Bulletin of Applied Economics, 2023, 10(2), 173-189
https://doi.org/10.47260/bae/10210

Asymmetric Effects of Exchange Rate Volatility on Taiwan-China Trade: A Non-Linear ARDL Analysis of 20 Industries

Ilia Tetin[1], Elizaveta Antonenko[2] and Guych Nuryyev[3]*

Abstract

This study investigates the long-run and short-run effects of exchange rate volatility on Taiwan's exports to and imports from China across 20 industries, employing a non-linear autoregressive distributed lag (NARDL) approach. The analysis covers the period from January 2004 to December 2022 and highlights industry-specific sensitivities and asymmetric impacts of exchange rate fluctuations. Our findings reveal the critical role of exchange rate volatility in shaping export and import performance across industries, with both positive and negative shocks exerting significant short-run and long-run effects. Asymmetric impacts of exchange rate fluctuations affect 87.96% of Taiwan's total exports to China in the long run and 72.11% in the short run. In contrast, the asymmetric impacts on imports influence 77.12% of Taiwan's total imports from China in the long run and 13.21% in the short run, demonstrating varying sensitivity across industries. These findings accentuate the necessity for industry-tailored trade policies and strategic considerations to better manage the risks and opportunities presented by exchange rate volatility in cross-strait trade.

JEL classification numbers: F14, F31, C22.
Keywords: Exchange rate volatility, Taiwan-China trade, Non-linear ARDL, Asymmetric effects.

[1] International College, I-Shou University, Kaohsiung, Taiwan.
[2] Independent researcher.
[3] International College, I-Shou University, Kaohsiung, Taiwan. *Corresponding author.

Article Info: Received: November 03, 2023. Revised: November 24, 2023. Published online: December 2, 2023.

1 Introduction

Exchange rate volatility is an essential factor in the realm of international trade, as it significantly influences the balance of payments between nations and presents considerable risks for businesses participating in foreign exchange transactions. In the aftermath of the Bretton Woods system's collapse in 1973, researchers have been keen to explore the implications of exchange rate volatility on trade flows, with notable contributions by Clark (1973), and Grauwe (1988).

The majority of early studies up conducted until the 2000s suffered from aggregation bias, leading to mixed or nonsignificant findings, as shown by McKenzie (1999). Initial efforts to overcome this aggregation bias, such as those by Klein (1990) and Stokman (1995), focused on analyzing one-digit SITC groups. However, the level of disaggregation generally remained low, causing individual industries to encompass a wide range of products. Péridy (2003) addressed both industry-specific and country-specific aggregation biases and demonstrated that the impact of exchange rate volatility varies across industries and destination markets. These findings highlight the potential for misleading conclusions when relying solely on aggregated data. Consequently, a substantial body of literature emerged, emphasizing the importance of considering disaggregated data on trade flows, as evidenced by Bahmani-Oskooee and Hegerty (2007).

The methodologies employed in studying exchange rate volatility have seen significant diversity. Polynomial Distributed Lags (PDL) models have been utilized by researchers such as Chen (2001), Cheung et al. (1997), Hsing and Savvides (1996), Moreno (1989), and Tang (2014). These models, while straightforward to implement and interpret, bear the limitation of their linear nature, and therefore, might fail to capture non-linear relationships accurately. On the other hand, Error Correction Models (ECM) have been put into practice by scholars such as Arize et al. (2000), Chen (2002), Fung (2008), and Fung and Liu (2009). While these models provide a window into short-run and long-run dynamics, they operate on the assumption of symmetric adjustment processes, which may oversimplify real-world phenomena. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, employed by Fang et al. (2009) and Wang and Barrett (2007) capture volatility clustering and time-varying volatility. However, they may be inadequate when it comes to analyzing asymmetric effects. Finally, the Autoregressive Distributed Lag (ARDL) models present a valuable and flexible framework for investigating both short-run and long-run dynamics in economic relationships (Bahmani-Oskooee et al. (2012), Chen (2008), Sun and Chiu (2010)). Their non-linear variant (NARDL) takes a step further by addressing asymmetric effects, see Bahmani-Oskooee et al. (2020), Baek and Nam (2021), Truong et al. (2022), and Chien et al. (2020).

Literature that has previously engaged with the disaggregation of trade data has largely concentrated on broader sectoral categorizations, which may still mask the heterogeneity inherent in trade responses within finer industry classifications. Moreover, the extant studies have primarily explored the trade effects of exchange rate volatility in the context of major economies or within global aggregates. There is a scarcity of research examining these dynamics within the frame of cross-strait relationships. Addressing this gap, our study formulates the following main research hypotheses to be empirically tested:

Hypothesis 1: *Exchange rate volatility between the TWD and CNY has a significant asymmetric impact on specific sectors of Taiwan's exports to China.*

Hypothesis 2*: Exchange rate volatility between the TWD and CNY asymmetrically affects specific sectors of Taiwan's imports from China.*

Building on these hypotheses, our study makes two pivotal contributions to the economic literature. Firstly, it deploys the Non-linear Autoregressive Distributed Lag (NARDL) model to dissect industry-specific trade data between Taiwan and China, refining the analysis to account for both non-linearities and asymmetries in exchange rate volatility impacts. This application is particularly pertinent, given the model's enhanced ability to delineate the differential effects of exchange rate movements on trade flows.

Secondly, the study progresses beyond the traditional aggregate-level examination by analyzing trade at a disaggregated industry level, spanning 20 distinct sectors. This methodological advancement addresses the aggregation bias prevalent in prior research, which often obscured the heterogeneity of industry responses to exchange rate changes. The granular approach adopted herein not only clarifies the varied sensitivity of industries to exchange rate fluctuations but also enriches the policy dialogue by providing insights tailored to the specificities of cross-strait trade dynamics.

The remainder of the paper is organized as follows: Section 2 describes the methodology, including the NARDL approach and data sources. Section 3 presents the empirical results and discusses the implications of these findings. Finally, Section 4 synthesizes the study's insights.

2 Materials and methods

2.1 Data and Sources

This research uses disaggregated export (X) and import (M) data for 20 industries (classified according to the two-digit Standard International Trade Classification, SITC). The data spans from January 2004 to December 2022. We obtain the bilateral trade flow data from Taiwan's Ministry of Finance Customs Administration data stream. Taiwan's GDP data comes from the Directorate General of Budget, Accounting and Statistics (DGBAS), while China's GDP data is sourced from the Federal Reserve Economic Data (FRED) database. We collect the nominal TWD/CNY exchange rate data from Yahoo Finance, which provides historical monthly exchange rate data. The consumer price indices (CPI) for both China and Taiwan are gathered from their respective national statistical agencies.

2.3 Real Exchange Rate Calculation

To maintain consistency in the measurement of real exchange rates, we compute the monthly CPI-based real exchange rates for the period from January 2004 to December 2022. We calculate the real exchange rate of TWD/CNY (RER) using the formula:

$$RER = \frac{NER \times CPI_{CN}}{CPI_{TW}} \tag{1}$$

where NER refers to the nominal exchange rate of TWD/CNY, and CPI_{CN} and CPI_{TW} represent the consumer price indices of China and Taiwan, respectively.

2.3 GARCH Model for Exchange Rate Volatility

Exchange rate volatility is the degree of fluctuation in the exchange rate over time. High volatility indicates rapid changes in the exchange rate, introducing uncertainty for businesses and affecting international trade. Following the approach by Bahmani-Oskooee and Hegerty (2009), as well as additional studies by Engle (1982) and Bollerslev (1986), we construct a GARCH model to estimate conditional variances. This model is widely used in the literature for its ability to capture time-varying volatility patterns, especially in the context of exchange rate volatility studies (Hansen and Lunde 2005; Bauwens, Laurent, and Rombouts 2006).

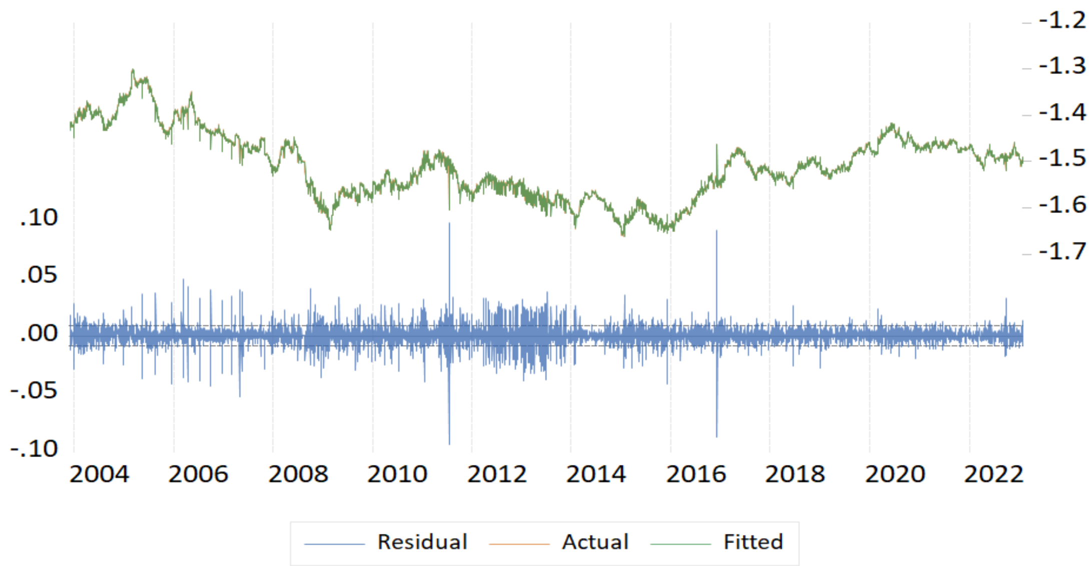
We estimate the exchange rate volatility model as follows:

$$log(RER_t) = a_0 + a_1\, log(RER_{t-1}) + \epsilon_t \tag{2}$$

where $log(RER_t)$ represents the natural logarithm of the real exchange rate at time t, a_0 and a_1 are the coefficients to be estimated, and ε_t is the error term. To estimate the conditional variance of ε_t, we employ the GARCH (1,1) model, specified as:

$$h_t^2 = c + \omega\epsilon_{t-1}^2 + \phi h_{t-1}^2 \tag{3}$$

where h_t^2 is the conditional variance at time t, c is a constant term, ω and ϕ are the GARCH and ARCH parameters, respectively, and ϵ_{t-1}^2 and h_{t-1}^2 are the lagged squared error terms and lagged conditional variances, respectively. After estimating the GARCH model (Figure 1), we obtain the conditional standard deviation V_t as a proxy for exchange rate volatility.



Source: Author's calculations

Figure 1: GARCH model for exchange rate volatility

2.4 Non-linear ARDL Model

Trade flows are conventionally assumed to respond to changes in independent variables in a symmetric manner. However, research by Shin et al. (2014) introduced the possibility of asymmetric effects, which means that positive and negative changes in independent variables could have different impacts on the dependent variable. In this study, we adopt this framework and analyze the impact of exchange rate movements on Taiwan-China trade by separating the effects into increased and decreased volatilities. Specifically, we decompose the TWD/CNY exchange rate volatility into two components: TWD depreciation (POS_t) and TWD appreciation (NEG_t).

We compute the partial sum of positive and negative changes in the natural logarithm of the TWD/CNY exchange rate, denoted as $log(V_t)$:

$$POS_t = \sum_{j=1}^{t} max(\Delta log(V_j), 0)\,; NEG_t = \sum_{j=1}^{t} min(\Delta log(V_j), 0). \tag{4}$$

Next, we estimate long-run models for exports and imports. The export model is as follows:

$$log(X_t) = \alpha_0 + \alpha_1 log(GDP_t^{CH}) + \alpha_2 log(RER_t) + \alpha_3 POS_t + \alpha_4 NEG_t + \epsilon_t \tag{5}$$

The import model is given by:

$$log(M_t) = \beta_0 + \beta_1 log(GDP_t^{TW}) + \beta_2 log(RER_t) + \beta_3 POS_t + \beta_4 NEG_t + u_t \tag{6}$$

Here, α_1 and β_1 represent the impact of China's and Taiwan's incomes on Taiwan's exports and imports, respectively. We expect a positive coefficient for α_1 and β_1, indicating that Taiwan's exports and imports increase with the growth of China's and Taiwan's incomes, respectively. Moreover, we anticipate $\alpha_2 > 0, \alpha_3 > 0$, as an increase in the RER_t, signaling TWD depreciation, should lower export prices and consequently lead to increased exports from Taiwan. In contrast, $\beta_2 < 0, \beta_3 < 0$ are expected to be negative, as the rise in the RER_t causes import prices to increase, resulting in decreased imports for Taiwan. For α_4 and β_4, which represent the impact of TWD appreciation NEG_t on exports and imports, we anticipate $\alpha_4 < 0$, $\beta_4, > 0$. This is because TWD appreciation is expected to make exports more expensive and imports cheaper, ultimately leading to decreased exports and increased imports for Taiwan.

To incorporate short-run dynamics, we rewrite the long-run models as error-correction models (ECMs), following the approach by Shin et al. (2014). These ECMs serve as extensions of the ARDL model proposed by Pesaran et al. (2001). This framework allows us to estimate both long-run and short-run effects simultaneously:

$$\begin{aligned}\Delta log(X_t) \\ &= \gamma_1 + \sum_{j=1}^{n_1} \gamma_{2,j} \Delta \log\left(X_{t-j}\right) + \sum_{j=0}^{n_2} \gamma_{3,j} \Delta \log\left(GDP_{t-j}^{CH}\right) + \sum_{j=0}^{n_3} \gamma_{4,j} \Delta \log\left(RER_{t-j}\right) \\ &\quad + \sum_{j=0}^{n_4} \gamma_{5,j} \Delta POS_{t-j} + \sum_{j=0}^{n_5} \gamma_{6,j} \Delta NEG_{t-j} + \lambda_1 \log(X_{t-1}) + \lambda_2 \log\left(GDP_{t-1}^{CH}\right) \\ &\quad + \lambda_3 \log(RER_{t-1}) + \lambda_4 POS_{t-1} + \lambda_5 NEG_{t-1} + \psi_t,\end{aligned} \tag{7}$$

$$\begin{aligned}\Delta log(M_t) \\ &= \delta_1 + \sum_{j=1}^{n_6} \delta_{2,j} \Delta \log\left(M_{t-j}\right) + \sum_{j=0}^{n_7} \delta_{3,j} \Delta \log\left(GDP_{t-j}^{TW}\right) + \sum_{j=0}^{n_8} \delta_{4,j} \Delta \log\left(RER_{t-j}\right) \\ &\quad + \sum_{j=0}^{n_9} \delta_{5,j} \Delta POS_{t-j} + \sum_{j=0}^{n_{10}} \delta_{6,j} \Delta NEG_{t-j} + \eta_1 \log(M_{t-1}) + \eta_2 \log(GDP_{t-1}^{TW}) \\ &\quad + \eta_3 \log(RER_{t-1}) + \eta_4 POS_{t-1} + \eta_5 NEG_{t-1} + \upsilon_t.\end{aligned} \tag{8}$$

The introduction of partial sum variables introduces nonlinearity within the models, leading to their classification as NARDL models. Despite this nonlinearity, the overall model remains linear when considering all variables together. NARDL equations are subject to the same OLS estimation procedures and diagnostic tests as their linear counterparts. The NARDL model can handle variables that are either integrated of order one $I(1)$, integrated of order zero $I(0)$, or a combination of both. However, if any of the variables are integrated of order two $I(2)$, inaccurate estimates may result. We use the Augmented Dickey-Fuller (ADF) test to check that any of the variables are integrated of order two $I(2)$.

Table 1 presents the Augmented Dickey-Fuller (ADF) test results for second-differenced variables in 20 different industries classified by SITC codes. The table displays each industry's trade share for both exports and imports, along with the respective ADF-test results (in second differences).

Table 1: Stationarity Test Results for Second-Differenced Variables Across Industries

SITC	Industry	Trade Share (Exports)	ADF-test (2nd diff)	Trade Share (Imports)	ADF-test (2nd diff)
01	Live Animals; Animal Products	0.25%	-12.257**	0.38%	-5.375**
02	Vegetable Products	0.11%	-7.246**	0.62%	-6.222**
03	Animal or Vegetable Fats & Oils & their Cleavage Products	0.02%	-14.257**	0.01%	-6.544**
04	Prepared Foodstuffs; Beverages, Spirits & Tobacco Products	0.40%	-4.024**	0.47%	-7.393**
05	Mineral products	1.47%	-6.711**	2.38%	-14.789**
06	Product of the Chemical or Allied Industries	10.50%	-6.472**	8.62%	-9.876**
07	Plastics & Articles Thereof; Rubber & Articles Thereof	9.18%	-11.351**	2.87%	-3.987**
08	Leather and related products	0.22%	-12.558**	0.59%	-15.974**
09	Wood and articles of wood	0.05%	-10.122**	0.48%	-6.564**
10	Pulp, Paper & Printing Products	0.55%	-15.094**	0.87%	-9.660**
11	Textiles & Textile Articles	2.59%	-16.623**	2.61%	-10.836**
12	Footwear, Headgear, Umbrellas; Artificial Flowers; Articles of Human Hair	0.08%	-10.602**	0.67%	-13.978**
13	Articles of Stone, Plaster, Cement; Ceramic Products; Glass & Glassware	0.98%	-10.962**	1.25%	-19.498**
14	Precious metals and stones, imitation jewelry, and coin	0.09%	-8.829**	1.17%	-9.793**
15	Base Metals & Articles of Base Metal	6.85%	-12.464**	9.04%	-10.525**
16	Machinery and mechanical appliances, electrical equipment, and parts	50.41%	-21.755**	58.04%	-15.267**
17	Vehicles, Aircraft, Vessels & Associated Transport Equipment	0.80%	-10.288**	2.02%	-14.488**
18	Optical, Photographic, Cinematographic, Medical or Surgical Instruments	14.75%	-7.679**	4.33%	-12.411**
20	Miscellaneous manufactured articles	0.41%	-6.143**	2.24%	-10.105**
21	Works of art, collectors' pieces, and antiques	0.29%	-14.686**	1.34%	-5.798**

Note: ** indicates statistical significance at the 1% level.

Additionally, the ADF test results for GDP_t^{TW}, GDP_t^{CN}, V, and RER are -19.981, -6.301, -7.057, and -11.822, respectively. All ADF test statistics are statistically significant at the 1% level, indicating that none of the variables are integrated in $I(2)$. This suggests that we can proceed with the NARDL approach.

In the estimation of all models, we include quarterly dummies to account for seasonal factors. Furthermore, we restrict the constant (case 2) in the models to provide a more accurate representation of the long-run relationships among the variables. To determine the optimal number of lags, we use the Akaike Information Criterion (AIC) (Akaike 1974). The AIC helps us select the most appropriate model by balancing goodness of fit and model complexity, with lower AIC values indicating better models. We estimate exports and imports models for each of the 20 industries to analyze the impact of exchange rate volatility on bilateral trade values between Taiwan and China.

2.5 Diagnostic tests and robustness check

To verify the robustness of the chosen equations, we conduct several diagnostic tests:

1. Ramsey RESET Test helps detect potential model misspecification, ensuring that our chosen model adequately captures the relationship between the variables. We check the null hypothesis H_0: the model has correct functional form.
2. CUSUM Test and CUSUM Squares Test assess the stability of the coefficients over time, which is crucial for ensuring the reliability of the model in the context of a changing economic environment. We check that the CUSUM and CUSUM Squares Test statistic remains within the critical bounds.
3. LM Test for Serial Correlation detects the presence of serial correlation in the residuals, which, if present, could undermine the validity of our inferences. We check the null hypothesis H_0: no serial correlation.
4. Breusch-Pagan-Godfrey Test examines the presence of heteroskedasticity in the residuals, which is essential for ensuring the accuracy of our estimated standard errors and hypothesis tests. We check the null hypothesis H_0: residuals have constant variance.

After estimation, we test for cointegration among the variables by applying the F-test to all lagged variables in NARDL equations. We reject the null hypothesis: $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = 0$ and $H_0: \eta_1 = \eta_2 = \eta_3 = \eta_4 = \eta_5 = 0$, respectively. The critical values for the F-test depend on the sample size and the chosen significance level. If the F-test statistic is greater than the upper bound value, we reject the null hypothesis of no cointegration, indicating the presence of a long-run relationship.

To investigate long-run asymmetric effects, we apply the Wald test ($Wald_{LR}$)on the normalized long-run coefficients of the POS and NEG variables in both export and import equations. The null hypothesis for this test is $H_0: \frac{\lambda_4}{-\lambda_1} = \frac{\lambda_5}{-\lambda_1}$ in the export equation and $H_0: \frac{\eta_4}{-\eta_1} = \frac{\eta_5}{-\eta_1}$ in the import equation. If the Wald test rejects these null hypotheses, it signifies that the normalized long-run coefficient estimates attached to the POS and NEG variables are significantly different, thereby establishing long-run asymmetric effects.

Next, we test for short-run cumulative asymmetric effects using the short-run Wald test ($Wald_{SR}$). This test examines the null hypothesis of $\sum \gamma_{5,j} = \sum \gamma_{6,j}$ for the exports equation and $\sum \delta_{5,j} = \sum \delta_{6,j}$ for the imports equation. If the corresponding F-statistics are greater than the critical value, we reject the null hypothesis, confirming the presence of short-run cumulative asymmetric effects.

3 Results

3.1 NARDL Exports models

In this section, we present the results of NARDL models estimated for exports across 20 industries, classified by SITC codes. Our analysis focuses on examining the diagnostic results of these models to assess their robustness and reliability which are crucial for validating the model's effectiveness in capturing the dynamics of export performance in relation to exchange rate volatility. The results provide insights into the short-run and long-run relationships between exchange rates and export volumes across different industries, highlighting the varying degrees of sensitivity and responsiveness to exchange rate changes.

The diagnostic results, detailed in Table 2, encompass a range of tests. The Ramsey RESET test results indicate that all models have a stable functional form at the 5% level (the lowest p-value being 0.06 for SITC 03). The LM test results suggest an absence of serial correlation (with the lowest p-value being 0.07 for SITC 12). The BPG test results show an absence of heteroscedasticity, except for SITC 17 and 20, where p-values are below 0.05. To address the heteroskedasticity issue in these industries we employ the Newey-West coefficient covariance matrix. The CU and CU2 tests assess coefficient stability over time, with "S" representing stable coefficients and "U" representing unstable coefficients. The ECM_{t-1} term represents the error correction term, which indicates how much of the disequilibrium in the short-run relationship is corrected in each period to converge toward the long-run equilibrium. The ECM_{t-1} term for all industries is negative and highly significant, indicating that the system corrects towards the long-run equilibrium.

Table 2: Diagnostic results for the non-linear ARDL model for exports

SITC	$adj.R^2$	RESET (F-stat)	LM (F-stat)	BPG (F-stat)	CU	CU2	ECM_{t-1}	Bounds test (F-stat)
01	0.429	0.945	1.531	0.989	S	S	-0.337	2.709*
02	0.761	1.517	0.399	0.516	S	S	-0.821	7.379**
03	0.585	3.852	0.686	0.602	S	S	-0.802	3.733**
04	0.802	0.058	1.152	0.893	S	S	-0.842	9.235**
05	0.436	0.593	0.956	0.658	S	S	-0.773	5.971**
06	0.414	0.689	0.335	1.059	S	S	-0.722	3.387*
07	0.661	0.159	0.324	0.897	S	S	-0.776	5.103**
08	0.687	0.299	0.501	1.814	S	U	-0.361	1.456
09	0.817	0.312	1.480	0.904	S	S	-0.058	2.040
10	0.683	0.249	0.203	0.390	S	U	-0.414	6.356**
11	0.877	0.684	0.855	1.007	S	S	-0.340	2.931*
12	0.667	0.920	2.897	1.129	S	S	-0.712	4.303**
13	0.295	0.354	0.761	1.402	S	S	-0.366	4.003**
14	0.443	0.309	1.643	1.242	S	S	-0.092	3.679**
15	0.745	1.146	0.079	1.265	U	S	-0.945	4.800**
16	0.802	0.376	0.444	1.460	S	S	-0.930	11.171**
17	0.314	1.386	1.669	1.918	S	S	-0.343	2.501
18	0.654	0.025	0.854	1.222	S	S	-0.420	6.402**
20	0.860	0.414	0.552	1.958	S	S	-0.202	2.719*
21	0.643	0.007	0.153	0.829	S	S	-0.144	2.931*

Note: The 5% critical values for the bounds test are 2.560 (stationary bound) and 3.490 (non-stationary bound); ** in the Bounds test indicates the presence of cointegration and * indicates inconclusive result. Included diagnostics are the adjusted R-squared ($\mathrm{adj.R}^2$), Ramsey RESET test, LM test for serial correlation, Breusch-Pagan-Godfrey (BPG) test for heteroskedasticity, CUSUM (CU) and CUSUM Squares (CU2) tests for coefficient stability, the error correction term (ECM_{t-1}), F-statistic for the bounds test, and cointegration status.

The F-statistic for the bounds test determines the presence of cointegration. Industries with F-statistic values below the 5% stationary critical value indicate no cointegration, while those with F-statistic values above the 5% non-stationary critical value indicate the presence of cointegration. Industries with F-statistic values between the critical values are marked as inconclusive. The majority of industries exhibit cointegration between the variables, suggesting the presence of long-run relationships. However, for certain industries without cointegration, specifically, SITC codes 08, 09, and 17 for exports estimating long-run relationships may not yield meaningful results. Consequently, our analysis focuses on industries with cointegration to ensure the reliability and validity of our findings.

We proceed to examine the long-run and short-run effects of exchange rates on Taiwan's exports to China across industries.

The positive coefficients of China's lagged GDP log ($\mathrm{GDP}_{t-1}^{\mathrm{CH}}$) in most industries (specifically SITC codes 02, 03, 04, 06, 07, 10, 16, and 18), as detailed in Table 3, affirm the hypothesis that growth in China's economy has a complementary effect on Taiwan's exports. This aligns with the economic theory which suggests that as economies expand, their increased capacity for imports can stimulate exports from trading partners. The significance at the 1% level across these sectors highlights the robustness of this relationship and underscores China's role as a pivotal market for Taiwan's industrial sectors. However, the anomalous negative coefficient $\log(\mathrm{GDP}^{\mathrm{CH}}_{t-1})$ observed for industry 12 is intriguing and prompts a discussion on the interplay between economic expansion and sector-specific trade patterns. It raises questions about the extent to which China's economic growth might be nurturing domestic industries that directly compete with Taiwanese exports or altering the demand for imports due to shifts in technology or consumer preferences.

Table 3: Long-run results of non-linear ARDL models for exports

SITC	$\log(\mathrm{GDP}^{\mathrm{CH}}_{t-1})$	$\mathrm{Log}(\mathrm{RER}_{t-1})$	POS_{t-1}	NEG_{t-1}	Constant	$Wald_{LR}$
01	2.992	2.165	-3.625	-0.012	-15.775	3.085
02	4.619**	9.830**	-10.449**	-1.624**	-25.120**	35.48**
03	2.667**	-5.765**	0.784	4.269**	-27.291**	6.966**
04	3.629**	1.489**	-3.706**	0.830**	-25.569**	42.811**
05	-0.066	1.736	2.761	-1.015	13.948	4.287*
06	1.496**	-1.763*	-1.535	1.437**	-2.782	4.775*
07	1.131**	-0.670	-0.398	0.993**	3.003	12.059**
10	0.869*	2.607**	0.414	0.298	7.846*	0.06
11	0.262	-1.170*	-1.057**	0.368	11.076**	4.194*
12	-1.162**	-3.991**	1.234	0.310	19.024**	1.462
13	0.314	-6.461**	2.291	1.510	2.023	0.315
14	-18.558	-58.909	20.926	0.019	126.895	1.538
15	-0.002	1.441	-0.579	-0.329	18.118**	0.289
16	0.786**	1.673**	1.019**	-0.024	11.335**	14.987**
18	2.599**	0.627	-1.455	2.589**	-11.424	10.107**
20	-1.480	-3.145	-5.202	-2.698	26.329	1.335
21	0.470	-3.004	-0.956	0.124	3.249	0.729

Note: * indicates a 5% significance level; ** indicates a 1% significance level.

Conversely, the real exchange rate, $\log(\mathrm{RER}_{t-1})$, presents a dichotomous effect on Taiwan's export landscape. For sectors such as machinery and electronic equipment (SITC codes 02, 04, 10, and 16), an appreciating Taiwan dollar does not deter export growth, potentially reflecting these industries' competitive advantages or inelastic foreign demand for their products. However, the adverse impact of a stronger Taiwan dollar on industries like textiles and footwear (SITC codes 03, 06, 11, and 12) suggests that these more traditional sectors may be price-sensitive and thus more vulnerable to exchange rate fluctuations.

The coefficients of POS_{t-1} and NEG_{t-1} represent the increased and decreased changes in the TWD/CNY exchange rate volatility, respectively. Focusing on the coefficients of increased volatility (POS) and decreased volatility (NEG), we observe that at least one of these coefficients is significant at the 1% level in 8 industries displaying cointegration (SITC codes 02, 03, 04, 06, 07, 11, 16, and 18). These industries represent 87.96% of Taiwan's total exports to China, suggesting that exchange rate volatility plays a critical role in shaping export performance across these sectors.

Regarding the short-run effects, our analysis omits certain industries, specifically those with SITC codes 08, 09, and 17, due to the absence of cointegration, as well as those with SITC codes 01, 10, and 21, since the estimated ARDL models did not exhibit short-run effects on positive and negative shocks, denoted by $\Delta\mathrm{POS}_t$ and $\Delta\mathrm{NEG}_t$.

The short-run estimates in Table 1A in the Appendix for the non-linear ARDL export model reveal that, for the majority of industries, at least one coefficient on $\Delta\mathrm{POS}_t$ and $\Delta\mathrm{NEG}_t$ is significant. This finding suggests a notable short-run impact of exchange rate volatility on exports within these industries. The Wald statistic indicates that asymmetric impacts in the short run are significant in 8 industries (SITC 03, 04, 05, 06, 07, 09, 12, 16), showing that exchange rate volatility asymmetrically influences these industries' exports. These industries account for 72.11% of total exports to China.

Industries with larger coefficient magnitudes for $\Delta\mathrm{POS_t}$ and $\Delta\mathrm{NEG_t}$ such as SITC 02, 03, 05, 06, and 20, which appear to be more sensitive to exchange rate volatility. Conversely, industries with smaller coefficients, including SITC 04, 07, 09, 12, 13, 15, 16, and 18, seem more resilient to exchange rate fluctuations. In some industries (SITC 03, 04, 06, 07, 09, and 12), the positive coefficients for $\Delta\mathrm{POS_t}$ suggest that increased exchange rate volatility has a positive impact on exports. On the other hand, negative coefficients for $\Delta\mathrm{NEG_t}$ in industries like SITC 02, 05, and 16 indicate that decreased exchange rate volatility negatively affects exports.

A closer look at the magnitudes and significance levels of $\Delta\mathrm{POS_t}$ and $\Delta\mathrm{NEG_t}$ coefficients show that positive shocks in exchange rate volatility have a more pronounced impact on exports in industries such as SITC 02 and 05, while negative shocks exert a stronger influence in industries like SITC 12 and 18.

Our analysis of the long-run and short-run effects of exchange rate volatility on Taiwan's exports to China robustly supports Hypothesis 1. We find significant asymmetric impacts across various industries, confirming that exchange rate volatility affects sectors differently.

3.2 NARDL Imports models

Building on the methodology applied to exports, this section shifts focus to the import side, analyzing the results of NARDL models for imports across 20 industries, as classified by SITC codes. While the approach mirrors that of the exports analysis, the emphasis here is on how exchange rate volatility influences import dynamics differently. Diagnostic results presented in Table 4 are instrumental in assessing the robustness and reliability of our models.

Table 4: Diagnostic results for the non-linear ARDL model for imports

SITC	$adj.R^2$	RESET (F-stat)	LM (F-stat)	BPG (F-stat)	CU	CU2	ECM_{t-1}	Bounds test (F-stat)
01	0.415	0.033	0.154	1.268	S	S	-0.436	4.986**
02	0.776	1.205	0.436	1.791	S	S	-0.268	16.184**
03	0.637	1.313	0.417	1.136	S	U	-1.076	10.607**
04	0.669	0.429	1.746	0.912	S	S	-0.388	2.592*
05	0.537	0.0029	0.964	1.101	S	S	-0.665	5.159**
06	0.462	3.348	0.852	1.446	U	S	-0.184	5.761**
07	0.844	3.164	3.244	1.009	S	S	-0.438	5.837**
08	0.619	1.060	0.040	0,951	S	S	-0.217	1.848
09	0.793	1.784	0.264	3.870	S	U	-0.378	2.840*
10	0.574	0.119	0.526	1.338	S	S	-0.669	6.701**
11	0.899	0.932	1.297	2.049	S	S	-0.507	13.886**
12	0.560	0.512	1.768	1.335	S	S	-0.108	2.343
13	0.674	2.391	0.886	0.480	S	S	-0.055	3.096*
14	0.574	0.473	3.000	1.162	S	S	-0.493	5.726**
15	0.677	1.518	1.488	0.653	S	S	-0.026	2.997**
16	0.769	0.247	0.745	1.225	U	S	-0.452	3.954**
17	0.669	2.855	0.575	0.575	S	S	-0.845	2.127
18	0.764	1.609	0.085	0.744	S	S	-0.442	3.483*
20	0.806	0.369	0.129	1.855	S	S	-0.656	10.686**
21	0.581	1.876	1.652	3.021	S	S	-0.095	4.986**

Note: The 5% critical values for the bounds test are 2.560 (stationary bound) and 3.490 (non-stationary bound); ** in the Bounds test indicates the presence of cointegration and * indicates inconclusive result.

Similar to the exports models, the Ramsey RESET test results indicate that all models have a stable functional form at the 5% level (the lowest p-value being 0.07 for SITC 06). The LM test results suggest an absence of serial correlation (with the lowest p-value being 0.06 for SITC 07). The BPG test results show an absence of heteroskedasticity, except for SITC 09 and 21, where p-values are below 0.05. To address the heteroskedasticity issue in these industries, we employ the Newey-West coefficient covariance matrix. The ECM_{t-1} term for all industries is negative and highly significant, indicating that the system corrects towards the long-run equilibrium.

The majority of industries exhibit cointegration between the variables, suggesting the presence of long-run relationships. However, for certain industries without cointegration, specifically SITC codes 08, 12, and 17, estimating long-run relationships may not yield meaningful results. Consequently, our analysis focuses on industries with cointegration to ensure the reliability and validity of our findings.

Table 5 enumerates the long-run coefficients of the non-linear ARDL model. The coefficients of $\log(GDP_{t-1}^{TW})$ display significant negative effects on imports for certain industries, specifically SITC codes 03, 14, 16, and 18, at the 5% significance level. This observation implies that Taiwan's GDP growth is generally correlated with a decline in imports from China for these industries. As Taiwan's economy expands, domestic production in these sectors may increase, diminishing the dependence on imports from China. This reduction could stem from technological advancements, enhanced production efficiency, or a shift in consumer preferences towards domestically produced goods. Conversely, a positive correlation between Taiwan's GDP and imports from China in industries 04, 05, and 20 indicates that as Taiwan's economy grows, the demand for imports from China in these sectors rises. Factors such as increased consumer demand, economies of scale in production, or a comparative advantage held by China in these industries may contribute to this trend, rendering imports from China more economically attractive.

Table 5: Long-run results of non-linear ARDL model for imports

SITC	$\log(GDP_{t-1}^{TW})$	$\mathrm{Log}(\mathrm{RER}_{t-1})$	POS_{t-1}	NEG_{t-1}	Const	$Wald_{LR}$
01	-0.917	-2.254	0.024	-0.695	23.302	0.570
02	4.711	-0.968	-0.889	0.966	-57.464	3.359
03	-7.393**	3.831**	1.130	-2.173**	124.444**	0.906
04	4.353*	3.799*	-4.067	-1.011	-46.972	5.316*
05	5.502**	0.911	-3.211*	1.598*	-65.511*	10.953**
06	6.828*	-4.954**	-1.249	2.495*	-93.374*	7.428**
07	-2.360	1.406	-0.975	-1.837**	51.074*	1.834
09	-0.063	1.200	-0.067	-0.408	15.045	0.059
10	0.129	-0.576	-1.644*	-0.620	10.324	2.769
11	0.200	-1.431**	-0.145	-0.251	9.881	0.060
13	-20.136	-4.133	9.080	-2.412	308.166	5.132*
14	-34.880**	0.035	7.818	-7.098	533.455**	16.298**
15	-122.977	52.871	-58.048	-52.973	1915.072	0.013
16	-3.699*	2.218*	-0.503	-2.248**	75.311**	5.095*
18	-6.750*	0.168	3.757*	-1.232	115.407*	7.839**
20	2.009**	0.825**	-0.241	-0.161	-14.594**	0.106
21	-1.208	-4.437	0.982	-0.534	25.609	0.267

Note: * indicates a 5% significance level; ** indicates a 1% significance level.

The real exchange rate variable, $\log(\mathrm{RER}_{t-1})$, provides mixed results. A significant positive relationship between the real exchange rate and imports is observed for industries with SITC codes 03, 04, 16, and 20, indicating that an appreciation of the Taiwan dollar leads to increased imports. This pattern may be attributed to the fact that these sectors might be less sensitive to exchange rate fluctuations, or they could benefit from specialized inputs or products that are more efficiently or uniquely sourced from China. In contrast, a significant negative relationship appears for industries with SITC codes 06 and 11, suggesting that the appreciation of the Taiwan dollar may negatively affect imports in these sectors. The negative relationship may result from these industries being more sensitive to exchange rate fluctuations.

Upon evaluating the coefficients of increased volatility POS_{t-1} and decreased volatility NEG_{t-1}, it is observed that at least one of these coefficients holds significance at the 5% level in 7 industries that exhibit cointegration (SITC codes 03, 05, 06, 07, 10, 16, and 18). These industries represent 77.12% of Taiwan's total imports from China, which underscores the critical influence of exchange rate volatility on import performance within these sectors. The significant coefficients suggest that the industries are sensitive to variations in exchange rate, and these fluctuations can have considerable implications for trade patterns, import demand, and overall trade balance. As a result, understanding and managing exchange rate volatility becomes an essential aspect of trade policy for both Taiwan and China to ensure continued growth and stability in their bilateral trade relations.

For short-run effects, specific industries are excluded from the analysis, such as those with SITC codes 08, 12, and 17 (lacking cointegration) and those with SITC codes 01, 09, 11, 13, and 21 (no short-run effects on positive and negative shocks). The nonlinear ARDL import model's short-run estimates in Table 2A in the Appendix reveal that, for the majority of industries, at least one coefficient on ΔPOS_t and ΔNEG_t is significant. This finding suggests a notable short-run impact of exchange rate volatility on imports within these industries. The Wald statistic indicates that asymmetric impacts in the short run are significant in 4 industries (SITC 05, 06, 10, 21). These industries comprise only 13.21% of total imports from China.

In summary, the data robustly supports Hypothesis 2. The evidence from both long-run and short-run analyses clearly demonstrates that exchange rate volatility between the TWD and CNY has significant, asymmetric impacts on specific sectors of Taiwan's imports from China. This finding is crucial for policymakers and businesses in understanding the dynamics of trade between Taiwan and China and in formulating strategies to mitigate the risks associated with exchange rate volatility.

4 Conclusion

Our study makes several key contributions to the literature, emphasizing the significant role exchange rate volatility plays in shaping export and import performance across industries within the Taiwan-China trade context. Import performance is notably influenced by exchange rate volatility, affecting 77.12% of Taiwan's total imports from China in the long run. However, asymmetric short-run effects are only significant in four industries, accounting for 13.21% of total imports from China, including chemical and mineral products, textiles, and works of art.

Exchange rate volatility also critically impacts export performance, affecting 87.96% of Taiwan's total exports to China in the long run. Asymmetric short-run effects are significant in eight industries, representing 72.11% of total exports to China. These industries, including machinery and mechanical appliances, electrical equipment, plastics, rubber, chemical products, mineral products, and others, dominate Taiwan's exports to China and are characterized by high-value-added products and strong global competitiveness. These products typically have less price elasticity and are less sensitive to exchange rate fluctuations because they offer unique features or advanced technology that cannot be easily substituted.

We find that certain industries (02, 03, 05, 06) are more sensitive to exchange rate volatility. This sensitivity is evident in both export and import performance, with significant long-run and short-run effects observed in these sectors.

For mineral products (SITC 05), exchange rate fluctuations directly impact international competitiveness, leading to changes in trade volumes. The industry's narrow profit margins mean that even minor exchange rate shifts can lead to substantial adjustments in trade quantities. Its integration into global supply chains also implies that exchange rate volatility can cause disruptions, affecting the volume of goods traded. The reliance on imported machinery and inputs links production costs to exchange rates, influencing the volume of final products traded internationally.

In the chemical or allied industries (SITC 06), reliance on imported raw materials makes input costs vulnerable to exchange rate variations. This sector faces stiff global competition, and exchange rate shifts can rapidly alter competitive dynamics, affecting exports and market shares. The capital-intensive nature of this industry, coupled with its sensitivity to investment further underscores its vulnerability. Additionally, compliance with stringent environmental and safety regulations, often involving globally sourced technologies, becomes more challenging and costly.

For vegetable products and animal or vegetable fats and oils (SITC 02 and 03), global trade dynamics make their trade volumes highly sensitive to exchange rate fluctuations. As commodities, they are subject to intense competition and price sensitivity, which translates into significant changes in trade volumes in response to exchange rate movements. Trade policies and tariffs compound these effects, influencing trade flows.

Understanding industry sensitivity enables policymakers to allocate support and interventions more effectively for economic stability and growth. Targeted measures, such as export credit insurance or currency hedging strategies, should be considered for these industries. Additionally, promoting research and development or encouraging investment in major export industries, such as Machinery and mechanical appliances, can help diversify the economy and enhance resilience against currency fluctuations.

By highlighting the importance of industry-specific effects and asymmetric impacts of exchange rate fluctuations, this study underscores the need for businesses to consider these factors when formulating trade strategies between Taiwan and China. For the industries involved, short-run effects suggest that businesses should proactively manage exchange rate risks. Understanding asymmetric impacts can guide strategic decisions on market entry, product diversification, and supply chain management. Businesses should monitor exchange rate trends and consider adjusting their pricing strategies or production plans accordingly to maintain profitability and competitiveness in the face of currency volatility. Policymakers could encourage collaboration between businesses and financial institutions to develop innovative financial products that help manage currency risk. Fostering growth in bilateral trade, particularly in key sectors, could be achieved by promoting industrial cooperation, encouraging investment in high-tech industries, and enhancing infrastructure connectivity between Taiwan and China.

Conflict of interest: The authors declare no conflict of interest

References

Akaike, Hirotugu. 1974. "A New Look at the Statistical Model Identification." In Selected Papers of Hirotugu Akaike, edited by Emanuel Parzen, Kunio Tanabe, and Genshiro Kitagawa, 215–222. Springer Series in Statistics. New York, NY: Springer New York. doi:10.1007/978-1-4612-1694-0_16.

Arize, Augustine C., Thomas Osang, and Daniel J. Slottje. 2000. "Exchange-Rate Volatility and Foreign Trade: Evidence from Thirteen LDC's." Journal of Business & Economic Statistics 18 (1): 10. doi:10.2307/1392132.

Baek, Jungho, and Soojoong Nam. 2021. "The South Korea–China Trade and the Bilateral Real Exchange Rate: Asymmetric Evidence from 33 Industries." Economic Analysis and Policy 71 (September): 463–475. doi:10.1016/j.eap.2021.06.007.

Bahmani-Oskooee, Mohsen, Parveen Akhtar, Sana Ullah, and Muhammad Tariq Majeed. 2020. "Exchange Rate Risk and Uncertainty and Trade Flows: Asymmetric Evidence from Asia." Journal of Risk and Financial Management 13 (6): 128. doi:10.3390/jrfm13060128.

Bahmani-Oskooee, Mohsen, and Scott W. Hegerty. 2007. "Exchange Rate Volatility and Trade Flows: A Review Article." Journal of Economic Studies 34 (3): 211–255. doi:10.1108/01443580710772777.

Bahmani-Oskooee, Mohsen, and Scott W. Hegerty. 2009. "The Effects of Exchange-Rate Volatility on Commodity Trade between the United States and Mexico." Southern Economic Journal 75 (4): 1019–1044. doi:10.1002/j.2325-8012.2009.tb00945.x.

Bahmani-Oskooee, Mohsen, Scott W. Hegerty, and Jia Xu. 2012. "Exchange-Rate Volatility and Industry Trade Between Japan and China." Global Economy Journal 12 (3): 1850268. doi:10.1515/1524-5861.1855.

Bauwens, Luc, Sébastien Laurent, and Jeroen V. K. Rombouts. 2006. “Multivariate GARCH Models: A Survey.” Journal of Applied Econometrics 21 (1): 79–109. doi:10.1002/jae.842.

Bollerslev, Tim. 1986. “Generalized Autoregressive Conditional Heteroskedasticity.” Journal of Econometrics 31 (3): 307–327. doi:10.1016/0304-4076(86)90063-1.

Chen, Hui-Chuan. 2001. “Taiwan’s Exports and Trade Imbalance against US and Japan: An Empirical Analysis.” Applied Economics 33 (10): 1283–1287. doi:10.1080/00036840122642.

Chen, Hui-Chuan. 2002. “Taiwan’s Exports and Trade Imbalance against US and Japan: An Empirical Investigation Based on Error Correction Model.” Applied Economics 34 (18): 2303–2309. doi:10.1080/00036840210141695.

Chen, Shyh-Wei. 2008. “Long-Run Aggregate Import Demand Function in Taiwan: An ARDL Bounds Testing Approach.” Applied Economics Letters 15 (9): 731–735. doi:10.1080/13504850600749032.

Cheung, Francis K., Maw Lin Lee, and Yi-Chen Wu. 1997. “Endogenous Export Prices and the Taiwan-US Trade Imbalance.” Applied Economics 29 (1): 23–31. doi:10.1080/000368497327362.

Chien, Mei-Se, Nur Setyowati, and Chih-Yang Cheng. 2020. “Asymmetric Effects of Exchange Rate Volatility on Bilateral Trade between Taiwan and Indonesia.” The Singapore Economic Review 65 (04): 857–888. doi:10.1142/S021759082050006X.

Clark, Peter B. 1973. “Uncertainty, Exchange Risk, and the Level of International Trade.” Economic Inquiry 11 (3): 302–313.

Engle, Robert F. 1982. “Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation.” Econometrica 50 (4): 987. doi:10.2307/1912773.

Fang, WenShwo, YiHao Lai, and Stephen M. Miller. 2009. “Does Exchange Rate Risk Affect Exports Asymmetrically? Asian Evidence.” Journal of International Money and Finance 28 (2): 215–239. doi:10.1016/j.jimonfin.2008.11.002.

Fung, Loretta. 2008. “Large Real Exchange Rate Movements, Firm Dynamics, and Productivity Growth.” Canadian Journal of Economics/Revue Canadienne d’économique 41 (2): 391–424. doi:10.1111/j.1365-2966.2008.00468.x.

Fung, Loretta, and Jin-Tan Liu. 2009. “The Impact of Real Exchange Rate Movements on Firm Performance: A Case Study of Taiwanese Manufacturing Firms.” Japan and the World Economy 21 (1): 85–96. doi:10.1016/j.japwor.2007.11.002.

Grauwe, Paul De. 1988. “Exchange Rate Variability and the Slowdown in Growth of International Trade.” Staff Papers - International Monetary Fund 35 (1): 63. doi:10.2307/3867277.

Hansen, Peter R., and Asger Lunde. 2005. “A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)?” Journal of Applied Econometrics 20 (7): 873–889. doi:10.1002/jae.800.

Hsing, Han-Min, and Andreas Savvides. 1996. “Does a J-Curve Exist for Korea and Taiwan?” Open Economies Review 7 (2): 127–145. doi:10.1007/BF01891900.

Klein, Michael W. 1990. “Sectoral Effects of Exchange Rate Volatility on United States Exports.” Journal of International Money and Finance 9 (3): 299–308. doi:10.1016/0261-5606(90)90011-N.

McKenzie, Michael D. 1999. “The Impact of Exchange Rate Volatility on International Trade Flows.” Journal of Economic Surveys 13 (1): 71–106. doi:10.1111/1467-6419.00075.

Moreno, Ramon. 1989. “Exchange Rates and Trade Adjustment in Taiwan and Korea.” Economic Review - Federal Reserve Bank of San Francisco, no. 2: 30.

Péridy, Nicolas. 2003. “Exchange Rate Volatility, Sectoral Trade, and the Aggregation Bias.” Review of World Economics 139 (3): 389–418. doi:10.1007/BF02659668.

Pesaran, M. Hashem, Yongcheol Shin, and Richard J. Smith. 2001. “Bounds Testing Approaches to the Analysis of Level Relationships.” Journal of Applied Econometrics 16 (3): 289–326. doi:10.1002/jae.616.

Shin, Yongcheol, Byungchul Yu, and Matthew Greenwood-Nimmo. 2014. “Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework.” In Festschrift in Honor of Peter Schmidt, edited by Robin C. Sickles and William C. Horrace, 281–314. New York, NY: Springer New York. doi:10.1007/978-1-4899-8008-3_9.

Stokman, A. C. J. 1995. "Effect of Exchange Rate Risk on Intra-EC Trade." De Economist 143 (1): 41–54. doi:10.1007/BF01388354.

Sun, Chia-Hung, and Yi-Bin Chiu. 2010. "Taiwan's Trade Imbalance and Exchange Rate Revisited." Applied Economics 42 (7): 917–922. doi:10.1080/00036840701720937.

Tang, Hsiao Chink. 2014. "Exchange Rate Volatility and Intra-Asia Trade: Evidence by Type of Goods." The World Economy 37 (2): 335–352. doi:10.1111/twec.12095.

Truong, Loc Dong, Ha Hoang Ngoc Le, and Dut Van Vo. 2022. "The Asymmetric Effects of Exchange Rate Volatility on International Trade in a Transition Economy: The Case of Vietnam." Buletin Ekonomi Moneter Dan Perbankan 25 (2): 203–214. doi:10.21098/bemp.v25i2.1636.

Wang, Kai-Li, and Christopher B. Barrett. 2007. "Estimating the Effects of Exchange Rate Volatility on Export Volumes." Journal of Agricultural and Resource Economics 32 (2). Western Agricultural Economics Association: 225–255.

Appendix

The following tables provide detailed short-run estimates of POS and NEG variables in the NARDL models for exports and imports across various SITC codes.

Table 1A: Short-run estimates of POS and NEG variables in NARDL exports models

SITC	Variable	Lag order								$Wald_{SR}$
		0	1	2	3	4	5	6	7	
02	ΔPOS_t	-2.659	-3.457	5.439*	3.753	0.451	-7.366**	5.812**	-1.729	1.133
	ΔNEG_t	0.451	1.257	0.430*	1.216	3.345**	0.928	-1.792**	2.107*	
03	ΔPOS_t	9.009**	0.111	5.847*	3.060	-0.766	7.470*	-	-	7.877**
	ΔNEG_t	-1.611*	-1.751	-3.701**	-2.210*	-0.502	-1.095	-	-	
04	ΔPOS_t	1.072	2.326	2.736*	-	-	-	-	-	4.070*
	ΔNEG_t	-0.130	0.749	-0.241	-	-	-	-	-	
05	ΔPOS_t	-8.707**	-8.628*	-8.871**	-6.833	-	-	-	-	4.460*
	ΔNEG_t	3.865**	1.003	-1.140	-1.577	-	-	-	-	
06	ΔPOS_t	-1.309	4.160**	3.412**	4.870**	4.651**	3.557**	0.533	-	6.946*
	ΔNEG_t	0.242	-1.330**	-1.409**	-0.879*	-0.100	-1.669**	0.389	-	
07	ΔPOS_t	0.919	0.260	1.035	0.877	1.283	1.847	-	-	6.882*
	ΔNEG_t	0.167	-0.478	-1.102**	-0.359	-0.608*	-0.508	-	-	
09	ΔPOS_t	1.853	0.178	2.358	-1.721	5.485**	-	-	-	4.287*
	ΔNEG_t	-0.681	-1.340*	-2.320**	-0.515	-1.101*	-	-	-	
11	ΔPOS_t	0.563	-	-	-	-	-	-	-	1.507
	ΔNEG_t	-0.203	-	-	-	-	-	-	-	
12	ΔPOS_t	-0.278	0.890	2.528**	2.459*	3.416**	2.275*	0.551	-	6.212*
	ΔNEG_t	0.025	-0.835**	-0.880**	-1.011**	-0.671*	-0.578	-0.879*	-	
13	ΔPOS_t	-1.870	0.632	2.020	-0.650	0.875	-0.201	-1.861	-0.688	0.138
	ΔNEG_t	0.224	-1.457**	-0.421	0.467	-0.152	-0.209	1.078*	1.726**	
14	ΔPOS_t	1.531	-	-	-	-	-	-	-	0.020
	ΔNEG_t	2.091*	-	-	-	-	-	-	-	
15	ΔPOS_t	-0.758	0.909	2.752**	0.413	1.382	1.395	0.044	-0.639	1.383
	ΔNEG_t	-0.422	-0.533	-0.392	0.288	-0.089	-1.131**	-0.188	0.660*	
16	ΔPOS_t	-2.520**	-1.284*	-1.010	-2.289**	-0.577	-0.432	-	-	7.795**
	ΔNEG_t	0.230	0.273	-0.231	0.344	-0.218	-0.713**	-	-	
18	ΔPOS_t	-1.435	1.976*	0.680	0.902	4.221**	3.757**	-	-	4.030
	ΔNEG_t	0.884*	-1.183**	-1.721**	-1.025**	-0.811*	-1.364**	-	-	
20	ΔPOS_t	0.590	1.537	3.606	-0.768	4.955**	2.023	3.362**	0.330	2.658
	ΔNEG_t	-0.590	-0.421	0.039	-0.182	-0.373	0.060	0.459	0.725	

Note: * indicates a 5% significance level. ** indicates a 1% significance level.

Table 2A: Short-run estimates of POS and NEG variables in NARDL imports models

SITC	Variable	Lag order								$Wald_{SR}$
		0	1	2	3	4	5	6	7	
02	ΔPOS_t	-0.502	-	-	-	-	-	-	-	1.594
	ΔNEG_t	0.833**	-	-	-	-	-	-	-	
03	ΔPOS_t	5.080	-7.675	-3.291	4.628	7.400	8.447	2.938	-	3.297
	ΔNEG_t	-3.872**	1.662	-1.460	-4.316**	-2.996*	-2.507	-2.830	-	
04	ΔPOS_t	-0.182	-0.646	1.716*	-0.120	1.934*	0.269	1.938*	0.001	0.372
	ΔNEG_t	-0.544	0.585*	0.280	0.199	0.221	0.056	0.062	0.618*	
05	ΔPOS_t	1.628	-0.384	1.241	2.857	2.859	1.555	5.190**	3.560*	5.734*
	ΔNEG_t	0.880	-0.638	-1.795**	-1.249*	-1.249*	-0.497	-1.017	-2.097**	
06	ΔPOS_t	1.733*	1.930*	-	-	-	-	-	-	10.014**
	ΔNEG_t	0.438	-0.832**	-	-	-	-	-	-	
07	ΔPOS_t	0.539	1.941**	1.690**	0.852	0.193	1.402**	1.341**	-0.720	3.437
	ΔNEG_t	-0.401*	0.210	0.307*	0.091	0.307*	-0.070	0.153	0.547**	
10	ΔPOS_t	0.254	2.157**	3.937**	2.159**	3.190**	3.439**	3.438**	0.770	17.007**
	ΔNEG_t	-0.309	-0.152	-0.119	0.033	-0.491*	-0.243	0.93	0.821**	
14	ΔPOS_t	4.799	-5.596*	1.022	4.029	4.074	11.039**	-3.169	-7.183*	0.083
	ΔNEG_t	-2.016*	3.174**	-1.740	-1.311	-0.448	0.417	3.424**	-0.03	
15	ΔPOS_t	-2.632	5.549**	3.705	2.345	1.317	7.702**	1.425	3.441*	3.321
	ΔNEG_t	-1.005	0.059	0.377	0.454	0.281	-1.460*	1.594*	1.161	
16	ΔPOS_t	-0.304	1.224*	2.622**	0.605	1.072	2.136**	0.861	-1.622**	1.432
	ΔNEG_t	-0.342	0.371	-0.045	0.346	0.511**	-0.154	0.308	0.974**	
18	ΔPOS_t	-0.456	-0.457	-2.496*	-1.671	2.626*	1.599	-2.420	-6.734**	2.524
	ΔNEG_t	-0.456	0.302	-0.495	-0.112	-0.180	1.140*	1.027*	0.889*	
21	ΔPOS_t	1.896**	-	-	-	-	-	-	-	5.683*
	ΔNEG_t	-1.023**	-	-	-	-	-	-	-	

Note: * indicates a 5% significance level, ** indicates a 1% significance level