



BAYES METHOD IN STATISTICAL STUDY OF SUSTAINABLE DEVELOPMENT OF REGIONS

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INTRODUCTION. Since the start of the pandemic, the International Monetary Fund has disbursed more than \$ 118 billion to 87 countries, including support for 54 low-income countries, particularly African countries, 13 times the average. The worsening of the pandemic, coupled with inflationary concerns, could send a double blow to many emerging and emerging economies if developed economies normalize monetary policy sooner than expected and fiscal conditions tighten. With this in mind, the development of the digital economy in the republic and in their regions is very important, because everyone has seen in practice exactly how much the digital economy is needed during the pandemic. Therefore, the role of the digital economy in the economies of

ABSTRACT

In this article, a descriptive analysis of the system of statistical indicators that characterize the sustainable development of the regions, econometric models of the transformation of the sustainable development of the regions into the standard of living of the population, statistical evaluation of the sustainable development of the Khorezm region's economy are studied.

countries is becoming increasingly important[6].

Today, the share of the digital economy in world GDP is 5.5%, and the share of digital technologies in various sectors of the economy and society is 22.5% of world GDP. This is mainly due to the contribution of developed countries.

It is clear that the development of the digital economy is playing a very important role in the overall development of the country. The Republic has also adopted a number of normative and legal acts in this regard, including the Decree of the President of the Republic of Uzbekistan dated October 5, 2020 PF-6079 "On approval of the Strategy" Digital Uzbekistan - 2030 "and measures for its effective implementation." One of the main advantages of the development of the



digital economy is the data presented in the form of digital statistics, which are a key factor in production in all areas of socio-economic activity, which increases the country's competitiveness, quality of life (low poverty) and economic growth. This is crucial to achieving the goal of our direct research.

In particular, it is not possible to create econometric models without data formed on the basis of statistical indicators. If the statistics are unreliable, it does not matter if the structured econometric models are put into practice. Therefore, it is important to know how and under what factors the economy of the country and its regions is developing on the basis of the development of the digital economy.

During our statistical study, we used a number of methods of econometrics and statistics, from which conclusions were drawn using the results obtained, taking into account that we propose a model for reducing poverty in the country and its regions. The main goal of the model is to reduce poverty in the country and its regions.

How can this be achieved? To this end, it would be expedient to work, first of all, to reduce the share of the poor among the population, but not to reduce the remaining population to the share of the poor. That is, it is necessary to reduce the level of poverty and increase confidence in the phenomenon of not reducing the share of the poor to the rest of the population. This is done through Bayesian statistics, which we also propose to implement Bayesian statistics in order to improve the sustainable development indicators of the regions.

METHOD. Bayesian statistics is a theory in the field of statistics based on the Bayesian

interpretation of probability, in which probability represents the level of confidence in an event. Confidence levels can be based on prior knowledge of an event, such as the results of previous experiences or personal beliefs about an event. This differs from a number of other interpretations of probability, such as the frequent interpretation that probability is seen as the limit of the relative frequency of an event after many tests.

The Bayes statistical method uses the Bayes theorem to calculate and update probabilities after new data have been obtained. The Bayes theorem describes the conditional probability of events based on data, as well as prior knowledge or beliefs about the conditions associated with the event or event. For example, in the Bayes conclusion, the Bayes theorem can be used to estimate the probability distribution or the parameters of a statistical model. Since Bayesian statistics considers probability as a level of confidence, the Bayes theorem can directly determine the probability distribution that quantifies confidence in a parameter or set of parameters.

The Bayesian conclusion is a method of drawing statistical conclusions in which the Bayesian theorem is used to update the probability of a hypothesis when more evidence or data is available. The Bayes conclusion is an important method in statistics, and especially in mathematical statistics. In the philosophy of decision theory, the Bayesian conclusion is closely related to the subjective probability, often referred to as the "Bayesian probability".

Bayesian statistics are named in honor of Thomas Bayes, who formed a peculiar case of the Bayes theorem in an article published in 1763. In several articles from the late 18th to the early 19th century, Per-



Simon Laplace developed a Bayesian interpretation of probability. Laplace used methods now considered Bayesian to solve a number of statistical problems. Many Bayesian methods were developed by later authors, but the term was not widely used to describe such methods until the 1950s. For much of the 20th century, Bayesian methods were despised by many statisticians because of their philosophical and practical considerations. Many Bayesian methods required a great deal of calculation to perform, and most of the methods widely used throughout the century were based on frequent interpretations. However, with the advent of powerful computers and new algorithms such as the Markov chain Monte Carlo, Bayesian methods have become more widely used in statistics in the 21st century. In particular, the Monte Carlo model has been used many times by Western scholars, along with Bayesian statistics, conclusions, and theorems.

The Bayes theorem is applied in Bayesian methods to update probabilities with confidence levels after new data have been obtained. Given two events A and B, the conditional probability of A is that B is true as follows:

where $P(B) \neq 0$. Although the Bayes theorem is the main result of probability theory, in Bayesian statistics it has its own interpretation. In the above equation, A usually represents the statement and B represents the rationale or new information that needs to be considered. $P(A)$ is the previous probability of an event A before considering the logical basis A that gives confidence in the event. The previous probability can also quantify the knowledge or information about the event

A. $P(B|A)$ is a probability function that can be interpreted as the probability B of the evidence considering the event A. The probability evidence B supports the statement A determines the level. $P(A|B)$ probability, A probability B is confirmed after reviewing the evidence. In fact, Bayes' theorem renews B's previous confidence in $P(A)$ when considering new evidence.

MODEL. In addition to Bayesian statistics, theorems, and conclusions, the Bayesian model has also been used and used in many studies. We will consider this model below. The Bayesian approach to model selection has several advantages. In particular, the Bayes approach is conceptually the same regardless of the number of models under consideration, and it is simple to interpret the Bayes factor and the probability of the next model.

From the given set of K factors, we evaluate all 2 K different models according to the degree of characterization given by the probability of the next model. Thus, we consider all possible models of the form,

$$M_i: R = X_i B_i + E, i=1, \dots, 2^K(1)$$

here, $X_i \in T^{(q_i+1)}$, q_i - the number of factors included in the model and B_i parameter matrix $(q_i+1) \times N$.

Given the pre-distribution,

$$\pi(B_i, \Sigma | M_i)$$

The limit probability for the parameters in the model is obtained as follows, M_i

$$m(R | M_i)$$

$$)= \int \int L(R | B_i, \Sigma, M_i) \pi(B_i, \Sigma | M_i) dB_i d\Sigma (2)$$

here, $L(R | B_i, \Sigma, M_i)$, M_i is a probability for the model. Marginal probability measures how well the model (and previous) fits the data. Model comparison can be done using Bayesian factors. M_i and M_j given by the Bayes Factor for

$$B_{ij} = (m(R | M_i)) / (m(R | M_j)) = \left(\int \int L(R | B_i, \Sigma, M_i) \pi(B_i, \Sigma | M_i) dB_i d\Sigma \right) / \left(\int \int L(R | B_j, \Sigma, M_j) \pi(B_j, \Sigma | M_j) dB_j d\Sigma \right)$$



$$d\Sigma)/(\int L(R|B_j, \Sigma, M_j) \pi(B_j, \Sigma|M_j) dB_j d\Sigma) \quad (3)$$

measures how much confidence in the relative e has changed M_j after seeing the data. M_i The front of a model $P(M_i)$, $i=1, \dots, 2^K$ If e probabilities are present, the Bayesian factor can be used to calculate the probability of the anterior (posterior) model.

$$P(M_i | R) = (m(R | M_i) P(M_i)) / (\sum_{j=1}^{2^K} [m(R | M_j) P(M_j)]) = [\sum_{j=1}^{2^K} [P(M_j)] / (P(M_i)) B_{ij}]^{-1} \quad (4)$$

Finally, we note that, if $P(M_i) = 1/2^K$ any, the probabilities of the anterior (posterior) model are given by normalized marginal probabilities.

$$P(M_i | R) = (m(R | M_i)) / (\sum_{j=1}^{2^K} [m(R | M_j)]) = [\sum_{j=1}^{2^K} B_{ij}]^{-1} \quad (5)$$

There are two main difficulties in choosing the Bayes model. First, we need to select the previous distributions for each model parameters. In general, these advantages should be informed, as advantages that are not misinformed lead to uncertain marginal probabilities. Second, we need to calculate the integration in the equation to obtain the Bayesian factors and the probability of the previous (posterior) model. To overcome these problems, we use the natural advantages for factor sensitivity, B and C for the covariance matrix, because C is a common and uncertain factor for all models, eliminating the Bayesian factor. For a given C , B_j the previous matrix is given with a normal distribution of variability

$$B_j | \Sigma, M_j \sim MN((q_j+1)*N) (B_j | B_j, \Sigma, Z_j^{-1}) \quad (6)$$

and C has the following properties

$$\pi(\Sigma) \propto [|\Sigma|]^{-1/2(N+1)} \quad (7)$$

Using the above expressions, M_i the marginal probability for the model can be obtained analytically. Let B_j 's get the smallest squares method estimator B_j and $S_j = (R - X_j B_j)' (R - X_j B_j)$. Then, M_i relative to the Bayesian factor for the model M_j

$$B_{ij} = (|Z_j|^{-N/2} |A_j|^{-N/2} C_{IW}(S_j^*, T, N)) / (|Z_j|^{-N/2} |A_j|^{-N/2} C_{IW}(S_j^*, T, N)) \quad (8)$$

$$\text{when } S_j^* = S_j + [(B_j - B_j)]^{-1} [Z_j^{-1} + [(X_j - X_j)]^{-1}]^{-1} [(B_j - B_j), A_j = Z_j + X_j X_j' \text{ and}$$

$$C_{IW}(S, v, q) = 2^{1/2} v^q \pi^{1/4} q(q-1) \prod_{i=1}^q \Gamma((v+1-i)/2) [S]^{-1/2} v \quad (9)$$

Without prior knowledge, it can be difficult to select previous parameters. Reflecting that there is no consensus in the literature on the identification of factors, it $B_j = 0$ is appropriate to use the views of Fernandez, Ley and Steel, Hall, Hwang and Satchell and other scientists for the previous covariance matrix, which is the previous mean value of B depending on a particular model. Thus,

$$Z_j = g(X_j X_j') \quad (10)$$

where $g > 0$. The parameter g is chosen so that the previous variance is larger than the least squares method. The Bayes factor is finally simplified

$$B_{ij} = [(g/(g+1))]^{1/2} N(q_i+1) / [(g/(g+1))]^{1/2} N(q_j+1) ((|S_j + B_j' g/(g+1) (X_j X_j' + B_j B_j')| / (|S_i + B_i' g/(g+1) (X_i X_i' + B_i B_i')|)^{1/2} T) \quad (11)$$

and we can easily calculate the probabilities of the previous (posterior) model given by Equation (5). Using these formulas, the Bayes model is developed and it can be determined that it can be applied in practice based on its evaluation. These are mainly used on the basis of the



application of Bayesian statistics, theorems and conclusions, and can be used in other cases as well.

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