

Tail Dependence Analysis Between the IDX Composite and the USD/IDR Exchange Rate Using the Quantile Correlation Coefficient

Rizki Fitriani Muin^{1*}, Nur Amaliya Tuanaya²

¹Information Technology Management, ITS, Surabaya, Indonesia

²Statistics, ITS, Surabaya, Indonesia

*Corresponding author: rizkifitrianimuin@gmail.com

ABSTRACT

This study examines tail dependence between the IDX Composite (IHSG) and the USD/IDR exchange rate using the Quantile Correlation Coefficient. The analysis employs cleaned daily data from 2 January 2014 to 30 December 2024. After matching trading dates and calculating log returns, the final sample comprises 2,361 return observations. To facilitate economic interpretation, the exchange-rate variable is transformed into a rupiah return, defined as the negative of the USD/IDR return; consequently, a lower rupiah return indicates rupiah depreciation. Pearson correlation is used as a benchmark, while quantile correlations are estimated at $\tau = 0.1$, 0.5, and 0.9 to compare dependence in the lower tail, at the median, and in the upper tail. The Pearson correlation between IHSG and rupiah returns is 0.188899. The estimated quantile correlations at $\tau = 0.1$, 0.5, and 0.9 are 0.214986, 0.153802, and 0.178168, respectively. These results indicate that the relationship between the IHSG and the rupiah is stronger in the lower tail than at the median. The study contributes to applied statistics by demonstrating the usefulness of quantile-based dependence measures for financial-risk analysis in an emerging-market context.

Keywords: quantile correlation; tail dependence; IHSG; USD/IDR; applied statistics

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1. INTRODUCTION

Stock markets and exchange rates are two closely interrelated indicators in an open economy. In Indonesia, movements in the IDX Composite (Indeks Harga Saham Gabungan, IHSG) are frequently associated with changes in the rupiah exchange rate against the US dollar. The IHSG is used because it measures the price performance of companies listed on the Indonesia Stock Exchange, whereas JISDOR is used because it is the USD/IDR spot reference rate published by Bank Indonesia [1], [2]. When the rupiah depreciates, market risk may increase through several channels, including higher import costs, greater foreign-currency debt burdens for firms, and potential foreign capital outflows from domestic financial markets [3], [4]. The relationship between the exchange rate and the stock market in Indonesia has also received considerable attention in recent literature, particularly during the COVID-19 period and subsequent episodes of market turbulence [5], [6].

Studies of the relationship between the IHSG and the exchange rate commonly use Pearson correlation [7]–[9]. However, Pearson correlation describes only the average linear association and cannot capture changes in dependence under extreme conditions [10]. In financial markets, relationships between variables often differ between normal and crisis conditions [11]. Studies published over the past five years show that relationships among financial and macroeconomic assets are nonlinear, vary across market regimes, and tend to be stronger at extreme quantiles or during periods of stress [12]. Therefore, a method is required that can measure dependence in specific parts of the distribution [13].

Choi and Shin [14] introduced the Quantile Correlation Coefficient as a dependence measure based on quantile regression. The method is defined as the signed geometric mean of two quantile-regression slopes: the quantile regression of Y on X and that of X on Y [15]. Its principal advantage is that it enables comparisons of dependence across several quantiles within the same distribution, such as the lower tail, median, and upper tail [16], [17]. A quantile-based approach is also consistent with the growing literature on quantile connectedness, quantile-on-quantile analysis, causality-in-quantiles, and dynamic quantile models for examining risk transmission in financial markets [18]–[20].

Against this background, this study applies the Quantile Correlation Coefficient to analyze tail dependence between IHSG returns and rupiah returns. The primary objective is to determine whether the relationship between the Indonesian stock market and the exchange rate is stronger under extreme conditions than under normal conditions.

The research questions are as follows: (1) What is the average relationship between IHSG returns and rupiah returns based on Pearson correlation? (2) How does the relationship between IHSG returns and rupiah returns differ across the lower tail, median, and upper tail? and (3) Is there evidence of tail dependence between the two variables?

This study aims to measure the relationship between the IHSG and the exchange rate using Pearson correlation and the Quantile Correlation Coefficient and to compare the strength of the relationship at $\tau = 0.1$, $\tau = 0.5$, and $\tau = 0.9$.

1.1. IDX Composite and the USD/IDR Exchange Rate

The IHSG is a broad indicator of stock-price movements on the Indonesia Stock Exchange. Conceptually, it represents the price performance of companies listed on the Main and Development Boards and is therefore widely used as a proxy for the Indonesian stock market. The USD/IDR exchange rate denotes the number of rupiah required to purchase one US dollar. This study uses JISDOR exchange-rate data because Bank Indonesia designates JISDOR as the USD/IDR spot reference rate, calculated from interbank transactions and published on each business day.

An increase in USD/IDR indicates rupiah depreciation, whereas a decrease indicates appreciation. In this study, the rupiah return is defined as the negative of the USD/IDR return to facilitate interpretation: a lower rupiah return indicates rupiah depreciation. Exchange-rate movements may affect the stock market through import exposure, foreign-currency liabilities, international capital flows, and changes in investors' risk perceptions. Indonesian evidence indicates that the exchange rate, interest rates, global variables, and pandemic-related events are associated with movements in the IHSG or Indonesian stock returns [21], [22].

1.2. Pearson Correlation and Its Limitations

Pearson correlation measures the average linear association between two variables. Its value ranges from -1 to 1. Although straightforward to apply, it does not distinguish between dependence under normal and extreme conditions. For financial data characterized by heavy tails and high volatility, an average dependence measure may conceal dependence in the tails of the distribution. This limitation is especially important because crises and global shocks can intensify volatility and spillovers and alter cross-asset correlations [23]. As a benchmark measure of average association, Pearson correlation is calculated as follows:

$$\rho = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \quad (1)$$

In emerging markets, the relationship between exchange rates and stock markets is not necessarily symmetric [24]. Quantile-on-quantile approaches can reveal exchange-rate-stock-market relationships that differ across quantiles [25], [26]. Nusair and Al-Khasawneh [27] emphasize the importance of nonlinear methods for analyzing the relationship between Asian exchange rates and stock prices. Tian et al. [9] document

negative tail dependence and risk spillovers between foreign-exchange and stock markets in emerging economies. These findings support the use of models that distinguish dependence under extreme conditions rather than relying solely on average relationships.

1.3. Quantile Correlation Coefficient

The Quantile Correlation Coefficient measures the sensitivity of a variable's conditional quantile to changes in another variable. A lower-tail quantile correlation greater than the median correlation indicates stronger dependence under adverse lower-tail conditions. In this study, $\tau = 0.1$ represents the lower tail, $\tau = 0.5$ the median, and $\tau = 0.9$ the upper tail.

Unlike Pearson correlation, this method focuses not only on average dependence but also on how the relationship changes at specific points of the distribution. Choi and Shin [14] show that quantile correlations can be compared across quantiles within the same distribution, making the measure suitable for assessing whether the relationship between two variables is stronger in the lower tail than at the median. Recent studies have also employed quantile-based methods to investigate dependence networks, risk transmission, and spillovers under extreme conditions, including quantile connectedness, quantile vector autoregression (VAR), and quantile-on-quantile methods [28].

The first quantile-regression model regresses the conditional quantile of the IHSG return on the rupiah return:

$$Q_Y(\tau | X) = \alpha_{2.1}(\tau) + \beta_{2.1}(\tau)X \quad (2)$$

The second quantile-regression model regresses the conditional quantile of the rupiah return on the IHSG return:

$$Q_X(\tau | Y) = \alpha_{1.2}(\tau) + \beta_{1.2}(\tau)Y \quad (3)$$

Based on the two quantile-regression slopes, the quantile correlation is calculated as follows:

$$\rho_\tau = \text{sign}(\beta_{2.1}(\tau))\sqrt{\beta_{2.1}(\tau)\beta_{1.2}(\tau)} \quad (4)$$

If the product of the two slopes is negative, the quantile correlation is set equal to zero:

$$\rho_\tau = 0, \quad \text{if } \beta_{2.1}(\tau)\beta_{1.2}(\tau) < 0 \quad (5)$$

2. MATERIALS AND METHODS

2.1. Data and Sample

This study uses cleaned daily data on the IHSG and USD/IDR. The IHSG serves as a proxy for the Indonesian stock market, while the exchange-rate series is Bank Indonesia's JISDOR, the daily spot. The matched price sample covers 2 January 2014 to 30 December 2024. After log returns were calculated and the initial missing observation was removed, the final analytical sample comprised 2,361 return observations.

Table 1 summarizes the study variables, sample period, number of observations, and variable transformations.

Table 1. Summary of the Research Data

Component	Description
Study variables	IHSG and the USD/IDR exchange rate
Matched price period	2 January 2014-30 December 2024
Number of price observations	2,362 observations
Number of return observations	2,361 observations
Data transformation	Log returns
Main variables	IHSG Return and Rupiah Return = - USD/IDR Return

2.2. Variable Definitions

Returns are calculated using the following log-return formula:

$$R_t = \ln \left(\frac{P_t}{P_{t-1}} \right) \quad (6)$$

For the IHSG, P_t denotes the IHSG closing value on day t . For the exchange rate, P_t denotes the USD/IDR value on day t . Because an increase in USD/IDR represents rupiah depreciation, this study defines the rupiah return as follows:

$$R_t^{\text{Rupiah}} = -R_t^{\text{USD/IDR}} \quad (7)$$

2.3. Analytical Procedure

The analysis was conducted sequentially to ensure that the data-processing, estimation, and interpretation procedures were transparent and reproducible. The analytical steps were as follows:

- Merge the daily IHSG and USD/IDR data using common trading dates.
- Clean the data by removing incomplete observations, duplicate dates, and values unsuitable for return calculations.
- Calculate the log returns of the IHSG and USD/IDR using the value on day t and the preceding day.
- Construct the rupiah-return variable as the negative of the USD/IDR return so that lower rupiah returns can be interpreted as rupiah depreciation.
- Compute descriptive statistics, including the mean, median, standard deviation, minimum, maximum, skewness, and kurtosis.
- Calculate Pearson correlations as measures of the average linear relationships among IHSG returns, USD/IDR returns, and rupiah returns.
- Estimate two quantile regressions at selected values of τ : the IHSG return on the rupiah return and the rupiah return on the IHSG return.
- Calculate the Quantile Correlation Coefficient from the two quantile-regression slopes at $\tau = 0.1$, $\tau = 0.5$, and $\tau = 0.9$, together with additional quantiles to examine the dependence pattern across the distribution.
- Conduct a paired bootstrap with 100 replications as a supporting assessment of estimate stability and differences in quantile correlation across quantiles.

- Compare the Pearson correlation, quantile-correlation, and bootstrap results to assess whether the relationship between IHSG and rupiah returns exhibits tail dependence.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Descriptive statistics are used to examine the initial characteristics of IHSG, rupiah, and USD/IDR returns. The results are summarized in Table 2.

Table 2. Descriptive Statistics of Returns

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
IHSG Return	2,361	0.000209	0.000732	0.010107	-0.068051	0.097042	-0.273722	11.393191
Rupiah Return	2,361	-0.000121	-0.000107	0.006454	-0.045780	0.037050	-0.098104	8.755306
USD/IDR Return	2,361	0.000121	0.000107	0.006454	-0.037050	0.045780	0.098104	8.755306

Table 2 shows that the kurtosis of IHSG returns is 11.393191, while the kurtosis of USD/IDR returns is 8.755306. Kurtosis values greater than 3 indicate heavy-tailed distributions. This finding supports the use of quantile-based methods because the return distributions cannot be fully characterized by average measures alone.

In addition to the numerical summary, daily returns are plotted to identify periods of elevated volatility. The time-series plot is presented in Figure 1.

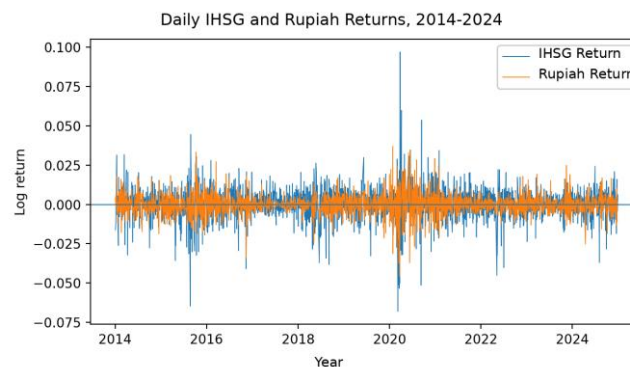


Figure 1. Daily IHSG and Rupiah Returns

Figure 1 reveals several periods of elevated volatility, particularly during episodes of market stress. The sharp return fluctuations further support the use of tail-dependence analysis.

3.2. Pearson Correlation

Pearson correlations were calculated to provide a benchmark description of average linear dependence. The results are presented in Table 3.

Table 3. Pearson Correlation

Variable Pair	Pearson Correlation
IHSG Return and USD/IDR Return	-0.188899
IHSG Return and Rupiah Return	0.188899

The Pearson correlation between IHSG and USD/IDR returns is -0.188899. The negative sign indicates that an increase in USD/IDR, or rupiah depreciation, tends to be associated with a decline in the IHSG. After the exchange-rate variable is transformed into the rupiah return, the Pearson correlation becomes 0.188899. Thus, rupiah appreciation tends to move in the same direction as an increase in the IHSG.

The relationship between rupiah and IHSG returns is also illustrated using a scatter plot, as shown in Figure 2.

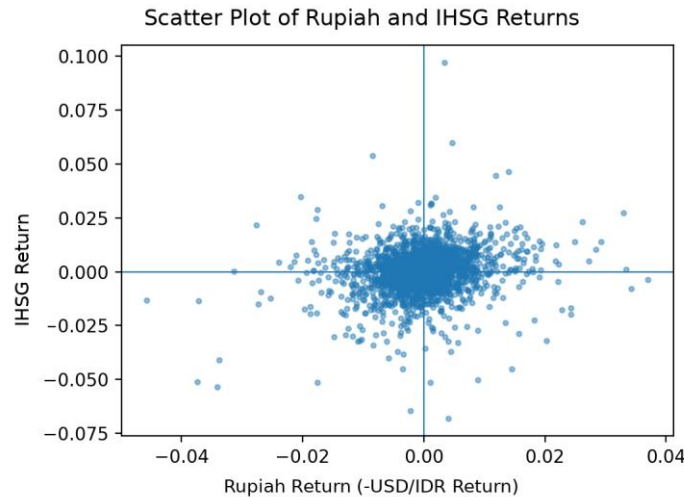


Figure 2. Scatter Plot of Rupiah and IHSG Returns

Figure 2 indicates a positive relationship between rupiah and IHSG returns, although the observations are widely dispersed. The broad dispersion suggests that average dependence alone is insufficient to characterize the behavior of the two variables under extreme conditions.

3.3. Quantile Correlation Coefficient Results

Following the average-correlation analysis, quantile correlations were estimated at the principal quantiles. The main results are presented in Table 4.

Table 4. Main Quantile Correlation Results

τ		IHSG on Rupiah	Rupiah on IHSG
0.100000	0.214986	0.353262	0.130834
0.500000	0.153802	0.264195	0.089537
0.900000	0.178168	0.260992	0.121628

Table 4 shows that the quantile correlation at $\tau = 0.1$ is 0.214986, exceeding the value of 0.153802 at $\tau = 0.5$. This result indicates that the relationship between IHSG and rupiah returns is stronger in the lower tail than at the median. The quantile correlation at $\tau = 0.9$ is 0.178168, also higher than the median value but lower than the lower-tail value.

The lower-tail relationship is considered stronger than the median relationship when the following condition is satisfied:

$$|\rho_{0.1}| > |\rho_{0.5}| \quad (8)$$

For the estimates obtained in this study:

$$0.214986 > 0.153802$$

To assess whether the pattern persists beyond the three principal quantiles, the model was also estimated at several additional quantiles (Table 5).

Table 5. Quantile Correlations Across Selected Quantiles

τ		IHSG on Rupiah	Rupiah on IHSG
0.050000	0.215611	0.346491	0.134168
0.100000	0.214986	0.353262	0.130834
0.250000	0.187030	0.311751	0.112205
0.500000	0.153802	0.264195	0.089537
0.750000	0.165755	0.279634	0.098252
0.900000	0.178168	0.260992	0.121628
0.950000	0.190470	0.309271	0.117304

The quantile-correlation estimates are plotted across the selected quantiles to facilitate comparison across the distribution (Figure 3).

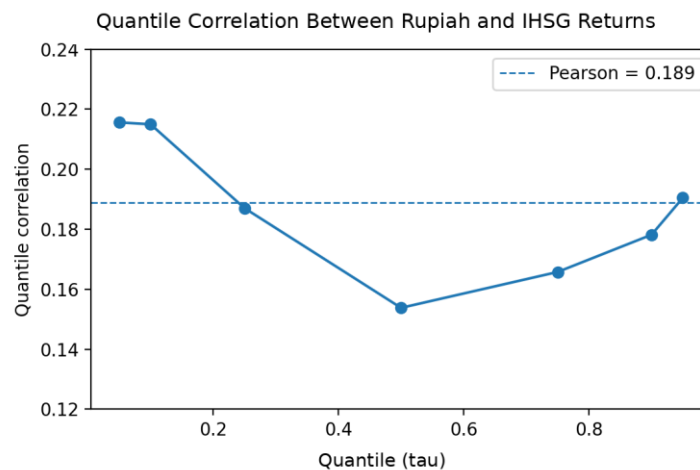


Figure 3. Quantile Correlation Pattern Across Selected Quantiles

Figure 3 shows that the quantile correlations are relatively higher in the lower and upper tails than at the median. This pattern suggests that the relationship between the IHSG and the rupiah is not constant across the return distribution.

3.4. Bootstrap Analysis

A paired bootstrap with 100 replications was conducted as a supporting assessment of estimate stability. The results are summarized in Table 6.

Table 6. Paired Bootstrap Summary Based on 100 Replications

Parameter	Estimate	Bootstrap SE	2.5% CI	97.5% CI	p-value
ρ at $\tau = 0.1$	0.214986	0.045763	0.127733	0.312685	
ρ at $\tau = 0.5$	0.153802	0.022039	0.111242	0.186000	
ρ at $\tau = 0.9$	0.178168	0.031350	0.127333	0.239838	
$\rho(0.1) - \rho(0.5)$	0.061183	0.038383	-0.008318	0.138338	0.110934
$\rho(0.1) - \rho(0.9)$	0.036817	0.043948	-0.025287	0.122261	0.402177
$\rho(0.9) - \rho(0.5)$	0.024366	0.026430	-0.022656	0.074369	0.356582

The bootstrap results show that the estimates of ρ at $\tau = 0.1$, $\tau = 0.5$, and $\tau = 0.9$ have confidence intervals that do not include zero. This finding indicates a positive relationship between rupiah and IHSG returns at all three principal quantiles. However, the difference between $\tau = 0.1$ and $\tau = 0.5$ has a p-value of approximately 0.110934, indicating that the difference is not statistically significant at the 5% level. Accordingly, the principal finding should be interpreted as evidence suggestive of lower-tail dependence rather than as conclusive statistical proof.

3.5. Discussion

From an economic perspective, the Pearson correlation results indicate that movements in the IHSG and USD/IDR are inversely related. An increase in USD/IDR, which represents rupiah depreciation, tends to be associated with a decline in the IHSG. After the exchange-rate variable is transformed into the rupiah return, the relationship becomes positive. This pattern is consistent with the expectation that rupiah appreciation is associated with more favorable stock-market conditions. The finding also accords with Indonesian studies that identify the exchange rate as an important variable in stock-market dynamics and macrofinancial risk [3]–[6].

Quantile correlation provides information that is not captured by Pearson correlation. The value of ρ at $\tau = 0.1$ is the highest among the three principal quantiles. Thus, the relationship between the IHSG and the rupiah is strongest in the lower tail, when the stock market is weakening and the rupiah is also under pressure. This pattern may arise because investors become more sensitive to exchange-rate risk during periods of uncertainty or market stress. This interpretation is consistent with evidence from tail-dependence and connectedness studies showing that cross-asset relationships tend to intensify under extreme conditions.

Nevertheless, the supporting bootstrap analysis indicates that the difference between the lower tail and the median is not significant at the 5% level. The study therefore identifies suggestive evidence of lower-tail dependence, which could be assessed more rigorously in future research using a larger number of bootstrap replications, a longer sample period, or asymptotic inference methods such as those developed by Choi and Shin [14]. Alternative approaches, including quantile connectedness, quantile-on-quantile analysis, and causality-in-quantiles, could also be used for comparison because they are widely employed in recent financial-risk research [8], [15], [17], [19], [20].

4. CONCLUSION

This study examines tail dependence between the IHSG and the USD/IDR exchange rate using daily data from 2014 to 2024. Following data cleaning, 2,361 return observations were analyzed. The rupiah return was defined as the negative of the USD/IDR return so that the lower tail represents rupiah depreciation.

The results show a Pearson correlation of 0.188899 between IHSG and rupiah returns. The quantile correlations are 0.214986 at $\tau = 0.1$, 0.153802 at $\tau = 0.5$, and 0.178168 at $\tau = 0.9$. Based on these estimates, the relationship between the IHSG and the rupiah is strongest in the lower tail. This finding suggests that the Indonesian stock market is more sensitive to exchange-rate pressure under adverse lower-tail conditions than at the median.

The findings are relevant to investors and risk analysts because they show that the relationship between the stock market and the exchange rate can vary across the return distribution. Average-based risk measures such as Pearson correlation should therefore be complemented by quantile-based measures to provide a clearer assessment of market behavior under extreme conditions.

4.1. Limitations and Future Research

This study has several limitations. First, the analysis uses daily data and includes only two variables: the IHSG and the exchange rate. Second, the bootstrap procedure uses only 100 replications; consequently, the inferential results should be regarded as preliminary supporting evidence. Third, the sample is not divided into subperiods such as the pre-pandemic, pandemic, and post-pandemic periods.

Future studies could use a larger number of bootstrap replications, compare multiple subperiods, include additional macroeconomic variables, or analyze sectoral indices alongside the IHSG. These extensions would provide a more detailed understanding of exchange-rate risk in the Indonesian stock market.

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ETHICS STATEMENT

This study uses secondary financial-market data for statistical analysis and does not directly involve human participants; therefore, approval from a human-research ethics committee was not required.

AUTHOR CONTRIBUTIONS

The authors were responsible for conceptualization, methodology, data processing, statistical analysis, visualization, preparation of the original draft, review, and editing of the manuscript.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the preparation of this article.

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