A Bayesian Belief Network to Infer Incentive Mechanisms to Reduce Antibiotic Use in Livestock Production

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Abstract

Efficient policy intervention to reduce antibiotic use in livestock production requires knowledge about the rationale underlying antibiotic usage. Animal health status and management quality are considered the two most important factors that influence farmers' decision-making concerning antibiotic use. Information on these two factors is therefore crucial in designing incentive mechanisms. In this paper, a Bayesian belief network (BBN) is built to represent the knowledge on how these factors can directly and indirectly determine antibiotic use and the possible impact on economic incentives. Since both factors are not directly observable (i.e. latent), they are inferred from measurable variables (i.e. manifest variables) which are influenced by these factors. Using farm accounting data and registration data on antibiotic use and veterinary services in specialized finisher pig production farms, a confirmatory factor analysis was carried out to construct these factors. The BBN is then parameterized through regression analysis on the constructed factors and manifest variables. Using the BBN, possible incentive mechanisms through prices and management training are discussed.

Keywords

Policy intervention, antibiotic use, Bayesian belief network (BBN), livestock production, incentive mechanisms

1. Introduction

The impact of antibiotic resistant bacteria, especially multi-resistant strains, on human health has become a major international concern (Salisbury, et al., 2002). Attention has focused on food-producing animals as one of several potential sources of antibiotic-resistant bacteria (WHO, 1997). As a result, in 1999, the European Union banned the sub-therapeutic use of four widely applied antibiotics in animal feed that are similar to drugs used in human medicine. In recent years, however, the therapeutic (over)use of antibiotics in infectious diseases treatment is believed to be a significant factor for increasing resistance (Witte, 1998, Phillips, et al., 2004, Martin, 2006). There are serious indications that the majority of the treated animals is likely not sick, at least not clinically visible. The question arises as to whether therapeutic antibiotics use is really intended for disease treatment or more for improving growth and feed efficiency (McNamara and Miller, 2002).

Although considerable uncertainty exists about the causal link between antibiotic use in livestock production and antibiotic resistance to human antibiotics, public health concern has made the reduction of antibiotic use in livestock production an urgent issue in public policy agenda. This is particularly the case in the Netherlands where antibiotics for human use is highly restricted. The intensive livestock sector is criticized to have used antibiotics excessively to achieve economic efficiency. To limit antibiotic resistance, the Dutch government aimed to reduce the use of antibiotics in livestock at least by 20% in 2011. Efficient policy intervention to reduce antibiotic use in livestock production requires knowledge regarding the rationale of antibiotic use, which can be used to design effective incentive mechanisms.

The use of antibiotics in livestock production is a complex issue (Bywater, 2004, Bester and Essack, 2010). Farmer's antibiotic use results not only from veterinary considerations, but also from their economic implications. As such, antibiotic use is intricately linked to the status of animal health and the style of farm management, which are again influenced by the characteristics of the farm and the farmer. Given the natural variability in the biological processes of farm animals, the relations among these factors are inherently uncertain. These uncertainties need to be taken into account when designing policy intervention. Bayesian belief networks (BBNs) with their associated methods is a powerful tool for dealing with uncertainty in decision making pertaining to human behavior (Jensen, 2002).

Bayesian networks have been successfully applied in a variety of disciplines, most notably in human medicine, and they are beginning to be more applied in ecological modeling (Borsuk, et al., 2004, Hammond, 2004), and microbial risk assessment in the food chain (Smid, et al., 2010). Recent research developments led to the creation of a number of integrated BBN models combining knowledge stemming from different disciplines. Such BBN models described in literature mainly relate to ecosystems and water management. For example, potential management strategies for salmon fisheries were evaluated by synthesizing the findings from the disparate biological and ecological stock assessment in combination with economic and sociological studies (Levontin, et al., 2010); the model for analyzing catchment management (Kragt, et al., 2009); the model for assessing the management of (Sadoddin, et al., 2009); and the model combining analysis of (Farmani, et al., 2009). Such a multidisciplinary approach is also a prerequisite in assisting policy makers with preferred incentive based policy instruments aimed at the reduction of non-therapeutic antibiotic use in livestock production.

This paper demonstrates the application of the BBN methodology to infer possible factors affecting antibiotic use in livestock production and how this knowledge can be used to design policy intervention to reduce antibiotic use. As an illustration, data from specialized fattening pig farms in the Dutch Farm Accountancy Data Network (FADN) were used to estimate parameters for the model. In Section 2, the FADN data and monitoring data on antibiotic use were first described to provide contextual information of this study. This is followed by the description of the key steps in building the BBN model. Section 3 then presents the resulting BBN model and illustrates how it can be used to infer the latent factors. Section 4 discusses the results and the implications for incentive design. Section 5 concludes the paper with an outlook on further research.

2. Material and methods

2. 1 Dutch FADN and monitoring data on antibiotic usage

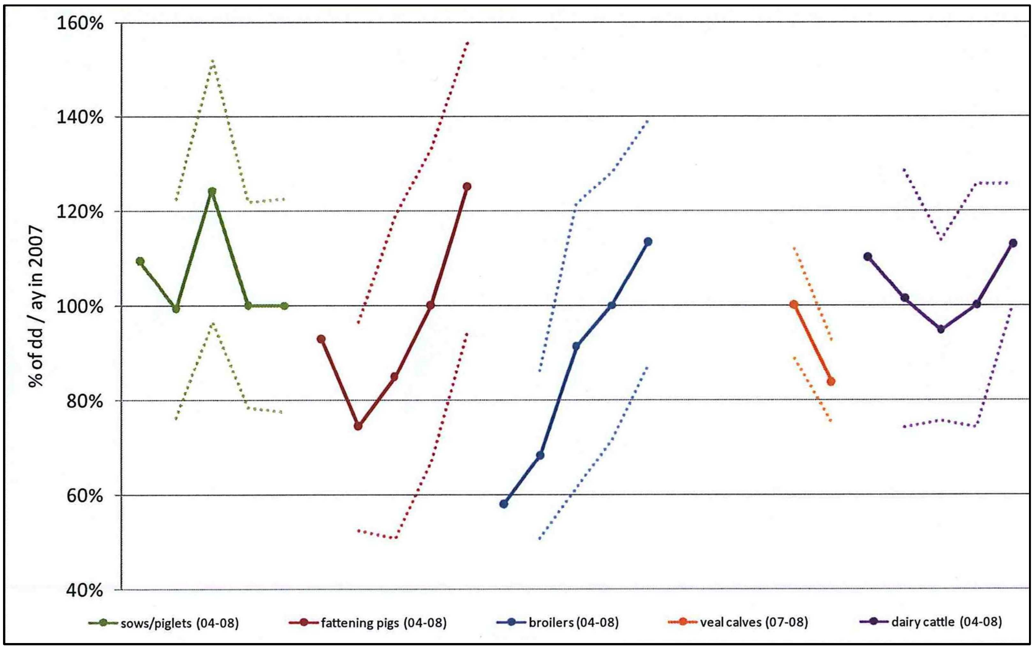
Due to its potential impact on public health, antibiotic usage in livestock production has been closely monitored and reported in the Netherlands (MARAN, 2008). Since 1998, FIDIN, a federation of the Dutch veterinary pharmaceutical industry, annually reports antibiotic sales figures in the Netherlands (FIDIN, 2009). Besides monitoring of total sales data at the national level, detailed monitoring of antibiotic use is also carried out on a stratified sample of Dutch farms that supply data to the FADN of LEI, part Wageningen UR. The Dutch FADN contains a representative sample of around 1500 agricultural and horticultural farms in the Netherlands (Vrolijk, et al., 2009). For livestock farms, the sampling details are shown in Table 1. The FADN database records economic data and technical performance indicators of the farms. Each year, a number of farms are replaced by other farms to ensure that the database of the Dutch FADN remains representative for Dutch livestock farming. Besides regular FADN information, detailed records have also been kept of the animal-medicine data and veterinary services. Containing veterinary, technical and economic information, these data offer insight not only into the exposure of farm animals to antibiotics but also into the underlying factors that could explain changes in antibiotic use.

Based on the monitoring data on the FADN farms, tendencies of antibiotic use in the livestock farms are shown in Figure 1 for the key subsectors (MARAN, 2008). Figure 1shows strong variations in the levels and trends of antibiotic use in different sectors. For example, while antibiotic use declined in other intensive farms, it steadily increased in fattening pig farms. The variations call for sector-specific analysis to understand the underlying factors. As an illustration, fattening pig farms are used in this study to apply the BBN methodology.

Table 1 Number of animals and farms in the Dutch FADN (2004-2009)

Variable name	Type of holding	2004	2005	2006	2007	2008	2009
Number of animals	Sows/piglets	17467	16790	13642	19861	19079	20806
	Fattening pigs	58617	58622	61503	128132	158210	159104
	Broilers	801914	1061981	2047487	1930923	2563231	2530313
	Veal calves	n.a.*	n.a.	n.a.	125125	131879	134446
	Dairy cows	3929	2962	3099	3025	7273	7382
Number of farms	Sows/piglets	49	46	34	42	47	48
	Fattening pigs	39	42	33	51	79	72
	Broilers	15	29	29	29	29	28
	Veal calves	n.a.	n.a.	n.a.	182	186	193
	Dairy cows	45	36	37	36	82	83
Total		148	150	125	336	432	424

*n.a. =no data available



Source: MARAN 2008

Figure 1 Antibiotic use in Dutch livestock sectors in 2004-2008 (reference year 2007)

2. 2 Developing the BBN

A BBN is a graphical model that incorporates probabilistic relationships among variables of interest. The probabilities connected to the arrows are conditional probabilities that show how the state of a variable effects the probability distribution for the states of another variable. The strength of BBN manifests itself in the possibility of reasoning about results given certain observations according to Bayesian rules. BBN can answer request of the form "what if" with respect to specific variables. Applied in this way, BBN are powerful probabilistic inference machine (Lauría and Duchessi, 2006). Constructing a BBN typically involves three steps. The first step is the development of the graphical structure indicating the relevant variables and dependencies. This step provides the basis for determining the degree of decomposition to be used in subsequent construction of the model. From a modeling perspective, this step requires developing a conceptual model to identify variables of interest and hypothesize their causal relationships. The conceptual model should provide insights into possible incentive mechanisms for farmers to reduce antibiotic use. The second step in constructing a BBN is the quantification of conditional relationships and the third step is building the graphical model which can visualize the quantitative relationships. These steps are explained below.

2.2.1 Step 1: The conceptual model for the BBN

The conceptual model is developed in consultation with experts from the veterinary science and agricultural economics. A schematic overview of the conceptual model is shown in Figure 1. The conceptual model is built upon the understanding that farmers' antibiotic use is not only an element of animal health management, but also conditioned by the general management strategy, which was chosen to maximize farming objectives. Since short-term profit maximization is often considered a rational behavioral assumption in modeling farmer's decision making, profitability of the farm is considered the key incentive variable for policy intervention. Since neither animal health status nor management quality can be observed directly, they are treated as latent variables of which information can be inferred from manifest variables. Manifest variables are observable variables whose variations are influenced by the latent variables (Bartholomew and Knott, 1999).

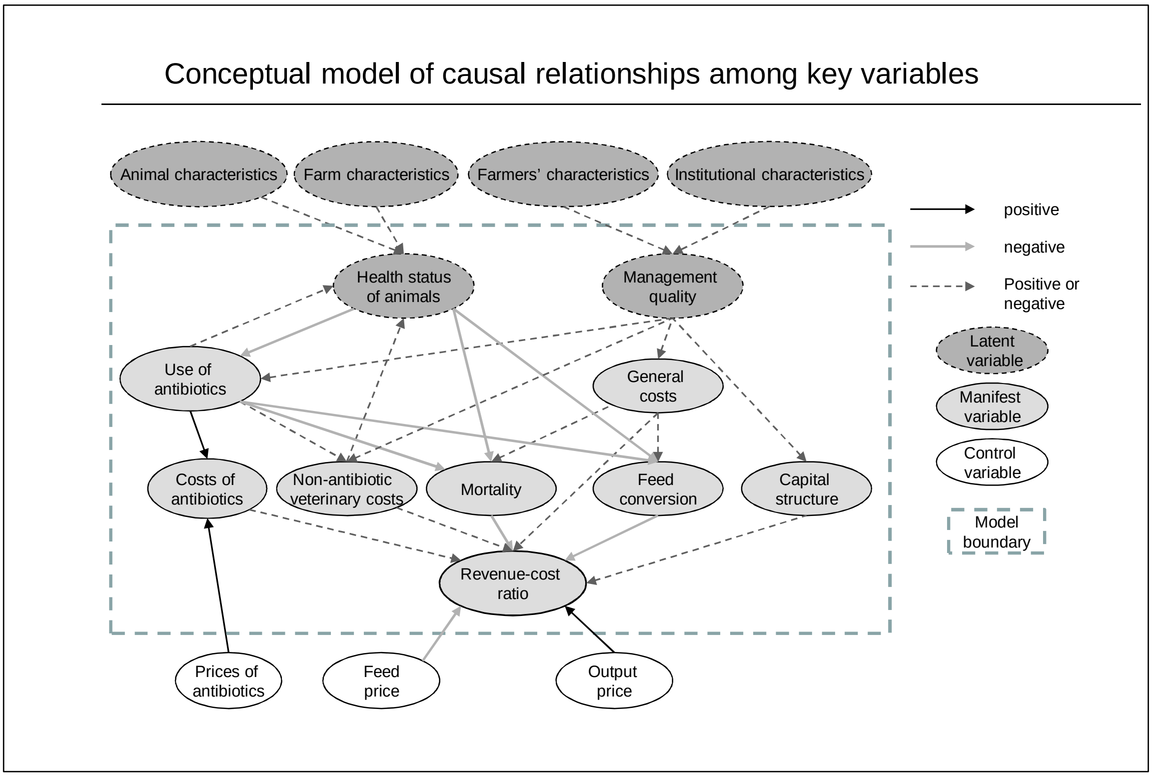


Figure 2 Conceptual model of the causal relationships among key variables

The conceptual model describes the boundary of our study and possible causal relationships among the manifest variables and latent variables. Prices of output, feed and antibiotics are indicated as control variables because they can be controlled externally to generate profit incentives for the farmer. While highlighting the central role of the animal health status and management quality in shaping profitability of farming, the conceptual model also indicates these factors are influenced by the specific characteristics of animals, farm, farmer, and the institutional environment. In view of the heterogeneous nature of these characteristics, considerable variations can be expected from the levels of animal health and management quality in different farms. Knowledge regarding the levels of these factors and how they can be inferred from the manifest variables is therefore essential for effective policy design.

In the context of pig production, a number of technical and economic performance indicators are identified as manifest variables to construct the latent factors. Technical indicators include mortality and feed conversion ratio (FCR) of pigs and the use of antibiotics. In animal husbandry, feed conversion ratio (FCR), also known as feed conversion rate, or feed conversion efficiency (FCE), is a measure of an animal's efficiency in converting feed mass into increased body mass. Lower FCR indicates higher efficiency and lower feed costs. Economic indicators are variables reflecting capital structure, various operating costs and revenue-cost ratio. The conceptual model reveals the complex relationship between on farm antibiotic use and profitability due to the interdependencies among various variables. On the one hand, high antibiotic use can improve profitability by reducing animal mortality and feed conversion ratio. On the other hand, high antibiotic use can imply poor animal health which manifests itself in higher mortality and feed conversion ratio, resulting in low profitability. Theoretically, it is impossible to ascertain whether antibiotic use will lead to higher or lower profitability. The influence of antibiotic use on the profitability of livestock production is therefore an empirical issue which can be assessed using relevant data.

2.2.2 Step 2: Quantification of conditional relationships

Based on the conceptual model, data were retrieved and processed to obtain quantitative information on the relationships among key variables. In particular, we combine the FADN data collected in the period 2004-2009 with registration data on animal medication and veterinary services (DAR) in the same period. DAR data are collected on a subset of the FADN-farms. The merged FADN-DAR dataset enables analysis on the economic impact of antibiotic use. A number of variables from the dataset and their descriptive statistics are described in Table 2.

Table 2 Definition and descriptive statistics of the variables used in the BBN model (N=284)

Variable name	Description	Unit	Mean	Std	Min	P50	Max
NDD	Number of daily dosages per average pig year	dosage/day /animal year	18.8	11.6	0.02	16.9	48.6
NonabCost	Costs of non-antibiotic health service and material per average animal	€/animal/year	56.8	38.0	3.9	45.2	163.8
FCR	Feed conversion ratio (the mass of the feed eaten divided by the body mass gain, all over a specified period of time)	Percentage	2.9	0.9	2.0	2.8	9.8
Mortality	Mortality of pigs (%)	Percentage	2.8	1.0	0.8	2.7	5.1
GenCost	General costs per animal per year	€/animal/year	219.0	84.3	101.2	198.8	415.0
DepCost	Depreciation costs per animal per year	€/animal/year	365.0	153.9	61.3	343.6	653.6
RCR	Revenue to costs ratio (%)	Percentage	87.7	13.9	62.3	89.4	122.2
Solvency	Solvency rate (%)	Percentage	64.1	26.6	10.5	62.8	99.9

Before quantifying the conditional relationships among the variables, a confirmatory factor analysis is first performed on the data to verify the existence of the two factors. Factor analysis is a statistical approach that is used to analyze interrelationships among a large number of variables and to explain these variables in terms of their common underlying dimensions (factors). In essence, the statistical approach is used to find a way of condensing the information contained in a number of original variables into a smaller set of factors with a minimum loss of information. Factors with eigenvalue greater than one are retained for further analysis (Child, 1990). Rotated factor loadings are then used to construct the factors and select variables for the BBN based on the ranking. The conditional relationships among the factors and the manifest variables are then obtained through regression analysis.

2.2.3 Building the BBN

Besides the choice of variables, BBN requires the conditional probabilities among variables to be known. These are collected in the conditional probability table (CPT). CPT's are the most important BBN parameters that summarize all knowledge about the probabilistic relationships among variables. The word "conditional" refers to the use of prior knowledge which can change due to improved information. In a BBN model, prior knowledge refers to the probability distribution of independent variables which can be updated when new information (evidence) is available.

The BBN methodology typically uses discrete states of the variables. Since the variables in the conceptual model are continuous, they must be discretized into levels of the variables. For this purpose, the statistical information of the variables is used to define relative levels of the variables in terms of "very low" to "very high". For all the variables, we used the 15th, 35th, 55th, and 75th quantile to discretize variables into five levels and call these levels "very low", "low", "average", "high" and "very high" respectively. The choice of the percentile is made to ensure equal distribution of the farms into different categories. The boundary values can differ in other populations of farms.

The BBN allows information to flow in the opposite direction of the causality (Jensen, 1996). The Bayesian network software GeNIe[1] is used to visualize the model structure and the quantitative relationships among the model variables. Statistical information of the data is used as the default situation without policy intervention. As a versatile and user-friendly development environment for graphical decision-theoretic models, GeNIe has been widely acknowledged in Bayesian network modeling (Korb and Nicholson, 2004) .

The BBN model can be used to infer the observable factors through the manifest variables. Information of the manifest variables In Bayesian terminology, an evidence on a variable is a statement or a piece of information of the certainties of its states (Jensen, 1996). If the information gives the exact state of the variable, it is called a hard evidence, otherwise it is called soft.

3. Results

3.1 Factors explaining antibiotic use

Confirming the theoretical expectation, the factor analysis on the technical and economic variables indicated two factors with eigenvalue greater than one. These two factors are then retained for further analysis. After the factor analysis, a Varimax rotation is performed to obtain insight into the nature of the factors. The rotated loadings of the variables on the factors are shown in Table 2.

Based on the rotated factor loadings, factor 1 appears to be mainly explained by depreciation cost, solvency and the use of antibiotics. More specifically, high level of depreciation cost correlates positively with high level of factor 1. The opposite holds for solvency. This may imply that the factor 1 can be strongly influenced by investment decisions that typically correlates with high depreciation and debt. Antibiotic use positively correlates with both factor 1 and factor 2, but to a greater extent to factor 1 than to factor2. Feed conversion ratio and non-antibiotic veterinary costs contribute considerably to factor 1, but to a much lesser extent. Variations in Factor 2 seem to be primarily determined by the level of general costs and the return to cost ratio. Mortality and feed conversion ratio are both positively correlated with factor 2. Since depreciation costs and level of solvency depend to a large extent on managerial decisions, factor 1 can be loosely interpreted as an indicator for

[1] GeNIe may be downloaded at no charge from http://genie.sis.pitt.edu/.

management quality. On the other hand, since mortality and revenue to cost ratio can be reasoned to be dependent on animal health status, Factor 2 can be interpreted as an indicator for animal health status.

Table 2 Rotated factor loadings of manifest variables.

	Factor1	Factor2
NDD	**0.271**	**0.109**
FCR	**-0.180**	**0.122**
Mortality	-0.043	**0.126**
GenCost	-0.029	**0.695**
DepCost	**0.685**	-0.045
RCR	0.037	**-0.650**
Solvency	**-0.606**	0.031

Using the rotated factor loadings, the two factors are constructed and discretized into five levels. To simplify the illustration, variables with factor loadings greater than 0.1 are retained to build the BBN model. The conditional probabilities among these two factors and the retained manifest variables are calculated through a regression analysis. The regression analysis assumes a multivariate normal distribution of the disturbance to the factors. Without prior information on the manifest variables, the basic structure of the BBN model is then shown in Figure 3. Besides indicating the relationships among variables with directed arrows, GeNIe also visualizes the strength of the relationships with the thickness of the arrows.

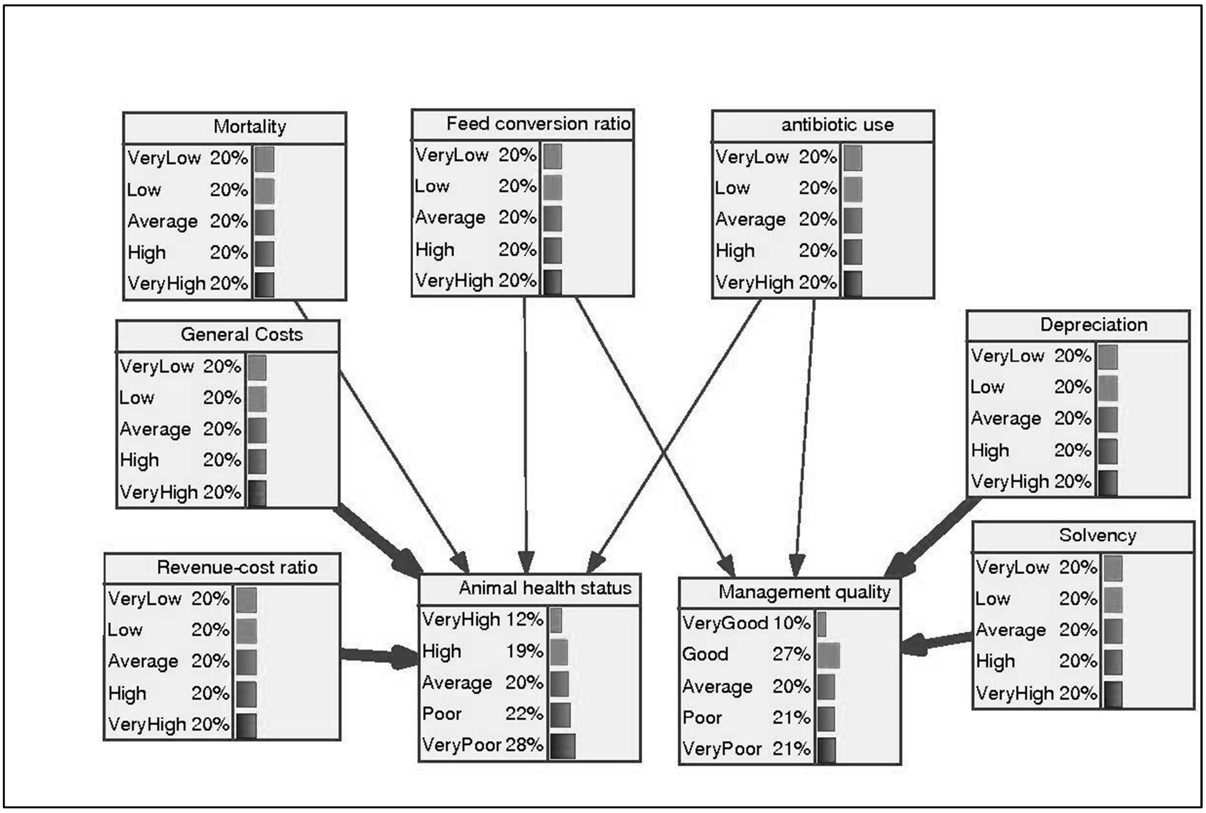


Figure 3 The Bayesian Belief Network (BBN) in GeNIE to infer animal health status and management quality

3. 2 Using the BBN model to infer animal health status and management quality

The BBN model captures the conditional relationships among the manifest variables such as antibiotic use and the unobservable factors of the fattening pig farms that are important in farmers' decision making. As such, the model can be used to infer the possible rationale underlying antibiotic use to gain insights into the incentive mechanisms that can influence farmers' behavior. For policy makers, it is important to distinguish which factor is more likely to be the main cause for high level of antibiotic use: animal disease status (the need for treatment) or management failure (the preference for more antibiotic use to avoid eventual diseases or generate other beneficial effects). For farms with different profiles, the BBN model can be used to show the possible composition of the causal factors. This can be done by setting evidence on various levels of antibiotic use, while keeping the prior distributions of other variables constant. As an illustration, Figure 4 shows the resulting distributions of the two factors with evidence set on the average level for all variables except antibiotic use.

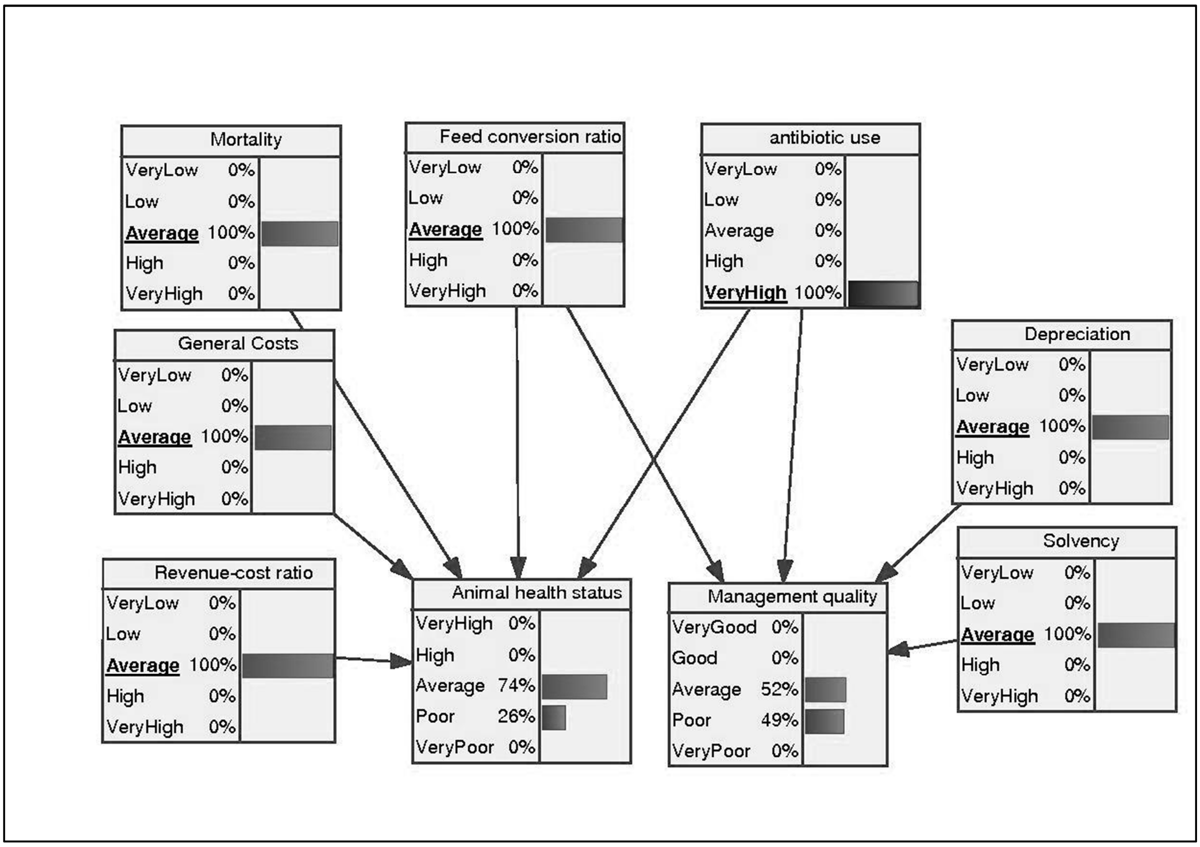


Figure 4 Using the BBN model to infer animal health status and management quality

Figure 4 shows a likelihood of 49% that, with other features in the average level, a fattening farm with very high antibiotic use has poor management quality in terms of antibiotic use. The likelihood that such a farm has poor animal health status is much lower (26%). This suggests that for such farms interventions should be targeted at improving management quality rather than improving animal health status. Similar analysis can be performed on other features.

4. Discussion

4. 1 Data and the parameterization of the BBN

The empirical relevance of the BBN model depends on the quality of data used to obtain the parameters. Due to the small size of the data set, the results of the BBN model presented in this paper should be interpreted with caution. Furthermore, statistical tests showed that some of the manifest variables in the data set are not normally distributed. This can be a feature of small sample set, but can also indicate inherent non-normality of the underlying population. To provide more reliable policy recommendation, a larger sample size may therefore be necessary. For more practical policy purposes, it is highly recommended to collect more data on animal diseases and entrepreneurial decisions.

In addition to statistical analysis on the data, model parameters can also be elicited from experts. In particular, CPT's derived from expert opinion can be used to validate the model. It should however be pointed out that using expert opinion on complex relationships among multiple variables is often subject to a limitation of human capacity in processing and interpreting large amount of data.

4. 2 Using BBN to infer incentives to reduce antibiotic use

The BBN model summarizes knowledge derived from the conceptual model and the empirical data regarding the quantitative relationships among factors related to both profitability and on farm antibiotic use. As such, it provides a natural framework to investigate the possible economic incentives of different interventions on antibiotic use for different types of farms. Policy intervention can be modeled as "evidence" on the manifest variables in the BBN-model or through sub-models to the BBN model through the control variables such as prices. For example, policy intervention can directly affect the level of antibiotic use through regulations. This is likely to have different economic implications for the farms due to the variations in animal health status and management quality. For example, farms with very high levels of antibiotic use and low level of animal health status would be the most influenced when no adjustments are made to improve the level of animal health status.

Economic theory and studies suggest that market-like mechanisms are likely to be more efficient in realizing policy goals by inducing the desired behavior voluntarily (see e.g., Pascual and Perrings, 2007). Without proper incentives, regulations that directly restrict antibiotic use per farm may incur high enforcement costs due to low level of voluntary compliance. Assume the overuse of antibiotics lies in the economic incentives offered by current markets and other institutions, one solution to the problem can lie in corrective institutional design. Based on the BBN model, a number of possible incentive mechanisms can be derived. For example:

1) Increasing the price of antibiotics; For farms with very high level of antibiotic use due to poor animal health status or management quality, this creates a disincentive to use antibiotics and as such generates the incentive to improve animal health or improve management health. For farms with low level of antibiotic use, changes in the price of antibiotics may only have limited impact.
2) A Bonus-malus system which raises the output price for antibiotic-free products and attaches a penalty to products produced with high level of antibiotic use. The bonus for antibiotic-free products creates economic incentive for farms with high level of animal health status to further reduce antibiotic use and the penalty generates disincentive for farms to apply antibiotics excessively. When excessive antibiotic use is caused by poor management quality, these incentives will likely induce changes in management quality in terms of antibiotic use. For example, alternative veterinary measures can be used to replace antibiotics.

Although the BBN model presented can be used to infer possible incentive mechanisms for different farms, in its current state it offers limited possibilities to calculate the economic incentives offered by specific interventions. For that purpose, the BBN should be expanded to include more detailed information regarding the costs and revenues of the farm. Another limitation of the model is that possible feedback effects among the variables cannot be included. This suggests however other modeling approaches such as system dynamics (see e.g., Forrester, 1971).

5. Concluding remarks

In this paper we show how the BBN methodology can be used to infer animal health status and management quality of livestock farms based on observed features of these farms. We also discussed how this knowledge can be used to support policy making in reducing antibiotic use in livestock production. Farm accounting data and registration data on medication and veterinary service were essential to parameterize the BBN model.

Effective policy intervention on antibiotic use often requires knowledge about the rationale of antibiotic use. Animal health and management quality are considered two important factors explaining farmer's behavior with regard to antibiotic use. Given the uncertainties about these two factors in different farms, the BBN methodology is shown to be a useful tool to infer this knowledge and possible incentive mechanisms. The modeling approach described in this paper is of a general nature and can be extended to other intensive livestock sectors such as the poultry.

The BBN model summarizes knowledge about animal health status and management quality of a fattening pig farm in the Netherlands. This knowledge can be used to obtain insight into the possible incentive mechanisms of policy intervention in the Dutch context. Based on the preliminary analysis, it is expected that price mechanisms in combination with management training can lead to the reduction of antibiotic use by livestock farms. Whether this reduction contributes to social welfare requires however further economic analysis on the wider economy. Future research should therefore consider the effect of policy intervention on other stakeholders.

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