historical time series data exist. Moreover, sensitivity analysis—as demonstrated in Saaty (2001)—of the individual model components provides the user with bounds on how significant changes must be in order to impact a forecast (crisis or no crisis, in this case).

## 4. The 1991 U.S. banking crisis

Now that we have sketched out the structure and mechanics of the ANP model, the remaining question is: How good is this model empirically, even though it captures the essence of previous econometric and judgmental forecasting research? Obviously, one shortcoming of judgmental forecasting is determining historical accuracy. Notwithstanding, it should be clear that we offer the ANP framework as a method to structure one's thinking about financial-crisis triggers or catalysts, especially when data do not exist or given numerous intangibles, such as an unstable political climate and changes to the legal or regulatory structure.

The ANP method derives a judgmental forecast of the event risk given the evaluator's knowledge of the current situation, institutions, structural and political changes, and the expectation of change. This framework is conceptually very different from econometric or time-series model forecasts of financial-crisis risk, which are based on "historical statistical experience."

Table 6
Variables used to back-test ANP model

| Variable/concept | Form | Average | S.D. | Max | Min |
|---|---|---|---|---|---|
| Wholesale energy prices | monthly percentage change | 0.6% | 2.8 pp. | 13.4% | – 14.0% |
| Wholesale food prices | monthly percentage change | 0.2% | 1.1 pp. | 9.5% | – 3.3% |
| Productivity | quarterly percentage change (AR) | 2.1% | 3.6 pp. | 13.3% | – 5.9% |
| Profit margin | first difference | 0.0 pts. | 0.4 pts. | 1.3 pts. | – 2.3 pts. |
| Inventory/sales ratio | growth (TQSAR) | – 0.33% | 2.52 pp. | 6.63% | – 7.84% |
| Corp. Financing ability | cash flow-to-investment ratio | 0.801% | 0.078 pp. | 0.955% | 0.600% |
| Consumer debt | monthly percentage change | 0.7% | 0.5 pp. | 2.3% | – 1.4% |
| Unemployment rate | level | 5.7% | 1.58 pp. | 10.8% | 2.5% |
| Capacity utilization rate | level | 82.1% | 3.52 pp. | 89.4% | 71.1% |
| Current account | current account to GDP ratio | – 0.8% | 1.4 pp. | 1.3% | – 4.5% |
| Monetary policy | change in Fed funds rate | 0.0 pt. | 0.6 pp. | 3.1 pts. | – 6.6 pts. |
| Tax policy | effective tax rates (corp. + personal) | 62.6 pts. | 12.1 pp. | 86.7 pts. | 47.7 pts. |
| Banking | nonfin. Corp. credit mkt borrowing (%) | 8.8% | 3.8 pp. | 17.1% | – 3.1% |
| Fiscal | Federal deficit/GDP ratio | – 1.39% | 2.0 pp. | 2.5% | – 6.4% |
| Currency | trade-weighted dollar growth | 5.5% | 6.86 pp. | 24.3% | – 10.0% |
| Contagion | change in export and import shares | 2.7% | 7.3 pp. | 37.4% | – 17.9% |

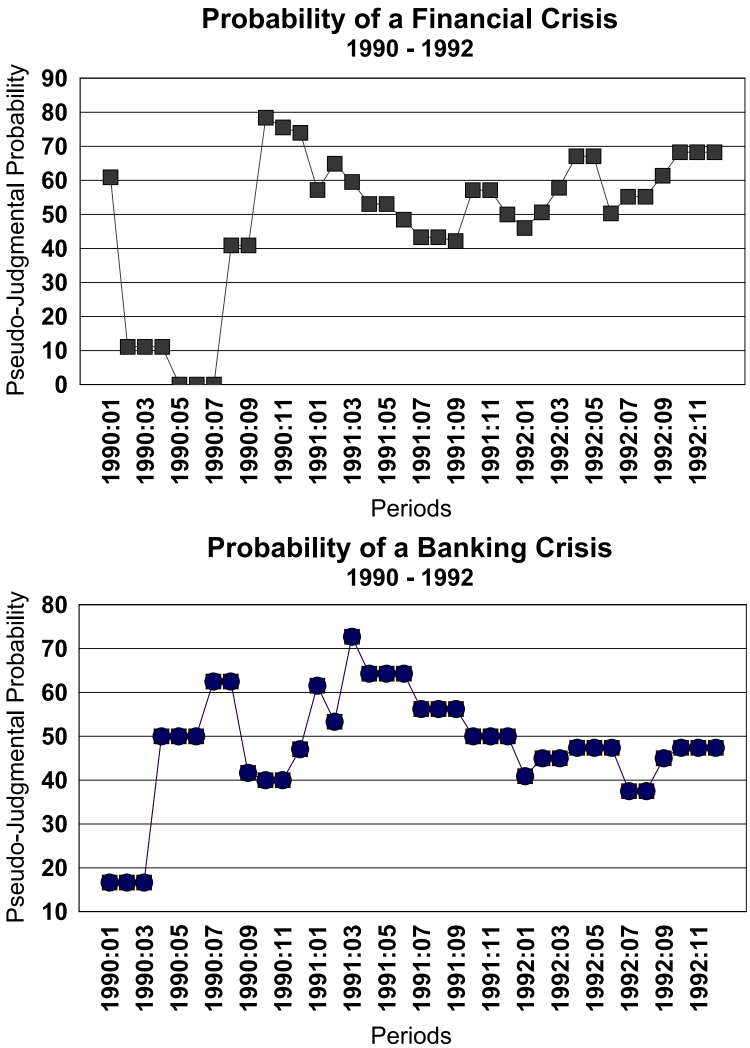


Fig. 2. Financial-crisis model back-testing exercise.

These methods rarely are interchangeable, but they can be complementary.

It is impossible to fairly use a judgmental forecasting method, such as this ANP model, to back-test how accurate the model "would have been" in signaling an event-driven financial crisis. Nonetheless, it is possible to test our model based on constructed decision rules, *provided historical data exist* to derive them and largely ignoring purely judgmental information that may have been available at the time. Obviously, this test will compromise the true benefit of including pure intangibles, but it will test the validity of the model structure. Of course, nothing will replace real-time testing of a judgmental forecasting model, rule-based historical testing is a second-best solution, though Armstrong and Collopy (1998) observed that forecast rules can work well when trends are not persistent and there is good knowledge about the situation. Rules are used here as a proxy for judgmental decision making and they facilitate testing of the ANP model. Yet, this relatively simplistic historical evaluation of the ANP model inputs using those rules cannot prove the ANP model's accuracy, only its validity.

Our test of the ANP financial-crisis forecasting model is based on whether it signaled the January 1991 banking crisis[3] in the U.S. economy as determined by Wolfson (1994). In lieu of human judgment, each indicator in the model was evaluated by the Goldstein, Kaminsky, and Reinhart (2000) "signaling technique," whereby an optimal threshold for each criterion was derived based on its histogram and a threshold signal was marked off when the value of the indicator crossed a given percentile. Thresholds were determined based on the individual indicator's distribution at 5%, 10%, 15%, 20%, and 25%, if the lower bound was of interest, or when the upper bound in the distribution was of interest, the threshold breakpoints were 75%, 80%, 85%, 90%, and 95% where the indicator change signaled the crisis point. This approach assumes: (1) Observations falling in the lower or upper 25% or less of the distribution are considered to be signals of increased risk (where the nature of the series determines whether the upper tail or lower tail is relevant). (2) The strength of those signals will be determined by how much of an outlier the actual value is relative to its histogram (or fitted distribution), which is a proxy for "perceived impact." (3) And, the signal rejection region (no crisis) is located in the remainder of the distribution. Our application of this threshold-search process was prompted by the successful use of it by Goldstein et al. in their determination of signals of financial vulnerability for emerging markets.

To implement the mechanical "pseudo-judgmental" evaluation (so as to allow for reproducibility) of historical information based on the fundamental evaluation scale, risk scores were assigned to observations based on how extreme the values were in the historical distribution for each series. Depending on whether an ANP model factor's lower tail or upper tail of the historical observations mattered (at least theoretically) for financial risk, the assigned risk scores and threshold points followed the rules shown in Table 5. For example, if the value of the current-account-deficit-to-GDP ratio (our empirical measure of foreign-debt reliance) was in the bottom 20% of the distribution, it was assigned a score of "5," but if it was in the bottom 5% of the distribution, then it was assigned a score of "9" on the fundamental scale.

Finally, a decision-making rule was applied as a back-testing simplification based on the two outcomes or alternatives: "crisis" (100% chance) or "no crisis" (0% chance). This rule mapped risk scores greater than "6" on the 1–9 scale (based on the maximum reading over the current and three previous month's readings) to the crisis outcome and everything else to the no crisis scenario for the individual component under analysis. This procedure was applied to each component, as shown in Table 6, and for each period.

Over the 1990–1992 period, the sequential model evaluation by those decision rules showed that the overall probability of a financial crisis rose from essentially zero earlier in 1990 to about 80% by October 1990, which seemingly would have warned of some looming form of financial crisis. The more specific probability of a banking crisis, meanwhile, which was less than 20% at the beginning of 1990 grew to over 60% by mid-1990, then receded a bit and rose to a peak of over 70% by March 1991. Wolfson's research determined that the beginning of the banking crisis was January 1991. As such, the model captured the growing banking-crisis risk during 1990, though its peak risk level occurred after the actual turning point date. The results are displayed in Fig. 2.

Although this empirical test of the ANP crisis-forecasting model was very encouraging, we must underscore the point that it is only illustrative of capturing the crisis dynamic within an ANP framework. The full power of the ANP framework was compromised necessarily by this back-testing exercise. Nevertheless, as a test of the mathematical structure of this model and the logic embodied in it, these results using the imbalance-crisis turning point model were very encouraging.

## 5. Conclusion

As a practical matter, Kahneman and Tversky (1973) observed that, "In making predictions and judgments under uncertainty, people do not appear to follow the calculus of chance or the statistical

[3] Wolfson (1994, p. 152) dates financial crises in the U.S. economy as beginning in August 1966, June 1970, May 1974, March 1980, June–August 1982, and January 1991. The January 1991 event was viewed as a banking crisis.

theory of prediction. Instead, they rely on a limited number of heuristics.'' This especially may be true when data limitations make a timely statistical forecast impossible. However, ANP offers a judgmental forecasting structure to evaluate those heuristics in a consistent manner.

In our paper, we presented a multiple criteria decision-making model with feedback to forecast financial crises using Saaty's Analytic Network Process. The model was back-tested for a period in the early 1990s when there was a banking crisis in the United States. It was not our intent to evaluate any individual forecaster's ability or collective forecasting accuracy, per se, but to evaluate the potential robustness of the crisis forecasting model's structure, which in turn might be used for real-time judgmental forecasting. We found that the ANP model approach indeed was a promising methodology to forecast the likelihood of event-driven cycles.

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