O.R. Applications

A Bayesian causal map for inflation analysis:
The case of Turkey

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Abstract

This paper proposes the use of Bayesian Causal Maps (BCM's) to analyze the complex structure of inflation in Turkey. In this study, a model of inflation is initially structured using a cognitive mapping technique; the dependent probabilities of the concepts are then calculated based on the detailed analysis of past data. Finally, a BCM is used to analyze the complex structure of inflation in Turkey. As a result, it will be possible to see the structure of the inflation model and to understand the basic consequences of any strategic change that may occur in the system.

Keywords: Economics; Forecasting; Cognitive mapping; Bayesian causal map; Turkish Inflation

1. Introduction

All traditional forecasting methods are based on the assumption that tomorrow’s world will be much like today’s (Le Bihan and Sedillot, 2000; Özatay, 2001; Stock and Watson, 1999; Ulengin et al., 2000). However, due to the high level of uncertainty concerning the future, a prediction of inflation through traditional forecasting is insufficient in understanding the real dynamics of inflation or in anticipating the major shifts that may occur in an uncertain macroeconomic environment.

Growth and inflation have always been among the most widely analyzed topics as well as being amongst those which have attracted the interest of macroeconomic forecast researchers (Hendry, 2001; Stock and Watson, 1999; De Brouwer and Ericson, 1998; Bonerjee and Russell, 2001). These two concepts constitute the general performance indicators of macroeconomics and, thus, macroeconomic policies are configured mostly based on...
their forecasted values. From the perspective of firms, on the other hand, the forecasts of these two concepts are the basic inputs that shape a wide spectrum of decision-making, from pricing to investment policies. Additionally, the more frequent publication of inflation data with respect to growth data as well as its more volatile character, increases the difficulty, thus, make its forecast technically more attractive.

The objective of this paper is to propose a model based on BCM in order to analyze the complex and uncertain structure of inflation (Önsel Sahin et al., 2004). Turkey’s inflation has been selected as a case study as it is well known that for years Turkey has been experiencing continuously high levels of inflation; thus it seems that in Turkey, the future seems to be more uncertain and complex than it has been for the last two or three decades. A new approach is therefore necessary in order to carry out/apply an accurate analysis of inflation.

The first section of the paper explains the main reason for selecting inflation as the basis of the analysis. In Section 2, the basic steps of the proposed model are given, with the structuring of the model using a cognitive mapping technique and the means of analyzing Turkish inflation through the use of the Bayesian causal map (BCM), derived from the cognitive map, also being investigated. Section 3 evaluates inflation in Turkey based on BCM’s. Finally, conclusions and further suggestions are given.

2. Why analyze inflation with a new approach?

In the economic literature, the models that aim to explain the dynamics of inflation were initially developed for Latin American countries, which tried to rally against inflation in the 1980s (Sheehy, 1980; Nugart and Glazacos, 1979; Tegene, 1988). The basis of these studies was to measure the pressure posed by monetary expansion on inflation and show that it was possible to reduce inflation through monetary policies. As a result of economic policies developed by Latin American countries in accordance with the IMF, it was possible to decrease the inflation to one-digit levels toward the end of the 1980s and there has been a reduction in inflation—targeting research during this period. However, the economic crisis and high level of devaluation problems that have been re-encountered in Latin American and African countries after 1990 made the inflation a hot topic again for them (Feliz and Welch, 1997; Deme and Fayissa, 1995; Moser, 1995; Mishkin and Savastano, 2001; Rigobon, 2002; Adam et al., 2001; Ndikumana and Boyce, 2003).

The research conducted for Western European and Asian countries, on the other hand, showed an important change, especially after the oil price increases in the 1980s (Morrison, 1987; Saini, 1982). Due to the fact that the developed countries managed to control their inflation levels in the mid-1980s, it was no longer seen as a macroeconomic problem for them. However, recently, due to the inclusion of new countries being relatively in weaker economic position, the researches on inflation forecasts have re-gained importance in the European Monetary Union (EMU) framework, and especially provided useful guide to the Union in the monetary policy development (Hubrick, 2005; Esposa et al., 2002).

Generally, all these models were causal models, which used regression for estimation. In these models, although the in-sample prediction power was higher, the out-sample prediction power was low, the basic reason being that in these model it was necessary to predict explanatory concepts as well. These models are used in particular to understand the structure and dynamics of inflation.

Due to the restricted and weak estimation power of causal regression models, time-series approaches such as the ARIMA and VAR models are generally preferred (Thomakos and Guerard, 2004; Moshiri and Cameron, 2000). In fact, these models have a better forecasting performance than regression analysis models. However, even in those models, the concept suffering from the highest deviation between its forecasted and real values is again inflation (Mcnees, 1986). Although Zarnowitz and Braun (1991) got better inflation estimations than other VAR models in their BVAR model, their results still show a very high deviation when compared to the forecast of other concepts.

On the other hand, the inflation estimation is even more difficult for Turkey, a highly inflationary
and indebted country. The yearly inflation rate was approximately 18% in the period 1970–1975, and with a very rapid acceleration period, reached 120% in 1980. At the beginning of the 1980s, however, a comprehensive stabilization and structural adjustment program was undertaken. As a result, the inflation rate fell to 30% in 1983, it stayed within 30–40% range until 1988 but again began to increase rapidly and fluctuated in 60–70% range until 1993. Finally, it reached three-digit levels (110%) with the surge of the financial crisis at the beginning of 1994 and was above 80% until 1998. The stand-by agreement with the International Monetary Fund and the re-functioning of the domestic debt market aimed to diminish the strength of the crisis. As a result, the inflation dropped to 50% in the 1999–2002 period, to 26% in 2003 and finally to 8.5% in 2004 (www.die.gov.tv). In fact, no other country witnessed such a high level of inflation over such a long period of time. Although there have been other countries facing higher levels of inflation, they never lasted more than 25 years. Those countries either managed to reduce the inflation rate to 10% per year or entered into a hyperinflation phase and then reduced inflation through a program. The inflation experience encountered in Turkey shows an interesting structure due both to the non-existence of hyperinflation and to its chronic nature (TUSIAD, 2002). Throughout the period in question, it has fluctuated to/at different levels and has shown persistence in staying at these levels (Fig. 1).

All of the above facts show that lowering the inflation rate to one-digit levels is an inevitable task for Turkish policy makers. Studies estimating the inflation rate in the pre-1980 period were mainly based on Fry’s model (1980), while those in the post-1980 period were based on Togan’s (1987). However, those traditional forecasting models that assume the future will be similar to the past are not suitable in attempts to estimate inflation when the future is uncertain and complex.

Therefore, it is necessary to propose a new approach in order to obtain a reliable answer to questions such as how much budget deficit reduction is necessary in order to decrease the inflation rate to one-digit levels or how to analyze the appropriateness of relying only on fiscal adjustment as opposed to using additional measures, etc.

3. The basic steps of the proposed model

The first step of the model is concerned with the structuring phase using the cognitive maps of related experts.
Cognitive mapping is a qualitative technique designed to identify cause and effect as well as to explain causal links. A cognitive map represents an individual's stated beliefs concerning a particular domain at a specific point in time (Eden, 1990). The term cognitive map has been used to describe several forms of diagrammatic representation of an individual's cognition. It is a representation of thinking about a problem that follows from the process of mapping (Eden, 2003). The basic elements of cognitive maps are very simple (Axelrod, 1976). The concepts used are represented as points and the causal links between these concepts are represented as arrows between these points. This kind of representation of causal assertions as a graph is called a cognitive map. As stated by Eden (2003), cognitive maps are not simply ‘word and arrow’ diagrams, or influence diagrams or a ‘mind-map’. Mapping processes often lead to the later development of influence diagrams as a lead into system dynamics simulation modeling. Cognitive mapping have been used in a variety of areas such as strategic change, joint venture formation, and software operations support exercise.

The cognitive maps are useful in describing deterministic decision problems. They analyze causal assertions of people to provide a qualitative interpretation of the concepts representing a decision problem. Cognitive maps represent domain knowledge more descriptively than other models, such as regression or structural equations. They provide a prescriptive framework for decision making and allow predictions in case of interventions (Nadkarni and Shenoy, 2001). In this paper, the basic reason of using cognitive maps is based on the fact that, in a world of incomplete data, individuals nonetheless make causal inferences that allow interpretation. Interactively generated maps that focus on causal relationships are attractive decision aids. That allows the decision maker to focus on action (Huff, 1990).

The basic drawback of the causal maps is that they do not model uncertainty with the decision concepts. However, identifying the level of uncertainty is important in making inferences because, as is the case with the concepts influencing the inflation, the observation of concepts may be uncertain, information may be incomplete, or the concepts involved may be vague. Additionally causal maps provide only a static representation of the decision concepts. They do not reveal how the beliefs of decision-makers about some target concepts change when decision-makers learn additional information about relevant situational concepts or decision options represented in the map. Such a dynamic approach is important not only in drawing inferences but also in learning about causal relations representing complex and uncertain decisions.

Recent advances in artificial intelligence such as Bayesian networks allow us to use causal maps to make inferences for decision making. In general, the relations represented in a Bayesian network do not have to be causal relations. However, a Bayesian network representation is sparse and efficient when the relations are causal and sparse. Bayesian networks allow us to make inferences efficiently even when we have many concepts in the network. Bayesian networks in which the dependence relations are causal are also called causal belief networks, causal probabilistic networks, etc. Therefore, in order to overcome the problems encountered with the cognitive maps, in the next step of the proposed model, the resulting aggregated cognitive map is converted into a Bayesian causal map (BCM).

A BCM, as proposed by Nadkarni and Shenoy (2001), is a special type of cognitive (causal) map with an associated set of probability tables. In other words, a combination of cognitive maps used for deterministic modeling and Bayesian belief nets used for uncertainty-based modeling can be called “Bayesian causal maps” (BCM) (Nadkarni and Shenoy, 2001, 2004). The maps consist of the nodes, representing the concepts and the arcs, representing relations between the concepts. The nodes of a BCM represent uncertain concepts and the arcs are the causal links between them (Fenton and Neil, 2000). The basic difference between cognitive maps and the BCM is that in the cognitive map, an arrow between two concepts implies dependence but the absence of the arrow doesn’t guarantee a lack of dependence. However, in BCM’s, given a sequence of concepts, an absence of an arrow from a concept to its successors implies conditional independence between the concepts.
From a mathematical point of view, the basic property of BCM’s is the chain rule: a BCM is a compact representation of the joint probability table over its universe (Jensen, 2002). From a knowledge engineering point of view, a BCM is a type of graphical model. It uses probability theory to manage uncertainty and complexity by explicitly representing the conditional dependencies between the nodes (concepts). The visual representation of BCM can be very useful in clarifying previously opaque assumptions or reasoning hidden in the head of an expert.

Fig. 2 summarizes the basic steps used in the proposed model. In this study, the proposed model is applied to represent and analyze the complex and uncertain structure of inflation in Turkey and a detailed analysis is realized in order to underline the dynamics of this complex inflation model.

3.1. Structuring the model using cognitive map

Cognitive maps have been used to represent managerial cognition at both the individual and group levels (Axelrod, 1976; Langfield-Smith and Wirth, 1992; Bougan et al., 1990; Eden, 2003). Cognitive maps are known as—cause maps—particularly when they are constructed by a group. However, the formalisms for cause maps will be the same as those for cognitive maps. The collection of cognitive maps is the source of creation of a strategy map—a cause map—which is the aggregate of many people’s thinking, including conflicting views and different perspectives on similar views (Eden and Ackermann, 1998). The technique has been used in the fields of international relations, administrative science, organizational behavior and management science (Fiol and Huff, 1992; Eden, 1993).

Different methods are used to collect individual and composite cognitive maps, depending on the purpose and the theory guiding the research. Thus, the self-Q method is designed especially for minimal intrusion and maximal disclosure of nodes, links and loops (Nugart and Glazakos, 1979). Although the self-Q interviews might be appropriate for the construction of initial cognitive maps, they are not suitable for the evaluation of composite cognitive maps.

Cognitive mapping in Axelrod’s sense, is designed to be a systematic, reliable way of measuring and analyzing the structure of an argument and not just its separate parts. Axelrod (1976) devised a mapping technique to represent the causal assertions embedded in decision makers’ arguments about policy and the decision-making environment. The data acquisition is generally based on document coding, questionnaire surveys or individual interviews. Once the cognitive map is derived, it can be useful in two ways: as a normative model and as an empirical model. As a normative model, a cognitive map claims to show how a person should make decisions. As an empirical model, a cognitive map claims to indicate how a person performs certain cognitive operations. In this sense, the cognitive mapping approach can be used as an aid to make correct deductions from the full complexity of many interrelated beliefs.

In another approach proposed by Eden and Ackermann (1998), a deliberately open structure is generally used for interviewing. However, in Eden and Ackermann’s latest paper (2004), documentations are also used to represent, store, analyze and make sense of the views of a number of experts in policy making analysis for the UK Home Office Prison Department. Eden’s approach, which is based on Kelly’s Personal Construct Theory, emphasizes joint work with
groups of individuals rather than compiled documents obtained from individual knowledge acquisition. It develops “aggregated maps” of groups of people using a team approach, in which the individual maps are discussed, reassessed and aggregated (Cropper et al., 1990).

Finally, Langfield-Smith, has created a shared map through the use of a group workshop where the participants identify similar ideas within the individual cognitive maps (Tegarden and Sheetz, 2003). Once an agreed set of “elements” are identified, then the participants identify a set of relationships between these elements. Once this is accomplished, the individual maps are merged to create a shared map, the shared map then being used to identify both shared and idiosyncratic beliefs.

In the proposed model, Axelrod’s sense of mapping is regarded as suitable. The purpose of this type of unstructured approach is to inductively explore a new or unfamiliar domain by posing questions such as: “What are the concepts relevant to the decision?” (Nadkarni and Shenoy, 2004). The unstructured approach yields a richer understanding of the processes that individuals engage in decision-making as well as gather important insights into the general knowledge that individuals have regarding the domain being evaluated.

### 3.1.1. Aggregated cognitive map of Turkish inflation

Due to the fact that many concepts or forces drive the future of Turkish inflation, in our case study, in order to obtain a mutually exclusive and selectively exhaustive list of driving forces the cognitive map is used for a group of experts. For this purpose, Interviews were conducted with three professors of economics from Istanbul Technical University’s Management Faculty. Each was initially asked to specify all the concepts that they thought had an influence or were influenced by inflation. The experts were encouraged to identify concepts that they would consider important for Turkish inflation and which might be relevant to the decision. This process continued until a comprehensive and exhaustive list of concepts was elicited.

Subsequently, the experts compared those concepts in a pair wise matrix where the rows represented causes and the columns effects and they specified whether the relation between each pair of concepts was ‘positive’, ‘negative’ or ‘zero’ (no relation). They entered a ‘0’ for no relation, ‘+’ for a positive relation and ‘−’ for a negative relation in each cell to specify the relation between two concepts in the matrix. A follow-up interview was then conducted with the corresponding experts in order to merge the group map from these notes. The experts decided that it would be appropriate to use the union set of all the concepts in order to consider the different points of view. As a result, the overall list of the variables of the aggregated map consists of all the variables stated by each of the three experts. A fragment of the resulting aggregated cognitive map is given in Fig. 3.

The resulting pair wise comparison matrix of this map was prepared by aggregating the relations according to the majority rule; the related adjacency matrix is given in Table 1. Since the number of experts was an odd number (3), majority rule was used to solve the conflicting views about the type (‘negative’, ‘positive’ or ‘no relation’) of the relations. A positive signed arrow was used if at least two of the experts stated a positive relation between the two related concepts. Moreover, in order to capture the different points of views, the prevention of the duplication of routes was not attempted, but just the opposite, they were displayed on the aggregated map representing multiple perspectives.

Although the use of a cognitive map alone is useful in describing a decision problem or for making inferences of very simple maps having few concepts, it becomes inadequate in complex maps such as the one derived for Turkish inflation. As can be seen from the map (Fig. 3) and Table 1, experts believe that 20 concepts (driving forces) can be accepted as either influencing or being influenced by inflation. Drawing inferences about concepts in such complex maps may be insufficient as cognitive maps do not model the uncertainty associated with the decision concepts. Besides, when decision makers obtain more information about a particular concept, the states of the other concepts, rather than change, stand the same (Nadkarni and Shenoy, 2001). In other words, they can only provide
Therefore in the proposed model, the second step consists of the conversion of the cognitive map into the BCM's. BCM's use a probabilistic inference procedure to make inferences about the concepts and to overcome the above-mentioned drawbacks.

The aggregated cognitive map analyzed in this study shows the existence of many loops due to the existence of a high number of concepts. The existence of loops is an indicator of the dynamic structure of the map (Eden and Ackermann, 1998). However, the circular relationships or causal loops destroy the hierarchical form of the graph and violate the acyclic structure that is required by a BCM. For causal networks, no calculation has been developed that can cope with feedback cycles (Jensen, 2002). Therefore, the network should not contain cycles. That is why, the first step in converting a cognitive map into a BCM is to analyze the loops. The loops may be due to coding mistakes that need to be corrected or may represent the dynamic relations between concepts across multiple time frames. In such cases, some parts of the linkages in the loop pertain to a current time frame while others pertain to a future time frame (Nadkarni and Shenoy, 2004). In such cases, disaggregating the concepts into two time frames can often solve the problem of circularity. Additionally, the experts should be informed that if two concepts have reciprocal influences, then the one with the more dominant causal influence is to be determined.

### 3.2. Analyzing the model through Bayesian causal maps

A fundamental assumption of a BCM is that when we multiply the conditionals for each concept, we get the joint probability distribution for all concepts in the network. For example, suppose that $A$ is serially connected to $C$ through $B$; then the chain rule for Bayesian networks yields,

$$P(A, B, C) = P(A) \cdot P(B \mid A) \cdot P(C \mid B)$$

In theory, the posterior marginal probability of a concept can be computed from the joint probability by summing out all other concepts one by one. In practice, such an approach is not computationally tractable when we have a large number of concepts because joint distribution has an exponential number of states and values.

Although BCM's create a very efficient language for building models of domains with inherent uncertainty, it is a tedious job to perform evidence transmission even for very simple BCM's.
|                                | Public sector deficit | Uncertainty rate | Exchange rate | Money stock | Short term capital flow | Wages | Size of informal economy | Uncertainty of government budget planning | Deficiencies in banking system planning | Severe income inequality | Macroeconomic inconsistency | Capacity utilization rate | Public sector debt | Budget deficit | Employment | Net foreign assets | Devaluation | Inflation | Inflation expectation |
|--------------------------------|----------------------|------------------|---------------|-------------|------------------------|-------|-------------------------|------------------------------------------|------------------------------------------|----------------------------|-------------------------|----------------------|-------------------|------------|------------------|-------------|----------|---------------------|
| Public sector deficit         | 0                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Uncertainty                   | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Interest rate                 | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Exchange rate                 | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Money stock                   | 0                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Short term capital flow       | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Wages                         | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Size of informal economy      | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Uncertainty of government     | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| budget planning               | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Deficiencies in banking       | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| system planning               | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Severe income inequality      | +                    | +                | 0             | +           | 0                      | 0     | 0                       | +                                        | –                                        | +                         | 0                       | +                   | +                  | +          | +                |
| Macroeconomic inconsistency   | +                    | +                | +             | +           | 0                      | +     | +                       | +                                        | +                                        | +                         | 0                       | +                   | +                  | +          | +                |
| Capacity utilization rate     | –                    | 0                | +             | +           | 0                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Public sector debt            | +                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Budget deficit                | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Employment                    | 0                    | 0                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Net foreign assets            | 0                    | 0                | 0             | 0           | 0                      | 0     | 0                       | 0                                        | 0                                        | 0                         | 0                       | +                   | +                  | +          | +                |
| Devaluation                   | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Inflation                     | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Inflation expectation         | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
| Inflation                     | +                    | +                | +             | +           | +                      | +     | +                       | +                                        | +                                        | +                         | +                       | +                   | +                  | +          | +                |
(Jensen, 2002). Fortunately, there are several commercial software tools such as Hugin (http://www.hugin.com) and Netica (www.norsys.com) which can carry out this operation.

In fact, causal maps can be used effectively in the construction phase of Bayesian networks (Nadkarni and Shenoy, 2004). They capture experts’ causal knowledge of a domain that other methods such as protocol analysis and repertory grids cannot capture. They represent domain knowledge more descriptively than other models such as regression or structural equations. In addition, causal mapping is more comprehensive, less time-consuming and causes less inconvenience to experts during knowledge elicitation than techniques such as protocol analysis and repertory grids. Finally, causal maps lend themselves to different types of statistical analysis, including matrix algebra and network analytic methods, system dynamics, decision trees and neural networks.

3.2.1. Bayesian causal map of Turkish inflation

In our case study, in order to eliminate the loops of the aggregated cognitive maps, the experts analyzed the map to distinguish direct and indirect relationships between concepts. The experts were instructed that an arrow between two concepts in the map should represent only a direct cause–effect relationship. At the end of the analysis, due to the direct versus indirect relation between the concepts in the original maps, some causal relations were found to be redundant.

Subsequently, in order to make a clear distinction between direct and indirect cause-effect relations and to understand the nature of relations between the concepts allowing incorporation of conditional independencies in the map, the experts were asked to revise the cause map in a way to assure that all concepts pertain to a specific time frame; namely month \( t \) (Nadkarni and Shenoy, 2004). In fact, after the revision the experts found out that only ten concepts have relation with inflation in month \( t \) time frame while the other causal relations pertain to a future time frame. A new concept (inflation \( t + 1 \)), was also added to the map. As a result, the public sector deficit, the interest rate, the exchange rate, the money stock, wages, public sector debt, the budget deficit, inflation expectation \( s \), inflation for time \( t \) and inflation for time \( t + 1 \) were accepted to be included in the revised map.

In fact, this reduction in the number of variables with respect to the initial map was the result of an attempt to analyze the Turkish inflation within a short term interval, namely month, in order to see the sudden changes that will occur in any of the related concepts.

After the re-organization of the map, the numerical parameters of the related concepts had to be determined. Each concept had a set of outcomes, called “states”. For the experts, constructing the network seems easier than stating the related probabilities because probability elicitation is generally a very difficult step in belief network building, as it may not be easy for experts to state multivariate beliefs (Sigurdsson et al., 2001; Nadkarni and Shenoy, 2001; Renooij and Witteman, 1999; Sucar and Arroya, 1998). Various tools and techniques are available to aid probability elicitation from experts specifically within BCM’s. However, the experts may not be able to determine all the probabilistic dependencies of a complex BCM. In this study, past data was used for the determination of numerical parameters. The related data gathered is based on the period January 1994 to December 2001. All the concepts were revised and converted to percentage values. For example, exchange rate values were changed into the increased rate of exchange rate values. After the revision of the concept values, a separate graph was prepared for each. Based on the graphs, the break points of the corresponding data were specified for each concept and the possible states of each concept were derived accordingly. An example of the break point analysis is given in Fig. 4 for the “interest rate” concept. The first break point is around 15%, the last around 84%. Since the values between these two increased uniformly, a third break point was determined between them. Therefore, interest rates data was classified into 4 states, “low”, “medium”, “high” and “extremely high”.

All the different combinations of the states of the concepts encountered during the period January 1994 to December 2001 were analyzed and the probabilities calculated, depending on this
combinatorial analysis. Probabilistic relations were provided for each node, expressing the probabilities of that node taking on each of its values, conditioned on the values of its parent nodes. The resulting map with joint probabilities calculated for Turkish inflation is given in Fig. 5. The map was structured through Netica software (www.norsys.com). The network has 10 nodes, 22 links and 924 conditional probabilities.

In order to calculate the joint probabilities for each of the concepts, the data gathered was filtered using Excel in a way to show the related combination configuration. For example, as can be seen from Fig. 5, inflation for time \((t + 1)\) is directly influenced by the money stock, public sector debt, budget deficit and inflation for time \((t)\). When the values of these four concepts are filtered using Excel, corresponding to their “low, high, high and low” labeled values relatively (see Table 2), it can be seen that during the period of January 1994 to December 2001, the probability of inflation \((t + 1)\) being “low” was 71.429\% (5/7), 28.571\% (2/7) for “medium” and 0\% (0/7) for “high”, according to the related values.

At this filtration stage, the experts judgments are taken again into account in order to eliminate all the combination of concepts which are impossible to occur together in the real life and also add some new combinations that cannot be directly seen based solely on past data but may be expected in the future due to some changes with respect to the past.

This learning process is thought to be a combination of using observed data and using expert knowledge. In fact, to obtain the joint probabilities using a Bayesian network based only expert knowledge is tedious and very time consuming.
The calculation of joint probabilities based solely on past data, however, will not permit to take in to account any expected changes in the future. The experts are expected to synthesize their past experience through this procedure. However, in graphical mapping packages such as Netica, the learning process depends on only observed data.

4. Evaluation of the results

The main reason for building the proposed BCM was to evaluate inflation in Turkey and to estimate the state of certain concepts based on given facts (Jensen, 2002). For a BCM, sensitivity analysis helps to study the effects of variations in the estimates of the network’s parameters on one or more posterior probabilities of interest (Coupé et al., 1999). Sensitivity analysis allows identification of those network parameters which are highly influential. In this study, sensitivity analysis was used to increase the efficiency of quantifying a belief network, as it directs the quantification effort towards crucial parameters.

The simplest type of sensitivity analysis is a one-way sensitivity analysis. In a one-way sensitivity analysis of a belief network, the estimates of the network’s parameters are varied one at a time, keeping all others fixed. The analysis then reveals the separate effects of variation of a parameter estimate on posterior probabilities. One-way sensitivity analysis has been carried out in this paper.

Several examples are presented in order to give an idea about the usage process of BCM for the analysis of Turkish inflation. Fig. 6 and Table 3 show the sensitivity analysis based on the money stock. Whilst the increase in the money supply increases inflation through demand-driven pressure on prices, a portion of the money supply, enlarged

![Diagram](image-url)

Fig. 6. First scenario for the inflation of Turkey.
due to dolarisation, is directed toward foreign currencies. Since the end of 2002, 54% of the total money deposit in the banking system has been held as foreign currency. The demand directed to foreign currency results in an increase in exchange rates. Due to the imported raw materials and parts used during production, cost-driven pressure affects prices and since pricing in Turkey is generally based on mark-up procedures, this increase in cost is reflected in prices. As a result, the money supply increases prices from two different directions. Increased exchange rates and inflation increase inflation expectation, which, in turn, increase inflation for the future period.

The second analysis is done on the budget deficit (see Fig. 7 and Table 4). The increase in the budget deficit results in an increase in the public sector deficit. Since this financial deficit is financed through debt rather than through the money supply, public sector debt increases very quickly. Due to the low impact of debt on inflation in the short to medium term, inflation shows very little change. This results in a dramatic increase in interest rates rather then in inflation. Debt maturity is particularly shortened due to the risks that are increased as a result of high debt levels, while real interest rates remain constant over the world average. Since the end of 2002, while real interest rates have

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<th>Table 3</th>
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<tr>
<td>Money stock</td>
<td>Inflation</td>
</tr>
<tr>
<td>Low</td>
<td>Low 0.34955</td>
</tr>
<tr>
<td>Medium</td>
<td>Medium 0.3894</td>
</tr>
<tr>
<td>High</td>
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</tr>
<tr>
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</tr>
<tr>
<td>Medium</td>
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</tr>
<tr>
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</tr>
<tr>
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</tr>
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<th>Findings according to the budget deficit variable</th>
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</tr>
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Fig. 7. Second scenario for the inflation of Turkey.
been between the 20–25% level, 60% of the total debt has had less than one year of maturity. The impact of interest rates on prices is also weak in Turkey; due to the fact that the banking sector uses collected funds in order to satisfy the government’s borrowing requirements and that private firms do not find it rational to borrow money with the current high real interest rates, the high interest rates are directly reflected in the cost structure of the firms. This, in turn, prevents the budget deficit.
showing its impact on inflation. Contrarily, high interest rates decrease investment and growth levels and increase unemployment that leads, in turn, to macroeconomic instability.

Another analysis can be done on wages. As can be expected, the increase of wages has a direct but limited impact on inflation (see Fig. 8). This is due to the very small ratio of labor cost within total costs and also due to the general tendency of arranging wage levels according to the inflation level of the past period. It can be seen that wages specified according to the past period’s inflation level do not have a reducing impact on inflation but do not increase it either. This results in a fixing mechanism over the current level of inflation.

The last analysis concerns inflation expectation. In Turkey, inflation expectations have a strong impact on inflation levels (see Fig. 9). Since contracts are made according to inflation expectations, an increase in expectation levels results in an increase in price levels. Additionally, the increase in inflation expectations accelerates dollarization, which results in an increase in exchange rates. This increase, in turn, has an increasing effect on prices, as previously illustrated.

5. Conclusion and further suggestions

In this paper, a method was proposed to estimate and analyze inflation using BCM’s, which are suitable for modeling uncertainty, and which can be used to support expert judgment in the process of analyzing inflation.

The econometric models based on time-series assume basically that the future behavior of a system will be similar to the past, at least for the near future. Although this assumption is unrealistic, it is generally used due to its ability to simplify the analysis. However, in the real world it is not possible to expect anything to remain constant for a period of time. In fact, this fact is also valid for inflation which is dynamic and changing over time due to different uncertainties. Therefore, in such situations, in order to take into account potential changes that may occur in the future, the use of expert opinion may be a useful guide. That is why, in this study, in addition to the use of past data for Turkish inflation, it is suggested to refer to the experts’ opinions both during the problem structuring phase, through cognitive maps as well as during the specification of Bayesian probabilities during problem analysis phase through BCM. As a result, with the help of BCM’s, both the structure underlying inflation can be analyzed and inferences can be made more easily and effectively. The structure that BCM’s provide is very important, not just for making effective inferences but also for understanding the complex structure of the situation.

BCM’s combine the strengths of both methods: cognitive mapping and Bayesian belief nets (Nadkarni and Shenoy, 2001). BCM’s are directed and acyclic graphs and have causal and conditional relations. In using them, decision makers can make both qualitative and quantitative inferences.

In the proposed method, a model of inflation is initially structured using a cognitive mapping technique, with the dependent probabilities of the concepts then calculated based on detailed analysis of the past data. Since the concepts identified are expressed as continuous concepts and the set of possible values are specified, the statistical relationships among the concepts are captured probabilistically. This in turn allows the specification of the joint probability distribution of several concepts in terms of conditional distributions for each concept. Since the conditional probabilities have been obtained, the BCM is used to analyze the complex structure of inflation. In this way, the knowledge acquisition phase, which is a hard and time consuming process, is made easier. In the case of impossibility of finding the numerical data for the concepts, a combined method of using both expert judgment and statistical values can be used. A result of this study is that it is possible to see the complex structure of the inflation model and to understand the basic consequences of any strategic change that may occur in the system.

In this study, the revised causal map of the Turkish inflation model was without feedback loop because it was based on a short period investigation, namely a month. In fact, this was in accordance with the acyclic graphical structure required by BNN. That is why, the use of BNN to analyze the uncertainties was appropriate. However, in a
case where circular relations exist and it is not possible to eliminate them, the system dynamics approach may be a better alternative with respect to BBN. This is especially the case where the aim to analyze a problem for a long period horizon because in this situation the circular relations will be unavoidable (Howick et al., 2004; Williams et al., 2003; Ackermann et al., 1997).

The proposed method was applied to Turkish inflation as a case study. In fact, through the understanding of the complex relationships among the concepts that influence or are influenced by Turkish inflation, the proposed method provides a useful guide for underlining the basic reasons of the failure of different policy changes that have been adopted by governmental authorities in their attempt to realize the expected decrease in the inflation level.

According to BCM results, the most efficient way to reduce inflation levels in Turkey is to adopt a tight monetary policy and reduce inflation expectation. As can also be seen in the analysis conducted in the previous section, although the budget deficit has a limited direct impact on inflation, it plays a basic role in reducing inflation expectations. The use of a tight monetary policy alone will be insufficient in reducing inflation expectations, especially if economic agents believe the government will not be able to sustain this policy for a long period. Whenever government attempts to reduce the budget deficit are perceived as sincere and sustainable by economic agencies, inflation expectations will be reduced. The simultaneous use of tight monetary policies together with policies to reduce the budget deficit lower inflation as well as inflation expectations in a short period and in the long run increase growth and employment levels by reducing real interest rates.

This proposed model is expected to reduce the skepticism of the authorities about the normative solutions that were formerly imposed on them. The authorities will not consider the proposed solutions to reduce inflation as a black-box solution but rather as a result of a detailed analysis that highlights all the important dimensions. They can also analyze very easily the impact of any policy that they are planning to adopt over the inflation level.

In fact, the economic program designed by Turkey in cooperation with the IMF after the 2001 crises involved two basic actions. First of all, the Central Bank of the Republic of Turkey became independent and had a sustainable tight monetary policy. Secondly, the government reduced its spending and generated a budget surplus. Within a year of the implementation of these policies, annual inflation in Turkey dropped from 50% to 20%. At the end of 2003, it again fell to 12%. These policies were retained in 2004 in order to reach one-digit inflation rates. These implemented policies are very similar to those proposed by the BCM model. The success of the anti-inflation program is an important validation of the ability of the BCM model to generate effective policies. However, as a further suggestion, it may be advisable to run a Monte Carlo simulation in order to investigate the accuracy of the estimation.

Finally, it is strongly recommended the study be conducted directly with the authorities or at least to have them included in the list of experts during the structuring phase. This will open up the policy planning process considerably by involving representatives of all the involved government agencies. In such a case, the structuring phase may become more effective and less time consuming, if all the experts are invited to a workshop where SODA (Strategic Options Development and Analysis) can be conducted (Eden, 1988). SODA would allow the group members to refine their ideas during the evaluation. In this study, due to the strong background of the selected experts, it was found sufficient to use only three experts in order to construct robust and detailed aggregated cognitive map. However, as a further suggestion, it may be more appropriate to increase the number of experts and to take into account not only the opinion of the academicians but of the policy makers as well in order to include different perspectives to the problem. Representatives of different “viewpoint” groups can be invited to a workshop in order to achieve an agreed cognitive map for the inflation problem. By this way it may also be possible to make separate discussion with each viewpoint group as well as between viewpoint group and analyses how their judgments show differences with respect to each other.
In fact, this may also result with a more complex map having a feedback structure. In such case, the framework can also be expanded through the inclusion of system dynamics (Andersen and Richardson, 1997; Lane, 2000). This will permit to understanding how the feedback structure of a system contributes to its dynamic behaviour and will provide different policies and strategies (Saysel et al., 2001). As a further research, the structure can be expanded to a more dynamic one by adding future time frames to the inflation structure. By this way, the analysis of the Turkish inflation within a longer time period will also be possible.

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