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Determinants of Remittance Inflows in Nepal: Evidence from Asymmetric Analysis NARDL

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Keywords

CCR, Crude oil price, DOLS, Exchange rate, GCC GDP, Geopolitical risk, Labor migration

ABSTRACT

Nepal is one of the most remittance-dependent economies in the world, and remittance inflows consistently account for over a quarter of GDP. The determinants of remittance inflows, particularly those related to the migration channel and the external macroeconomic environment, remain poorly understood. This paper addresses this gap by analyzing the asymmetric determinants of remittance inflows to Nepal from 1993 to 2024 using the Nonlinear Autoregressive Distributed Lag (NARDL) model. The NARDL bounds test is used to confirm the existence of the long-run cointegrating relationship between the variables. The analysis shows that a negative change in the exchange rate has a large and significant impact on remittance inflow, and geopolitical risk has a positive and significant long-run impact. The labor permit is positive, but marginally significant. In the short term, changes in GCC GDP and negative exchange rate movements have a strong negative impact on remittance inflows, and the error-correction term indicates that about 63.5 percent of short-term disequilibrium is corrected within one year. The Wald test is used to assess the statistical significance of asymmetry, thereby supporting a nonlinear framework. The core findings are supported by robustness checks using FMOLS, DOLS, and CCR, particularly for negative exchange rate changes, geopolitical risk, and labor permits. These findings suggest that exchange rate depreciation and geopolitical uncertainty are important channels determining remittance inflows in Nepal, and that policy actions should account for the asymmetry in their impacts.

Introduction

In the last thirty years, remittances have emerged as an important factor in Nepal's macroeconomic environment. Outward migration became one of the major livelihood strategies for Nepali households since the 1990s, when the government liberalized foreign employment policies and international demand for low-cost labor in the Gulf Cooperation Council (GCC) economies began to rise amid the oil boom. By the 2010s, remittance inflows were the largest source of foreign exchange in the country, surpassing foreign direct investment, official development assistance, and export earnings. Remittance receipts increased between FY 2003/04 and FY 2014/15 alone by 58.6 billion to 589.5 billion, and their contribution to GDP increased by 10.9 percent to 27.7 percent (Mishra & Kunwar, 2020). The increase in this dependency has significant macroeconomic stability consequences for household consumption. Any unexpected decrease in remittance inflows due to a slowdown in host countries' economies, changes in oil markets, geopolitical shocks or changes in exchange rates can destabilize the balance of payments, tighten household budgets and put pressure on Nepal's economy, which relies heavily on imports.

However, existing studies have focused more on the impacts of remittances on inflation, economic growth, poverty, household welfare, financial stability, and institutional quality. Most existing studies are based on descriptive analyses or linear econometric techniques that assume that increases or decreases in explanatory variables have equal and opposite effects. This is a serious constraint, given that global evidence strongly suggests asymmetric relationships between remittances and major drivers such as exchange rates and oil prices (Al-Assaf, 2024; Foudeh & Al-Abdulrazag, 2023). There is a lack of systematic research on the determinants of remittance inflows into Nepal.

This paper fills these gaps in four ways. First, it does not examine the effects of remittance inflows; rather, it directly analyzes the determinants of remittance inflows, treating them as the dependent variable. Second, it includes both the migration-side variables that are the number of labor permits issued by the Nepal Department of Foreign Employment and external macroeconomic variables, such as the aggregate GDP of GCC countries, crude oil price, USD/NPR exchange rate, and geopolitical risk index, in a single analytical framework. Third, it uses the NARDL model of Shin et al. (2014) to estimate whether the effects of positive and negative exchange rate and crude oil price shocks on remittance inflow are asymmetric. Fourth, it tests the robustness of the long-run results using FMOLS, DOLS and CCR estimators.

Based on the identified research gaps, this study has the following objectives: first, to identify and analyze the key determinants of remittance inflow in Nepal by treating remittance inflow as the dependent variable rather than a causal factor. Second, to examine whether the effects of exchange rate and crude oil price shocks on Nepal's remittance inflow are asymmetric by applying the NARDL method and assess the role of the geopolitical risk index. Third, to use both domestic migration supply variables (labor permits issued by DoFE) and external macroeconomic variables (GCC GDP, crude oil price, USD/NPR exchange rate, and geopolitical risk index) within a single analytical framework and to verify the robustness of the long-run estimates using alternative cointegration estimators, specifically FMOLS, DOLS, and CCR.

Literature Review

This study has four theoretical foundations: Neoclassical Migration Theory, New Economics of Labor Migration Theory, Exchange Rate Incentive Theory and Asymmetric Adjustment Theory. These theories are directly connected to the determinants of Nepal's remittance inflows, since they explain why individuals migrate, why migrants remit money home, the impacts of exchange-rate movements on remittance behavior, and why positive and negative shocks do not have the same impact.

Neoclassical Migration Theory holds that migration is an economic choice. This theory argues that individuals leave low-wage regions in pursuit of good income and jobs in high-wage regions. Sjaastad (1962) described migration as an investment in human capital, in which people weigh the anticipated returns and costs of the movement. Harris and Todaro (1970) pointed out that migration choices depend on the anticipated income disparities between the origin and destination regions. The theory applies to the current study because the majority of Nepalese migrate to other countries due to insufficient job opportunities or low wages in Nepal. This theory thus justifies the use of a labor permit as an explanatory variable in the study.

The New Economics of Labor Migration Theory views migration as a household decision, rather than an individual one. Stark and Bloom (1985) argued that migration is a common household strategy to reduce income risk, circumvent local market constraints and enhance family welfare. This theory is most applicable to Nepal, since foreign labor migration is usually a family decision. Most Nepalese families have at least one member who has migrated to a foreign country, and the rest of the family relies on remittance income. The new Economics of Labor Migration Theory justifies the use of a labor permit in this research.

Exchange Rate Incentive Theory posits that exchange-rate changes may affect remittance-sending behavior. Exchange Rate Incentive Theory has no single founder; rather, it is supported by remittance studies such as El-Sakka and McNabb (1999) and Yang (2008), which show that exchange-rate conditions can influence migrants remittance-sending behavior. Migrants tend to earn income in foreign currency, and their families spend remittances in local currency. As the Nepalese rupee weakens against the US dollar, the same number of foreign currencies will buy more Nepalese rupees. This can motivate migrants to remit more money through an official system. These reasons justify using the USD/NPR exchange rate as an independent variable in the current research paper.

Asymmetric Adjustment Theory describes how positive and negative fluctuations of economic variables do not necessarily affect each other equally. Classical linear models assume the same effect for the rise and fall of a variable, but this might not hold in actual economic behavior. Shin et al. (2014) proposed a nonlinear ARDL model that enables researchers to distinguish positive and negative changes in the explanatory variables and to test their short-run and long-run asymmetric effects. This theory can be directly applied to the current study, since Nepal's remittance inflows can respond differently to positive and negative shocks in exchange rates and crude oil prices.

Sijapati et al. (2015) analyzed trends in Nepal's labor market and migration and found that after the 1990s, foreign labor migration became a significant livelihood source due to limited domestic employment and income disparities. They reported that in FY 2013/14, about half a million labor permits were issued, and remittance inflows were approximately 30 percent of GDP. They also indicated that 74 percent of labor migrants were classified as unskilled, implying that Nepal's remittance inflows are closely tied to demand for low-skilled labor in the countries where the migrants work. Mishra and Kunwar (2020), in an analysis of foreign labor migration in Nepal, found that the GCC countries and Malaysia are the most popular destinations for Nepali migrant workers. Their work is relevant to labor permits, immigration destinations, and remittance inflows in Nepal. Yet, the research is largely descriptive and lacks an econometric test.

Dangal et al. (2023) examined a nonlinear relationship between remittance inflows and inflation in Nepal using the NARDL. They found that in the long run, remittance inflows and inflation exhibited an asymmetric cointegrating relationship. They further contended that previous cointegration procedures, such as Engle-Granger, Johansen and ARDL, failed to adequately address asymmetric relationships. This is highly relevant to the current study, as it justifies the use of NARDL to study Nepalese remittances. Panthi and Devkota (2023) tested the association between remittance inflows, institutional quality, and economic growth in Nepal. They used the ARDL bounds testing method and ECM and found that remittance inflows positively and significantly influence Nepal's economic growth, although remittances are predominantly consumed.

Niimi and Özden (2006) examined the determinants of remittance flows at the cross-country level and found that migration stock is a major driver of remittance inflow. This finding is important for the present study because a labor permit can serve as a proxy for Nepals migration flows. The logic is simple: when more Nepali workers obtain labor permits and move abroad, remittance inflows increase. Cal and Dell'Erba (2009) studied the relationship between financial crises and remittances and found that host-country real GDP and immigrant stock are among the most relevant explanatory variables for remittance outflows.

Alharbi (2022) examined remittance outflows and non-oil economic growth in Saudi Arabia using the NARDL model. The study argued that Saudi Arabias oil revenue is channeled through government expenditure and development projects, thereby increasing demand for foreign labor. Foudeh and Al-Abdulrazag (2023) reviewed studies showing that oil prices have asymmetric effects on remittance flows in both sending and receiving countries. They noted that positive oil price shocks significantly influenced remittance outflows from Saudi Arabia, while negative shocks were insignificant in some studies. They also cited evidence of asymmetric effects of oil prices on remittances to Pakistan and India. Al-Assaf (2024) examined oil price volatility and trade balance in GCC countries using panel ARDL and NARDL models. The study found that GCC trade balances respond asymmetrically to oil price changes and that the NARDL model gives richer results than the linear ARDL model. This supports the present study because GCC countries are oil-dependent economies, and changes in crude oil prices may affect their income, fiscal spending, private-sector activity, and demand for foreign workers. Therefore, crude oil prices are expected to affect Nepals remittance inflows through the GCC labor-demand channel.

Mutascu (2023) examined oil prices and geopolitical risk using frequency-domain causality and found that oil prices can predict geopolitical risk in both the short and long run, particularly through the geopolitical threat component. This study supports the inclusion of the geopolitical risk index in the present model because geopolitical uncertainty and oil market movements are closely linked. Minesso et al. (2024) explained that geopolitical risk can affect oil prices through two channels. First, the economic activity channel reduces global demand by increasing uncertainty, lowering consumption and investment, and disrupting trade. Second, the risk channel raises oil prices by increasing fears of future oil supply disruption. For Nepal, geopolitical risk matters because remittance inflow depends heavily on workers employed in GCC economies, a region exposed to oil-market shocks, conflict risk, and regional uncertainty.

The major study gap is the use of explanatory variables, including combined GCC GDP, crude oil price, exchange rate, labor approval and the geopolitical risk index, which is a new study on remittance inflows in Nepal. The other gap is that the Nepal-based studies have failed to properly integrate domestic migration-side variables and external host-country variables into a single framework. The labor permit captures the supply side of migration from Nepal, and GCCGDP captures the host-country income. The currency incentive for sending remittances is captured by the exchange rate. Uncertainty in destination and global markets is captured in geopolitical risk. These variables have not been tested together in the existing Nepalese literature. Third is a methodological gap. Linear ARDL, VAR, OLS or descriptive studies are used in many studies. These techniques assume the same effect for positive and negative shocks. Foreign literature demonstrates that the impacts of oil prices and exchange rates may be asymmetric. Hence, a nonlinear model is required. The fourth gap is the little application of geopolitical risk in the remittance inflow literature of Nepal. The geopolitical risk index has been widely used in the international literature lately due to its applicability to macroeconomic determinants. This is an important variable, since many Nepali migrants are employed in GCC countries, where oil prices, geopolitical uncertainty, the risk of conflict, policy changes, and labor market conditions are closely linked. Uncertainty that may affect migrant income, employment stability, and the timing of remittance transfers can be captured by the geopolitical risk index.

Materials and Methods

This study uses annual time-series data covering the period from 1993 to 2024. The dependent variable is Nepal's remittance inflow, while explanatory variables are the combined GDP of GCC countries, crude oil price, USD/NPR exchange rate, geopolitical risk index and the number of labor permits issued to Nepali workers by the DOFE. All variables are expressed in natural logarithms to reduce scale differences and stabilize for data analysis. Table 1 presents the symbols and sources of variables.

Table 1
Symbol and Source of Variables

Variable	Symbol	Measurement	Source
Remittance inflow	LREM	Log of annual remittance inflow (USD)	World Bank (2024)
GCC GDP combined	LGCCGDP	Log of combined GDP of six GCC countries (USD)	World Bank (2024)
Crude oil price	LCOIL	Log of equally weighted average crude oil price (USD/barrel)	Macrotrends (2024) and Federal Reserve Bank of St. Louis (2024)
Exchange rate	LEXCH	Log of USD/NPR exchange rate	World Bank (2024)
Geopolitical risk	LGPR	Log of Caldara-Iacoviello geopolitical risk index	Caldara and Iacoviello (2022)
Labor permit	LLAB	Log of annual labor permits issued by DoFE	Department of Foreign Employment (2023), ILO / Labor Migration Report

Source: Author Calculation

This study uses a quantitative time-series research design. The empirical analysis comprises six stages: descriptive and correlation analyses, unit root testing, NARDL estimation with bounds testing, short-run error correction modelling, diagnostic and stability testing, and robustness checks.

The baseline model functional form is:

$$LREMt = f(LGCCGDP_t,\ LCOIL_t,\ LEXCH_t,\ LGPR_t,\ LLAB_t) \quad (1)$$

Where *LREM* is the natural log of Nepal's remittance inflow, *LGCCGDP* is the log of the combined GCC GDP, *LCOIL* is the log of the crude oil price, *LEXCH* is the log of the USD/NPR exchange rate, *LGPR* is the log of the geopolitical risk index, *LLAB* is the log of labor permits, and *t* denotes time.

The linear econometric form is:

$$LREM_t = \beta_0 + \beta_1 LGCCGDP_t + \beta_2 LCOIL_t + \beta 3 LEXCH_t + \beta_4 LGPR_t + \beta_5 LLAB_t + \varepsilon t \quad (2)$$

Where β_0 is the intercept, β_1 through β_5 are the slope coefficients, and t is the error term.

The NARDL approach of Shin et al. (2014) decomposes the explanatory variables of interest into positive and negative partial sums.

In this study, crude oil price and the exchange rate are decomposed as follows:

$$LCOIL_t^{+} = \sum_{j=1}^{t} \max(\Delta LCOIL_j,\, 0) \tag{3}$$

$$LCOIL_t^{-} = \sum_{j=1}^{t} \min(\Delta LCOIL_j,\, 0) \tag{4}$$

$$LEXCH_t^{+} = \sum_{j=1}^{t} \max(\Delta LEXCH_j,\, 0) \tag{5}$$

$$LEXCH_t^{-} = \sum_{j=1}^{t} \min(\Delta LEXCH_j,\, 0) \tag{6}$$

In equations (3) to (6), $LCOIL^{+}$ and $LEXCH^{+}$ capture the cumulative positive (increasing) changes in crude oil price and exchange rate, respectively, while $LCOIL^{-}$ and $LEXCH^{-}$ capture the cumulative negative (decreasing) changes. Separating positive and negative allows the model to test whether increases and decreases in each variable produce different effects on remittance inflow.

The full NARDL long-run equation estimated in this study is:

$$\begin{aligned}\Delta LREM_t = {} & \alpha_0 + \lambda_1 LREM_{t-1} + \lambda_2 LGCCGDP_{t-1} + \lambda_3 LCOIL_{t-1}^{+} + \lambda_4 LCOIL_{t-1}^{-} \\ & + \lambda_5 LEXCH_{t-1}^{+} + \lambda_6 LEXCH_{t-1}^{-} + \lambda_7 LGPR_{t-1} + \lambda_8 LLAB_{t-1} + \sum_i \delta_i \Delta X_{t-i} + \varepsilon_t\end{aligned} \tag{7}$$

Where, Δ is the first-difference operator, α_0 is the constant, λ_1 through λ_8 are the long-run level coefficients, and represents the short-run dynamic coefficients for lagged changes in all explanatory variables X. The long-run coefficients for the decomposed variables are derived as follows: the coefficient on $LCOIL^{+}$ is $-\lambda_3/\lambda_1$, the coefficient on $LCOIL^{-}$ is $-\lambda_4/\lambda_1$, the coefficient on $LEXCH^{+}$ is $-\lambda_5/\lambda_1$, and the coefficient on $LEXCH^{-}$ is $-\lambda_6/\lambda_1$.

The ARDL bounds-testing method is adopted in this study instead of the Johansen or Engle-Granger tests because it is more applicable to small samples. With only 32 annual observations, Johansen uses too many degrees of freedom across variables, yielding unstable results. While Engle-Granger estimates the long-run and the short-run relationship in two separate steps, any error in the first step will carry over to the second. ARDL can avoid both of these problems by estimating everything in a single equation. Within the ARDL family, the nonlinear version (NARDL) is used in this study. NARDL works well across different data frequencies, whether annual, quarterly, monthly, or half-yearly, and produces reliable long-run estimates even with a limited number of observations. In this study, the exchange rate and oil price are unlikely to affect remittance inflow in the same way in both directions. A weaker rupee gives migrants an immediate incentive to remit more, but a stronger rupee does not reduce remittances by the same amount, since household expenses back home are fixed. Similarly, when oil prices rise, GCC countries hire more workers, but when oil prices fall, jobs don't disappear at the same pace; it takes time. A regular ARDL model assumes both directions work the same way, which isn't realistic here. NARDL is used instead, so the model can actually test this difference rather than assume it away.

Table 2

Lag Length Selection

Model selection method	Akaike Information Criterion (AIC)
Maximum lag length tested	1 (automatic selection)
Number of candidate models evaluated	128
Selected model	ARDL (1,1,0,0,0,1,1,0)
Deterministic specification	Unrestricted constant, no trend (Case 3)
Estimation sample	1995–2024 (30 observations after adjustment)

Source: Author Calculation using EViews 13

The Akaike Information Criterion (AIC) is used for lag selection in this study with a maximum lag of 1. With only 32 annual observations, selecting a higher lag would estimate too many parameters and reduce degrees of freedom, making the results unreliable. AIC is better in small samples. Table 2 presents the summary of lag length selection for the study.

Results

Descriptive Analysis

Table 3 presents the descriptive statistics of all study variables. It includes mean, standard deviation, minimum, maximum, skewness, kurtosis, and observations.

Table 3

Descriptive Statistics (Natural log form)

Statistics	lrem	lgccgdp	lcoil	lexch	lgpr	llab
Mean	6.970	13.627	3.825	4.402	4.570	11.848
Standard Deviation	1.952	0.732	0.680	0.290	0.289	1.887
Minimum	4.205	12.509	2.543	3.884	3.930	7.666
Maximum	9.190	14.599	4.716	4.902	5.172	13.640
Skewness	-0.208	-0.280	-0.397	0.069	0.261	-1.164
Kurtosis	-1.764	-1.617	-1.225	-0.898	0.248	0.234

Source: Author Calculation

Table 3 shows that the mean value of lgccgdp is the highest at 13.627, followed by llab at 11.848, and lcoil has the lowest at 3.825. The standard deviation shows that lrem and llab have higher values, meaning their values changed more; lexch and lgpr have lower standard deviations, showing more stable movement. The skewness values are mostly close to zero, except for llab, which is negatively skewed. This means the distribution of llab is more stretched toward lower values. The kurtosis values are mostly below 3, suggesting that the variables are relatively flat and lack extreme peaks.

Correlation Analysis

The correlation coefficient ranges from -1 to +1, where a value closer to +1 indicates a strong positive relationship, a value closer to -1 indicates a strong negative relationship, and a value close to 0 indicates a weak relationship. Table 4 presents the correlation matrix.

Table 4

Correlation Matrix (Natural log form)

Variable	lrem	lgccgdp	lcoil	lexch	lgpr	llab
lrem	1.000					
lgccgdp	0.979	1.000				
lcoil	0.845	0.910	1.000			
lexch	0.878	0.849	0.637	1.000		
lgpr	0.151	0.141	0.149	0.307	1.000	
llab	0.872	0.883	0.862	0.828	0.296	1.000

Source: Author Calculation

Table 4 shows that lrem has a very strong positive correlation with lgccgdp, with a coefficient of 0.979. This indicates that remittance and GDP move in the same direction. lrem also has strong positive relationships with lexch, llab, and lcoil, with correlation values of 0.878, 0.872, and 0.845, respectively. This means these variables tend to increase together. The correlation between lgccgdp and lcoil is also strong at 0.910, showing a positive relationship. Similarly, lgccgdp and llab have a strong correlation of 0.883. lgpr has weak correlations with most variables, especially with lrem, lgccgdp, and lcoil. The correlation results show that most variables are positively related; this indicates only the direction and strength of the relationships between variables. The high pairwise correlations among lrem, lgccgdp, lexch and llab indicate that multicollinearity should be formally assessed, which is addressed using the Variance Inflation Factor in a diagnostic test.

Unit Root Test

Before conducting the NARDL model, it is necessary to make sure that all variables are I(0), I(1), or a mixture of both. If it is I(2), then the NARDL model is inappropriate to perform. ADF and PP tests were conducted with trend and constant specification. Table 5 presents the results of the ADF and PP tests.

Table 5

Unit Root Test

	LREM	LCOIL	LEXCH	LGCCGDP	LGPR	LLAB
ADF Level t-stat	-0.2756	-1.8171	-1.9098	-1.4802	-3.3440	-1.5954
ADF Level p-value	0.9878	0.6720	0.6254	0.8148	0.0799*	0.7716
ADF 1st Diff. t-stat	-3.3678	-5.5758	-5.4514	-4.6777	-6.5632	-7.1205
ADF 1st Diff. p-value	0.0750*	0.0005***	0.0006***	0.0040***	0.0000***	0.0000***
PP Level t-stat	-1.1220	-1.7747	-2.1632	-1.6195	-2.9498	-1.4618
PP Level p-value	0.9088	0.6925	0.4923	0.7618	0.1618	0.8211
PP 1st Diff. t-stat	-3.3297	-5.9064	-5.4594	-4.6413	-6.5671	-7.6569
PP 1st Diff. p-value	0.0808*	0.0002***	0.0006***	0.0044***	0.0000***	0.0000***
Decision	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)

Note. Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively
Source: Author calculation using EViews 13

Table 5 shows that most variables are non-stationary in levels but become stationary after first differencing. LCOIL, LEXCH, LGCCGDP, and LLAB are stationary in first differences in the ADF and PP tests, so they are of order I(1). LREM also becomes stationary after first differencing. LGPR is weakly stationary at level in the ADF test at the 10 percent level, but the PP test does not confirm stationarity at level; therefore, it is more conservative to treat LGPR as I(1) because it becomes stationary at first difference in both tests. Unit root test results confirm that none of the variables are integrated of order two, I(2). Therefore, the data are suitable for the NARDL bounds testing approach.

NARDL Bound Testing for Cointegration

The unit root test had identified that the variables were integrated at I(1), the next step was to test whether there was any long-run relationship between the variables. This was done using the NARDL bounds test. Table 6 presents Conditional error correction regression in which each explanatory variable enters as a one-period lagged level (long-run) or as a first difference (short-run), and Table 7 presents the NARDL bound test for cointegration result.

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Table 6
Conditional Error Correction Regression (1,1,0,0,0,1,1,0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LREM(-1)*	-0.63545	0.223381	-2.8447	0.0108
LGCCGDP(-1)	-0.4233	0.333959	-1.26753	0.2211
LCOIL_P**	0.354095	0.196111	1.805581	0.0877
LCOIL_N**	0.151675	0.184528	0.821964	0.4219
LEXCH_P**	-0.28779	0.619241	-0.46475	0.6477
LEXCH_N(-1)	-8.50527	2.981343	-2.85283	0.0106
LGPR(-1)	0.284711	0.1253	2.272225	0.0356
LLAB**	0.088715	0.041797	2.122515	0.0479
D(LGCCGDP)	-1.17101	0.419525	-2.79127	0.0121
D(LEXCH_N)	-5.34209	2.467518	-2.16497	0.0441
D(LGPR)	0.129028	0.107932	1.195453	0.2474
C	6.268195	4.340812	1.444014	0.1659
Model Statistic	Value			
R-squared	0.774317			
Adjusted R-squared	0.6364			
S.E. of regression	0.115433			
F-statistic	5.614369			
Prob(F-statistic)	0.000668			
Durbin-Watson stat	1.938026			

Source: Author calculation using EViews 13

Table 6 presents the conditional error-correction regression results. Each explanatory variable is a one-period-lagged level, used to test the joint null of no long-run levels relationship and no first-difference relationship, capturing short-run dynamics. The regression is estimated under Case 3 (unrestricted constant, no deterministic trend), consistent with the lag-selection specification reported in Table 2. The overall equation is statistically significant (F = 5.614, p = 0.00068), and the negative and significant coefficient on the lagged dependent variable is consistent with the existence of an error-correcting long-run relationship.

Table 7
NARDL Bounds Test for Cointegration

Test Statistic			Value			
F-statistic			6.583240			
t-statistic			-2.844704			
Critical values	10% I(0)	10% I(0)	5% I(0)	5% I(1)	1% I(0)	1% I(1)
Sample size = 30	2.384	3.728	2.875	4.445	4.104	6.151
Asymptotic	2.030	3.130	2.320	3.500	2.960	4.260

Source: Author calculation using EViews 13

Table 7 shows that the computed F-statistic is 6.583240, exceeding the upper bound critical value at the 1% level, 6.151. Thus, the null hypothesis of no level relationship is rejected. This proves the presence of a cointegrating relationship between the variables in the long run. Therefore, the NARDL model can be used to estimate long-run and short-run relationships.

NARDL Level Form Estimates and Long Run Estimates

The long-run coefficients were estimated after cointegration was determined. The positive and negative partial sum components in the NARDL framework enable the study to test whether the effects of positive and negative changes differ. Table 8 and 9 present the level-form and long-run estimates of the NARDL model.

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Table 8

Level Form Estimates of the NARDL Model (1,1,0,0,0,1,1,0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LREM(-1)	0.364547	0.223381	1.631951	0.1201
LGCCGDP	-1.17101	0.419525	-2.79127	0.0121
LGCCGDP(-1)	0.747705	0.263664	2.835829	0.011
LCOIL_P	0.354095	0.196111	1.805581	0.0877
LCOIL_N	0.151675	0.184528	0.821964	0.4219
LEXCH_P	-0.28779	0.619241	-0.46475	0.6477
LEXCH_N	-5.34209	2.467518	-2.16497	0.0441
LEXCH_N(-1)	-3.16317	1.911837	-1.65452	0.1154
LGPR	0.129028	0.107932	1.195453	0.2474
LGPR(-1)	0.155683	0.103902	1.49837	0.1514
LLAB	0.088715	0.041797	2.122515	0.0479
C	6.268195	4.340812	1.444014	0.1659

Source: Author calculation using EViews 13

Table 8 shows level form estimates, with an R-squared of 0.997646 and a highly significant F-statistic (693.42, p = 0.000000), indicating that explanatory variables together explain almost all the variation in remittance inflow. The Durbin-Watson statistic of 1.938 is close to 2, suggesting no major autocorrelation problem in this regression. Among the individual variables, LGCCGDP, LGCCGDP(-1), LEXCH_N, and LLAB are significant at the 5% level, while LCOIL_P is marginally significant at the 10% level. While LEXCH_P, LCOIL_N and LGPR are not significant in this level-form regression.

Table 9

Long-Run Estimates of the NARDL Model (1,1,0,0,0,1,1,0)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGCCGDP(-1)	-0.666141	0.583609	-1.141417	0.2654
LCOIL_Pos	0.557232	0.427740	1.302735	0.2056
LCOIL_Neg	0.238688	0.309562	0.771052	0.4485
LEXCH_Pos	-0.452893	1.078405	-0.419965	0.6784
LEXCH_Neg(-1)	-13.384570	1.699207	-7.876952	0.0000
LGPR(-1)	0.448044	0.184966	2.422305	0.0237
LLAB	0.139608	0.068549	2.036626	0.0534

Source: Author calculation using EViews 13

Table 9 shows that LEXCH_N (-1) has a significant negative effect on remittances in the long run, with a coefficient of -13.384570 and a probability value of 0.0000. This shows that adverse exchange rate movements have a considerable impact on remittances in the long-run. The coefficient of LGPR(-1) is positive and significant, with a value of 0.448044 and a probability of 0.0237, indicating that geopolitical risk has a positive long-run effect on remittances. The level of significance of LLAB at the 10% threshold is positive and marginally significant, with a probability value of 0.0534. LGCCGDP(-1), LCOIL_P, LCOIL_N, and LEXCH_P are not statistically significant because their p-values exceed 0.05.

Short Run Error Correction

To test the short-run dynamics and the speed at which the model would restore the long-run equilibrium following a shock, the error correction model was estimated. Table 10 presents the short-run error correction results of the NARDL model.

Table 10 shows a -0.635453 coefficient of COINTEQ (-1) that is statistically significant at the 1% level. This proves that there is a stable short-run-to-long-run adjustment process. The coefficient suggests that about 63.5% of the disequilibrium is corrected during a given period. D(LGCCGDP) has a significant negative effect on remittances in the short run, as does D(LEXCH_N). This implies that any change in GCC GDP and negative exchange rate movements reduces remittances in the short run. D(LGPR) is positive; however, it is marginally significant at the 10% level.

Table 10
Short-Run Error Correction (1,1,0,0,0,1,1,0)

Test Statistic	Value			
COINTEQ(-1)	-0.635453	0.074299	-8.552608	0.0000
D(LGCCGDP)	-1.171006	0.190927	-6.133272	0.0000
D(LEXCH_N)	-5.342094	1.111052	-4.808138	0.0001
D(LGPR)	0.129028	0.065853	1.959339	0.0613
C	6.268195	0.714984	8.766907	0.0000
Model statistic	**Value**			
R^2	0.774317			
Adjusted R^2	0.738208			
F-statistic	21.44377			
Prob(F-statistic)	.000000			
Durbin-Watson stat	1.938026			

Source: Author calculation using EViews 13

Wald Test for Asymmetric Effects

A Wald test was conducted to examine whether the positive and negative effects of the decomposed variables are equal. Table 11 presents the Wald test for asymmetric effects.

Table 11
Wald Test for Asymmetric Effects

Test Statistic	Value	df	Prob.
F-statistic	4.840995	(2, 18)	0.0208
Chi-square	9.681991	2	0.0079
Restriction	**Value**	**Std. Error**	
C(4) - C(5)	0.202420	0.155584	
C(6) - C(7)	5.054302	2.918775	

Source: Author calculation using EViews 13

Table 11 shows testing asymmetry for LCOIL and LEXCH, respectively. The probability value of the F-statistic is 0.0208, while the probability value of the Chi-square statistic is .0079. Since both values are below .05, the null hypothesis of symmetry is rejected. This confirms the presence of asymmetric effects in the model. Therefore, positive and negative changes do not affect remittances in the same way.

Diagnostic Tests

Diagnostic tests are statistical tests that examine whether the estimated model meets the basic assumptions for obtaining valid estimates. Diagnostic tests assess the stability and validity of the estimated model.

Serial Correlation and Heteroskedasticity Test

The Breusch-Godfrey serial correlation LM test is used to detect whether the residuals are correlated across time. Harvey's heteroskedasticity test is used to examine whether the error term variance is constant across observations. Table 12 presents the results of the heteroskedasticity and serial correlation tests.

Table 12
Heteroskedasticity and Serial Correlation Test

Test	Null Hypothesis	Statistic	P-value	Result
Harvey Heteroskedasticity Test	Homoskedasticity	F = 2.187839	0.0678	Insignificant at 5% level
		Obs*R-squared = 17.16310	0.1031	Supports homoskedasticity
Breusch-Godfrey Serial Correlation LM Test	No serial correlation up to 1 lag	F = 0.006744	0.9355	No serial correlation
		Obs*R-squared = 0.011896	0.9131	Supports no serial correlation

Source: Author calculation using EViews 13

Table 12 shows the Harvey heteroskedasticity test, where the p-value of the F-statistic is 0.0678, and the p-value of Obs*R-squared is 0.1031, which are greater than the value 0.05; the null hypothesis of homoskedasticity cannot be rejected at the 5 percent significance level. This means that the model does not suffer from a serious heteroskedasticity problem, although the F-test value is slightly close to the 10 percent significance level, suggesting only weak borderline evidence. The Breusch-

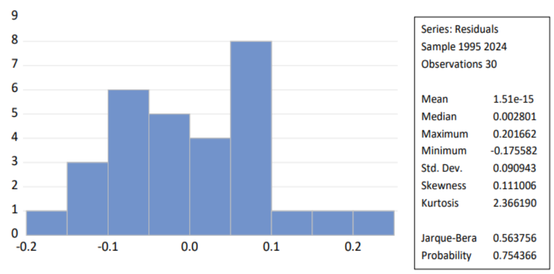
Godfrey serial correlation LM test reports p-values of 0.9355 for the F-statistic and 0.9131 for Obs*R-squared. Both are far above 0.05, so the null hypothesis of no serial correlation cannot be rejected. The diagnostic results suggest that the model is econometrically acceptable.

Normality Test

The normality test is used to examine whether the model residuals are normally distributed. The Jarque-Bera statistic and probability value determine the normality of the result. Figure 1 presents the normality test result of NARDL.

Figure 1

Normality Test



Source. Author Calculation using EViews 13

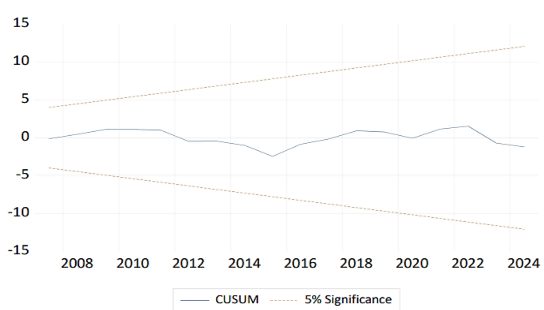
Figure 1 shows that the Jarque-Bera statistic is 0.563756 with a probability value of 0.754366, which is greater than 0.05. This means that the residuals are normally distributed, and the model satisfies the normality assumption.

CUSUM, CUSUMSQ and Recursive Residual

Figure 2, 3 and 4 present the CUSUM, CUSUMSQ and Recursive residual.

Figure 2

CUSUM

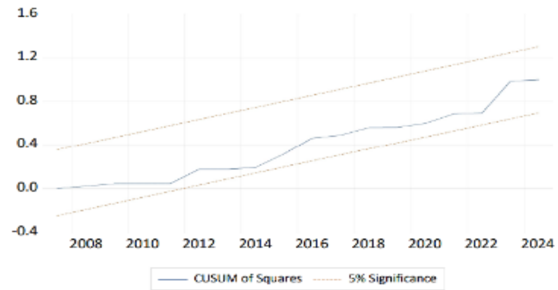


Source. Author Calculation using EViews 13

Figure 2 and 3 show that the blue CUSUM and CUSUMSQ lines remain within the 5 percent line over the study period. This suggests that the model is stable and that there is no evidence of serious structural change. Similarly, Figure 4 shows that the recursive residual plot lies within ś2, supporting model stability.

Figure 3

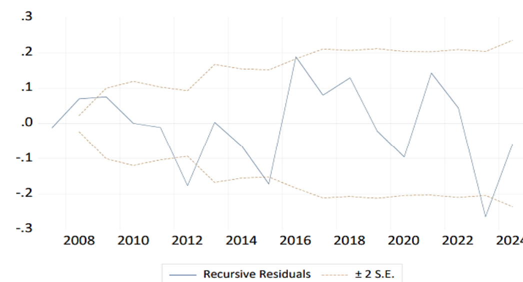
CUSUMQ



Source. Author Calculation using EViews 13

Figure 4

Recursive Residual



Source. Author Calculation using EViews 13

Multicollinearity (Variance Inflation Factor)

To check whether the high pairwise correlations in Table 4 reflect a serious multicollinearity problem, the Variance Inflation Factor (VIF) was calculated. Table 13 presents the VIF results.

Table 13 shows that LGCCGDP (27.65), LCOIL (18.37), and LEXCH (12.31) exceed the VIF threshold of 10, while LLAB (9.10) is close to it, and LGPR (1.37) shows no collinearity. This is expected in this study, since macroeconomic annual time series data are highly correlated, with GCC GDP, crude oil prices, and the exchange rate all driven by the same global commodity and labor-demand cycle. Pesaran et al. (2001) state that the ARDL is an extension of the regression model. Gujarati and Porter (2009) state in chapter 10, page 347 of Basic Econometrics, In one situation, however, multicollinearity may not pose a serious problem. This is the case when R2 is high, and the regression coefficients are individually significant as revealed by the higher t values (p. 347). O'Brien (2007) states that VIF values above 10 do not, by themselves, invalidate a regression, and that fixed rules of thumb should be interpreted alongside sample size and the strength of the underlying relationships. This is supported by the study's long-run results, particularly for LEXCH_N, LGPR, and LLAB, which remain consistent across the NARDL model and the FMOLS, DOLS, and CCR robustness checks, as well as diagnostic tests. The presence of high VIF therefore reduces the precision of some individual coefficients, especially LGCCGDP, but does not undermine the overall validity or consistency of the results.

Table 13

Variance Inflation Factor

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
LLAB	0.009385	379.3722	9.10371
LGPR	0.060185	354.6527	1.366728
LGCCGDP	0.189255	9905.849	27.64679
LEXCH	0.53701	2936.726	12.31447
LCOIL	0.145919	618.4944	18.37501

Source. Author Calculation using EViews 13

Robustness Check (FMOLS, DOLS and CCR)

To test the validity of the long-run NARDL outcomes, robustness tests were performed using (FMOLS, DOLS and CCR. These techniques are widely used to address potential endogeneity and serial correlation in long-run relationships. Hence, if the signs and significance of the core variables are consistent with the results produced by these alternative methods, the long-run estimates can be considered more robust. Table 14 presents the FMOLS, DOLS and CCR output.

Table 14

Robustness Check Results Using FMOLS, DOLS, and CCR

Variable	FMOLS Coef.	Prob.	DOLS Coef.	Prob.	CCR Coef.	Prob.
LGCCGDP	-0.3869	0.116	-0.4041	0.2138	-0.3860	0.1881
LCOIL_P	0.0978	0.4315	0.0991	0.5477	0.0972	0.5248
LCOIL_N	0.2441	0.0667	0.2612	0.1329	0.2438	0.1241
LEXCH_P	1.4689	0.0000	1.5338	0.0005	1.4642	0.0002
LEXCH_N	-12.3359	0.0000	-12.3519	0.0000	-12.3364	0.0000
LGPR	0.1766	0.0168	0.1740	0.0520	0.1771	0.0607
LLAB	0.0701	0.0131	0.0704	0.0454	0.0714	0.0233
C	7.7734	0.0192	7.9881	0.0637	7.7462	0.0531
Model statistic	FMOLS	DOLS	CCR			
R^2	0.994496	0.994895	0.994493			
Adjusted R^2	0.992745	0.993342	0.992741			
S.E. of regression	0.159647	0.156400	0.159692			
Long-run variance	0.006761	0.012035	0.006761			

Source: Author calculation using EViews 13

Table 14 shows the results of the robustness check of FMOLS, DOLS and CCR. In all three models, the coefficient of LEXCH_N is negative and significant. This suggests that negative exchange rate changes have a large impact on remittance inflow. The coefficient is approximately -12.34 across models and indicates that the result is not sensitive to the choice of long-run estimator. LEXCH_P is positive and significant in the three robustness models. In the long run, a positive change in the exchange rate raises remittance inflow, but this is not the case in the NARDL long-run estimate, where LEXCH_P was not significant. So, the positive effect of exchange rate changes should be taken with caution. The coefficient for LGPR is positive in the three models. It is significant in FMOLS at the 5% level, and in DOLS and CCR at approximately the 10% level. This confirms the NARDL result of a positive impact of geopolitical risk on remittances. Similarly, LLAB is positive and significant across all three robustness models, supporting the view that labor has a positive long-run effect on remittances. The coefficient of LGCCGDP is negative but insignificant in all three models. LCOIL_P is positive and insignificant in all models. LCOIL_N is positive and statistically significant only for the FMOLS model. Overall, the above results indicate that the main long-run results are robust, particularly for negative exchange rate changes, geopolitical risk and labor.

Discussion

The objective of this research is to study the determinants of remittance inflows in Nepal using a nonlinear model that captures asymmetry. Variables are cointegrated in the long run; the error correction term is negative and significant; and the Wald test indicates that positive and negative shocks have different effects on remittance inflows. The diagnostic and stability tests also

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confirm that the model is satisfactory, with no serious issues of serial correlation or heteroskedasticity, well-behaved residuals, and stable parameters. This indicates that the key results can be considered with confidence.

The key finding of the study is the long-run effect of negative exchange rate changes on remittance inflows, which is supported by the FMOLS, DOLS and CCR tests. It supports the Asymmetric Adjustment Theory, as the study finds that the impact of exchange rate changes is not symmetric in both directions. This finding is consistent with El-Sakka and McNabb (1999), Yang (2008), and Foudeh and Al-Abdulrazag (2023), who imply that remittance behaviour is responsive to the macroeconomic incentives and may respond asymmetrically to shocks. For Nepal, the exchange rate is not only a macroeconomic variable but also one of the most important channels through which remittance inflows fluctuate.

Another key finding is that geopolitical risk has a positive and significant long-run impact on remittance inflow, whereas the short-run impact is also positive but only marginally significant. It can be explained by the New Economics of Labor Migration. This theory suggests that migration and remittances are not just individual decisions but also family decisions made to manage risks and secure family welfare. If uncertainty increases in the destination countries or globally, migrants and their families might increase remittances as a precautionary measure. For countries like Nepal, with migrants working in destination countries sensitive to risks, geopolitical uncertainty can influence remittance dynamics.

The result for labor permits is also important. It is positive and significant at 10% in the NARDL long-run model and positive and significant in the robustness checks. This is consistent with the Neoclassical Migration Theory and the New Economics of Labor Migration. Remittance inflows increase as the number of labor permits issued increases. This is consistent with the national and international literature reviewed in the study, such as Sijapati et al. (2015), Mishra and Kunwar (2020), and Niimi and Özden (2006), which proposes that migration volumes play a significant role in determining the remittance flows.

The short-run coefficient on GCC GDP is negative and significant, contrary to the popular belief that higher host-country income leads to higher remitters' earnings and, in turn, higher remittance outflows. So, the Nepalese case is not as straightforward as the idea that more growth in the GCC's GDP means more remittances. Cal and Dell'Erba (2009) and Alharbi (2022) support the role of host-country income and demand. The coefficient of crude oil price is not statistically significant in the main long-run model. That does not necessarily mean that oil is unimportant. It just means that the impact of oil prices might be indirect, affecting the economy through the other variables. This is consistent with the literature reviewed in the study. Foudeh and Al-Abdulrazag (2023) and Al-Assaf (2024) point out that oil economies respond to shocks asymmetrically, whereas the present study shows that the direct independent effect of oil is not strong. This finding is important because it implies that, in Nepal, oil prices might not be a major driver of remittance inflows once other macroeconomic and migration-related factors are considered.

Conclusion

This study investigated the factors affecting remittance inflow in Nepal, using annual data for the period 1993-2024 in an NARDL model. The findings indicate that a long-run relationship exists between remittance inflows, the GDP of the Gulf Cooperation Council (GCC), crude oil prices, exchange rates, geopolitical risk and labor permits. The key findings are that negative exchange-rate changes have a strong and significant negative impact on remittance inflows, while geopolitical risk has a positive and significant impact on remittance inflows in the long run, and labor permits have a positive impact, as confirmed by the robust checks. In the short run, GCC GDP and negative exchange rate changes affect remittance inflows, while the error correction term implies that 63.5 percent of the short-run equation is corrected in one year. The Wald test indicates that the relationship is asymmetric; therefore, a nonlinear model is more appropriate than a linear one in this context. These results are consistent with the theoretical grounds of this study.

This study has limitations that need to be acknowledged. First, annual secondary data were used because only annual data are published for Nepal during the study period, and quarterly or monthly data are not available, which limits the power of the NARDL asymmetric and short-run results. Second, using GDP as a composite variable across six countries might hide country-specific effects. Third, multicollinearity is present among some regressors, as indicated by the VIF results in Table 13, which may reduce the precision of coefficient estimates, particularly for LGCCGDP. Fourth, the exclusion of dummy variables for major-specific events, such as COVID-19, means this study could not capture temporary disturbances in remittance behavior. Last, the number of labor permits may not reflect the estimated number of Nepali workers abroad due to illegal migration, renewals, early returns or death.

Implications

The policy implication of these results is that the government should not consider remittance inflows a constant or stable source of foreign exchange Reserves. Since labor permits matter, Nepal should also strengthen migration governance by providing more pre-migration training, worker protection, and faster, more transparent labor permit processing, along with bilateral labor market agreements with key labor markets. While labor permits support remittance inflows, continued high rates of foreign employment may also cause a domestic labor shortage. If this is not addressed, it could contribute to social, economic, and political instability in the long run. Since geopolitical risk matters, Nepal should also build a remittance risk-monitoring system that covers the GCC countries to enable policymakers to respond to geopolitical shocks. Lastly, given that remittance inflows are vital to household welfare, policies should focus on the productive use of remittances through migrant savings, financial education, and investment tools that help households invest some of their remittance income in small enterprises, agriculture, and local jobs. For future avenues, future studies could use quarterly or monthly data once it becomes available for Nepal to better capture short-run asymmetric dynamics or use different econometric and machine learning models.

Artificial Intelligence (AI) Use and Disclosure

In the preparation of this manuscript, AI tools were used minimally for assistance in language editing. AI tools were not used for data collection, data analysis, interpretation of results, or conclusions, and the author takes full responsibility for the accuracy and integrity of the manuscript.

Similarity and Originality Confirmation

The manuscript is original, not under review elsewhere, and complies with TUJ publication ethics.

Conflict of Interest

The authors declare no conflict of interest.

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Data Availability

Data available from the corresponding author on request.

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