



Analysis of Jakarta Composite Index Volatility and Macroeconomic Determinants on the Frequency of Initial Public Offerings in the Indonesia Stock Exchange

Basel Onn¹

Padjadjaran University Faculty of Economics and Business Jatinangor

*Corresponding Author e-mail: baselonn12@gmail.com

Article History:

Received : 25-08-2026

Revised : 19-10-2026

Accepted : 20-10-2026

Keywords: *IPO Frequency, Inflation, Initial Public Offering, Stock Market, Market Volatility*

Abstract: *This study examines the short-run and long-run relationships between Jakarta Composite Index (JCI) volatility, macroeconomic factors, and the frequency of Initial Public Offerings (IPOs) in Indonesia over the period 1995–2024. Using 30 annual observations from the Indonesia Stock Exchange, Investing.com, and the World Bank, the study applies the Autoregressive Distributed Lag (ARDL) model and Error Correction Model (ECM). The results indicate that JCI volatility and inflation have significant negative long-run relationships with IPO frequency, while the crisis dummy has a significant positive relationship. In contrast, the long-run coefficients for the CBOE Volatility Index (VIX) and JCI returns are not statistically significant. In the short run, changes in JCI volatility are positively and significantly associated with IPO frequency, whereas changes in the crisis dummy are negatively and significantly associated with IPO frequency. Changes in the VIX show negative associations, with the contemporaneous coefficient significant at the 10% level and the lagged coefficient significant at the 5% level. Changes in JCI returns do not show a statistically significant relationship with IPO frequency. The error correction term is negative and statistically significant, indicating an adjustment toward the estimated long-run equilibrium. Overall, the findings suggest that the relationships between market conditions and IPO frequency differ between the short and long run. However, the results should be interpreted in light of the limited annual observations and the operational definition of the crisis dummy.*

How to Cite: Basel Onn. (2026). Analysis of Jakarta Composite Index Volatility and Macroeconomic Determinants on the Frequency of Initial Public Offerings in the Indonesia Stock Exchange. 4(4). pp.518-531. <https://doi.org/10.61536/escalate.v4i4.782>



<https://doi.org/10.61536/escalate.v4i4.782>

This is an open-access article under the [CC-BY-SA License](https://creativecommons.org/licenses/by-sa/4.0/).



Introduction

The decision to conduct an Initial Public Offering (IPO) is a crucial strategic step and carries high risks for a company because it is determined not only by internal fundamental and managerial readiness, but also by momentum and stock market conditions (market timing). Baker and Wurgler (2002) explain that the decision to issue shares is closely related to market conditions, so changes in market conditions are an important consideration for companies in determining the right time to conduct an IPO. In this context, market volatility is one source of uncertainty in the company valuation process. When the market experiences turmoil, determining the initial public offering price becomes increasingly difficult due to increased uncertainty regarding the company's value. This situation can create a dilemma for companies: whether to postpone expansion plans or proceed with an IPO, facing the risk of a less than optimal valuation in the eyes of investors.

This phenomenon is evident in the dynamics of IPO activity on the Indonesia Stock Exchange (IDX) from 1995 to 2024. During the 1998 Asian financial crisis, increased JCI volatility was accompanied by a drastic decrease in the number of companies conducting IPOs, from just three companies to 21 companies the previous year. This situation suggests that market shocks can hamper IPO activity. However, a different pattern was observed during the COVID-19 pandemic from 2020 to 2022. Despite the market facing high shocks and volatility, the IDX recorded 51 companies conducting IPOs in 2020, increasing to 54 companies in 2021. The difference in response between the Asian financial crisis and the COVID-19 pandemic demonstrates an inconsistent relationship between market uncertainty and IPO activity. This raises questions about whether market volatility actually hinders Indonesian companies from conducting IPOs or can actually create opportunities for companies to enter the capital market when market conditions are under pressure.

Research issues are increasingly evident in the influence of volatility on the mechanism of initial public offering (IPO) price formation. Increased JCI volatility can increase uncertainty regarding a company's fair value (intrinsic value), leading investors to demand a higher risk premium or price discount to compensate for the uncertainty (Angelini & Foglia, 2018; Rydqvist & Hogholm, 1995). This situation has the potential to increase underpricing and the costs of issuing shares that companies must bear. The increased cost of capital can further encourage companies to postpone or cancel IPO plans until market conditions stabilize. In addition to market volatility, macroeconomic shocks such as inflation also influence investor purchasing power and the overall cost of capital. Therefore, the relationship between market volatility, macroeconomic variables, and IPO frequency requires a more in-depth examination within the context of the Indonesian capital market.

Another issue relates to the lack of comprehensive mapping of the Indonesian IPO market's response to market uncertainty. The existing literature does not clearly indicate whether the IDX is a highly sensitive market to volatility, leading companies to delay IPOs during volatile market conditions, or whether it exhibits a certain resilience that allows for increased IPO activity during and after a crisis. The differences between the Asian financial crisis and the COVID-19 pandemic indicate that the impact of market uncertainty on IPO activity does not always follow the same pattern. Therefore, an analysis is needed to clarify whether the influence of market volatility and macroeconomic variables on IPO frequency is only a temporary response to shocks or persists over the long term.

This problem is also related to the limitations of previous research approaches, which mostly use static approaches such as OLS, which have not fully captured the dynamics of IPO activity's response to market shocks based on the time dimension. IPO decisions are responses that can change according to market conditions. Volatility shocks can cause panic and delays in the short term, but a company's need to obtain funding for expansion can encourage it to pursue another IPO in the long term. Therefore, this study aims to analyze and test the significance of market volatility and macroeconomic variables on the frequency of IPOs in Indonesia in the short and long term. The urgency of this research lies in the need to understand whether these influences are temporary or persistent, thus providing a more accurate basis for understanding market timing, IPO market resilience, and the considerations of companies and regulators in dealing with changing market conditions. The novelty of this study lies in the use of the Autoregressive Distributed Lag (ARDL) method to distinguish and



measure short-term and long-term effects simultaneously, including examining the adjustment process of IPO activity towards equilibrium after experiencing market shocks.

Research methods

This study uses a quantitative approach with an explanatory research type to analyze the influence and dynamic relationship of macroeconomic variables on the frequency of Initial Public Offerings (IPOs) in Indonesia during the period 1995 to 2024. The data used are secondary data in the form of annual time series which include IPO frequency, JCI volatility, JCI returns, inflation, crisis dummy, and CBOE Volatility Index (VIX). This study uses the Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al. (2001) because it can be used to analyze short-term and long-term relationships in data with different levels of stationarity, namely $I(0)$ and $I(1)$. The ARDL model combines Autoregressive (AR) components, which use past values of the dependent variable, and Distributed Lag (DL) components, which include current and past values of the independent variables, thus allowing the relationship between variables to be analyzed dynamically based on the time dimension (Gujarati & Porter, 2009). The research model specifications refer to and replicate several previous studies, namely Hashmi and Chang (2020), Javangwe and Takawira (2022), and Mehmood et al. (2021).

The research instruments consisted of secondary data obtained from the Indonesia Stock Exchange, Investing.com, and the World Bank. IPO frequency data was obtained from the Indonesia Stock Exchange, JCI volatility and return data were obtained from Investing.com, and inflation data was obtained from the World Bank. The crisis dummy variable was processed based on the periods of the Asian financial crisis from 1998 to 1999, the global financial crisis of 2009, and the COVID-19 pandemic crisis from 2020 to 2022, with a value of 1 for the crisis period and 0 for the non-crisis period. The data were then processed using Microsoft Excel and STATA 16. The analysis technique was carried out through the stages of stationarity testing using the Dickey-Fuller Test, determining the optimum lag based on the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion or Bayesian Information Criterion (SBC/BIC), and cointegration testing using the Bounds Test (Pesaran et al., 2001). If a cointegration relationship is found, the analysis is continued with the Error Correction Model (ECM) and Error Correction Term (ECT) tests to determine the speed of adjustment towards long-term equilibrium (Gujarati & Porter, 2009; Wooldridge, 2012). Next, a heteroscedasticity test is carried out using the White Test, an autocorrelation test using the Breusch-Godfrey Test, a partial test using the t-test, a simultaneous test using the F-test, a coefficient of determination (R^2), a residual normality test using the Jarque-Bera Test, and a parameter stability test using CUSUM and CUSUMSQ. The cointegration test using the Bounds Test refers to Pesaran et al. (2001), while the cointegration and dynamic relationship tests also consider the approaches of Engle and Granger (1987) and Brooks (2008).

The research population covers all Initial Public Offering (IPO) activities recorded in Indonesia during the period 1995 to 2024. Because the research uses secondary data in the form of annual time series, the research sample is determined based on all available observation periods and relevant to the research variables, thus covering annual observations from 1995 to 2024. The research analysis unit is annual data on the frequency of IPOs in Indonesia along with the variables used to explain these dynamics, namely JCI volatility, JCI returns, inflation, crisis dummies, and VIX. Thus, the research does not use individual respondents, but rather uses all available time series observations within the research period.

The research procedure begins with the collection and compilation of annual secondary data from 1995 to 2024 from the Indonesia Stock Exchange, Investing.com, and the World Bank. All data is then organized by time period and research variables. The next stage is data processing using Microsoft Excel and STATA 16, followed by stationarity testing using the Dickey-Fuller Test to ensure the level of integration of each variable and avoid the possibility of spurious regression (Gujarati & Porter, 2009; Enders, 2014). Once the stationarity level is known, the optimum lag is determined based on the AIC and SBC/BIC values. Then the ARDL model is estimated to identify the dynamics of the relationship between variables. Next, a Bounds Test is performed to determine the existence of a long-term cointegration relationship (Pesaran et al., 2001). If cointegration is present, the model is continued with ECM and ECT estimation to measure the speed of adjustment towards long-term equilibrium. The next



stage includes testing for heteroscedasticity, autocorrelation, partial correlation, simultaneous correlation, coefficient of determination, residual normality, and parameter stability using CUSUM and CUSUMSQ. All test results are then used to analyze the effect of JCI volatility and macroeconomic variables on the frequency of Indonesian IPOs in the short and long term, in accordance with the research objectives.

Results and Discussion

Descriptive Statistics

Table 1. Descriptive Statistics

Variables	Obs	Average	Standard Deviation	Minimum	Maximum
Dependent Variable					
IPOFREQ	30	26	19.04	3	79
Independent Variables					
JCI Volatility	30	20.35	9,027	8,224	48.76
IHSGRETURN	30	13.85	31.43	-50.64	86.98
INF	30	8,269	10.30	1,560	58.45
VIX	30	110.8	28.57	62.16	185.8

Source: Data Processing Results

The IPOFREQ variable indicates the number of companies conducting initial public offerings (IPOs) each year. During the observation period, the average IPO frequency on the Indonesia Stock Exchange was 26 companies per year. The lowest IPO activity was recorded at 3 companies, while the highest recorded was 79 companies in a single year. The standard deviation of 19.04 indicates significant fluctuation and dispersion in IPO activity from year to year.

The JCI VOLATILITY variable measures the level of stock market fluctuations. The average JCI volatility during the observation period was 20.35%. The lowest volatility level was 8.224%, while the highest volatility spike reached 48.76%. The standard deviation of 9.027% indicates that market volatility is quite variable, deviating by approximately 9.027% from its average value.

The IHSG RETURN variable represents the aggregate market return rate. The average JCI return has historically been positive at 13.85%. However, this variable has a very extreme range, with the deepest decline reaching -50.64% and the highest surge reaching 86.98%. This high market risk is also reflected in the standard deviation value of 31.43%, which is significantly higher than the average value, indicating high uncertainty in the returns investors receive.

The INF variable reflects macroeconomic price pressures. The average inflation rate over the 30 years of observation was 8.269%. The most stable and lowest inflation rate was 1.560%, while the highest inflation rate ever spiked sharply, reaching 58.45%. The standard deviation of 10.30%, which is greater than the average, indicates significant price shocks, or hyperinflation, in certain years within the observation period.

The VIX variable had an average value of 110.8 during the observation period. The lowest uncertainty value was recorded at 62.16, while the highest level of market panic soared to 185.8. The standard deviation of 28.57 indicates the magnitude of the dispersion, or average deviation, of the VIX index's movement around its mean value.

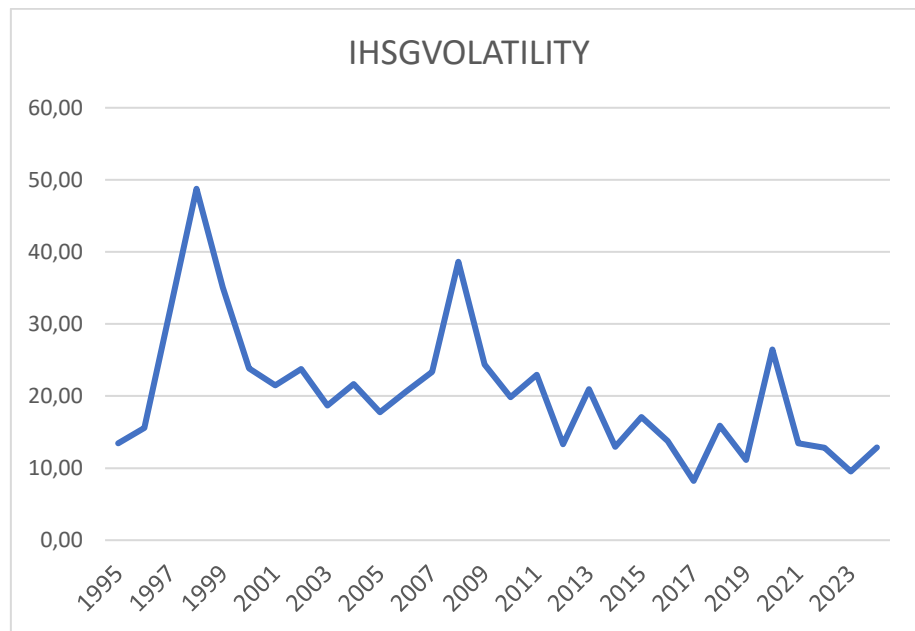


Figure 1. JCI Volatility Graph

Source: Investing, Processed by the Author

Figure 1 shows the volatility of the Jakarta Composite Index (JCI) during the 1995–2024 period, confirming that the Indonesian capital market operates within a highly dynamic risk cycle, characterized by three extreme spikes during major crisis periods. The highest spike occurred during the 1998 Asian Financial Crisis, reaching 48%, followed by the spillover effect of the 2008 Global Financial Crisis at around 38%, and the uncertainty shock of the COVID-19 pandemic in 2020, which triggered volatility to surge above 25%. Outside of these three crisis phases, volatility tends to fluctuate in a moderate range of 10% to 25%, with the lowest point reaching below 10% around 2017.

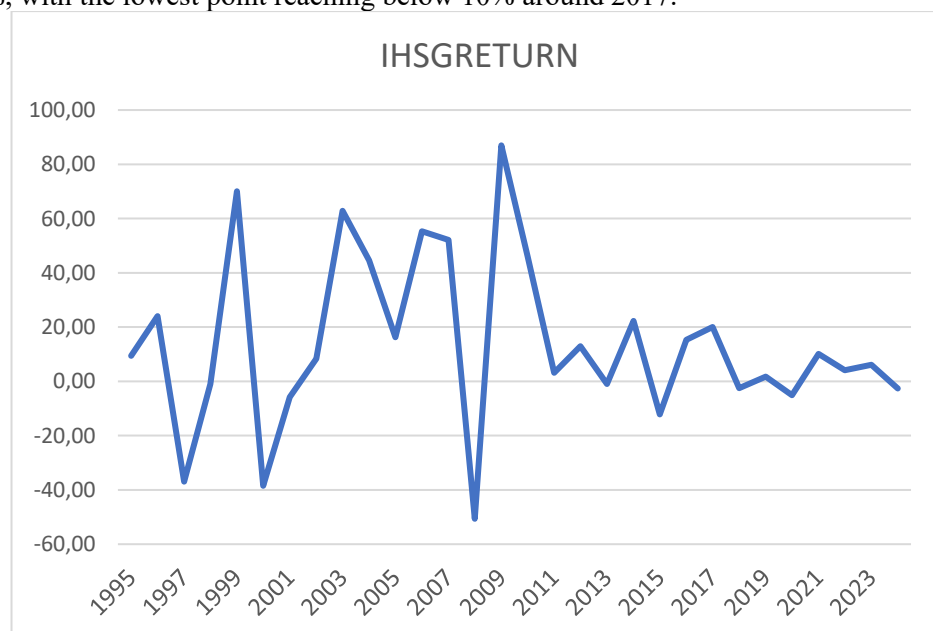


Figure 2. IHSG Return Graph

Source: Investing

The visualization of the JCI returns for the 1995–2024 period shows a shift in market behavior from a highly volatile phase to a more stable one. In the first 15 years, the market responded to crises with extreme contractions (such as the -50% plunge in 2008) that were always followed by rebounds. aggressive (surging to nearly 90% in 2009). However, from 2010 until the end of the observation period, the return movement narrowed and tended to stabilize in a moderate range (-10% to 20%).

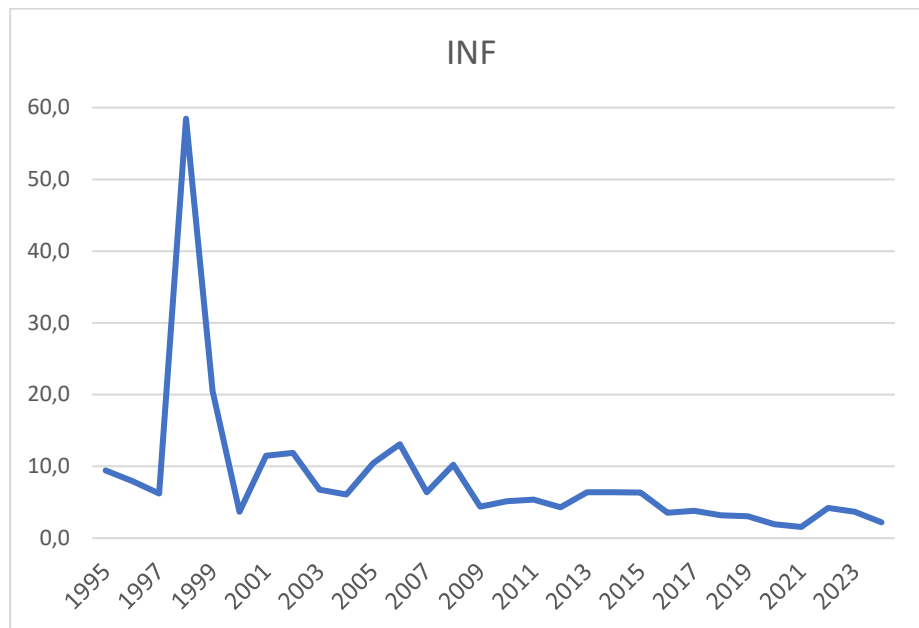


Figure 3. Indonesian Inflation Graph

Source: World Bank

The visualization of the inflation rate for the 1995–2024 period was dominated by a single extreme hyperinflationary spike approaching the 60% level due to the 1998 Asian Financial Crisis. Following this shock, the inflation rate gradually subsided and has persistently entered a very stable phase below the 5% level since the 2010s.

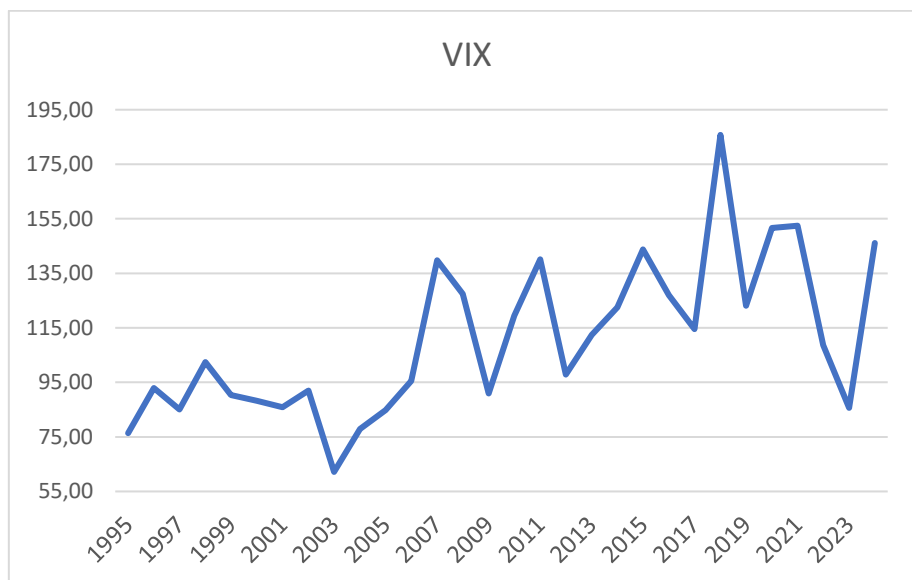


Figure 4. VIX Index Chart

Source: Investing, Processed by the Author

The visualization of the External Volatility Index (VIX) for the period 1995–2024 shows a highly volatile and increasing trend of market uncertainty in the United States. Unlike domestic volatility, which peaked in 1998, extreme spikes in the VIX are highly responsive to international

shocks, as evidenced by the sharp escalation during the 2008 Global Financial Crisis and the records highest soaring to nearly 185 levels due to massive panic during the COVID-19 pandemic in 2020.

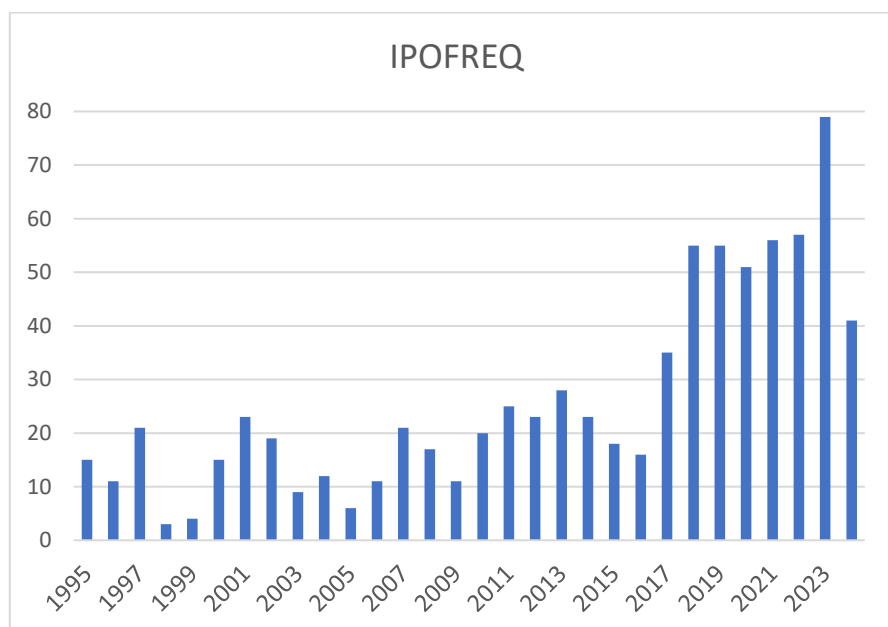


Figure 5. Indonesian IPO Frequency Graph

Source: Indonesia Stock Exchange

The IPO frequency (IPOFREQ) graph visualization for the 1995–2024 period reveals two starkly contrasting phases. Between 1995 and 2016, the trend tended to be flat with low fluctuations, with the number of new issuers consistently below 30 companies per year and reaching its lowest point in 1998–1999. However, since 2017, the graph has shown a sharp upward trend, peaking at a historic high of nearly 80 companies in 2023. Following this extreme surge, the graph concludes with a steep vertical decline in 2024, with the IPO frequency plummeting back to around 40 companies.

Annual Volatility Measurement

Before entering the regression stage, it is necessary to measure the volatility of the Jakarta Composite Index (JCI). In this study, the level of market uncertainty is proxied using the volatility of the Jakarta Composite Index (JCI). Because the econometric model used is based on annual data, daily index movements need to be aggregated. The first step is to calculate the daily JCI return, which is then measured for its fluctuation level using the standard deviation value. This daily standard deviation value indicates how far the daily index movement deviates from its average over a given year.

Since the daily standard deviation does not yet represent annual risk, the next step is to annualize the risk. In accordance with common practice and standards in the financial derivatives literature, a proxy for historical volatility is calculated using the standard deviation of daily returns (Ederington & Guan, 2006). To obtain the annualized metric, the daily standard deviation is multiplied by the square root of the number of trading days in a year (Ederington & Guan, 2006). In this study, 244 days are assumed to represent the average trading days on the Indonesia Stock Exchange over the past 30 years. Mathematically, the equation is written as follows:

$$\text{Volatilitas Tahunan} = \sum \sigma \text{return harian IHSG} \times \sqrt{244}$$

Through this mathematical conversion, all daily fluctuations occurring throughout the year are transformed into a single metric, the annual volatility percentage (IHSGVOLATILITY) in Figure 4.1. This calculated figure then becomes the time-series data tested in an econometric model to determine its impact on the frequency of initial public offerings (IPOs).



Research result

1. Stationarity Test Results

This study utilizes the Dickey-Fuller (DF) test to test the stationarity of the research variables. Based on the guidelines of Gujarati and Porter (2009), this method is commonly relied upon because the inclusion of the dependent variable lag in it has proven effective in eliminating serial autocorrelation interference in the error term. The testing process is carried out in stages, starting from the basic level (level) to find stationary variables at degree $I(0)$, up to the first derivative level (first difference) for degree $I(1)$. The null hypothesis (H_0) proposed is that the data is non-stationary (has a unit root). Rejection of H_0 can only be done if the test probability value is lower than 5% ($\alpha = 0,05$), or the absolute value of the calculated statistic exceeds its critical point (Gujarati & Porter, 2009). Based on the reading of Table 4.2, the unit root test proves that all variables are stationary at the level level or degree $I(0)$, except for the IPOFREQ variable. This stationary status is statistically confirmed by a probability value <0.05 and a test value that exceeds the critical limit. On the other hand, the IPOFREQ variable fails to reject the null hypothesis at the level level due to the probability magnitude being above 0.05. This condition is in line with the view of Gujarati and Porter (2009) that the general characteristics of economic data often contain long-term stochastic trends, so that naturally these variables are more often integrated at the first difference or $I(1)$ level.

Table 2. Stationarity Test Results

Variables	Dickey Fuller(DF)				
	Level (Z(t))	Prob.	First Different (Z(t))	Prob.	Information
IPOFREQ	-1,622	04719	-5,407	0.0000	I(1)
JCI Volatility	-2,886	0.0470	-	-	I(0)
IHSGRETURN	-6,032	0.0000	-	-	I(0)
INF	-4,067	0.0011	-	-	I(0)
VIX	-3,273	0.0161	-	-	I(0)

Source: Data Processing Results

Following up on the findings at the level level, further testing at the first difference level showed that the IPOFREQ variable successfully achieved stationarity with a probability level <0.05 . This is in line with the view of Gujarati and Porter (2009) that the first difference transformation is a reliable instrument to eliminate unit root problems in time series. Based on these results, it can be concluded that the IPOFREQ variable is legitimately integrated at the first order or $I(1)$. Overall, the composition of the data in this study is a pure mixture of variables of degree $I(0)$ and $I(1)$, and no variables were detected at all integrated at order $I(2)$. This crucial finding validates the feasibility of the data for further analysis using the Autoregressive Distributed Lag (ARDL) method.

Referring to Pesaran et al. (2001), the existence of mixed variables $I(0)$ and $I(1)$ ensures that the modeling estimation can be executed without violating the fundamental assumptions of *bounds testing*. With all these econometric prerequisites fulfilled, the research procedure is ready to move to the next stage, namely determining the optimum lag length calibrated using the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) indicators, before leading to the estimation of ARDL model parameters.

2. Optimal Lag Selection

Determining the lag length is an essential step in modeling. This phase requires a precise balance: the tested lag must be long enough to eliminate potential autocorrelation, yet short enough to avoid the risk of Error Correction Model (ECM) errors. *over-parameterization*. This excess parameter condition must be avoided because it has the potential to drastically reduce the degrees of freedom, especially in tests with limited observation samples (Pesaran et al., 2001).

To accommodate these limitations, this study limits the maximum lag to order 2 based on two main arguments. First, referring to the guidelines of Narayan and Smyth (2006), a lag limit of 2 is the most ideal and capable specification for capturing behavioral dynamics in annual frequency data.



Second, the limited data structure requires the application of the parsimony principle to maintain the form of the regression model simple and rational, so that its estimation efficiency is not compromised (Gujarati & Porter, 2009). Excessive expansion of lag parameters without essential justification will ultimately only shrink the degrees of freedom and inflate the variance.

Operationally, the identification of the optimum lag is executed through the ARDL procedure in STATA software with reference to the Schwarz Bayesian Criterion (BIC), in line with the approach applied by Narayan and Smyth (2006). The BIC criterion was specifically chosen because it has a much stricter penalty mechanism for each additional variable or new parameter (Pesaran et al., 2001). Due to this severe penalty characteristic, the BIC indicator will automatically recommend a shorter and more efficient lag structure when compared to the Akaike Information Criterion (AIC).

Table 3. Results of Optimal Lag Selection

Optimal Lag	Base
(2,2,0,1,2,1)	BIC

Source: Data Processing Results

The test results generally indicate varying lag dynamic structures for each model. This demonstrates the high flexibility of the ARDL approach in allocating different lag lengths for each variable according to the inherent characteristics of the data (Pesaran et al., 2001). Furthermore, this selected optimum lag design will be applied as the basis for estimating the long-run equilibrium relationship and ECM parameters in the next analysis stage.

3. Cointegration Test

To detect the existence of long-term equilibrium in ARDL modeling, an essential step that must be carried out is the Bounds Test cointegration test as proposed by Pesaran et al. (2001). Confirmation of the existence of a long-term relationship between these variables is evaluated statistically by comparing the obtained F-statistic value to the critical values of the lower bound and upper bound.

Table 4. Cointegration Test Results (Bound Testing)

F-Statistic			t-Statistic			Conclusion
Mark	CV	CV	Mark	CV	CV	
	I(0)	I(1)		I(0)	I(1)	Cointegration
6,396	3.41	4.68	-5,934	-3.43	-4.79	

Source: Data Processing Results

Based on the data presented in Table 4, the model consistently indicates a strong cointegration relationship. The rejection of the null hypothesis in all specifications is based on the F-statistic value being above 4.68 and the t-statistic being less than -4.79.

The success of bounds testing in detecting cointegration has two important implications. Methodologically, these results validate the use of the ARDL approach to map long-run relationships between variables (Pesaran et al., 2001). Operationally, cointegration status provides absolute justification for including ECT elements in ECM modeling. *speed of adjustment* towards equilibrium can be quantified (Alwago, 2023).

4. Long-Term Estimation Results

Based on the ARDL regression results on the long-term estimates in Table 5, the dynamics of initial public offering (IPO) frequency in Indonesia are empirically influenced by macroeconomic fluctuations and market sentiment. The main finding highlights the JCI volatility variable (IHSGVOLATILITY), which has a negative and significant relationship at the 1% level, with a coefficient of -1.297, which means that every 1% increase in volatility will reduce the frequency of IPOs by 1,297 companies.



Table 5. Long-Term ARDL Estimation Results

Variables	Coefficient	Prob.
JCI Volatility	-1.2972	0.000***
INF	-0.5192	0.019**
DummyCrisis	31,7147	0.000***
VIX	0.1094	0.247
IHSGRETURN	-0.0822	0.296
R ²	0.8193	-
Adj. R ²	0.656	-
Obs.	28	-

Source: Data Processing Results

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Pressure on capital market activity in the long term also comes from macroeconomic factors, as indicated by the inflation variable (INF) with a negative and significant coefficient of -0.519 at the 5% level, meaning that every 1% increase in inflation will reduce the number of IPO companies by 0.5 companies. Then, this model reveals an anomaly in the crisis variable (DUMMYCRISIS), which actually provides a positive and significant relationship with a coefficient of 31.71 at the 1% level, meaning that on average, during a crisis period, the value of the dependent variable will be higher by 31 companies compared to the non-crisis period.

On the other hand, several indicators have been shown to have no long-term determinant role. The global uncertainty indicator (VIX) and the historical market rate of return (IHSGRETURN) do not show a statistically significant relationship to IPO frequency.

5. Short Term Estimation Results

The short-term dynamics analysis in Table 6 provides crucial insights into the market's immediate response and corporate funding tactics. The reliability of the Error Correction Model (ECM) specification is absolutely validated through the adjustment coefficient, or Error Correction Term, which is negative and significant at the 1% level of -1.175. This means that short-term imbalances or shocks that occurred in the previous period will be corrected by 117.5% in the current period to return to the long-term equilibrium point.

Table 6. Short-Term ARDL Estimation Results

Variables	Coefficient	Prob.
D. IHSG VOLATILITY	1.8439	0.001***
LD.IHSGVOLATILITY	0.8888	0.013**
D. DUMMY CRISIS	-36,097	0.000***
D.VIX	-0.1737	0.086*
LD.VIX	-0.2016	0.036**
D.IHSGRETURN	0.1197	-0.0434
ECT	-1.1754	0.000***
ARDL Spec.	(2,2,0,1,2,1)	

Source: Data Processing Results

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regarding issuer behavior on the stock exchange, the dynamics of short-term JCI volatility in the current period (D.IHSGVOLATILITY) and the previous year's lag (LD.IHSGVOLATILITY) have a positive and significant relationship, with coefficients of 1.844 and 0.889, respectively. Conversely, the spike in short-term global uncertainty (D.VIX & LD.VIX) has a negative and significant relationship, with coefficients of -0.174 and -0.202, respectively.

The stock exchange's response to the shock effects of a crisis also exhibits dynamics that contrast with its long-term track record. The crisis shock variable (D.DUMMYCRISIS) in the initial year of the shock immediately suppresses IPO frequency extremely, as indicated by a negative

coefficient of -36.10 at the 1% significance level. This represents a momentary liquidity paralysis and initial panic in the capital market before corporate adaptation mechanisms kick in. Meanwhile, in line with long-term estimates, short-term fluctuations in the JCI return momentum (D.IHSGRETURN) remain insignificant in stimulating the acceleration of corporate IPOs.

6. Autocorrelation Test

The autocorrelation assumption test in this study was executed using the Breusch-Godfrey Lagrange Multiplier (BG-LM) method. This approach is based on the null hypothesis (H_0) that the model residuals are free from serial autocorrelation interference, where the evaluation relies on the Chi-Square (χ^2) distribution statistical value (Gujarati & Porter, 2009). Within the ARDL methodology framework, fulfilling this non-autocorrelation assumption is an absolute requirement to ensure the validity and reliability of the bounds testing procedure (Pesaran et al., 2001). Referring to table 7 of the estimation results, the obtained probability value exceeds the 5% significance level ($= 0.05$). This statistical condition indicates that H_0 fails to be rejected (Gujarati & Porter, 2009), so empirically it can be concluded that the entire model specification has validly met the criteria for being free from serial autocorrelation problems. $\chi^2 \chi^2 \alpha$

Table 7. Autocorrelation Test Results

$\chi^2(1)$	df	$Prob > \chi^2$	Conclusion
3,652	1	0.0560	No Autocorrelation

Source: Data Processing Results

7. Normality Test

To ensure the appropriateness of the error term distribution, this study applies a residual normality test based on the Skewness-Kurtosis approach, which asymptotically conforms to the Jarque-Bera test principle. This test is based on the null hypothesis (H_0) that the residuals simultaneously follow a normal distribution (Gujarati & Porter, 2009). Based on the estimation results in Table 4.8, the research model shows a Prob value $>$ which exceeds the 5% significance threshold ($= 0.05$). This condition indicates that H_0 cannot be rejected (Gujarati & Porter, 2009). Thus, it can be concluded that the model has validly met the residual normality assumption, which also ensures that all statistical inferences in this modeling are valid and free from underlying distribution bias. $\chi^2 \alpha$

Table 8. Normality Test Results

Pr(Skewness)	Pr(Kurtosis)	$\chi^2(2)$	$Prob > \chi^2$	Conclusion
0.3209	0.9968	1.05	0.5910	Normal

Source: Data Processing Results

8. Parameter Stability Test

To evaluate the structural reliability of the model, this study applies the Cumulative Sum (CUSUM) stability test, which relies on recursive residuals. This approach tests the null hypothesis (H_0) that all parameters in the model are structurally constant and stable over the observation period (Pesaran et al., 2001). Referring to the CUSUM test results, the movement of statistical values is proven to remain within the critical limit corridor at all significance levels (1%, 5%, and 10%). This condition means that H_0 fails to be rejected. Thus, it can be concluded that the estimated model parameters have robust structural stability, making them very suitable and valid for representing the long-term equilibrium dynamics between variables.

Table 9. Parameter Stability Test Results

CUSUM Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%	Conclusion
0.2641	1.1430	0.9479	0.850	Stable Parameters

Source: Data Processing Results

9. Economic Analysis

Economic analysis aims to interpret the direction and magnitude of the influence of independent variables on dependent variables, as represented by the estimated parameter coefficient values.



Furthermore, this analysis stage plays a crucial role as a validation tool to ensure that the empirical findings generated by the model align with the postulates of economic theory and are consistent with previous studies.

Domestic stock market uncertainty (IHSG volatility) has a significant negative impact on the long-term IPO rate. This conclusion confirms previous literature (Amorim et al., 2021; Angelini & Foglia, 2018), which states that volatility consistently hinders IPO activity. High structural volatility represents fundamental fragility, which drives up risk premiums. As an economic rationale, the threat of a rising cost of equity and the risk of failed share acquisitions force companies to adopt conservative measures by delaying corporate actions. On the other hand, short-term JCI volatility actually provides a significant positive stimulus. This dual response demonstrates the effectiveness of market timing tactics in the domestic market, where issuers exploit price fluctuations as a crucial window of opportunity to go public at a time when market valuations are peaking.

The inflation rate (INF), a reflection of domestic price stability, has a significant negative impact on the capital market ecosystem in long-term projections. Validation of this condition supports the conclusion of Mehmood et al. (2021) that persistently high inflation automatically weakens real purchasing power and triggers monetary tightening policies in the form of interest rate hikes. The surge in the benchmark interest rate creates a crowding-out effect that draws liquidity from the stock market to bank savings instruments, while simultaneously increasing companies' cost of capital. This contractionary macroeconomic condition cumulatively eliminates the attractiveness of the capital market as an efficient expansionary funding channel for prospective issuers.

On the other hand, in the long-term equilibrium, the crisis variable (DUMMYCRISIS) contributes positively and significantly to the surge in the frequency of new share listings. Empirically, the post-crisis phase tends to crystallize a new macroeconomic equilibrium. Monetary easing stimulus through a low-interest rate regime, combined with relaxed stock exchange regulations, effectively stimulates corporations to raise public funding for restructuring. In contrast, the shock effect of the crisis on short-term dynamics proves highly destructive, with a negative and significant coefficient. This phenomenon confirms the study by Amorim et al. (2021), which explains that the initial shock of the crisis triggered panic selling and an immediate liquidity crisis, forcing issuers to immediately suspend their entire expansion agenda.

Furthermore, the historical stock market return variable (IHSGRETURN) has consistently been shown to have no statistically significant effect on either the long-term equilibrium framework or the dynamics of short-term corrections. This empirical finding aligns with Angelini and Foglia (2018), who theoretically confirm that past stock market returns are not a rational basis for corporate management in executing public offerings. Issuers have been shown to adopt rationality in formulating funding strategies. The decision to go public is far more sensitive to projected future risks and uncertainty (volatility) than to historical price movements, which, in essence, cannot guarantee successful future share absorption.

In line with this, the global market uncertainty indicator (VIX) has been shown to have no statistically significant impact on long-term equilibrium. This empirical condition indicates that the resilience of IPO activity in the domestic capital market is much more dependent on the solidity of national macroeconomic fundamentals than fluctuations in global sentiment. Nevertheless, the domestic market exhibits very high sensitivity to external shocks in the short-term. Rising global volatility exerts significant negative pressure that instantly hinders the realization of new share listings. The transmission channel of this phenomenon stems from the threat of capital outflow and global panic, which will trigger a flight of foreign capital to safe-haven assets. This condition directly disrupts the availability of liquidity on the domestic stock exchange, thus encouraging prospective issuers to behave rationally by delaying their offering period.

Conclusion

This study shows that JCI volatility and macroeconomic conditions have different effects on the frequency of Initial Public Offerings (IPOs) in Indonesia in the short and long term. In the long term, JCI volatility has a negative and significant effect on IPO frequency, with a coefficient of -1.297, while inflation also has a negative and significant effect of -0.519. Conversely, the crisis dummy has a positive and significant effect of 31.715, while the VIX and JCI returns show no significant effects. In the short term, changes in JCI volatility have a positive and significant effect, while changes in the crisis dummy and VIX exert negative pressure on IPO frequency. The ECT value of -1.175 and significant indicates a strong adjustment process towards long-term equilibrium after a shock. These findings indicate that companies can exploit market fluctuations for market timing in the short term, but persistent volatility and high inflation ultimately hinder IPO activity.

The limitations of this study lie in the relatively limited number of observations due to the use of annual data from 1995 to 2024. Furthermore, the use of macroeconomic variables and market indicators does not cover all institutional factors, company microeconomics, liquidity conditions, interest rates, and industry characteristics that could potentially influence IPO decisions. Therefore, further research is recommended to use higher-frequency data, expand the explanatory variables, and consider a nonlinear or regime-switching approach to identify differences in IPO responses under normal and crisis conditions. Practically, the study's findings provide implications for prospective issuers to consider volatility and inflation when determining the timing of their IPOs, while regulators and the Indonesia Stock Exchange (IDX) can strengthen market stability, maintain liquidity, and provide policies that support the sustainability of IPO activity during periods of economic stress.

Bibliography

- Alwago, W. O. (2023). The nexus between health expenditure, life expectancy, and economic growth: ARDL model analysis for Kenya. *Regional Science Policy & Practice*, 15(5), 1064–1085. <https://doi.org/10.1111/rsp3.12588>
- Amorim, D. P. L., Camargos, M. A., & Ferreira, C. M. B. L. (2021). Macroeconomic factors and initial public offerings in Brazil. *Global Business Review*, 1–18. <https://doi.org/10.1177/09721509211003696>
- Angelini, E., & Foglia, M. (2018). The relationship between IPO and macroeconomics factors: An empirical analysis from UK market. *Annals of Economics and Finance*, 19(1), 319–336.
- Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *The Journal of Finance*, 57(1), 1–32. <https://doi.org/10.1111/1540-6261.00414>
- Brooks, C. (2008). *Introductory econometrics for finance* (2nd ed.). Cambridge University Press.
- Ederington, L. H., & Guan, W. (2006). Measuring historical volatility. *Journal of Applied Finance*, 16(1). <https://ssrn.com/abstract=926167>
- Enders, W. (2014). *Applied econometric time series* (4th ed.). John Wiley & Sons.
- Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251–276. <https://doi.org/10.2307/1913236>
- Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill.
- Hashmi, S. M., & Chang, B. H. (2020). Asymmetric effect of exchange rate volatility on India's cross-border trade: Evidence from global financial crisis and multiple threshold nonlinear autoregressive distributed lag model. *Australian Economic Papers*, 60(1), 64–97. <https://doi.org/10.1111/1467-8454.12194>
- Javangwe, K. Z., & Takawira, O. (2022). Exchange rate movement and stock market performance: An application of the ARDL model. *Cogent Economics & Finance*, 10(1), Article 2075520. <https://doi.org/10.1080/23322039.2022.2075520>
- Mehmood, W., Mohd-Rashid, R., Ong, C. Z., & Abbas, Y. A. (2021). Factors driving IPO variability: Evidence from Pakistan Stock Exchange. *Journal of Economics, Finance and Administrative Science*, 26(52), 300–316. <https://doi.org/10.1108/JEFAS-04-2021-0036>
- Narayan, P. K., & Smyth, R. (2006). What determines migration flows from low-income to high-income countries? An empirical investigation of Fiji-U.S. migration 1972–2001. *Contemporary Economic Policy*, 24(2), 332–342. <https://doi.org/10.1093/cep/byj019>
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level



relationships. *Journal of Applied Econometrics*, 16(3), 289–326. <https://doi.org/10.1002/jae.616>
Rydqvist, K., & Högholm, K. (1995). Going public in the 1980s: Evidence from Sweden. *European Financial Management*, 1(3), 287–315. <https://doi.org/10.1111/j.1468-036X.1995.tb00021.x>
Wooldridge, J. M. (2012). *Introductory econometrics: A modern approach* (5th ed.). Cengage Learning.

