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Modeling the News Impact on Volatility to Refugees Movement from LMICs: An APARCH Approach

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Abstract

Political and economic instability, armed conflicts, and weather abnormalities may introduce a high degree of volatility to the refugee movement. Refugee movement volatility is said to be asymmetric when positive and negative shocks of the same magnitude affect it differently. APARCH is one of the GARCH extension types of models that are popularly used to capture asymmetric volatility. In this paper, an attempt is made to model the volatility of the yearly refugee movement for the low-and middle-income countries using the APARCH model. The key finding of this study is that GARCH-extension type models indicating past volatility of the annual number of refugees is significant, influencing current volatility. The News Impact Curve is derived from the fitted APARCH model, which confirmed the presence of asymmetry in the volatility of the refugee movement. The News Impact Curve of the models for both groups of countries described that negative shocks of the same magnitude have a larger impact on volatility to refugee movement than positive shocks.

Keywords: LMICs, refugees, APARCH, volatility, news impact curve, new diagnostic tests

1. Introduction

Migration, and the public attitudes toward migrants and migration, traditionally received much attention in the public debate. More recently, as a result of the European refugee crisis and as many European countries struggle to cope with the influx of asylum seekers and refugees, the likes of which have not been seen in Europe since the Second World War, this attention and interest become even more noticeable among scholars, policymakers, and the public (De Coninck & Joris, 2021). At the world level, the media drives public perception of migration, generating crisis narratives and scapegoats for social problems and economic hardship of the critical moment, taken as reasons for the move (Mountz & Mohan, 2022). Low-and middle-income countries (LMICs) host the major part of the world's refugee population by origin (Gutmann, 2015; OECD, 2017). Empirical studies demonstrate that both economic conditions and violent conflicts are important determinants of the flow of refugees in developed countries (Gutmann, 2015). The world is facing a historic high of people forcibly displaced as a result of persecution, violence, or human rights violations (OECD, 2017). Globally, refugees consist of 48 percent women and 52 percent men (Raymer et al., 2023), but the gender composition of asylum seekers and refugees can also differ. Some refugees arrive in the country of destination under formal resettlement schemes. Refugees may be young people with high-level employment qualifications or single-mother families. Of those asylum seekers arriving in Europe, men outnumber women. Women make up about a third of asylum applications in Europe. Partly this is due to the way the data are collected; women are more likely to seek asylum as part of a family or to be married, also women are typically not the primary applicants (Reimer et al., 2023).

To explore the expanse of the effect of international mobility and develop evidence-based migration policy, policymakers need accurate estimates of present migration and credible forecasts of their future change (Caballero Reina et al., 2024). As a very significant part of inward migration from developing to developed countries, asylum migration is much better documented and quite fairly well data exist as asylum migrants are officially registered with the authorities of the country of destination (Barthel & Neumayer, 2015). The number of internationally displaced persons reached a record 26 million in 2019 (IOM, 2020), including over 4 million asylum seekers, and the number of UNHCR-mandated refugees doubled between 2013 and 2020. Due to the long-term conflict in some countries (for example, Afghanistan, Congo, Myanmar, Syria and Sudan) and the so-called refugee crises in Europe (2014-2015 and currently in Ukraine) and other continents (for example, in South America due to the Venezuelan crisis) the number of refugees has already increased (Solano et al., 2022). The term "refugee crisis" or "European migration crisis" refers to the events that began in the summer of 2014 until the end of 2016, which saw the largest influx of asylum seekers to Europe since the Second World War (De Coninck et al., 2021). There are well-established smuggling routes from Central and North Africa, as well as from the Middle East to Europe, with other routes bringing asylum migrants from Asia (Bartel & Neumeier, 2015). The common use of human trafficking routes by asylum migrants from geographically close countries is also confirmed by the presence of nationals of these close countries on refugee boats that often land on the coasts of the Canary Islands, Lampedusa or Malta (Bartel & Neumeier, 2015).

To address the challenges posed by growing numbers of refugees, many Western European countries as well as the US and other developed countries relied on tightening policies over the last decades (Gutmann, 2015). Solano et al. (2022); Barthel and Neumayer (2015) illustrate how asylum policies in Europe became more restrictive in response to increasing numbers of asylum seekers during the 1990s. Over the last decade, many Western European countries also faced a large number of asylum applications from citizens from war-zone countries in the Middle East and Africa. This inflow introduced challenges at local, national and supranational levels, especially about the settlement and integration of refugees and asylum seekers, with debates becoming increasingly politicized and disputable (De Coninck, 2023). The issue of migration to the EU is high on the agenda of European policy, news as well as the public. In 2018, EU leaders reached a long-awaited agreement on the (re)settlement aspects of refugees and asylum seekers. Although this long-awaited EU summit was seen as a delayed political response to Europe's refugee crisis in 2015, this agreement was the result of an EU summit dominated by the political crisis over how to deal with irregular immigration in Europe (De Koninck et al., 2019).

The paper aims to rigorously evaluate the predictive ability of GARCH extension-type models in terms of volatility to refugee movement for LICs and MICs. To our knowledge, models such as APARCH (asymmetric power autoregressive conditional heteroscedastic models); despite their application for economic and financial time series, have not been used in the demographic literature. As a result, this study includes the APARCH model, bridging the gap in the literature. This study therefore contributes to the literature by demonstrating the negative impact of large shocks on the volatility of the refugee's mobility from LICs and MICs. The remainder of this paper is organized as follows. In Section 2, the conceptual framework of the research is described. Section 3 presents the data and methods specification of the APARCH model. Section 4 presents the empirical results of the study. Sections 5 discuss the results and Section 6 concludes.

2. Conceptual Framework

The 1951 Convention relating to the status of refugees was adopted after the Second World War to address the problem of large numbers of displaced people living in Europe outside of their country of origin and was extended in 1967 to become a general regime for the protection of those who cross national borders to escape persecution (Bubb et al., 2009). Therefore, the 1951 Convention mainly consists of the obligation of states not to return refugees who enter their territory to their country of persecution. Under the Convention, the allocation of the burden of refugee protection is largely determined by the choice of refugees to migrate. Furthermore, countries themselves are responsible for determining which migrants are eligible for refugee status (Bubb et al., 2009). Following the signing of the Refugee Convention in 1951, according to De Coninck (2020, p. 4), a refugee is legally defined as "someone who has been forced to flee his or her country because of persecution, war, or violence. A refugee has a well-founded fear of persecution for reasons of race, religion, nationality, political opinion or membership in a particular social group". Migrants are considered to be individuals who decide to move based on their own free will, for reasons of personal convenience and without the intervention of an external compelling cause such as war or natural catastrophe (De Coninck, 2020). These definitions and categories are however somewhat arbitrary. Thus, they fail to grasp the complex reality of migrants' motives and movements across time and cultures, but it also cannot be denied that the use of these categories has important legal and social consequences for the groups involved. However, these definitions are somewhat similar to current UN definitions, as refugees are considered to leave their country due to political events, while economic migrants move for economic reasons (De Koninck, 2020). Thus, according to UNHCR (1967), refugee is a person who, "owing to a well-founded fear of persecution for reasons of race, religion, nationality, membership of a particular social group or political opinions, is outside the country of his nationality and is unable or, owing to such fear, is unwilling to avail himself of the protection of that country."

The drivers and temporal dynamics of forced migration are characteristically complex, and conventional models are insufficient to explain and predict them (Qi & Bircan, 2023). Human migration and displacement rank among the most urgent global societal challenges of the 21st century. Whether international or internal, labor migration, temporary or circular labor migration or forced migration, migration is complex in its endless forms and variations. In addition, various global changes are intensifying and accelerating changes including e.g., climate change, water scarcity, the rise of xenophobia and nationalism, war and conflict, technological advancements, and food insecurity, so we are entering a new era of human mobility (Mountz & Mohan, 2022). Mechanisms relevant to the migration process can be very complex and contextually unexpected. In the case of forced migration, drivers may evolve over time (Qi & Bircan, 2023), thus, the initial displacement may be caused by strong pressure factors, such as armed conflicts, economic crises, extreme weather conditions, famine, among other sudden events. The decision to migrate further after displacement can be shaped by destination-related pull factors, intervening obstacles and individual factors. Theoretically, the threat-based decision model suggests that perceived and unbearable threat to personal security is the main driver for people to migrate away from the war zone (Qi & Bircan, 2023). Therefore, empirical studies reported high rates of migration during armed conflicts, civil war, genocide and human rights violations (Qi & Bircan, 2023).

Economic theory predicts that asylum seekers will seek asylum in wealthy countries with low unemployment and high rates of economic growth (Neumayer, 2004). Wealthy countries are likely to be more generous in their welfare resources, and low unemployment and high economic growth make it easier to find work. Therefore, these countries represent the most attractive alternative to the poor living conditions and employment opportunities in the countries of origin.

The destination countries with former colonies may receive a larger proportion of asylum seekers exactly from these countries (Neumayer, 2004). This is simply because there are often long-term ex-colonial residents living in the destination country who can help find jobs and who can provide some relief from the culture shock related to migration to a foreign country. Additionally, there are often available direct flights between these countries, but not with other potential destinations. Likewise, according to network theory, a greater proportion of asylum seekers previously and long-term residents from a particular country of origin reduce the costs of migration for others to settle in the country of destination (Neumayer, 2004). This is because already existing asylum seekers provide valuable information channels to those left behind and can help new arrivals find their way to their country of destination.

3. Data and Methods

The major econometric purpose of this study is to explore the application of the GARCH extension-type APARCH model when applied to the task of modeling refugee's mobility from low and middle-income countries using annual data on the number of refugees. The data consisted of the annual total number of refugees by origin from low and middle-income countries from 1990 to 2022 determined by World Bank estimates (World Bank, 2023) and UNHCR data (UNHCR, 2023). The development of econometrics led to the creation of adjusted methodologies for modeling the mean and variance. Generalized conditional autoregressive heteroskedasticity (GARCH) models are based on the assumption that the random components in the models represent changes in volatility (Dritsaki, 2017). The GARCH models allow the conditional variance to depend on the prior lags. The GARCH model is an infinite-order ARCH model (Engle & Ng, 1993). The ARIMA model (as a mean model) with Autoregressive Conditional Heteroscedastic (ARCH) and the Generalized ARCH (GARCH) models with its generalization (as a variance model) are largely used to capture the sudden fluctuations of any time series (Rakshit et al., 2023). Thus, the GARCH model is very popular for solving the volatility of any time series. The process $\{\varepsilon_t\}$ is said to follow an ARCH (q) if the conditional distribution of $\{\varepsilon_t\}$ considering the available information (ψ_{t-1}) up to t-1 time period can be presented as in eq. (1) below:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \text{ and } \varepsilon_t = \sqrt{h_t}\, v_t \quad (1)$$

where v_t presents the innovation, which is independently and identically distributed with zero mean and unit variance (Rakshit et al., 2023). The distribution of innovation varies with the distribution of the corresponding dataset. The conditional variance h_t for an ARCH (q) is presented as in eq. (2):

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2,\ \alpha_0 > 0, \alpha_i \geq 0\ \forall\, i \text{ and } \sum_{i=1}^{q} \alpha_i < 1 \quad (2)$$

In order for an ARCH model to provide satisfactory accuracy, a vast number of parameters are needed. To solve this problem, a closer form known as the generalized ARCH (GARCH) model was suggested independently of each other (Rakshit et al., 2023). In a GARCH model, the conditional variance also is a linear function of its own lags. Thus, the conditional variance of a GARCH (p, q) model is specified as in eq. (3).

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j\, h_{t-j}$$

on condition that

$$\alpha_0 > 0, \alpha_i \geq 0\ \forall\, i, \beta_j \geq 0\ \forall\, j \quad (3)$$

Exponential GARCH (EGARCH), Asymmetric Power ARCH (APARCH) and GJR-GARCH models are the most commonly used asymmetric GARCH types of models (Rakshit et al., 2023; Caporin & Costola, 2018). The PARCH model is an extension of GARCH with extra terms added to account for possible asymmetries (Alam & Rahman, 2012). In the APARCH model (Rakshit et al., 2023), the conditional variance h_t has some asymmetric power. Therefore, h_t of the APARCH model can be specified as in eq. (4):

$$h_t^{\frac{\delta}{2}} = \alpha_0 + \sum_{j=1}^{p} \beta_j\, h_{t-j}^{\frac{\delta}{2}} + \sum_{i=1}^{q} \alpha_j\, (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^{\delta} \quad (4)$$

where $\gamma(-1 < \gamma < 1)$ represents the asymmetric parameter and $\delta(> 0)$ presents the power term parameter. The power parameter for both models in our study was fixed to 1. The focus of the study was on the conditional variance, rather than the conditional mean, therefore the attention was on the unpredictable part of the refugee's mobility.

In addition, this study applies the News Impact Curve which measures how new information is incorporated into volatility estimates (Engle & Ng, 1993). Accordingly, the News Impact Curve is a qualitative measure of visualizing the past return shocks to current volatility, thus emphasizing the inferred relationship between ε_{t-1} and h_t (Rakshit et al., 2023). The News Impact Curve plots the change in conditional variance versus the change or shock in past news. Precisely, the News Impact Curve uses the estimated specification of the GARCH equation to plot values of the conditional volatility h_t versus ε_{t-1}, while setting $\varepsilon_{t-s} = 0$ for $s > 1$ and keeping all lagged h_{t-v} for $v \geq 1$ constant at the unconditional variance (IHS, 2020). When calculating the News Impact

Curve, all available information up to the $t-1$ time period is considered constant, and by replacing all lagged conditional variances with the unconditional variance, then the News Impact Curve is a function of the shock only (Caporin & Costola, 2018; Rakshit et al., 2023). For a symmetric GARCH model, the News Impact Curve is symmetric with the line of symmetry $\varepsilon_{t-1} = 0$ and for any asymmetric model, either the curve is asymmetric or the equation of the line of symmetry is $\varepsilon_{t-1} \neq 0$ (Rakshit et al., 2023). Hence, in our case, the idea of a News Impact Curve characterizes the impact of past refugees' mobility shocks on the refugees' volatility implicit in a volatility GARCH model. The ability to forecast refugee mobility volatility was important too. Evidence of predictability has therefore led to different theoretical and empirical approaches. The most interesting of these approaches are "asymmetric" or "leverage" volatility models, in which good and bad news have different predictability of future volatility. Statistically, this effect occurs when an unexpected drop in something (bad news) increases predictable volatility more than an unexpected increase in something (good news) of similar magnitude.

4. Results

The estimated model was APARCH (1,1) to the first difference of log yearly refugees (DLOG(REFUGEES)) from 1990-2022 using backcast values for the initial variances, e.g., the smoothing parameter $\lambda = 0.7$. The dependent variable is the yearly total number of refugees. Stationarity of the basic time series is a prior assumption for GARCH modeling (Rakshit et al., 2023). The stationarity of the total number of refugees was tested using the Augmented Dickey-Fuller (ADF) test. This test determined the possibility of the presence of a unit root in the refugee series. After both refugees' series for LICs and MICs were stationary, no further differentiation was performed. The graph of the refugees' series (Figures 1-2) clearly shows volatility clustering. Jarque-Bera statistic was used to test the normality of the Refugees series. After proper transformation of the Refugees series, according to the Jarque-Bera statistics, the Refugees series is normal at a 99% confidence interval for LICs and MICs models, since probability was 0.5526 for the LICs model and 0.3257 for the MICs model, respectively, which is larger than the 0.01. (See Appendix: Residual Diagnostics/Histogram–Normality Test including descriptive statistics and a histogram of the standardized residuals for LICs and MICs model). Furthermore, it was tested if there any remaining ARCH effects in the residuals, using Heteroskedasticity ARCH LM Test with specifying the number of lags. The results of the ARCH LM test are presented in Table 1:

Table 1. Heteroskedasticity ARCH Test

Heteroskedasticity ARCH-Low income countries model	
F Statistics 2.1248	Prob. F(1,29) 0.1557
Observation*R-squared 2.1163	Prob. Chi-Square (1) 0.1457
Heteroskedasticity ARCH-Middle income countries model	
F Statistics 0.3382	Prob. F(1,29) 0.5654
Observation*R-squared 0.3573	Prob. Chi-Square (1) 0.5500

Source: Author's calculations.

Thus, from the results of Heteroskedasticity ARCH Test for both groups of countries, it was found that there is only small evidence of remaining ARCH effects.

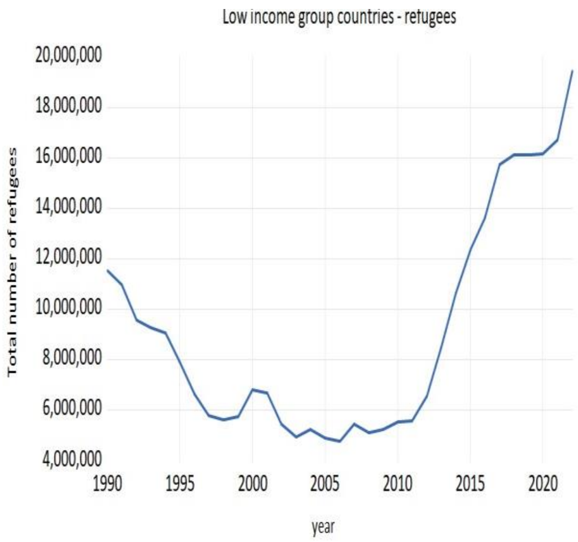

Figure 1. Total number of refugees in LICs

Source: Author's design.

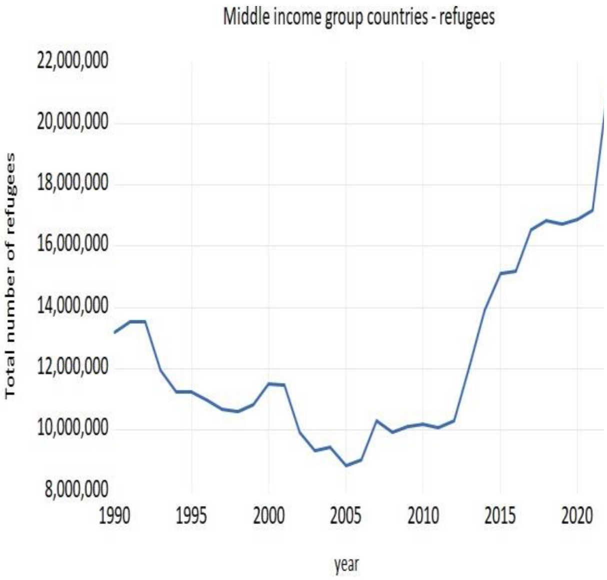

Figure 2. Total number of refugees in MICs

Source: Author's design.

The results for both groups of countries are presented in Table 2-3. The major output from PARCH estimation (Table 2-3) provides the standard output for the mean equation and for the variance equation, which comprises the coefficients, standard errors, z-statistics and p-values for the coefficients of the variance equation. The ARCH parameters are compatible with α and the GARCH parameters with β. The last part of the regression results in Table 2-3 represents the typical set of summary statistics using the residuals from the mean equation. Since there are no regressors in the mean equation, measures such as the R-squared are not meaningful, thus in our case R-squared is negative. In both models, the sum of the ARCH and GARCH coefficients ($\alpha + \beta$) is very close to 1, and it indicates that volatility shocks are statistically significant and quite persistent. This implies that volatility shocks have permanent effects on refugee's mobility.

Table 2. APARCH results — Low income countries model

Dependent variable: DLOG(REFUGEES)				
Method ML ARCH – Normal distribution				
Sample (adjusted): 1991-2022				
Included observations: 32 after adjustments				
Coefficients variance computed using outer product of gradients				
Presample variance: backcast (parameter=0.7)				
@SQRT(GARCH) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(-1) + C(5)*SQRT(GARCH(-1))				
Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	-0.0011	0.0220	-0.0487	0.9612
Variance equation				
C(2)	0.0301	0.0030	9.9104	0.0000
C(3)	-0.6279	0.0086	-72.562	0.0000
C(4)	0.0993	0.1823	0.5445	0.5861
C(5)	1.2550	0.0014	869.65	0.0000
R-squared	-0.0231	Mean dependend var		0.0163
Adjusted R-squared	-0.0231	S.D. dependent var		0.1158
S.E.of regression	0.1171	Akaike info criterion		-1.4710
Sum squared resid	0.4254	Schwarc criterion		-1.2420
Log likelohood	28.537	Hannan-Quinn criterion		-1.3951
Durbin-Watson stat	0.8010			

Source: Author's calculations.

Table 3. APARCH results — Middle income countries model

Dependent variable: DLOG(REFUGEES)				
Method ML ARCH – Normal distribution				
Sample (adjusted): 1991-2022				
Included observations: 32 after adjustments				
Coefficients variance computed using outer product of gradients				
Presample variance: backcast (parameter=0.7)				
@SQRT(GARCH) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(-1) + C(5)*SQRT(GARCH(-1))				
Variable	Coefficient	Std.Error	z-Statistic	Prob.
C	0.0112	0.0107	1.0479	0.2947
Variance equation				
C(2)	0.0105	0.0021	4.8991	0.0000
C(3)	-0.5714	0.0005	-1201.9	0.0000
C(4)	0.1810	0.1157	1.5643	0.1177
C(5)	1.2839	0.0003	3602.7	0.0000
R-squared	-0.0027	Mean dependend var		0.0150
Adjusted R-squared	-0.0027	S.D. dependent var		0.0749
S.E.of regression	0.0750	Akaike info criterion		-2.6204
Sum squared resid	0.1745	Schwarc criterion		-2.3914
Log likelohood	46.927	Hannan-Quinn criterion		-2.5445
Durbin-Watson stat	1.1475			

Source: Author's calculations.

Table 2-3 depicts that in both models, in the mean equation, the constant C is not significant at 1% as their probabilities are greater than 0.01. In the variance equation, all the coefficients of the terms (except the RESID (-1)), the constant C in the variance equation, (ABS(RESID(-1)) and @SQRT(GARCH(-1)) are statistically significant at 1% in the APARCH model since their probabilities are less than 0.01 which signifies that past volatility of refugees mobility is significant, influencing current volatility. The residuals from the refugee's data showed noticeably persistent volatility, a sign of a potential ARCH/GARCH effect.

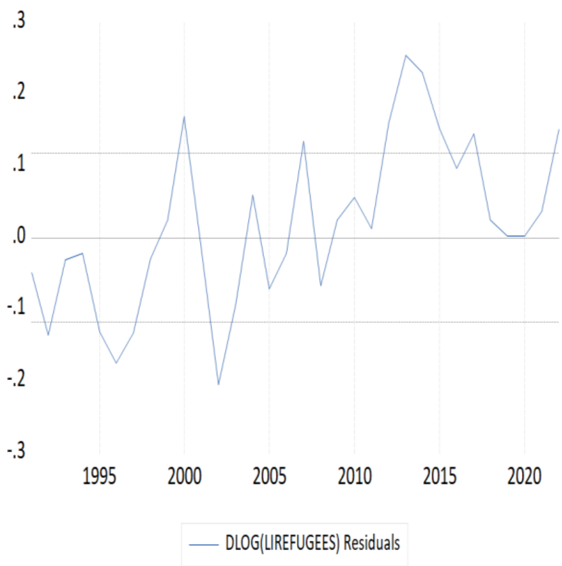

Figure 3. Residuals of LICs model

Source: Author's design.

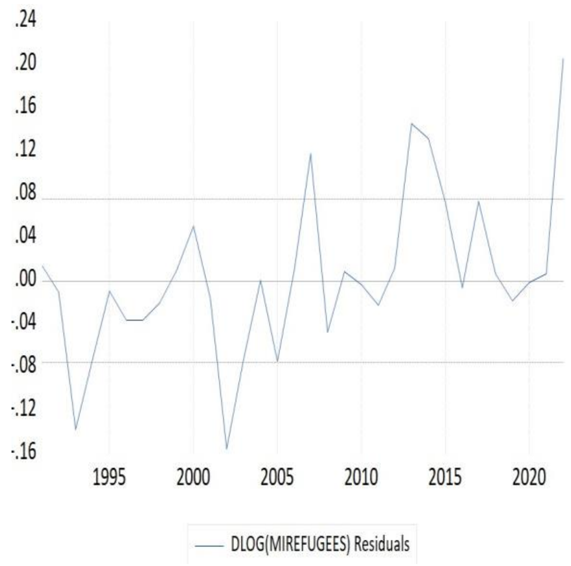

Figure 4. Residuals of MICs

Source: Author's design.

Figures 5-6 show News Impact Curves based on estimates coming from the Normal distribution. Thus, Figure 5-6 report the News Impact Curves for the APARCH model for LICs and MICs groups of countries. The News Impact Curves are plotted on the absolute values of ϵ_{t-1} to emphasize the asymmetry. The News Impact Curves reveal the impact of the positive (negative) shocks. The asymmetry is due to a greater effect of negative shocks on the increase of the variance concerning positive shocks. This asymmetry is slightly more pronounced in the LICs model than in the MICs. The News Impact Curve of both asymmetric volatility models (Figure 5-6) captures the leverage or asymmetric effect by allowing either the slope of the two sides of the news impact curve to differ or the center of the news impact curve to be located at a point where ε_{t-1} is negative. The GARCH News Impact Curve of both LICs and MICs models captures the asymmetry in the effect of news on volatility to refugee mobility because it has a steeper slope on its negative side than on its positive side.

The GARCH model is said to be symmetric because it does not take into account the signs of shocks and only considers the magnitude of the effects of shocks on volatility (Rakshit et al., 2023). Thus, it cannot capture volatility responses that may differ depending on whether positive and negative shocks are of the same magnitude. The volatility of any time series is said to be asymmetric when positive and negative shocks of the same magnitude affect it differently (Rakshit et al., 2023).

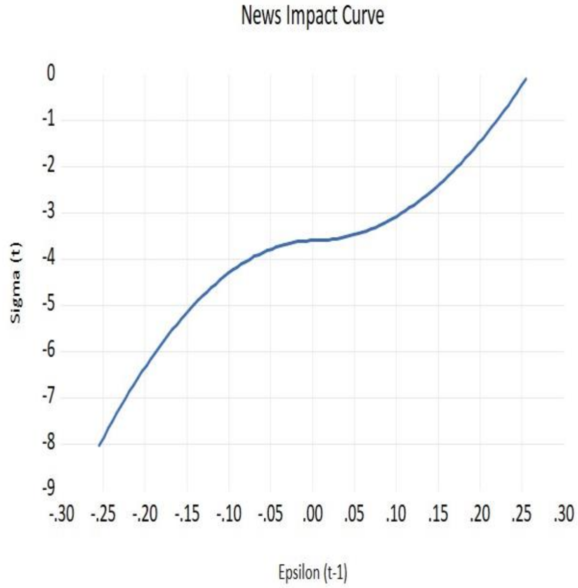

Figure 5. News impact curve of LICs model

Source: Author's design.

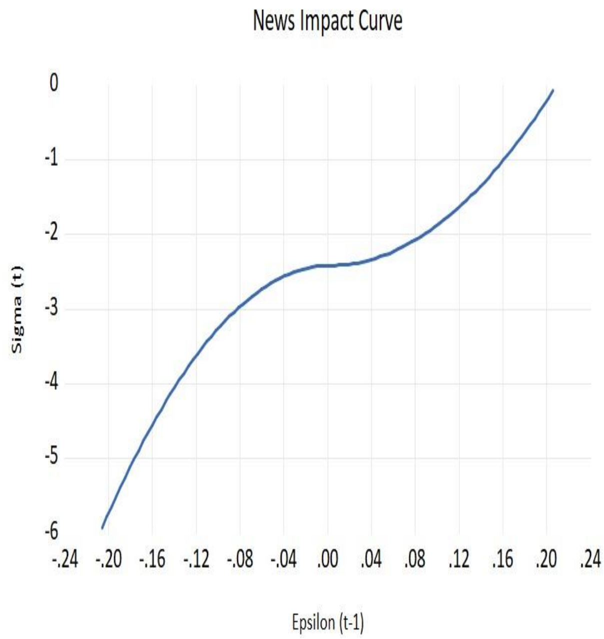

Figure 6. News impact curve of MICs model

Source: Author's design.

New diagnostic tests (News Impact Curve, Sign Bias Test, and Nyblom Stability Test) are presented to reveal the empirical relationships between news and volatility focusing on the asymmetric effect of news on volatility. Additionally, the new diagnostic tests were designed to determine whether the volatility estimates adequately represent the data.

The Sign Bias Test (Engle & Ng, 1993), (Table 4) provides a test for misspecification of the conditional variance model. The test regresses the squared residuals against dummy variables based on the sign of the prior residuals. If the GARCH model is specified correctly, the sign of the prior residuals should have no effect on the current squared residuals. The null hypothesis is that the regression parameters are zero. If the coefficient distributed with the Normal distribution turns out to be significant, this means that the positive or negative error terms, i.e. external shocks affect the variance differently to predict the response variable (Ali, 2013). Accordingly, on the other hand, if the coefficient is insignificant, it means that there is no bias due to the sign of the disturbances. In addition, when the positive or negative size bias test statistics, as well as the joint test statistics, are significant for a model it means that the model has some problem in capturing the impacts of news on volatility (Engle & Ng, 1993). The Sign Bias Test is proposed by Engle and Ng. The null hypothesis said that the positive and negative shocks have the same impacts on the volatility. The Sign Bias Test regresses a dummy for positive and negative sign bias on the squared residuals (Narayan & Narayan, 2009) and the results are calculated for both APARCH models; LICs and MICs (Table 4).

For the LICs model, the negative Sign Bias Test is significant at 5%, which means that there is an asymmetry in the second moments and positive and negative shocks have different effects. On the other hand, for the MICs model, none of the four tests rejects the null hypothesis. Therefore, it can be concluded that there is no asymmetry in the second moments and positive and negative shocks have the same effect. This means that the size of the shock is irrelevant.

Table 4. Engle-Ng Sign Bias Test results

Sign Bias Test results for Low income countries APARCH model		
Null Hypothesis: No leverage effects in standardized residuals		
	t-Statistic	Prob.
Sign-Bias	0.3005	0.7661
Negative-Bias	-0.4410	0.6627
Positive-Bias	2.0359	0.0517
Joint-Bias	4.7739	0.2145
Sign Bias Test results for Middle income countries APARCH model		
Null Hypothesis: No leverage effects in standardized residuals		
	t-Statistic	Prob.
Sign-Bias	-0.6327	0.5322
Negative-Bias	-0.2360	0.8152
Positive-Bias	1.4396	0.1615
Joint-Bias	5.0876	0.1915

Source: Author's calculations.

The Nyblom Stability Test (Table 5) is a test of parameter stability or structural change (IHS, 2020). The test generates individual statistics for each parameter in the mean equation as well as the variance equation and a joint test of the null hypothesis is that the parameters are constant over time. Nyblom test estimates the variance of the errors in the parameter (Ali, 2013). If the parameter is a constant, then the variance of the error term is zero. If the parameter is not a constant but related to the past values of the parameter, then the error term has variance (Ali, 2013; Narayan & Narayan, 2009).

In our hypothesis testing, the stability of the parameters is not rejected. The test results support the null hypothesis that the estimated parameters are stable, i.e. do not change over time.

Table 5. Nyblom Stability Test

Nyblom Stability Test results for Low income countries APARCH model				
Null Hypothesis: Parameters are stable				
Variable	Statistic	1% Crit.	5% Crit.	10 % Crit.
C	0.0738	0.748	0.470	0.353
C(2)	0.0730	0.748	0.470	0.353
C(3)	0.0708	0.748	0.470	0.353
C(4)	0.0732	0.748	0.470	0.353
C(5)	0.1461	0.748	0.470	0.353
Joint	1.6582	1.880	1.470	1.280
Nyblom Stability Test for Middle income countries APARCH model				
Null Hypothesis: Parameters are stable				

Variable	Statistic	1% Crit.	5% Crit.	10 % Crit.
C	0.0300	0.748	0.470	0.353
C(2)	0.0326	0.748	0.470	0.353
C(3)	0.0330	0.748	0.470	0.353
C(4)	0.0326	0.748	0.470	0.353
C(5)	0.1121	0.748	0.470	0.353
Joint	0.9557	1.880	1.470	1.280

Note: Critical values from Hansen 1990.

Source: Author's calculations.

If looking at the conditional variance for both models (Figure 7-8), it is slightly larger for the model of MICs, but for most of the sample, the GARCH-M effect is relatively large for both models (LICs and MICs). Oscillations in refugee mobility during the period 1990–2022 have been relatively high. It is not also surprising therefore that the conditional standard deviation of refugee's mobility in LICs and MICs in this period is also high (Figures 9-10). This high pattern of conditional deviation is apparent for the whole sample period.

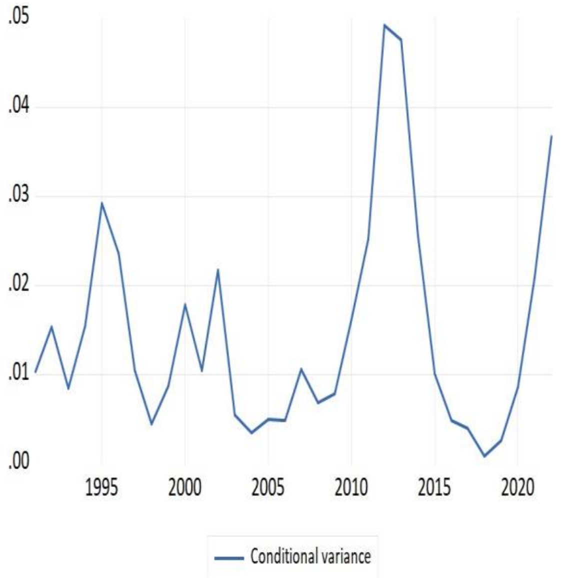

Figure 7. Conditional variance of LICs model

Source: Author's design.

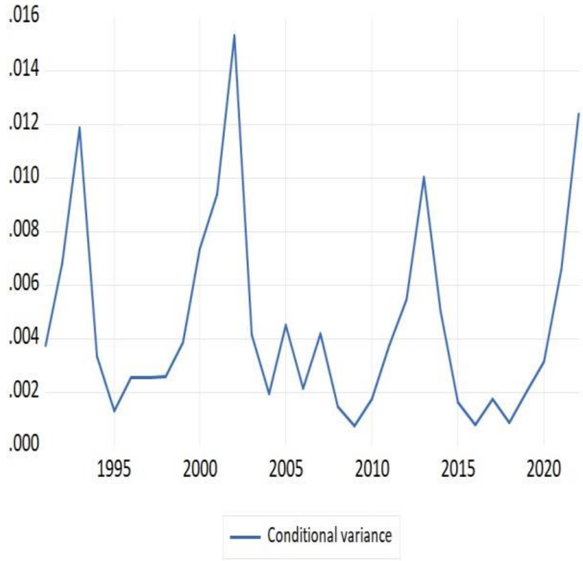

Figure 8. Conditional variance of MIC models

Source: Author's design.

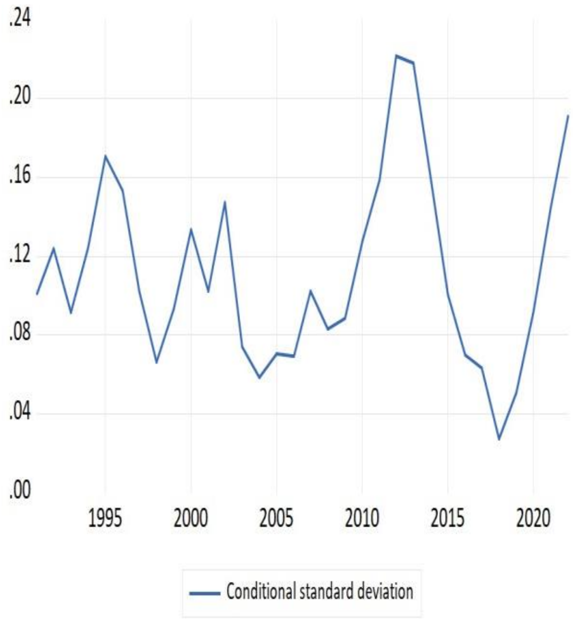

Figure 9. Conditional standard deviation of LICs model

Source: Author's design.

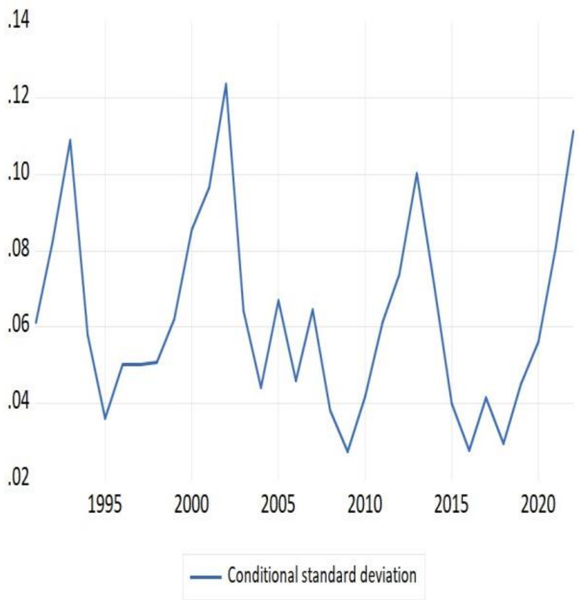

Figure 10. Conditional standard deviation of MICs model

Source: Author's design.

5. Discussion

The asymmetric volatility of the refugee's movement from LICs and MICs was studied in this paper. It was seen that the refugee series for both LICs and MICs reveal asymmetric volatility of their mobility. The key finding of this study is that GARCH-extension type models indicating past volatility of the annual number of refugees is significant, influencing current volatility. The APARCH model as a GARCH extension model successfully reveals the shape of the news impact curve which is a useful approach to modeling conditional heteroskedasticity. From their appropriate News Impact Curves, positive shocks of the same magnitude are considered to have less of an influence on volatility than negative shocks.

The results indicate that the GARCH extension models are the best at parsimoniously capturing the asymmetric effect. For both selected asymmetric variance models, the negative shocks were much more noticeable with degrees of greater influence on refugee's mobility oscillations than their positive shocks of the same magnitude. Both models for LICs and MICs found that negative shocks introduce more volatility than positive shocks; this effect is particularly evident for the largest shocks. The refugee's mobility volatility can be influenced by factors such as armed conflicts, civil war, economic crises, chaos in a country, extreme weather conditions (Qi & Bircan, 2023), etc. In addition, some of the asymmetric volatility of refugee mobility may be the result of political and economic instability (Gutmann, 2015). The findings showed that the degree of these types of influences is slightly greater in LICs than in MICs. The degree of asymmetry was much more visible due to the relatively lower prevalence or absence of positive shocks. These small differences between the news impact curves of the two models may have important implications for the decision of refugees to move. Therefore, this means that a significant difference in predicted volatility after the arrival of some major news leads to a significant difference in the current refugee movement in LICs and MICs. The APARCH class model shows that in the variance equation, the coefficients of the terms are significant for both LICs and MICs indicating that the risk volatility is significantly affected by the past squared residual terms and that the previous annual instability of the movement of refugees significantly affects the current instability accordingly.

Overall, as indicated before, the results for both groups of countries show a greater impact on the volatility of negative, rather than positive, return shocks. According to Caporin and Costola (2018); the leverage effect is a negative association between the shocks on returns and the following shocks on volatility. As a result, after a negative returns shock, it is expected volatility to refugee's mobility to increase while after a positive shock on returns, a decrease in the volatility to refugee's mobility should be observed. In other words, volatility tends to rise in response to bad news and fall in response to good news (Dritsaki, 2017; Caporin & Costola, 2018; Ali, 2013). A negative shock has a long-lasting impact, causing volatility to take a long time to return to pre-shock levels (Ali, 2013). If leverage coincides with a negative association between shocks and volatility, one would expect to observe that positive shocks lead to a decrease in volatility rather than an impact on the volatility of a magnitude smaller than that of negative shocks (Caporin & Costola, 2018). Understanding the effect of the "asymmetric" or "leverage" volatility models means that the good and bad news have different predictability of future volatility to refugee's mobility from LICs and MICs. This effect occurs when bad news, e.g., civil war, in LICs and MICs increases predictable volatility to refugee movement more than the good news of similar magnitude, e.g., direct humanitarian aid to host countries.

The interpretation of the coefficients of the News Impact Curve is important to specifically understand the impact of large shocks on the volatility of the refugee's mobility from LICs and MICs. This information can be used to undertake relevant arrangements to prevent high volatility in the future. A proper understanding of refugee's oscillations from LICs and MICs can be helpful for policymakers to act at the right time to minimize their movement out of their countries. Predicting the asymmetric volatility of refugee mobility can be considered in future research. Therefore, the effect of external and internal shocks separately on the asymmetric volatility of refugee mobility may be explored in future research scopes.

6. Conclusions

This research work provides a new approach to empirical research on refugee volatility. A lot of existing empirical studies have already focused on the standard detailed picture of refugee movements with an in-depth investigation of their main socio-economic and political determinants, as well as providing recommendations to policymakers. This study employs an original approach with the using of GARCH extension models and therefore holds great promise of a much more insightful and technically sophisticated study. Specifically using the GARCH extension — APARCH type of model and modeling the volatility of the refugee's mobility from low and middle-income countries when using only the annual data of the total number of refugees will have to be taken more seriously. Throughout this research work, the approach to this topic that simultaneously allows for contemporary and sophisticated analyses of different contexts and specific circumstances can provide a basis for deriving recommendations for policymakers and politics as well. This paper emphasizes the News Impact Curve as a standard measure of how news is incorporated into volatility estimates for the annual number of refugees. In this way, the study should make a valuable contribution to the work of policymakers in implementing sustainable and developmental responses to international forced displacement as well as to improve understanding of the international refugee movement and displacement.

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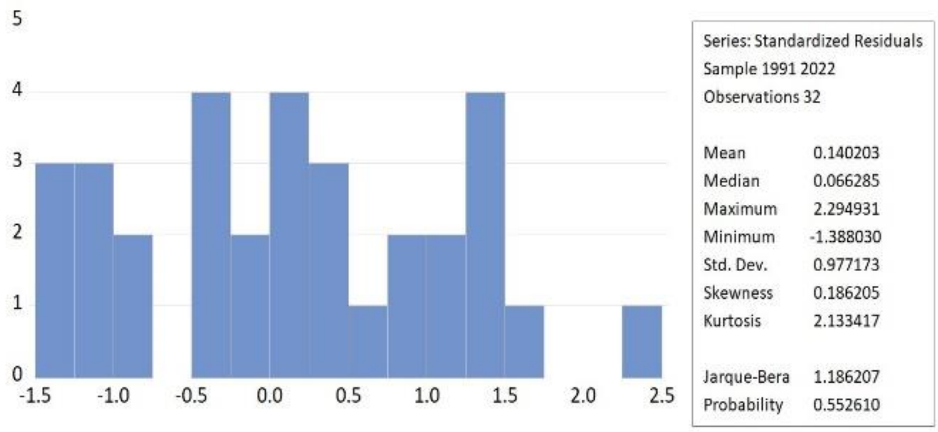
Appendix

A: Figure — Residual Diagnostics/Histogram–Normality Test displays descriptive statistics and a histogram of the standardized residuals for LICs model.



B: Figure — Residual Diagnostics/Histogram–Normality Test displays descriptive statistics and a histogram of the standardized residuals for MICs model.