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INDONESIA–MALAYSIA TRADE UNDER GLOBAL UNCERTAINTY AND EXCHANGE RATE VOLATILITY

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ABSTRACT

Exchange rate uncertainty and global economic disruptions are widely recognized as key determinants of international trade flows, yet their sectoral and asymmetric dimensions remain underexplored, particularly for emerging-market bilateral trade relationships. This study examines the effects of exchange rate volatility and global crises on Indonesia–Malaysia bilateral trade at the sectoral level. Using monthly time-series data spanning January 2006 to May 2023, we employ Autoregressive Distributed Lag (ARDL) and Nonlinear ARDL (NARDL) frameworks to capture both short-run and long-run trade dynamics, as well as sector-specific asymmetric effects. Exchange rate volatility is estimated via a GARCH framework. The Global Financial Crisis (2008) and the Covid-19 pandemic (2020) are structurally identified as exogenous crisis episodes. Exchange rate volatility exerts a meaningful and persistent long-run effect on bilateral trade, confirming that price-based uncertainty is a significant driver of trade patterns. Global crises, by contrast, produce effects that are narrow, transitory, and heterogeneous across sectors. Evidence of asymmetric exchange rate effects is detected, though these effects are marginal and lack systematic consistency across sectors. Collectively, the findings suggest that bilateral trade responds more strongly to persistent exchange rate dynamics than to discrete global shocks. This study contributes to the literature by integrating sectoral disaggregation, nonlinear modeling, and structurally identified crisis periods, offering a more nuanced understanding of trade behavior under uncertainty in the context of an important South-South trading relationship.

1. INTRODUCTION

Geographical proximity plays a significant role in determining the bilateral trade dynamics. More specifically, such proximity is a major determinant of trade intensity in the gravity model (Banik & Roy, 2021; Batra, 2006; Mishra & Jena, 2019), where transport and transaction costs are lowered, logistics improved, and market access improved. Apart from geographical elements, the bilateral ties are strengthened by socio demographic parallels between two countries, which comprise language religious and consumption patterns. Such “soft” factors decrease informational barriers, reinforce confidence on part of economic agents, and makes trade transactions more seamless, which is essential for maintaining the flow of bilateral economic exchanges (Narayan & Nguyen, 2016; Rahman et al., 2019). In combination, these structural and socio-cultural attributes indicate a relatively integrated, potentially resilient Indonesia–Malaysia trade relationship.

Yet while structural proximity guarantees nothing about stable trade performance during global uncertainty. We cannot ignore external shocks like volatility of exchange rate and global crises which contribute beyond nature. Theoretically, exchange rate fluctuations can influence trade through its effect on expectation of return and perception of risk. In line with Clark (1973), greater uncertainty caused by increased volatility, may reduce trade. Exchange rate changes, meanwhile, represent relative prices and can therefore directly influence export competitiveness and cost structures (Chit et al., 2010; Chowdhury, 1993). At the same time, global crises add more uncertainty by slowing demand and disrupting supply chains leading to knock-on effects that threaten the stability of international trade ties.

The world economy has witnessed two major crises over the last 20 years—the Global Financial Crisis (2008) and the Covid-19 pandemic (2019)—both of which have caused significant distortions to global international trade patterns. As illustrated by Indonesia-Malaysia bilateral trade data, this distortion is visible across industry groups. In the high-tech sector, trade balance values remained relatively suppressed and volatile throughout the observation period, before registering a sharp upward movement in the most recent years. The low-tech sector, by contrast, exhibited a comparatively narrower range of fluctuation with more persistent moderate levels, though similarly affected during crisis windows. In terms of absolute trade values, both sectors recorded notable dips coinciding with the 2008 Global Financial Crisis and the 2019 Covid-19 pandemic periods, with high-tech trade showing greater amplitude of recovery post-crisis compared to low-tech trade based on author's calculation.

Trade is impacted via various channels – demand shocks, supply chain disruptions and greater uncertainty. Moreover, exchange rate fluctuations are an especially important driver of producers' behaviour when uncertainty is present (see also the third factor). On the theoretical front, since volatility leads to uncertainty in expected returns; investors respond differently. Producers with low risk tolerance will decrease their participation in international markets whilst those of high risk tolerance can take advantage of changes in exchange rate to increase profit margins (Asteriou et al., 2016; Chowdhury, 1993; Clark, 1973). Thus, the total effects of exchange rate volatility on trade are theoretically unclear and empirically inconclusive.

But the impact of global crises on international trade varies by context. While crises by their nature are associated with a general decrease in trade flows, the magnitude and duration of these effects differ considerably across countries and sectors suggesting that the transmission of global shocks is conditional rather than universal (Ando & Hayakawa, 2022). This heterogeneity underscores the need for attention to structural characteristics—like sectoral composition and level of economic integration—in understanding trade responses in the face of uncertainty. Empirical literature on the relationship between exchange rate volatility and trade is large, but still some crucial gaps exist. Existing analyses predominantly use aggregate trade data, likely hiding sector-specific nuances and resulting in insufficient conclusions. Furthermore, although nonlinear methods like NARDL have been applied to capture asymmetries effects, little has they combined with specific identification of crisis periods which are necessary for a proper joint evaluation of the role of both exchange rate uncertainty and global shocks on economies. This study fills these voids by analyzing Indonesia–Malaysia trade using a structural ARDL and NARDL approach across several sectoral levels covering the two sides over identified crisis periods. We present an analysis that relies on industry-level data, classified according to the technological intensity Lall (2000) in order to capture heterogeneous trade responses, investigate both short- and long-run dynamics, and learn about asymmetric adjustment within a unified framework. We are able to do this because studying these three dimensions together helps us understand how trade adjusts when there is uncertainty in more than one aspect of the bilateral trade system. Joint consideration of sectoral heterogeneity, nonlinear adjustment, and crisis-specific dynamics extends the trade literature.

2. RESEARCH METHODS

Emirical Framework in this study are based on Chit et al. (2010) and initiates a sectoral time-series approach on monthly Indonesia–Malaysia trade data ranging from 2006m1 to 2023m5, which is then summarised into high-, medium- and low-tech (Lall, 2000). Table 1 presents the product classification scheme adopted in this study, grouping commodities from primary products through to high-technology manufacturing based on Lall (2000).

Table 1. Product Clasification

Clasification	Commodity Group	Commodity Description
Primary Products	Agriculture and Plantation	Live Animals, Meat, Fish, Shells, Live Plants, Roots, Fruits, Coffee, Tea, Rubber, Leather
Natural Resources Manufacturing	Agro-Based Manufacturing	Flour, Processed Rubber, Oil, Processed Meat, Sugar, Processed Chocolate, Processed Flour, Processed Vegetables and Fruits, Fruit Essence, Processed Beverages, Cigarettes, Sawn Timber, Wood Pulp, Paper, Cotton
	Mineral-Based Manufacturing	Cement, Mineral Fuels, Inorganic Chemicals, Gelatin, Stone Industry, Glass, Processed Precious Metals
Low Technology Manufacturing	Textiles	Leather, Fur, Plant-Based Textiles, Hand-Made Textiles, Fiber Textiles, Carpets, Woven Fabrics, Laminated Fabrics, Knitted Fabrics, Clothing, Shoes, Head Accessories, Other Accessories
	Non-Textiles	Plastics, Processed Steel, Processed Brass, Processed Aluminum, Iron-Based Equipment, Furniture, Toys
Medium Technology Manufacturing	Automotive	Passenger Vehicles, Commercial Vehicles, Ships, Motorcycles, Spare Parts
	Processing	Chemical Industry, Pharmaceuticals, Fertilizers, Tanning Industry, Perfume, Cosmetics, Soap, Explosives, Photography
	Machinery	Vehicle Engines, Pumps, Vehicle Transmissions
High Technology Manufacturing		Telecommunications, Televisions, Transistors, Turbines, Computers, Aircraft, Optics

We implement a baseline model using an Autoregressive Distributed Lag (ARDL) specification, as it is useful for capturing the short-run and long-run dynamics with mixed integration orders. This study explores the dynamic relationship between exchange rate, global shocks and bilateral trade using ARDL framework that estimates short-run adjustments and long-run equilibrium relationships altogether. In terms of conceptual underpinnings, this specification follows the trade elasticity literature in that it captures both short- and long-run response to changes in fundamentals—i.e. adjustment frictions in international trade.

Furthermore, the baseline estimation model used in this study can be seen as follows:

$$\Delta lnTB_{it} = \beta_0 + \sum_{j=1}^{n1} \beta_1 \Delta lnTB_{t-j} + \sum_{j=0}^{n2} \beta_2 \Delta lnRER_{t-j} + \sum_{j=0}^{n3} \beta_3 \Delta lnVOL_{t-j} + \sum_{j=0}^{n4} \beta_3 \Delta lnCOVID_{t-j} + \sum_{j=0}^{n3} \beta_3 \Delta lnGFC_{t-j} + \delta_1 lnTB_{t-1} + \delta_2 lnRER_{t-1} + \delta_3 lnVOL_{t-1} + \delta_4 lnCOVID_{t-1} + \delta_3 lnGFC_{t-1} + \varepsilon_t \quad (1)$$

Where TB is the trade balance given by the ratio of imports and exports for industry TB= (Imports, Exports), RER is the real exchange rate, VOL is the exchange rate volatility, while GFC and COVID are dummy variables that stand for global crisis periods. Given this possibility of nonlinear effects, exchange rate volatility can be decomposed into positive and negative partial sums under Nonlinear ARDL (NARDL) framework which is used to extend the model as follows:

$$\text{VOL}pos: \sum_{j=1}^{t} \Delta lnVOLp_j^{POS} = \sum_{j=1}^{t} \max(\Delta lnVOL_j, 0) \quad (2)$$

$$\text{VOL}neg: \sum_{j=1}^{t} \Delta lnVOLp_j^{NEG} = \sum_{j=1}^{t} \min(\Delta lnVOL_j, 0) \quad (3)$$

For the Structure, TB trade balance (calculated as imports divided by exports per industry). Thus, this ratio specification presents the trade position between Indonesia and Malaysia in which higher values of this ratio contain more reliance on imports than grievance exports. The measure used in the analysis, which is based on ratios, enables us to capture not only trade volume differences but also shifts in competitiveness by sector. To account for the possible nonlinear responses, exchange rate volatility is decomposed into positive and negative changes. Such decomposition enables the model to identify times where uncertainty is increasing as opposed to decreasing, reflecting that the response of economic agents can be different for increasing volatility versus decreasing volatility.

These decomposed variables are fed into the ARDL specification to estimate asymmetric effects loading on exchange rate shocks. The decomposed variables are then included in the ARDL specification, replacing the volatility variable with which we can estimate effects of exchange rate fluctuations asymmetrically as follows:

$$\Delta lnTB_{it} = \beta_0 + \sum_{j=1}^{n1} \beta_1 \Delta lnTB_{t-j} + \sum_{j=0}^{n3} \beta_3 \Delta lnRER_{t-j} + \sum_{j=0}^{n4} \beta_4 \Delta lnVOLp_{t-j} + \sum_{j=0}^{n5} \beta_5 \Delta lnVOLn_{t-j} + \sum_{j=0}^{n5} \beta_6 \Delta GFC_{t-j} + \sum_{j=0}^{n5} \beta_7 \Delta Covid19_{t-j} + \delta_1 lnTB_{t-1} + \delta_3 lnRER_{t-1} + \delta_4 lnVOLp_{t-1} + \delta_5 lnVOLn_{t-1} + \delta_5 GFC_{t-1} + \delta_5 Covid19_{t-1} + \varepsilon_t \quad (4)$$

We use a GARCH framework to model exchange rate volatility in order to capture time-varying uncertainty in exchange rate movements. By definition, volatility is the measure of uncertainty in relative prices, which are at the core of firms' expectations and risk assessments when making international trade decisions (Nadal et al. Exchange rate factor has volatility clustering and persistence characteristics, which is suitable for modeling with GARCH approach. The ARDL and NARDL models are then based on the predicted volatility series to analyze its effect on bilateral trade dynamics.

$$REER_t = \beta_0 + REER_{t-1} + u_t \quad (5)$$

$$h_t^2 = \beta_0 + \beta_1 u_{t-1}^2 + .. + \beta_q u_{t-n}^2 + \theta_1 h_{t-1}^2 + .. + \theta_q h_{t-n}^2 + \mu_t \quad (6)$$

As was noted by Ditzen et al. (2025), the timing and duration of global shocks may have different effects, across cases, meaning that the effectiveness by which global shocks propagate changes from case to case. In this regard, this study uses a structural break test following Dietzen measure to determine the specific periods in which global crises affect on Indonesia-Malaysia trade balance. It gives a more precise definition of crisis windows, making it impossible to define them arbitrarily in terms of periodization and guarantees that the following estimation of the model captures properly the real dynamics of shock propagation.

The baseline model is estimated using the Autoregressive Distributed Lag (ARDL) approach after the relevant crisis periods are defined. Bound Test that consists of the F-statistics criterion (Pesaran, 2015) and significance of the lagged Error Correction Term (ECT) to test for Cointegration. The F-statistic that surpasses the upper bound and ECT is negative with ($p < 0.05$), confirming a valid long-run relationship at levels and convergence towards equilibrium A series of diagnostic tests are employed to confirm the robustness of the results, i.e., Kolmogorov test for normality; Lagrange Multiplier (LM) test for autocorrelation; and Ramsey's RESET test for misspecification. It also tests parameter stability using CUSUM and CUSUMQ tests; the former falls under "S" for stable or "U" for unstable indicating that estimated measures are robust in time.

3. RESULTS AND DISCUSSION

3.1. RESULTS

At the beginning of the research findings section, several tests will be presented to fulfill the data requirements used for estimating the baseline model in Eq. 1. The initial step in the estimation stage is determining the best volatility model to explain the prediction of the Rupiah to Ringgit exchange rate volatility. There are several steps in determining the best model, namely 1) stationarity testing, 2) determination of the Ordo moving average (MA) and autoregressive (AR), 3) ARIMA model testing, and 4) heteroscedasticity testing. The results of the entire volatility modeling process can be seen in Table 2.

Table 2. Volatilation Estimated Model for Rupiah-Ringgit

Component	Parameter	Value	t-stat	Sig.
Unit Root (I(0))	Level	0.259	-	No Stationer
	First Difference	0.000	-	Stationer
Model Order	AR	2	-	-
	MA	1	-	-
Mean Equation	AR	0.222	2.334	***
	MA	0.315	2.329	***
	ARIMA (const)	0.224	-	-
	ARIMA	0.510	2.328	***
Heteroskedasticity Test	ARCH-LM	0.0015	-	Significant
Variance Equation	ARCH	0.880	2.297	***
	GARCH	0.363	2.288	***

Source: Processed data (2026)

The results of the volatility estimation indicate that the most appropriate model to capture the dynamics of the Rupiah-Ringgit exchange rate is the GARCH specification. This conclusion is supported by the heteroskedasticity test (ARCH-LM), which yields a probability value of 0.0015, well below the 5% significance level, confirming the presence of ARCH effects. Furthermore, the estimated coefficients in the variance equation show that both ARCH (0.880) and GARCH (0.363) terms are positive and statistically significant, implying strong volatility persistence and clustering behavior. Prior to this, the unit root test reveals that the series is non-stationary at level (0.259) but becomes stationary after first differencing (0.000), justifying the use of ARIMA-based modeling. The selected ARIMA (2,1,1) structure, with significant AR and MA components, adequately captures the mean equation before incorporating volatility dynamics.

The next step is to determine the effective period of global crisis impacts in the Indonesia-Malaysia trade context. Using a structural break test following Dietzen's approach, the results reveal that the duration and timing of crisis effects vary substantially across sectors and types of global shocks. This heterogeneity suggests that a uniform crisis window would be inappropriate and potentially bias the estimation. Therefore, the identified break periods are used to construct crisis dummy variables, where a value of 1 is assigned during the effective impact period and 0 otherwise. For instance, the Global Financial Crisis (GFC) dummy for the primary sector takes the value of 1 from 2008m8 to 2008m12. This approach ensures that the crisis variable more accurately reflects the actual transmission of external shocks into the Indonesia-Malaysia trade balance dynamics. The full structural break results across all sectors are summarised in Table 3.

Table 3. Structural Break Result

Sector	Period	Start	Finish	Total Period
Primary	GFC	2008m8	2008m12	4
	Covid-19	2020m6	2020m11	5
Agriculture	GFC	2008m8	2008m10	2
	Covid-19	2020m6	2020m11	5
Mineral	GFC	2008m8	2008m11	3
	Covid-19	2020m9	2020m12	3
Textile	GFC	2008m8	2008m12	4
	Covid-19	2020m4	2021m4	12
Non-Textile	GFC	2008m8	2008m12	4
	Covid-19	2020m6	2020m12	6
Process	GFC	2008m8	2008m11	3
	Covid-19	2020m9	2020m12	4
Automotive	GFC	2008m6	2008m12	6
	Covid-19	2020m6	2020m12	6
Engineering	GFC	2008m7	2008m11	5
	Covid-19	2020m4	2022m4	24
High-Tech	GFC	2008m8	2008m12	4
	Covid-19	2019m11	2021m9	22

Source: Processed data (2026)

Results of ARDL estimation are shown in the Table 4, where both long-run–short run relations on trade behavior as Indonesia–Malaysia observed can be seen that the long run relationships is more applicable than short-run dynamics. Although exchange rate (REER) and volatility (VOL) variables as short-run coefficients do not look very stable in all specifications, they are much more robust in terms of long run coeffcents and most of the time being statistically significant. This response pattern implies slow adjustment by traders to exchange rate movements and points at the presence of rigidities related with contractual arrangements, production planning, and adaptation on markets.

The positive long-run effects of exchange rate volatility, in particular, son research show that uncertainty in relative prices influences trade decision over time and not immediately. This lack of short-run significance stems from the fact that firms will not change their exposure until they have noticed a fundamental shift in exchange rate conditions. Likewise, the long-run effects for Industrial Production Index (IIP) also appear to be considerably stronger and less time-variant which could possibly suggest that real sector fundamentals play a significant role in defining actual trade potential and capabilities as well as competitiveness. These results support the notion that bilateral trade dynamics are determined more by persistent price mechanisms and long run economic fundamentals, rather than their short-term or transitory components.

Model Validity: The Bound Test result reported in model I, II and III all reveal the existence of cointegration supported by negative and statistically significant error correction term (ECT) across specifications indicating convergence toward long-run equilibrium.

The models are also found to be generally well-specified and stable based on a number of diagnostic tests. The relatively high R² value observed in one specification might reflect overfitting or structural differences and should be interpreted accordingly.

Table 4. ARDL Estimation Result

Variable	Lag	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export	t-2	-0.161	-0.176	-0.338***	0.025	-0.166**	-0.258**	-0.176	-0.356**	-0.367**
	t-3	-0.090	-0.079	-0.053	0.019	-0.102	-0.122	0.016	-0.264*	-0.032
	t-4	-0.045	-0.110	0.001	0.009	0.037	0.050	0.006	-0.053	-0.012
REER	t	-0.073	-0.073	-0.239	-0.223	0.583	-1.414	0.673	1.891**	0.584
	t-2	-1.546	-1.546	-1.000	0.655	-0.080	-3.821	-2.718**	-1.367	-1.879**
	t-3	0.722	0.722	0.664	-0.715	0.932	-2.092	0.492	2.168**	0.404
	t-4	-0.646	-0.646	-1.869*	-1.071	0.159	4.111	0.204	1.883*	-0.320
VOL	t	-0.143	-0.151**	-0.046	-0.009	-0.178**	-0.269	-0.055	0.028	0.088
	t-2	-0.027	-0.090	-0.097	-0.048	-0.032	-0.181	-0.086	-0.056	-0.041
	t-3	0.014	-0.070	-0.072	0.150**	-0.035	0.594	-0.188**	-0.101	0.055
	t-4	-0.039	0.000	0.122	0.048	0.058	-0.434	0.032	-0.060	-0.020
IIP	t	-0.55	-0.22	0.373	-0.03	-0.21	0.16	0.081	-0.11	-1.59*
	t-2	0.56	-0.71	-0.20	0.669	-0.47	0.039	-1.82**	-0.10	-0.52
	t-3	-0.87	-0.88	-1.2**	0.512	-1.26**	-0.92*	-0.32	-0.99	-3.24**
	t-4	0.779	-0.76	0.124	0.291	0.008	-0.02	-0.68	-0.03	0.034
GFC	t	-0.031	-0.113	0.110	0.108	0.298	-0.409	0.170	0.007	0.094
	t-2	0.073	-0.165	0.263	-0.086	0.024	-1.018	-0.008	0.723***	0.153
	t-3	-0.149	0.105	0.221	0.109	0.170	-0.494	0.202	0.591***	0.140
	t-4	-0.270	-0.052	0.161	0.072	-0.265	0.205	0.329	0.166	-0.074
Covid-19	t	0.455**	-0.041	0.001	0.044	-0.017	-0.118	0.170	-0.441**	0.185
	t-2	-0.094	-0.095	-0.029	-0.122	-0.075	-0.045	-0.107	-0.374**	-0.010
	t-3	-0.270	-0.028	-0.132	0.111	-0.144	-0.225	-0.096	-0.137	0.055
	t-4	-0.096	-0.126	0.186	0.195	-0.174	-0.358	-0.246	-0.124	0.014
Long-run REER	–	0.386	1.170**	3.78***	0.844***	0.928**	2.84***	2.105***	-0.030	0.481
Long-run VOL	–	-0.409***	-0.592***	-0.82***	-0.07	-0.5***	-0.5***	-0.418***	-0.286***	-0.078
Long-run IIP	–	1.414**	2.008**	3.721**	0.344*	0.911***	0.176***	0.784**	0.936**	0.392
Long-run GFC	–	-0.388	0.310	-2.42	-0.34	-0.75	-6.760	-0.082	-0.919**	-0.432
Long-run Covid-19	–	0.604	1.822	0.496	0.046	0.803	-0.415	0.803	-0.015	-0.330**
Obs	–	209	209	209	209	209	209	209	209	209
R²	–	0.263	0.310	0.34	0.342	0.271	0.382	0.824	0.341	0.495
Bound Test	–	15.616***	14.863***	7.461***	29.89***	14.66***	15.61***	19.265***	35.95***	20.39***
ECT (t-1)	–	-0.383***	-0.343***	-0.2***	-0.61***	-0.37***	-0.37***	-0.454***	-0.7***	-0.471***
LM Test	–	4.314**	18.740	15.61**	0.019	12.65	25.15***	7.943**	6.183**	11.897**
JB Test	–	6.271**	21.040	25.32*	48.75**	12.06***	1.672	1.059	42.94***	7.862*
RESET	–	0.560	2.300*	11.77*	1.02	0.31	10.44***	8.28***	0.74	11.93**
CUSUM	–	1.134 S	1.205 S	1.822 S	0.748 S	0.830 S	0.967 S	0.617 S	0.604 S	1.135 S

Table 5. NARDL Estimation Result

Variable	Lag	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Export	t-2	-0.189**	-0.428***	-0.377***	0.018	-0.301**	-0.514***	-0.344***	-0.387***	-0.283**
	t-3	-0.035	-0.192**	-0.228**	0.055	-0.096	-0.216**	-0.202**	-0.229**	-0.072
	t-4	-0.019	-0.052	-0.043	-0.021	-0.019	-0.088	0.031	-0.039	0.012
REER (+)	t	-1.202	-1.233	-0.418	-2.080*	0.191	-0.219	1.624	0.723	-1.013
	t-2	-0.614	-2.493	-0.868	-0.333	-0.222	-2.695**	-2.812**	-3.505**	-2.663*
	t-3	-2.101	1.176	0.364	-2.090*	-1.392	0.821	-0.633	1.098	-1.448
	t-4	0.193	0.012	-1.482	-1.620	1.083	-1.254	-2.851**	-0.326	-0.258
REER (-)	t	0.500	-0.317	-0.305	-0.258	0.855	-1.783	0.525	1.733*	0.751
	t-2	0.980	-1.515	-0.740	0.558	-0.133	-4.441	-2.446**	-1.273	-2.016**
	t-3	-0.955	0.500	1.218	-0.719	1.009	-5.675	0.469	2.126**	0.409
	t-4	0.245	-0.770	-1.797*	-0.976	0.215	1.795	0.338	1.855*	-0.332
VOL (+)	t	-0.164	-0.021	-0.066	0.005	-0.243**	-0.730	-0.083	0.068	-0.011
	t-2	0.093	-0.111	-0.189	-0.016	0.062	-0.213	-0.208	-0.156	0.046
	t-3	0.048	0.069	-0.231*	0.121	-0.108	0.724	-0.197	-0.113	0.044
	t-4	-0.069	-0.079	0.043	0.005	-0.039	0.119	0.062	0.007	-0.002
VOL (-)	t	-0.169	0.002	-0.068	0.008	-0.234**	-0.782	-0.088	0.075	-0.031
	t-2	0.090	-0.126	-0.172	-0.003	0.057	-0.424	-0.200	-0.156	0.055
	t-3	0.054	0.077	-0.236*	0.130	-0.108	0.537	-0.194	-0.117	0.051
	t-4	-0.062	-0.080	0.021	0.006	-0.033	0.041	0.071	0.018	0.005
IIP	t	-0.57	-0.02	0.563	0.433	-0.43	0.807	0.152	0.278	-1.23**
	t-2	0.559	-0.33	0.032	0.893	-0.6	0.508	-1.66**	0.279	-0.76
	t-3	-0.78	-0.9	-0.740	0.607	-1.25*	-0.45	-0.49	-1.12	-2.82***
	t-4	0.724	-0.88	0.317	0.415	-0.06	0.247	-0.37	0.485	0.159
GFC	t	0.005	-0.187	0.176	0.125	0.331*	-0.541	0.161	0.005	0.147
	t-2	0.081	-0.092	0.181	-0.094	0.003	-1.972	0.003	0.699*	0.146
	t-3	-0.161	0.105	0.165	0.093	0.127	-1.276	0.204	0.579**	0.131
	t-4	-0.266	-0.093	0.146	0.078	-0.234	-0.273	0.336	0.216	-0.071
Covid-19	t	0.462**	-0.091	-0.070	0.037	0.008	-0.091	-0.070	-0.440**	0.194
	t-2	-0.108	-0.022	0.046	-0.135	-0.019	-0.022	-0.150	-0.348*	-0.011
	t-3	-0.283	-0.059	-0.110	0.117	-0.127	-0.059	-0.125	-0.109	0.058
	t-4	-0.087	-0.088	0.165	0.205	-0.182	-0.088	-0.233	-0.159	0.002
Long-run REER (+)	–	0.223	0.890	1.168*	0.88***	0.191	2.673**	2.173**	-0.236	0.428
Long-run REER (-)	–	-0.036	0.577	1.597	0.728***	0.157	4.973	1.987***	-0.486	0.663
Long-run VOL (+)	–	-0.413*	-0.924**	0.478	-0.05	-0.22	1.656	-0.298	0.080	0.079
Long-run VOL (-)	–	-0.355	-0.750*	0.171	-0.04	-0.25	1.976	-0.187	-0.169	0.039
Long-run IIP	–	1.385**	0.216**	0.213**	0.192	2.714**	4.011**	1.864**	2.211**	0.330
Long-run GFC	–	-0.404	0.172	-2.183	-0.33	-0.79	-2.856	-0.050	-0.948**	-0.41
Long-run Covid-19	–	0.571	1.758*	-0.053	-0.05	-0.77	-0.473	-0.918	-0.004	-0.314**
Obs	–	209	209	209	209	209	209	209	209	209
R^2	–	0.285	0.363	0.315	0.385	0.325	0.872	0.355	0.512	0.355

Source: Processed data (2026)

Estimation Results for both global crisis variables shows that the negative effect of either GFC or Covid-19 on trade between Indonesia and Malaysia, generally speaking is not significant and not persistent across models. Although short run effects are evident in a few instances, such significant effects are not achieved on average in the long run which indicates that global shocks appear to create temporary breaks rather than transformations in the bilateral trade relationship. One reason for this pattern can be found in the indirect nature of crisis transmission: demand contraction, supply-chain disruptions and policy responses. In contrast to exchange rate movements which are constant and permanent relative prices shocks, global crises are onetime shocks followed by a period of adjustment in addition to recovery. Consequently, they are normally lost over time as markets stabilize and trade flows revert to their natural trend. Furthermore, crisis variables might not be very meaningful in some other sectors due to measurement limitations; for instance, even the usage of dummy variables may fail to capture global shocks with heterogeneous intensity across segments.

This finding is in line with the NARDL estimation (Table 5) that shows asymmetric effects of exchange rate changes although limited. Estimates of differences between positive and negative realizations in the real exchange rate and its volatility are not uniformly significant, indicating that appreciation or depreciation do not consistently elicit substantially different trade responses. This result suggests that trade adjustments are approximately symmetric, which may stem from Indonesia–Malaysia having a relatively integrated bilateral trade relationship. Price transmission in this context is likely to be sectoral similar, lowering the likelihood of directional asymmetry. Lastly, contractual settlements, invoicing patterns and even hedging behavior may also reduce short term nonlinear reactions so that firms are more reactive to persistent trends rather than temporary shocks. While there is some evidence of sector-specific asymmetry, across models these effects are not generally strong, suggesting that nonlinear adjustment exists but on a conditional rather than structural basis. In summary, the results imply that bilateral trade dynamics are dominated by partial or episodic asymmetry rather than a strong and pervasive nonlinear structure.

3.2. DISCUSSION

The results show that currency level and volatility matter more for Indonesia–Malaysia bilateral trade, compared with global macroeconomic shocks. We analyze these dominances in terms of the underlying transmission mechanisms. This is because changes in the exchange rate directly impact on relative prices, export competitiveness and profit margins, makes trade decisions dependent on these variables in a more constant and systematic way. Similarly, global crises are exogenous and episodic shocks where the impact is transmitted through policy responses, market adjustments and existing trade linkages. As a result of this, even if crises are followed by short-run disruptions in exchange rate policy, the incentives and expectations aspect of exchange rate dynamics is more long-lasting.

The other end of the spectrum sees global crises like the Global Financial Crisis (GFC) and the Covid-19 pandemic implicated, but only for a limited time and largely non-persistent. Long run effects are not consistently observed (even if short-run effects are visible for some sectors), which could indicate that the shocks triggered by a crisis tend to be transitory. This is consistent with previous evidence that global shocks do induce temporary changes in trade patterns, rather than structural changes (Ando & Hayakawa, 2022; Bricongne et al., 2010).

This is likely the result of both firm behavior and policy adjustment, with production, sourcing, and trade financing responding relatively quickly to avoid lasting disruptions (Giotopoulos & Vettas, 2018). The trade patterns we observe are accordingly adjustment and recovery processes rather than structural changes that prove persistent.

Simultaneously, the limited impact of global crises can also be explained in structural and institutional proximity terms. The literature on the gravity model underscores that proximity, cultural and linguistic similarities and prior trade networks compounds such resilience in bilateral trade relationships (Anderson, 2004; Narayan & Nguyen, 2016). As for Indonesia and Malaysia, the regional proximity and socio-cultural connections lower transaction costs as well as facilitate quicker coordination between economic agents. These ‘soft border’ parameters facilitate faster adjustment and also provide a broad impetus for trade continuity in the times of uncertainty (Batra, 2006). This results in lower responsiveness of bilateral trade flows to external shocks, which underscores the importance of structural integration for dampening the effects of crises.

Results from the NARDL also confirm that asymmetric effects associated with changes in the exchange rate do exist but are not predominant. Although some sectors show different responses to an appreciation and a depreciation of the currency, these effects are not universally aggregated enough across models for asymmetry to be structural rather than conditional. This pattern could indicate that exchange rate changes—irrespective of their direction or sense—are absorbed in a similar way, and are reflected in what may be loosely interpreted as relatively symmetric price transmission across sectors. Third, firms can hedge, invoice in different currencies, and engage in contract arrangements that attenuate nonlinear responses and facilitate a more uniform adjustment over time. The reported findings align with prior evidence of asymmetric exchange rate effects that differ according to the sectoral composition and empirical specification (Bahmani-Oskooee & Aftab, 2017; Heriqbaldi et al., 2023). In addition, asymmetry may only appear in special settings and under exceptional conditions, like the high uncertainty or structural fragility rather than an inherent characteristic of trade survival dynamics (Bahmani-Oskooee et al., 2015).

Last but not least, the methodological framework and specifically the inclusion of structural break analysis and extensive diagnostic testing safeguard the robustness of results. Structural break methods enable endogenous identification of crisis occurrences, reflecting timing and duration of shocks between sectors and enhancing estimation (Altansukh & Osborn, 2022; Ditzen et al., 2025). This minimizes mis-specification risks linked to a randomized definition of crises and enhances the credibility of the empirical results (Clemente et al., 2017). The constant significance of the error correction term and the stability proved by diagnostic tests further indicate that estimated relations are not spurious. However, model specification differences show that sensitivity to model selection especially lag length and complexityremains a key issue for robust inference.

4. CONCLUSION

In this study, we investigate how exchange rate volatility and global crises affect Indonesia–Malaysia bilateral trade balance using the sectoral ARDL and NARDL method based on structurally identified crisis periods. The results point to three important takeaways. The first result is that, when it occurs, exchange rate volatility has always been a statistically significant and most important determinant of trade in the long run, suggesting that uncertainty in relative prices is a key element behind trade. Second, the impact of global crises—the Global Financial Crisis and Covid-19—

are roughly limited, short term and sectoral, indicating that bilateral trade structures are fairly insulated from episodic external shocks. Third, there exist nontrivial asymmetric effects of exchange rate movements at play, a signal that returns are conditionally rather than structurally nonlinear.

To our knowledge, this study is the first to simultaneously incorporate sectoral disaggregation of employment into a nonlinear model of endogenous crisis period identification within a single empirical framework. Using heterogeneity across sectors, as well as differentiating between continuous and episodic types of uncertainty, the analysis offers a more complete perspective of bilateral trade under a global shock. From the public policy viewpoint, the results indicate that more emphasis should be placed on reducing exchange rate volatility in order to boost trade performance. It could include larger interventions in the foreign exchange market, tighter microeconomic policy coordination and broader availability of hedging instruments for international-trade firms. Decreasing ongoing exchange rate uncertainty can provide more durable support to bilateral trade stability than reactive measures taken in times of crisis. In spite of these contributions, some limitations should be recognised. However, dummy variables does not fully reflect the transmission of global shocks and its intensity; other drives including political trade policy measures, supply chain disruptions and financial integration are not directly considered. These limitations open opportunities for future research to explore different uncertainty measures and the larger structural impacts on trade resilience.

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