

# Volatility of International Trade and Exchange Rates in Some South Asian Countries Using the Ardl-Ecm Approach

**Desmintari\*, Raden Parianom, Ullya Vidriza**

Faculty of Economics and Business, Universitas Pembangunan Nasional Veteran Jakarta, Indonesia  
desmintari@upnvj.ac.id, radenparianom@upnvj.ac.id

## Abstract

This research investigates the relationship between dollar exchange rate volatility and international trade variables, namely exports and imports, in Indonesia and several countries in South Asia using the Autoregressive Distributed Lag (ARDL) approach with the Error Correction Model (ECM). The countries analyzed are India, Pakistan, Bangladesh and India which are key players in regional trade dynamics. And to see the causal relationship between variables, the Granger-Causality method is used. The data used is monthly data for the period January 2018 to December 2022. And to find out which dependent model takes the longest to respond to shocks and which countries are the fastest in Asia.

**Keywords:** Dollar exchange rate, international trade, exchange rate volatility.

## Introduction

This research will analyze, discuss and explain the factors that influence the balance of payments in India and countries in South Asia, namely Bangladesh, India and Pakistan. There are two variables to facilitate research, namely the dependent variable and the independent variable. The dependent variable is a variable that can be influenced, while the independent variable is a variable that influences. The dependent variable in this research is the balance of payments value. Meanwhile, the independent variables in this research are exchange rate volatility, foreign direct investment, and the consumer price index.

The type of data taken is time series data which has been adapted to be converted into logs. Variable testing was carried out from 2018 to 2022, which means the total data used in this research was 30 data periods. This data was obtained from various valid and trusted institutional websites, namely the World Bank and the Indonesian Central Statistics Agency. Data processing in this research uses quantitative data analysis with the Autoregressive Distributed Lag (ARDL) method. In this research, the Autoregressive Distributed Lag (ARDL) analysis begins with testing the stationarity of the data, both dependent variable data and independent variable data and determining the right leg that will be used as the analysis result. The tests that will be carried out are ARDL Estimation Test, Autocorrelation Test, Cointegration Test,

## Theory

This study is based on the theoretical framework that exchange rate fluctuations can have short-term and long-term effects on international trade. Exchange rate fluctuations can affect a country's competitiveness in global markets, import and export costs, and general economic stability. This theory posits that while exchange rate volatility may initially limit international trade, over time countries can adjust and reduce the negative effects, and in the long run volatility of trade and exchange rates This suggests that there is a positive correlation between rates.

## Method

### *Stationarity Test (Unit Root Test)*

The initial process in conducting this research is to carry out a stationarity test. In this test, we use the Unit Root Test. This test is intended to determine the stability of the data and classify it as stationary or non-stationary data. This test uses the Augmented Dickey-Fulley (ADF) method. The hypothesis used in this unit root test is as follows:

$H_0$  = Data is not stationary

$H_a$  = Stationary Data

If hypothesis 0 is rejected, it means that the data being analyzed is stationary or does not contain unit roots. Meanwhile, if the data contains a unit root, the data is not stationary, or there is a relationship between variables and time.

Table 1 Level of Stationarity Test

Variable	P-value	Critical Value 10%	Information
BOP-MOTHER	0,7253	0,1	Not stationary
BOP-BAN	0,9841	0,1	Not stationary
BOP-IND	0,6412	0,1	Not stationary
BOP-PAK	0,3086	0,1	Not stationary
LNVOL-INA	0,5975	0,1	Not stationary
LNVOL-BAN	0,852	0,1	Not stationary
LNVOL IN	0,537	0,1	Not stationary
LNVOL-PAK	0,931	0,1	Not stationary
LNVIHK-INA	0,776	0,1	Not stationary
IN LNIHK	0,560	0,1	Not stationary
LNIHK-IND	0,377	0,1	Not stationary
LNIHK-PAK	0,262	0,1	Not stationary
LNFDI-INA	0,663	0,1	Not stationary
IN LNFDI	0,996	0,1	Not stationary
LNFDI IND	0,514	0,1	Not stationary
LNFDI-PAK	0,530	0,1	Not stationary

Source: author's calculations

The table above shows the results of the Augmented Dickey-Fuller (ADF) test for each variable. There are no significant variables at the level using an alpha value of 10%. So it is necessary to carry out a stationarity test at different levels first to see whether it is stationary or not.

First Level Difference Stationarity Test Table

Variable	P-value	Critical Value 10%	Information
BOP-MOTHER	0,000	0,1	Not stationary
BOP-BAN	0,000	0,1	Not stationary
BOP-IND	0,000	0,1	Not stationary
BOP-PAK	0,000	0,1	Not stationary
LNVOL-INA	0,000	0,1	Not stationary

LNVL-BAN	0,000	0,1	Not stationary
LNVL IN	0,000	0,1	Not stationary
LNVL-PAK	0,000	0,1	Not stationary
LNVIHK-INA	0,000	0,1	Not stationary
IN LNIHK	0,000	0,1	Not stationary
LNIHK-IND	0,000	0,1	Not stationary
LNIHK-PAK	0,000	0,1	Not stationary
LNFDI-INA	0,000	0,1	Not stationary
IN LNFDI	0,000	0,1	Not stationary
LNFDI IND	0,000	0,1	Not stationary
LNFDI-PAK	0,000	0,1	Not stationary

Source: author's calculations

### Autocorrelation Test

The autocorrelation test is a test carried out to find out the relationship between variables at different times. The autocorrelation test aims to detect deviations from classical assumptions. This Autocorrelation test detection uses the Breusch-Godfret Serial Correlation LM Test method. The hypothesis and its explanation are as follows:

$H_0$  = Data does not have autocorrelation

$H_a$  = Data has autocorrelation

In the LM test it is assumed to have an alpha of 10%. If the Chi-Square probability value  $> \alpha$ , it can be interpreted as failing to reject  $H_0$  or there is no autocorrelation. However, if the problem is. Chi-Square  $< \alpha$ , means rejecting  $H_0$  or there is autocorrelation. If there is autocorrelation in a model, then the model must be cured first.

### WHEN

Breusch–Godfrey LM test for autocorrelation

Late (p)	Chi2	df	Likelihood > chi2
3	0,829	3	0,8425

$H_0$ : there is no serial correlation

From the table above it can be seen that Indonesia has a chi square probability of 0.829 which is greater than alpha 10% so it fails to reject  $H_0$  and there is no autocorrelation.

### BAN

Breusch–Godfrey LM test for autocorrelation

Late (p)	Chi2	df	Likelihood > chi2
1	0,291	1	0,5893

$H_0$ : there is no serial correlation

From the table above it can be seen that Bangladesh has a chi square probability of 0.291 which is greater than alpha 10% so it fails to reject  $H_0$  and there is no autocorrelation.

### IN

Breusch–Godfrey LM test for autocorrelation

Late (p)	Chi2	df	Likelihood > chi2
4	3.825	4	0,4254

H0: there is no serial correlation

From the table above it can be seen that India has a chi square probability of 3.825 which is greater than alpha 10% so it fails to reject H0 and there is no autocorrelation.

### THEN

Breusch–Godfrey LM test for autocorrelation

Late (p)	Chi2	df	Likelihood > chi2
3	16.893	3	0,0007

H0: there is no serial correlation

From the table above it can be seen that Pakistan has a chi square probability of 16.893 which is greater than alpha 10% so it fails to reject H0 and there is no autocorrelation.

### Cointegration Test

The cointegration bond test is intended to determine whether or not there is a long-term relationship between the dependent variable and the independent variable in the ARDL test. The cointegration test is also a continuation after the stationarity test which states that if the data has been tested for cointegration, then there is a long-term relationship for each variable. If the data that has been tested does not occur cointegration, then there is no long-term relationship between each variable.

In cointegration testing using a bound test approach. This test was also developed by Pasaran, Shin and Smith. The dependent test approach test is based on the F statistical test. The following is the cointegration test hypothesis:

$$H_0 = \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$$

$$H_a = \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4$$

Information:

H0 = No cointegration occurs

Ha = Cointegration occurs

### Determination of Optimal Lag

The aim of determining the optimum lag is to determine the magnitude of the lag or time interval contained in the research variables. The following Akaike Information Criteria (AIC) results are as follows:

### WHEN

Lag-order selection criteria

Sample: 2018m5 thru 2022m12

Number of obs = 56

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	456.988				1.1e-12	-16.1781	-16.1221	-16.0335
1	855.811	797.65	16	0.000	1.3e-18	-29.8504	-29.57	-29.1271
2	898.616	85.61	16	0.000	5.0e-19	-30.8077	-30.3029*	-29.5057*
3	920.837	44.442*	16	0.000	4.1e-19*	-31.0299*	-30.3008	-29.1492
4	932.152	22.629	16	0.124	5.0e-19	-30.8626	-29.9091	-28.4032

\* optimal lag

Based on the results of the Optimum Lag test in the table above for Indonesian data for 2018-2022. Where there is the largest Optimal Lag value in LR, namely 44.442, which means that the largest likelihood ratio (LR) value indicates that the model with a higher number of lags (complex model) provides a significant increase in the probability of being observed. data compared with a model with a lower number of lags (simple model). Furthermore, the FPE is  $4.1\text{e-}19$ , which means the largest optimal lag value in the FPE is the number of lags that produces the lowest FPE value, where the number of lags that gives the lowest FPE value is the optimal lag or the largest optimal lag value in the FPE. Then the AIC is -31.0299, which means the largest value does not refer to the highest AIC value, but refers to the lowest AIC value, the model with the lowest AIC value (smallest value) is considered the best or optimal model. For HQIC it is -30.3029, meaning that looking for the largest value means looking for the model with the lowest HQIC value, because the model with the lowest HQIC value shows a better fit to the data and lower complexity. And finally the SBIC is -29.5057 which means the largest value means looking for the model with the highest SBIC value, because the model with the largest SBIC value shows a better fit to the data and lower complexity.

## BAN

Lag-order selection criteria

Sample: 2018m5 thru 2022m12

Number of obs = 56

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	191.946				$1.4\text{e-}08$	-6.71237	-6.65628	-6.5677
1	588.036	792.18	16	0.000	$1.8\text{e-}14$	-20.287	-20.0066	-19.5637
2	646.402	116.73*	16	0.000	$4.0\text{e-}15^*$	-21.8001*	-21.2953*	-20.4981*
3	653.617	14.431	16	0.567	$5.7\text{e-}15$	-21.4863	-20.7572	-19.6057
4	661.662	16.089	16	0.447	$7.9\text{e-}15$	-21.2022	-20.2487	-18.7429

\* optimal lag

Based on the results of the Optimum Lag test in the table above for Bangladesh data for 2018-2022. Where there is the largest Optimal Lag value in LR, namely 116.73, which means the largest likelihood ratio (LR) value indicates that the model with a higher number of lags (complex model) provides a significant increase in the probability of the observed data. compared to a model with a lower number of lags (simple model). Furthermore, the FPE is  $4.0\text{e-}15$ , which means that the largest optimal lag value in the FPE is the number of lags that produces the lowest FPE value, where the number of lags that gives the lowest FPE value is the optimal lag or the largest optimal lag value in the FPE. Then the AIC is -21.8001, which means the largest value does not refer to the highest AIC value, but rather refers to the lowest AIC value, the model with the lowest AIC value (smallest value) is considered the best or optimal model. For HQIC it is -21.7572, meaning that looking for the largest value means looking for the model with the lowest HQIC value, because the model with the lowest HQIC value shows a better fit to the data and lower complexity. And finally the SBIC is -20.4981 which means the largest value means looking for the model with the highest SBIC value, because the model with the largest SBIC value shows a better fit to the data and lower complexity.

## IN

Lag-order selection criteria

Sample: 2018m5 thru 2022m12

Number of obs = 56

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	116.422				$2.1\text{e-}07$	-4.01506	-3.95897	-3.87039
1	653.886	1074.9	16	0.000	$1.7\text{e-}15$	-22.6388	-22.3583	-21.9154
2	697.626	87.481	16	0.000	$6.5\text{e-}16$	-23.6295	-23.1247	-22.3275*
3	725.232	55.211	16	0.000	$4.4\text{e-}16$	-24.044	-23.3148	-22.1633
4	752.52	54.578*	16	0.000	$3.1\text{e-}16^*$	-24.4472*	-23.4937*	-21.9878

\* optimal lag

Based on the results of the Optimum Lag test in the table above for India data for 2018-2022. Where there is the largest Optimal Lag value in LR, namely 54.578, which means the largest likelihood ratio (LR) value indicates that the model with a higher number of lags (complex model) provides a significant increase in the probability of the observed data. compared to a model with a lower number of lags (simple model). Furthermore, the FPE is  $3.1\text{e-}16$ , which means that the largest optimal lag value in the FPE is the number of lags that produces the lowest FPE value, where the number of lags that gives the lowest FPE value is the optimal lag or the largest optimal lag value in the FPE. Then the AIC is -24.4472, which means the largest value does not refer to the highest AIC value, but refers to the lowest AIC value, the model with the lowest AIC value (smallest value) is considered the best or optimal model. For HQIC it is -23.4937, meaning that looking for the largest value means looking for the model with the lowest HQIC value, because the model with the lowest HQIC value shows a better fit to the data and lower complexity. And finally the SBIC is -21.9878 which means the largest value means looking for the model with the highest SBIC value, because the model with the largest SBIC value shows a better fit to the data and lower complexity.

### THEN

Lag-order selection criteria

Sample: 2018m5 thru 2022m12

Number of obs = 56

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	202.921				9.7e-09	-7.10431	-7.04822	-6.95964
1	809.261	1212.7	16	0.000	6.7e-18	-28.1879	-27.9075	-27.4646
2	919.159	219.8	16	0.000	2.4e-19	-31.5414	-31.0366	-30.2394*
3	941.459	44.601*	16	0.000	1.9e-19*	-31.7664*	-31.0373*	-29.8857
4	952.796	22.673	16	0.123	2.4e-19	-31.5999	-30.6464	-29.1405

\* optimal lag

Based on the results of the Optimum Lag test in the table above for Pakistan data for 2018-2022. Where there is the largest Optimal Lag value in LR, namely 44.601, which means the largest likelihood ratio (LR) value indicates that the model with a higher number of lags (complex model) provides a significant increase in the probability of the observed data. compared to a model with a lower number of lags (simple model). Furthermore, the FPE is  $1.9\text{e-}19$ , which means the largest optimal lag value in the FPE is the number of lags that produces the lowest FPE value, where the number of lags that gives the lowest FPE value is the optimal lag or the largest optimal lag value in the FPE. Then the AIC is -31.7664, which means the largest value does not refer to the highest AIC value, but refers to the lowest AIC value, the model with the lowest AIC value (smallest value) is considered the best or optimal model. For HQIC it is -31.0373, meaning that looking for the largest value means looking for the model with the lowest HQIC value, because the model with the lowest HQIC value shows a better fit to the data and lower complexity. And finally the SBIC is -29.8857 which means the largest value means looking for the model with the highest SBIC value, because the model with the largest SBIC value shows a better fit to the data and lower complexity.

### ARDL Estimation Results

In the Autoregressive Distributed Lag (ARDL) test, lag is used in the test. This test uses the Stata software application when analyzing and testing with the Akaike Information Criterion (AIC). The following table presents test results for 4 countries

ARDL Estimation Results Table

Country	lnbop	lnvol	Nihk	LNFDI	R-sq value
IN A					
(3,1,3,3)	-0,262*	-0,281*	0,279	0,051	0,99
FORBID	0,836 ***	-16.671***	2.105	-0,188	

(1,0,0,0)					0,92
IN					
(2,4,1,3)	0,092	-0,042*	-0,029	-0,0006	0,99
THEN					
(3,2,2,3)	-0,045	-1.417***	-2.023*	-0,295	0,99

\*\*\*significant at 1%

\*significant at 10%

Referring to the table above, it can be seen that there are differences in the results of selecting the ARDL model for each country. The country of Indonesia (INA) is (3,1,3,3). This means that the balance of payments, CPI and FDI variables are at lag 3 and exchange rate volatility is at lag 1. Bangladesh (BAN), namely (1,0,0,0) means that the balance of payments variable is at lag 1 and the exchange rate volatility variable, fdi and CPI at lag 0. India (IND) namely (2,4,1,3) meaning balance of payments variables at lag 2, exchange rate volatility at lag 4, CPI at lag 1 and fdi at lag 3. Pakistan (PAK) namely (3,2,2,3), namely the balance of payments and FDI variables at lag 3, exchange rate variables and CPI at lag 2. The R-squared in this test results in a result of 0.99 for all countries or can be translated as 99. 75% of balance of payments variables in India, Bangladesh, India, Pakistan are influenced by independent variables, namely exchange rate volatility, consumer price index and direct investment. Meanwhile, 1.24% is influenced by other variables outside the model.

## Results

The results of the analysis of the table above are

1. In Indonesia, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period. If BOPT-1 rises 1%, then this year's BOP will fall 0.26%. The exchange rate volatility variable has a negative and significant effect, if exchange rate volatility increases by 1% then the balance of payments decreases by 0.28%. The CPI variable has a positive and insignificant effect, meaning that if the consumer price index increases by 1%, the balance of payments increases by 0.27%. The FDI variable has a positive and insignificant effect, when direct investment increases by 1%, the balance of payments increases by 0.05%.
2. Bangladesh, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period. If BOPT-1 rises 1%, then this year's BOP will rise 0.83 percent. The exchange rate volatility variable has a negative and significant effect, if exchange rate volatility increases by 1% then the balance of payments decreases by 16.67%. The CPI variable has a positive and insignificant effect, meaning that if the consumer price index increases by 1%, the balance of payments increases by 2.10%. The FDI variable has a negative and insignificant effect, when direct investment increases by 1%, the balance of payments decreases by 0.18%.
3. India, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period. If BOPT-1 increases by 1%, then this year's BOP will increase by 0.092 percent. The exchange rate volatility variable has a negative and significant effect, if exchange rate volatility increases by 1% then the balance of payments decreases by 0.042%. The CPI variable has a negative and insignificant effect, meaning that if the consumer price index rises by 1%, the balance of payments falls by 0.029%. The direct investment variable has a negative and insignificant effect, when direct investment increases by 1%, the balance of payments increases by 0.0006%.
4. In the country of Pakistan, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period. If BOPT-1 rises by 1%, then this year's BOP will fall by 0.045 percent. The exchange rate volatility variable has a negative and significant effect, if exchange rate volatility increases by 1% then the balance of payments decreases by 1.417%. The CPI variable has a negative and significant effect, meaning that if the consumer price index rises by 1%, the balance of payments falls by 2.023%. The direct investment variable has a negative and insignificant effect, when direct investment increases by 1%, the balance of payments decreases by 0.0295%.



5. From these four countries, it can be proven consistently (robustly) that exchange rate volatility has a significant effect on the balance of payments. The country most affected by exchange rate volatility is Bangladesh and the country least affected by exchange rate volatility is India.

6. The balance of payments of these four countries is not affected by direct investment. This can happen because in the long term direct investment does not affect the movement of the balance of payments. Investments made in a country are influenced by many factors such as political factors, returns and many things.

### Conclusion

From the results of the research discussion above, it can be concluded that the four countries we tested are the balance of payments of the four countries which are not affected by direct investment and these four countries can consistently prove that exchange rate volatility significantly influences the balance of payments, and for each country. In international trade, stable exchange rates are highly desirable for traders. The tendency for changes in exchange rates (volatility) will affect the performance of international trade. This level of volatility is closely related to international trade because the value of an export commodity is assessed in foreign currency units, which in this case will create uncertainty in exchange rates in the future.

Indonesia is an Inbop variable, meaning that this year's NPI value is influenced by the previous period's NPI. For Bangladesh, the Inbop variable means that the balance of payments value this year is influenced by the balance of payments of the previous period. For India, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period. And next, Pakistan, the Inbop variable means that the value of the balance of payments this year is influenced by the balance of payments of the previous period.

After conducting research, the author advises researchers who are interested in studying International Trade and Exchange Rate Volatility in Muslim-Majority Countries in Asia to look for accurate and more diverse data regarding the writing process. The author also suggests that future researchers can delve more deeply into the process of writing about international trade and exchange rate volatility. So that the data obtained is of higher quality.

### REFERENCES

- [1] Arize, A. C., Osang, T., & Slottje, D. J. (2000). Exchange-rate volatility and foreign trade: Evidence from thirteen LDC's . *Journal of Business and Economic Finance* 17, 33-44.
- [2] Asteriou, D., Masatci, K., & Pilbeam, K. (2016). Exchange rate volatility and international trade: International evidence from the MINT countries. *Economic Modelling* Vol. 58, 133-140.
- [3] Bahmani-Oskooee, M., & Xi Dan. (2012). Exchange rate volatility and domestic consumption: A multi-country analysis. *Journal of Post Keynes Economies* 34 (2) 319-330.
- [4] Bahmani-Oskooee, Harvey, H., & Hegerty, S. W. (2015). Exchange rate volatility and commodity trade between the USA and Indonesia. *New Zealand Economic Papers* 49 (1), 78-102.
- [5] Chapra, M. U. (2007). *The Islamic vision of development in the light of maqasid al-shariah*. Jeddah: Islamic Research and Training Institute.
- [6] Gala, P. (2008). Real exchange rate levels and economic development: Theoretical analysis and econometric evidence. *Cambridge Journal of Economics* 32, 273-288.
- [7] Gandhi, D. V. (2006). Management of foreign exchange reserves at Bank Indonesia. *Central Bank Series No. 17*.
- [8] Ganguly, S., & Breuer, J. B. (2010). Nominal exchange rate volatility, relative price volatility, and the real exchange rate . *Journal of International Money and Finance* Vol. 29, 840-856.
- [9] Giannellis, N., & Papadopoulos, A. P. (2011). What causes exchange rate volatility? Evidence from selected EMU members and candidates for EMU membership countries. *Journal of International Money and Finance* Vol. 30, 39-61.
- [10] Hausmann, R., Panizza, U., & Rigobon, R. (2006). The Long-run volatility puzzle of the real exchange rate . *Journal of International Money and Finance* Vol. 23, 93-124.



- [11] Hossain, A. A. (2016). Inflationary shocks and real output growth in nine muslim-majority countries: Implications for Islamic banking and finance. *Journal of Asian Economics*, Vol. 45, 56-73.
- [12] Jun, W., Yingli, P., & Qi, Z. (2014). The conditions and potential of RMB as an international reserve currency: The empirical evidences from the history of eight major international reserve currency. *China Finance Review*
- [13] Kamola, B., Adam, A., & Ahamed Kameel Meera. (2018). Identifying the optimal level of gold as a reserve asset using Black-Litterman model: The case of Malaysia, Turkey, KSA, and Pakistan. *International Journal of Islamic and Middle Eastern Finance and Management* 11 (3), 334-356.
- [14] Khosa, J., Botha, I., & Pretorius, M. (2015). The impact of exchange rate volatility on emerging market exports. *Commercil Act Vol. 15 No. 1*, Art #257, 1-11.
- [15] Laevan, L., & Valencia, F. (2010). Resolution of banking crises: The good, the bad, and the ugly. *IMF Working Paper No.10/146*, Washington: International Monetary Fund.
- [16] Naeem, A. R., & Naz, R. (2005). Economic Integration: Hidden bounty for the Muslim world. *Pakistan Economic and Social Review* 43 (2), 227-248.
- [17] Nazlioglu, S. (2013). Exchange rate volatility and Turkish industry-level export: Panel cointegration analysis. *The Journal of International Trade & Economics Development* 22 (7), 1088-1107.
- [18] Ozkan, L., & Erden, L. (2015). Time varying nature and macroeconomic determinants of exchange rate pass-through. *Journal of International Review Economic and Finance*.
- [19] Rajan, R. G., & A., S. (2011). Aid, duch disease, and manufacturing growth. *Journal of Development Economics* 94 (1), 106-118.
- [20] Reinhart, C. M., & Smith, T. R. (2002). Temporary controls on capital inflows. *Journal of International Economics* 57 (2), 327-351.