IJSA (2025), Vol. 9, No. 2, 181-193
DOI: https://doi.org/10.29244/ijsa.v9i2p181-193

Indonesian Journal of Statistics and Its Applications
Available at https://journal-stats.ipb.ac.id/index.php/ijsa
e-ISSN: 2599-0802

A Bayesian Approach for Wilcoxon Signed-Rank Test and Its Application to the Farmer's Exchange Rate in Indonesia*

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Abstract

The Wilcoxon Signed-Rank Test (WSRT) is a nonparametric statistical method based on ranks to test two paired samples. Researchers often use a frequentist approach in testing by utilizing test statistics or p-values. This approach has limitations in providing information about the rejection of the alternative or null hypothesis. These limitations have spurred interest in Bayesian-based testing, known as the Bayes Factor. The advantage of the Bayesian approach is that it can measure how much the data support one hypothesis over another. However, there is a problem with using the Bayesian approach in WSRT, since there is no distribution of the rank, implying that no likelihood can be formed from the data rank. Van Doorn proposed a Bayesian approach for this test by using a latent normal approach, modelling the data rank as coming from latent variables that are normally distributed. The objective of this study is to test whether there is a difference between the farmer exchange rate in 2021 and 2022 in Indonesia. We used the Wilcoxon Signed Rank Test with a Bayesian approach, as described by Van Doorn. The test employs the Bayes factor to conclude by transforming the rank of the data using a latent variable that assumes a normal distribution. The analysis was conducted by constructing a posterior population of difference (δ) of 475,000 using the Gibbs Sampling algorithm. The values of the Bayes Factor (BF_{10}) is of 3076.07 and concluded that there is a difference in the farmer exchange rate in Indonesia between 2021 and 2022. This Bayes Factor indicates extreme evidence of a significant difference in the farmer exchange rate in Indonesia between 2021 and 2022.

Keywords: Bayes Factor Evidence, Bayesian Wilcoxon Test, Farmer's Exchange Rate, Gibbs Sampling Algorithm, Latent Normal Model

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* Received: Aug 2024; Reviewed: Dec 2024; Published: Dec 2025

1. Introduction

The Wilcoxon Signed-Rank test is a nonparametric, rank-based method used to test the difference between two paired sample means. Researchers often use the classical (frequentist) approach, which uses statistical tests or p-values to test hypotheses. However, the frequentist p-value approach has the disadvantage of providing little information regarding the degree of truth. This has given rise to renewed interest in Bayesian-based testing known as the Bayes Factor (van Doorn et al., 2020). The advantage of the Bayesian approach is that it can measure how far the data supports one hypothesis compared to another hypothesis (Dienes, 2014).

According to Van Doorn et al., (2020), the main challenge in developing Bayesian hypothesis tests for ranking data is the lack of a likelihood function, due to the fact that rankings has no uniform distances among ranks and cannot be expressed in a commonly known distribution. This difficulty can be overcome by modeling ranking data through latent variables with a normal distribution. By using a latent normal approach, the distribution problem of rankings can be addressed through latent variables, thus obtaining the likelihood function for the data and implementing a Bayesian approach (van Doorn et al., 2020).

Farmer Exchange Rate (NTP, *Nilai Tukar Petani*) is a measure tool for calculating the purchasing power of agricultural products with consumer goods and services for both household needs and production process costs (Kementerian Pertanian, 2015). According to the Central Statistics Agency (BPS), the Farmer's Exchange Rate (FER) in Indonesia increased by 2.57% in 2022 compared to 2021, with the 2021 FER reaching 104.64 and the 2022 FER reaching 107.33. The distribution of FER across Indonesia's provinces is shown in Figure 1.

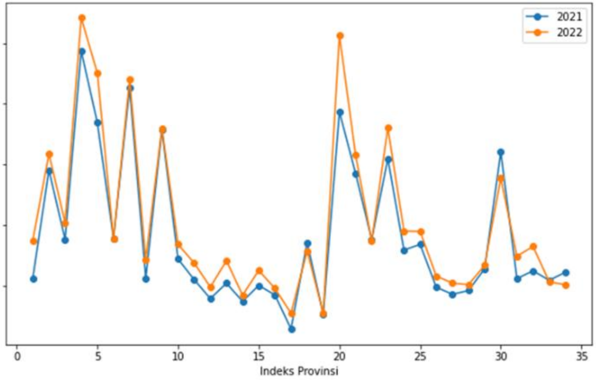

Figure 1: Indonesian Farmer Exchange Rate 2021-2022 by Province

Based on Figure 1, there are fluctuations in the farmer's exchange rate in each province, indicating that there are differences in the farmer's exchange rate in Indonesia in 2021 and 2022. However, those differences do not necessarily indicate a statistically significant difference, hence it needs further statistical testing. In this study, the Bayesian approach will be applied to the Wilcoxon Signed-Rank Test as proposed by van Doorn et al. (2020), to determine whether there are significant differences in the farmer's exchange rate in Indonesia between 2021 and 2022. Although this approach has been developed in methodological studies, to date it has not been widely applied to the analysis of sectoral data such as the Farmer's Exchange Rate, specifically in the Indonesian context. Therefore, this study aims to fill this gap and provide a more informative alternative approach in hypothesis testing on ranking data.

2. Methodology

2.1 Materials and Data

The study employed a Bayesian approach using the Wilcoxon Signed-Rank Test. The data used were secondary data sourced from the Indonesian Central Bureau of Statistics. The data used in this study were farmer exchange rates in Indonesia for 2021 and 2022, covering 34 provinces. The 2021 FER is the X variable, and the 2022 FER is the Y variable.

2.2 Research Methods

Two Samples Pair Test Based on Bayes Approach

Bayes Factor is a measure used in Bayesian statistics to describe the strength of evidence from one hypothesis to another. The Bayes Factor of hypothesis one to the null hypothesis, BF_{10}, measures how likely the observed data is under the alternative hypothesis (H_1) compared to the null hypothesis (H_0) (Kelter, 2020). In the case of the Wilcoxon Signed-Rank Test with parameter δ, Van Doorn et al., (2020) used the Bayes Factor based on the Savage-Dickey ratio, where the form of is as follows:

$$BF_{10} = \frac{P(\delta = \delta_0|H_1)}{P(\delta = \delta_0|X, H_1)} \tag{1}$$

where $P(\delta = \delta_0|H_1)$ is the density function of the prior distribution at $\delta = \delta_0$ under H_1 dan $P(\delta = \delta_0|X, H_1)$ is the density function of the posterior distribution at $\delta = \delta_0$ under H_1. The test criteria are to reject H_0 if $BF_{10} > 1$ and accept H_0 if $BF_{10} < 1$. The strength of the rejection or acceptance of H_0 can be seen in Figure 2.

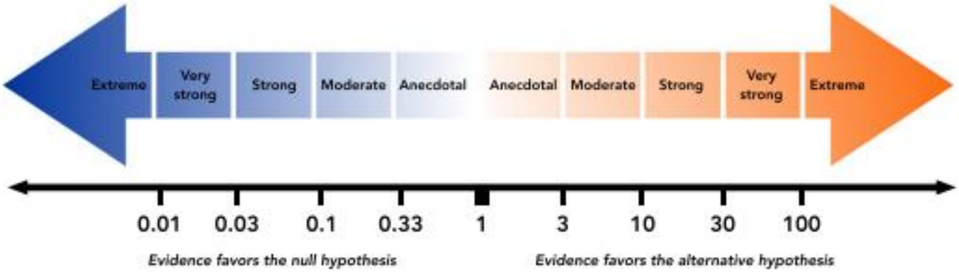

Figure 2Classification Diagram of Bayes Factor Interpretation (BF_{10})
Source: (Quintana & Williams, 2018)

Framework of Development of the Posterior Distribution

In testing the case of two paired samples, van Doorn et al., (2020) used the following framework. Suppose there are n data pairs $(X_1, X_2, \dots, X_n)$ and $(Y_1, Y_2, \dots, Y_n)$. In the frequentist approach, the research hypothesis in the Wilcoxon Signed-Rank Test is as follows:

- $H_0: Median(D) = \delta$
- $H_1: Median(D) \neq \delta$

where $Median(D) = Median(X) - Median(Y)$.

Data used in the Wilcoxon Signed-Rank Test is the difference between X_i and Y_i notated $d_i = x_i - y_i$, and $|d_i|$ is ranked as r_i^d. In Bayesian analysis, the ranking r_i^d

cannot be used due to the constraint of the unavailability of a likelihood function for ranked data, but this can be overcome by using a latent normal approach. The main objective of this framework is to construct a population of posterior distributions that will be used in the calculation of Bayes Factor. van Doorn et al., (2020) used that framework to develop posterior distributions is based on the concept that observed rankings come from latent variable data that cannot be observed directly. By using latent variables, the test hypothesis can be formulated as follows:

- $H_0: \mu_{Q^D} = \delta$
- $H_1: \mu_{Q^D} \neq \delta$

where $\mu_{Q^D} = \mu_{Q^X} - \mu_{Q^Y}$. Q^D is a latent random variable that generates a rank variable and δ is the difference in the mean values of the latent variables X and Y. It should be noted that μ_{Q^X} dan μ_{Q^Y} do not actually exist. The method proposed by van Doorn et al., (2020) is simulation-based, that is the process of constructing a posterior distribution is carried out by generating latent variable. This generation must be consistent in accordance with the original data rank. To ensure this consistency, the data generated must be within the appropriate interval. This can be done by using a truncated normal distribution, $Q_i^d \sim N_{\left(a_i^d, b_i^d\right)}(|\delta|, 1)$. The variance in the latent normal distribution is set at 1 because the data used in this test uses ranks rather than original data, where there is no information about the variance of the ranked data. Figure 3 shows the relationship between the rank data, the latent variable, and its interval limits.

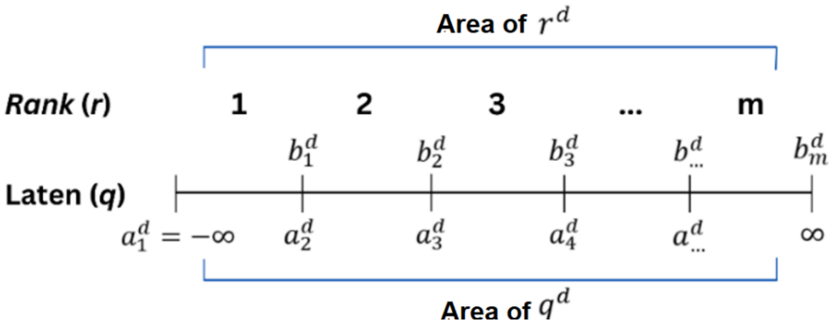

Figure 3: Area of $-\infty < q^d < \infty$ and $r^d = \{1,2,3, \dots m\}$

The lower and upper thresholds for the latent value q_i^d are defined as follows, respectively (van Doorn et al., 2020):

$$a_i^d = \max_{j; r_j^d < r_i^d} (q_j^d) \tag{2}$$

$$b_i^d = \min_{j; r_j^d > r_i^d} (q_j^d) \tag{3}$$

where a_i^d is the lower bound of normal laten q_i^d for the i-th rank, and b_i^d is the upper bound of normal laten q_i^d for the i-th rank.

Gibbs Sampling Algorithm of van Doorn's

Markov Chain Monte Carlo (MCMC) is a statistical method used to generate random samples from complex distributions. Gibbs sampling is a type of MCMC algorithm that is applied when the joint probability distribution of the parameters is unknown, but the conditional distribution of each variable is known. (Walsh, 2004). Van Doorn et al., (2020) assumed the variance of δ distributed as inverse gamma (α, β), where $\alpha = 1$

dan $\beta = \frac{\delta^2+\gamma^2}{2}$. For the prior of δ, Van Doorn et al., (2020) used Cauchy distribution with parameter γ. The Gibbs sampling algorithm steps to construct the posterior distribution population of δ are as follows.

a. For each i in $(1, \dots, n)$, generate sample Q_i^d from truncated normal distribution with lower and upper limit given by a_i^d and b_i^d respectively, as in (2) and (3).

$$\left(Q_i^d \middle| q_{i'}^d, \delta, r_i^d\right) \sim N_{\left(a_i^d, b_i^d\right)}(|\delta|, 1) \quad (4)$$

b. Generate δ:

$$(\delta | q^d, g) \sim N\left(\mu_\delta, \sigma_\delta^2\right) \quad (5)$$

where

$$\mu_\delta = \frac{gn\overline{q^d}}{gn+1} \quad ; \quad \overline{q^d} = \frac{1}{n}\sum_{i=1}^{n} q_i^d \quad (6)$$

$$\sigma_\delta^2 = \frac{g}{gn+1} \quad (7)$$

c. Generate g

$$(g|\delta) \sim Inverse\ Gamma\left(1, \frac{\delta^2+\gamma^2}{2}\right) \quad (8)$$

where γ is the scale parameter Cauchy prior distribution for δ.
The above steps are repeated until the posterior population δ is formed. The number of repetitions typically used is more than 100,000.

Convergence Evaluation

One of the requirements in Markov Chain Monte Carlo (MCMC) is that the Markov chain must reach convergence. One method is the Gelman-Rubin statistic (Gamerman & Lopes, 2006). MCMC is said to converge or be stationary if the Markov chain is no longer influenced by its initial value. The variance between chains (B) and the variance within chains (W) are calculated as follows.

$$B = \frac{N}{M-1}\sum_{m}^{M}(\bar{\theta}_m - \bar{\bar{\theta}})^2 \quad (9)$$

$$W = \frac{1}{M(N-1)}\sum_{m}^{M}\sum_{j=1}^{N}(\theta_m^j - \bar{\theta}_m)^2 \quad (10)$$

where N is the population size of each chain and M is the number of chains. The Gelman-Rubin statistics are defined as follows.

$$R = \sqrt{\frac{\left(1-\frac{1}{N}\right)W + \left(\frac{1}{N}\right)B}{W}} \quad (11)$$

The R value is usually always greater than 1. If $N \to \infty$ then $R \to 1$, the closer R to 1 is better. According Gamerman & Lopes (2006), $R < 1.2$ is acceptable.

Farmer's Exchange Rate

The Farmer's Exchange Rate (FER) is a measurement tool for calculating the purchasing power of agricultural products for consumer goods and services, both for household needs and production costs (Kementerian Pertanian, 2015). The Farmer's Exchange Rate is used as an indicator to determine the level of farmer welfare in a given year compared to a base year. The higher FER, the more prosperous the farmer is.

3. Results and Discussion

3.1 Data Description

The first step is to calculate the difference value $(d_i = x_i - y_i)$ which is presented in Table 1.

Table 1: The Different Data

No.	X	Y	D
1	101.20	107.46	-6.26
2	119.06	121.73	-2.67
⋮	⋮	⋮	⋮
33	100.86	100.62	0.24
34	102.19	100.12	2.07

The next step is to describe the data. The results of the descriptive statistical calculations for the two variables and their differences are presented in Table 2.

Table 2: Descriptive Statistics

Variable	Average	Variance	Maximum		Minimum	
			Max. Value	Province	Min. Value	Province
X	108.02	141.07	138.72	Riau	92.84	Bali
Y	110.34	173.14	144.19	Riau	95.41	NTT
D	-2.32	9.04	4.32	Kalimantan Barat	-12.66	Sulawesi Barat

Based on the table above, the average farmer exchange rate (FER) in Indonesia in 2021 was 108.02. Riau Province had the highest FER at 138.72, while Bali Province had the lowest at 92.84. In 2022, the average FER in Indonesia was 110.34. Riau Province again had the highest FER at 144.19, while East Nusa Tenggara (NTT) Province had the lowest at 95.41. The average FER data difference in Indonesia was -2.32. West Kalimantan Province had the highest FER difference at 4.32, while West Sulawesi Province had the lowest at -12.66. The high variance value indicates high diversity in FER data, with values reaching 141.07 in 2021, 173.14 in 2022, and 9.04 in the difference. The histograms of the two variables and their differences are presented in Figure 4-6.

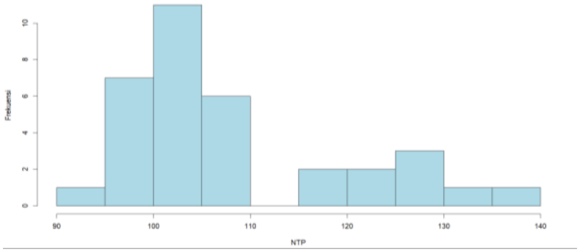

Figure 4: Histogram of $\boldsymbol{X}$

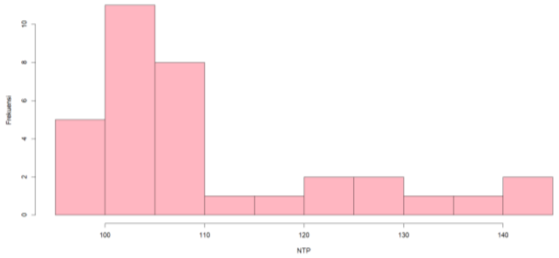

Figure 5: Histogram of $\boldsymbol{Y}$

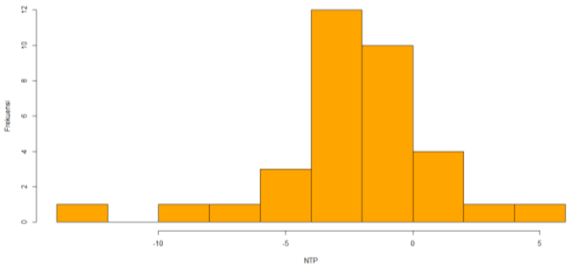

Figure 6: Histogram of $\boldsymbol{D}$

Based on the three figures above, the 2021 FER data in Figure 4 ranges from 90 to 140, with the highest range value being 100 to 105 and a frequency of 11. In Figure 5, the 2022 FER data ranges from 95 to 145, with the highest range value being 100 to 105 and a frequency of 11. The distribution of FER in 2022 is slightly shifted to the right compared to 2021, indicating an increasing trend in FER. In Figure 6, the difference in FER data ranges from -14 to 6, with the highest range value being -4 to -2 and a frequency of 12. Considering that the difference is calculated as the 2021 FER minus the 2022 FER, the negative value in the difference indicates that most FERs experienced an increase of 2 to 4 points, although there were some areas that experienced a decrease. Overall, the trend indicates an increase in FER.

3.2 Normality Test

The normality test was conducted using the Shapiro-Wilk test to determine whether the data were normally distributed or not. The data to be tested for normality was the data difference (d) in Table 1 with the following hypothesis formulation:

- H_0 : Data normally distributed
- H_1 : Data not normally distributed

The test results the test statistic T_3 is 0.9196 and the p-value is 0.0157. Since the p-value < 0.05, H_0 is rejected. Thus, it can be concluded that the data is not normally distributed at a significant level of 5%

3.3 Developing Posterior Distribution of δ

The hypothesis formulation of the Bayesian-based Wilcoxon Signed-Rank Test is as follows:

- $H_0: \mu_{Q^D} = \delta$ (There is no significant difference between the farmer's exchange rate in 2021 and 2022)
- $H_1: \mu_{Q^D} \neq \delta$ (There is a significant difference between the farmer's exchange rates in 2021 and 2022)

The first step is to determine the rank of the absolute difference between each of the 34 observational data presented in Table 3.

Table 3: Ranking of Data Differences

No.	d_i	Sign	$\lvert d_i \rvert$	r_i^d
1	-6,26	–	6,26	32
2	-2,67	–	2,67	20
⋮	⋮	⋮	⋮	⋮
33	0,24	+	0,24	3
34	2,07	+	2,07	15

After getting r_i^d, the next step is to determine the initial value $\delta = 0$ and $g = \frac{\overline{q^d}^2}{\sigma_\delta^2} + 1$, with $\sigma_\delta^2 = 1$. Then determine the initial latent value $q_{i'}^d$ which is a random number generated from the normal distribution $Q_{i'}^d \sim N(0,1)$ of $n = 34$. After that, these values are converted into absolute values and sorted from smallest to largest. The results of the initial latent value $q_{i'}^d$ in the first iteration are presented in Table 4.

Table 4: Sorted Nilai $\boldsymbol{Q_{i'}^d \sim N(0,1)}$ Values in the First Iteration

Random	Absolut value	$q_{i'}^d$ ordered	rank
-0.1066	0.1066	0.0814	1
1.6144	1.6144	0,1066	2
⋮	⋮	⋮	⋮
0.6854	0.6854	2.3579	33
0.6027	0.6027	2.4838	34

The results of the table above will be adjusted to the value of r^d. At $i = 1$, the value of $r_1^d = 32$, then find the value of sorted $q_{i'}^d$ at rank 32, that is 2.3406, so that the value of $q_{1'}^d = 2.3406$ is obtained. The value of $q_{i'}^d$ in the first iteration is presented in Table 5.

Table 5: Values of r_i^d and $q_{i'}^d$ at the First Iteration

i	r_i^d	$q_{i'}^d$
1	32	2.3406
2	20	0.7028
⋮	⋮	⋮
33	3	0.1087
34	15	0.6027

After obtaining the value of $q_{i'}^d$, the lower and upper threshold values can be found using equations (2) and (3). The upper and lower threshold values for the value of q_i^d in the first iteration are presented in Table 6. It should be noted that if the value of $a_i^d = -\infty$, it is set to 0, because basically the rank cannot have a negative value.

The next step is to generate 34 samples of q_i^d from the truncated normal distribution $\left(Q_i^d \middle| q_{i'}^d, \delta, r_i^d\right) \sim N_{\left(a_i^d, b_i^d\right)}(|\delta|, 1)$ according to the respective values of a_i^d and b_i^d. First, find the cumulative distribution function (CDF) value of each lower limit $(p_1 = P(Z \leq a_i^d))$ and upper limit $(p_2 = P(Z \leq b_i^d))$. Then, generate one sample $u \sim Uniform(p_1, p_2)$ which is converted into a quantile value or Z score. The value is given a difference sign obtained from Table 3, if d_i=0 then it is given a random (+/-) sign. The truncated $d_i = 0$ value in the first iteration is presented in Table 7.

Table 6: Values of a_i^d and b_i^d at the First Iteration

i	a_i^d	b_i^d
1	2.2575	2.3579
2	0.6854	0.7651
⋮	⋮	⋮
33	0.1066	0.1303
34	0.5467	0.6081

Table 7: Values of Trancuted q_i^d at the First Iteration

i	p_1	p_2	u	Z	q_i^d
1	0.9880	0.9908	0.9893	2.3006	-2.3006
2	0.7535	0.7779	0.7586	0.7018	-0.7018
⋮	⋮	⋮	⋮	⋮	⋮
33	0.5424	0.5518	0.5517	0.1301	0.1301
34	0.7077	0.7284	0.7147	0.5672	0.5672

After obtaining q_i^d, the next step is to generate a sample of the posterior distribution δ. First, generate one sample $(\delta|q^d, g) \sim N(\mu_\delta, \sigma_\delta^2)$, where $\mu_\delta = \frac{gn\overline{q^d}}{gn+1}$ and $\sigma_\delta^2 = \frac{g}{gn+1}$. Next, generate one sample $(g|\delta) \sim Inverse\ Gamma\left(1, \frac{\delta^2+\gamma^2}{2}\right)$ with the δ value obtained from the previous generation and γ of $\frac{1}{\sqrt{2}}$. The result of the g sample is used to generate the next δ sample. This process is iterated 10 times so that the δ value at the 10th iteration is used as the first δ sample, which is -0.8159.

After obtaining the first sample δ, 100,000 iterations were performed. The iterations began with calculating the values of a_i^d and b_i^d. In the first iteration, the sorted and adjusted $Q_{i'}^d \sim N(0,1)$ values were used, as shown in Table 5. The second iteration used the $q_{i'}^d$ values obtained in the first iteration, as shown in Table 7. Subsequent iterations (the third to the 100,000th iteration) used the $q_{i'}^d$ values from the previous iteration. The results of these iterations yielded a population of $\delta^1, \delta^2, \delta^3, \dots, \delta^{100.000}$ with values (-0.8159;-0.6747;-1.0772;…;-1.1322).

The above steps were carried out five times to obtain five sets or chains of the δ population which are visualized in Figure 7. The construction of these five Markov chains was intended to carry out the Gelman-Rubin test. Based on Figure 7, the δ value is in the range of -2 to 0. Next, a burn-in process is carried out visually based on Figure 7. This process is carried out to eliminate the influence of the initial value. The burn-in process is carried out for 5,000 samples in each chain because at the 5000th iteration it appears to be stable. Thus, five sets of δ populations are obtained, $\{\delta_m^j\}$, $m = 1, 2, 3, 4, 5;\ j = 1, 2, \dots, 95000$.

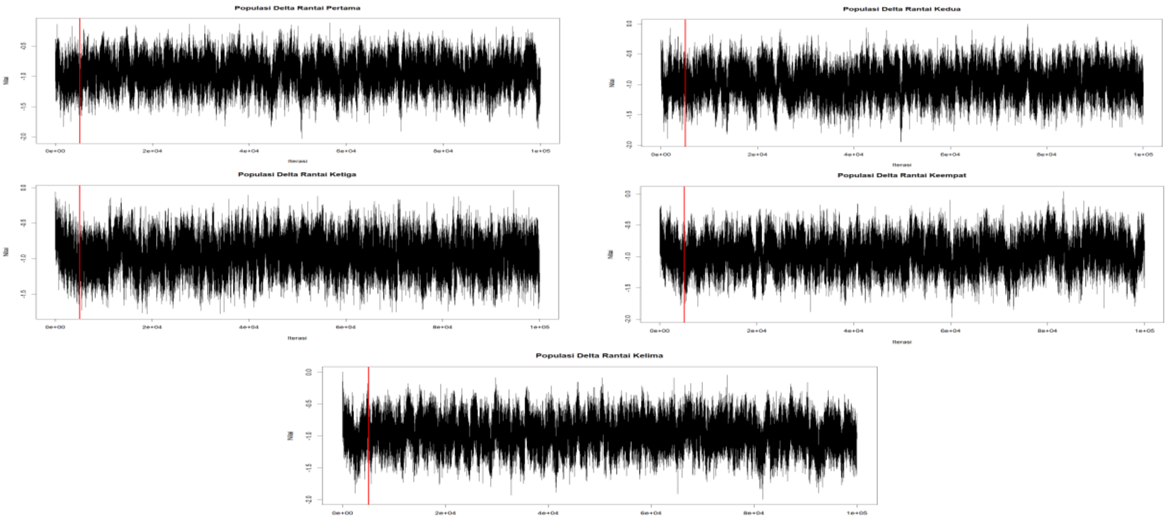

Figure 7: Plot of $\boldsymbol{\delta}$ for Five Chains

3.4 Evaluation of Convergence

The obtained population δ will be tested for convergence using the Gelman-Rubin statistic. Based on the analysis results with N=95,000 and M=5, the following values were obtained:

Table 8: The Values of δ

$\bar{\delta}_1$	$-0{,}9463$
$\bar{\delta}_2$	$-0{,}9641$
$\bar{\delta}_3$	$-0{,}9490$
$\bar{\delta}_4$	$-0{,}9586$
$\bar{\delta}_5$	$-0{,}9671$
$\bar{\bar{\delta}}$	$-0{,}9570$

The within and between chain variability are as follows.

$$B = \frac{N}{M-1}\sum_{m}^{M}(\,\bar{\delta}_m - \bar{\bar{\delta}})^2$$

$$B = \frac{95.000}{5-1}[(-0{,}9463 - (-0{,}9570))^2 + \cdots + (-0{,}9671) - (-0{,}9570))^2] = 7{,}8808$$

$$W = \frac{1}{M(N-1)}\sum_{m}^{M}\sum_{j=1}^{N}(\delta_m^j - \bar{\delta}_m)^2$$

$$W = \frac{1}{5(95.000-1)}[(-1{,}0732 - (-0{,}9463))^2 + \cdots + (-0{,}9438 - (-0{,}9671))^2] = 0{,}0487$$

The Gelman-Rubin statistics are

$$R = \sqrt{\frac{\left(1-\frac{1}{N}\right)W + \left(\frac{1}{N}\right)B}{W}}$$

$$R = \sqrt{\frac{\left(1-\frac{1}{95.000}\right)0{,}0487 + \left(\frac{1}{95.000}\right)7{,}8808}{0{,}0487}} = 1{,}0008$$

Since the $R = 1.0008 < 1.2$, the Markov chain of population δ has converged. Since it has converged, the five sets of population δ are combined into 475,000 $(\delta^1, \delta^2, \ldots, \delta^{475.000})$ and the Bayes Factor calculation can be performed. The visualization of the posterior population histogram δ is presented in Figure 8.

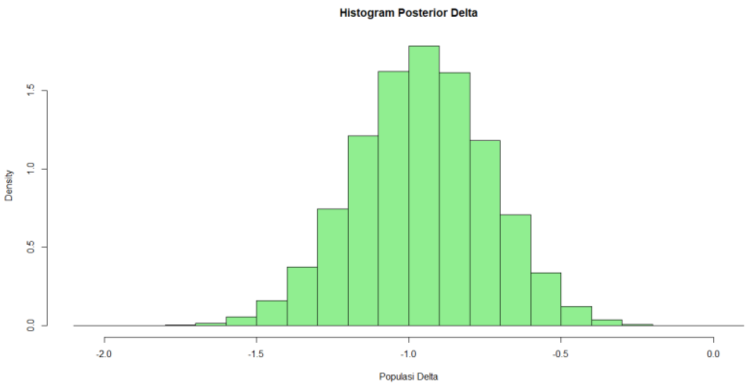

Figure 8: Histogram of Posterior $\boldsymbol{\delta}$

Based on Figure 8, the histogram is symmetrical and resembles a normal distribution, indicating that the population is normally distributed. The δ value tends to center around -1, indicating that the data difference tends to be around -1. Because this distribution is symmetrical, the mean, median, and mode of this data difference are likely to be at the center of the distribution, around -1. Considering that the δ difference is the latent value of the 2021 FER minus the latent value of the 2022 FER, this means that the average or most simulation results indicate that the 2022 FER increased by approximately 1 point compared to the 2021 FER.

3.5 The Values of Bayes Factor

The Bayes Factor calculation in this test uses the Savage-Dickey ratio. The prior distribution δ is the Cauchy distribution with parameter $\gamma = \frac{1}{\sqrt{2}}$.. Based on the analysis, it is obtained that the value of the density function of the distribution $f(\delta|\gamma)$ at the point $\delta = 0$ is 0.4501582. Meanwhile, the value of the density function of the posterior distribution $\hat{f}(\delta|Data)$ at the point $\delta = 0$ (calculated using the R logspline package with the dlogspline() function) is 0.000146342. Hence

$$BF_{10} = \frac{P(\delta = \delta_0|H_1)}{P(\delta = \delta_0|X, H_1)} = \frac{f(\delta|\gamma)}{\hat{f}(\delta|Data)}$$

$$BF_{10} = \frac{0.4501582}{0.000146342} = 3076.07$$

Since $BF_{10} = 3076{,}07 > 1$, H_0 is rejected and H_1 is accepted. With such a BF_{10} value, it means that the data is 3076.07 times more likely to be in H_1 than in H_0 Based on the interpretation classification in Figure 1, the strength of the evidence for rejecting H_0 in the data is included in the extreme category. Therefore, it can be concluded that the BF_{10} value of 3076.07 provides extreme evidence that there is a significant difference in the farmer's exchange rate in Indonesia in 2021 and 2022.

Table 9: The Mean, Median, and *Credible Interval* 95% of Posterior δ Population

Mean	Median	*Credibel Interval* 95%	
		Lower Limit	Upper Limir
-0.9570	-0.9548	-1.3958	-0.5312

From Table 9, the posterior population mean δ is -0.9570 and the median is -

0.9548. The 95% credible interval indicates the range within which the true δ value is estimated to lie with a 95% confidence level. This interval is derived from the lower limit of the 2.5% quantile of -1.3958 and the upper limit of the 97.5% quantile of -0.5312. With these values, the difference in the 2021 and 2022 FER (δ) from the simulation results is estimated to be within the range [-1.3958; -0.5312] with a 95% confidence level.

Based on the Bayesian Wilcoxon Signed-Rank Test, it was found that most farmers' exchange rates (FER) increased from 2021 to 2022. This indicates a statistically significant difference between the two years, supporting the alternative hypothesis H_1. This increase in the FER indicates an improvement in farmers' purchasing power in 2022 compared to the previous year. This could be attributed to improved commodity prices, subsidy policies, or a shift towards a more efficient production cost structure. This finding aligns with a study by Wahyudi & Agustian (2025) which found an upward trend in the FER from 2020 to 2024.

4. Conclusion and Suggestion

This study concludes that there is a significant difference between farmers' exchange rates in Indonesia in 2021 and 2022. By applying a Bayesian approach to the Wilcoxon Signed-Rank Test, this study provides strong evidence that changes in farmers' exchange rates are not simply random but reflect real differences between years. This approach also offers an informative alternative for analyzing ranked data, which was previously difficult with conventional statistical methods. In the future, this Bayesian approach can be further developed to analyze other economic indicators in the agricultural sector or other sectors that use paired, ranked data.

Acknowledgements

The authors are very grateful to the reviewers who have provided very valuable suggestions and input so that this article becomes better.

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