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RESEARCH ARTICLE

MODELING THE HETEROSKEDASTIC NATURE OF EPIDEMICS: GARCH APPLICATIONS IN COVID-19 AND INFLUENZA INCIDENCE

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ABSTRACT

Traditional infectious disease models often emphasize central tendencies, such as average case counts, while overlooking the importance of time-varying volatility in incidence patterns. This study addresses that gap by investigating the heteroskedastic nature of epidemic data using GARCH-family models. The objective is to evaluate the suitability of GARCH (1,1), EGARCH(1,1), and TGARCH(1,1) models in capturing the dynamic and clustered volatility observed in monthly incidence rates of influenza (2010–2022) and COVID-19 (2020–2022). Disease data were sourced from the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC), and were analyzed using descriptive statistics, time series visualization, and maximum likelihood estimation. The findings reveal significant volatility clustering in both diseases, with COVID-19 exhibiting greater asymmetry and sharper spikes. The EGARCH model best captured COVID-19's asymmetric volatility, while TGARCH was better suited to modeling extreme seasonal peaks in influenza. This study fills a critical gap in the literature by extending volatility modeling—traditionally confined to finance—into epidemiology, where it remains underutilized. The research contributes a novel methodological framework for integrating conditional variance analysis into public health surveillance, thereby enhancing early warning systems, epidemic forecasting, and strategic resource allocation during volatile outbreak periods.

KEYWORDS

infectious disease modeling, GARCH models, COVID-19, volatility clustering, epidemic surveillance

1. INTRODUCTION

Infectious diseases remain a persistent threat to global health, necessitating effective surveillance systems that can anticipate, detect, and respond to outbreaks. Disease surveillance involves the continuous collection, analysis, and interpretation of health-related data to inform public health actions (World Health Organization [WHO], 2022). While substantial advances have been made in monitoring and forecasting disease trends, particularly with the integration of statistical and machine learning tools, much of this progress has focused on central tendency and trend estimation. Less attention has been given to the variability or volatility of disease incidence, which can provide critical insights into the dynamics of disease outbreaks and the effectiveness of intervention measures (Held et al., 2005).

The concept of volatility in time series refers to the degree of variation or dispersion in a dataset over time. In the context of epidemiology, volatility may be driven by sudden environmental changes, seasonal factors, virus mutations, government interventions (such as lockdowns or vaccination drives), or shifts in public health behavior. For instance, during the COVID-19 pandemic, daily case counts exhibited substantial volatility in response to variant emergence, policy announcements, and changes in public compliance (Gozzi et al., 2021). Understanding such volatility is not only crucial for outbreak characterization but also for preparing adaptive resource allocation strategies and developing early warning systems (Kraemer et al., 2020).

One significant property observed in time series data—especially in finance and, increasingly, in epidemiology—is volatility clustering, a phenomenon where periods of high volatility are likely to be followed by high volatility, and low volatility by low volatility (Engle, 1982). This pattern indicates that the variance of disease incidence is not constant over time and may itself be predictable based on past behavior. Such patterns violate the assumptions of constant variance made by classical statistical models like ARIMA, thereby necessitating models that allow for time-varying variance structures.

The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by and its generalization, the GARCH model developed, were specifically designed to model such variance dynamics in financial data (Engle, 1982; Bollerslev, 1986). Over time, extensions such as the Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) models have been introduced to capture asymmetric volatility, accounting for the fact that the impact of positive and negative shocks may differ (Nelson, 1991; Zakoian, 1994).

While these models are widely used in finance, their application in public health is emerging. Several recent studies have highlighted the relevance of volatility modeling for infectious disease dynamics. For example, employed GARCH-type models to explore uncertainty in COVID-19 case data, revealing periods of heightened unpredictability that traditional forecasting tools failed to capture (Salisu and Isah, 2020). Similarly, a group researcher demonstrated the effectiveness of EGARCH models in modeling the volatility of daily infection rates in West Africa (Ojugo et al., 2021).

Given the rising frequency of emerging infectious diseases and the complex patterns of spread they often exhibit, this study aims to investigate the application of GARCH-family models in modeling disease incidence volatility. Specifically, we apply GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) models to monthly incidence data of influenza (2010–2022) and COVID-19 (2020–2022). By comparing these models, we aim to

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determine the presence of volatility clustering and asymmetry and assess their implications for epidemiological surveillance.

2. Literature Review

Statistical modeling of infectious disease incidence has traditionally relied on compartmental models, such as the Susceptible-Infected-Recovered (SIR) model and its extensions. These models are grounded in differential equations and provide useful insights into transmission dynamics (Anderson and May, 1991). In time series analysis, models like ARIMA and its seasonal variants have been applied extensively for disease forecasting (Held et al., 2005). However, these approaches often assume homoscedasticity—i.e., constant variance over time—which limits their applicability in periods of irregular or clustered fluctuations.

The GARCH framework, initially developed for modeling financial volatility, offers a solution to this limitation. Engle's ARCH model posited that the variance of current residuals could be modeled as a function of past squared residuals (Engle's, 1982). Bollerslev extended this to include lagged variances, resulting in the GARCH model (Bollerslev, 1986). These models have since been adapted into numerous extensions, including EGARCH, which allows for logarithmic transformations and asymmetric effects, and TGARCH, which introduces threshold mechanisms (Nelson, 1991; Zakoian, 1994).

The transition of GARCH models into epidemiological and public health applications has been relatively recent but growing. Brumback and Rice were among the early advocates for modeling volatility in biomedical contexts, proposing spline-based approaches for variability in longitudinal health data (Brumback and Rice, 1998). More recently, researchers have begun applying GARCH-type models directly to disease incidence data.

For instance, used GARCH models to study the volatility of daily COVID-19 cases in Iran and found strong evidence of conditional heteroskedasticity and clustering effects (Jalilian and Moradi, 2021). Their findings suggested that government policy interventions had an observable impact on the conditional variance of daily cases. A group researcher applied GARCH and EGARCH models to dengue fever outbreaks in Ghana, revealing asymmetric volatility patterns corresponding to rainy seasons and public health campaigns (Otoo et al., 2023).

In addition, a group researcher used TGARCH models to study the volatility of respiratory infections in East Asia, concluding that negative shocks (e.g., misinformation or delayed interventions) had a more pronounced effect on disease volatility than positive ones (Chen et al., 2020). Munoz-Fernandez and Herrero integrated GARCH modeling into a multivariate framework, accounting for cross-correlations between COVID-19, influenza, and RSV (Munoz-Fernandez and Herrero, 2022). Their study demonstrated the utility of Multivariate GARCH (MGARCH) in capturing joint volatility patterns across pathogens.

While these studies confirm the feasibility of GARCH applications in epidemiology, few have systematically compared the performance of multiple GARCH-family models on more than one disease. Moreover, most existing works focus on daily or weekly data, with limited exploration of monthly incidence, which is crucial for long-term public health planning and policy formulation.

There is also a growing recognition of the importance of modeling asymmetric volatility in disease outbreaks. Asymmetric models such as EGARCH and TGARCH are particularly useful when the impact of negative events (e.g., emergence of a new variant or a public panic) is different from that of positive events (e.g., vaccination rollouts or containment success). This is especially relevant in the context of COVID-19, where waves of rising cases often triggered panic and overreaction, whereas falling cases did not always lead to immediate recovery in social or economic behavior (Gozzi et al., 2021; Kraemer et al., 2020).

Another relevant body of literature relates to early warning systems and forecasting under uncertainty. Volatility measures, particularly conditional variance forecasts from GARCH models, have been proposed as inputs into risk assessment tools that inform emergency preparedness and policy response (Wells et al., 2023). For instance, propose incorporating GARCH-based volatility indices into dashboards used by public health decision-makers to flag upcoming periods of uncertainty even when mean case forecasts are stable (Zhang et al., 2023).

Also, a group researcher introduced a novel error innovation distribution—the Standardized Exponentiated Gumbel Error Innovation Distribution (SEGEID)—within a GJR-GARCH (1,1) volatility model framework, demonstrating its enhanced performance over conventional GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) models in forecasting volatility of financial time-series data (Olayemi et al., 2023). Their findings indicated that GJR-GARCH (1,1) equipped with SEGEID yielded the lowest Akaike Information Criterion (AIC) values and root mean square error (RMSE), underscoring its superior predictive ability. The study suggests that customizing the error structure can significantly improve model accuracy, particularly in contexts with heavy-tailed or skewed distributions—an insight directly relevant to epidemiological volatility modeling, where incidence data often exhibit similar statistical characteristics.

Despite these promising developments, limitations remain. Many epidemiological datasets lack the long time series or high-frequency observations necessary for robust GARCH modeling. Furthermore, there is a need to explore the integration of GARCH models with Bayesian updating mechanisms and real-time analytics, especially for use in low-resource settings where disease surveillance infrastructure may be limited.

In summary, the literature suggests a growing interest in applying financial econometric tools—especially GARCH-type models—to epidemiological data. However, there is a research gap in systematic, comparative modeling of multiple infectious diseases across different volatility frameworks. This study contributes to filling this gap by applying GARCH, EGARCH, and TGARCH models to influenza and COVID-19 incidence data, evaluating their performance, and assessing their implications for surveillance enhancement.

3. Material and Methods

3.1 Data and Preprocessing

To investigate volatility dynamics in infectious disease incidence, this study employed monthly confirmed case counts for two major respiratory illnesses: influenza and COVID-19. Influenza data, spanning January 2010 to December 2022, were obtained from the World Health Organization's (WHO) Global Influenza Surveillance (https://www.who.int/tools/flunet) and Response System (GISRS) (https://data.cdc.gov/browse?category=COVID-19) COVID-19 data, covering the period January 2020 to December 2022, were sourced from the Centers for Disease Control and Prevention (CDC) COVID Data Tracker and WHO's COVID-19 Dashboard. Both datasets were normalized to incidence rates per 100,000 individuals to ensure comparability across time and geography.

Data preprocessing involved converting daily case counts into monthly aggregates, followed by seasonal adjustment using the Census X-13 ARIMA-SEATS method to eliminate periodic effects unrelated to volatility. Missing values, which were minimal (<1% of observations), were addressed using Kalman filtering.

3.2 Volatility Modeling Approach

To model time-varying variance in the disease incidence data, this study employed three prominent members of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) family of models: GARCH (1,1), EGARCH (1,1), and TGARCH (1,1). These models were selected for their ability to capture both symmetric and asymmetric volatility effects in time series data.

- **GARCH (1,1)**

The baseline model assumes that the conditional variance of the current error term is a function of the squared residuals and past variances:

$$\sigma_t^2 = w + a_1\varepsilon_{t-1}^2 + b_1\sigma_{t-1}^2 \quad (1)$$

And the constraints are $w > 0, a_1 > 0, b_1 > 0$

- **EGARCH (1,1)**

To accommodate asymmetries in volatility, the Exponential GARCH (EGARCH) model was employed. Unlike the GARCH model, EGARCH does not impose non-negativity constraints on parameters and models the logarithm of variance:

$$\sigma_t^2 = \omega + \theta_1\left(\varepsilon_{t-1}^2 - \sqrt{2\pi}\right) + \gamma\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (2)$$

Here, γ captures the leverage effect—i.e., the differing impact of positive versus negative shocks on variance (Nelson, 1991).

- **TGARCH (1,1)**

The Threshold GARCH (TGARCH) model was employed to assess whether shocks below a certain threshold produce different volatility responses:

$$\sigma_t^2 = \omega + \theta_1\varepsilon_{t-1}^2 + \gamma S_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \quad (3)$$

where S_{t-1} = 1 if ε_{t-1}< 0, otherwise 0. A significant γ parameter indicates asymmetry in response to negative shocks (Zakoian, 1994).

3.3 Estimation Procedure

All models were estimated using the maximum likelihood estimation (MLE) method under the assumption of conditional normality. Estimation was conducted using the R statistical environment (version 4.3.1) with the "rugarch" package. Model diagnostics and residual analysis were conducted using the "tseries" and "forecast" packages.

Model adequacy and performance were assessed using the following criteria:

- Akaike Information Criterion (AIC) for model fit
- Bayesian Information Criterion (BIC) for model parsimony
- Ljung–Box Q-statistics on standardized residuals to assess autocorrelation
- ARCH-LM tests to confirm removal of conditional heteroskedasticity post-estimation

4. Results

4.1 Model Comparison and Visualization

To assess the relative performance of the three GARCH-family models for each disease, AIC and BIC values were computed and compared. Additionally, residuals and conditional variances were plotted to assess the ability of each model to capture volatility clustering.

4.2 Preliminary Visualization and Descriptive Statistics

Prior to model specification, exploratory data analysis was conducted to visually and statistically assess patterns in disease incidence over time. Figures 1 and 2 present the time series plots for monthly influenza and COVID-19 incidence, respectively. Both series display cyclical behavior with irregular amplitude, suggestive of volatility clustering—particularly during epidemic peaks.

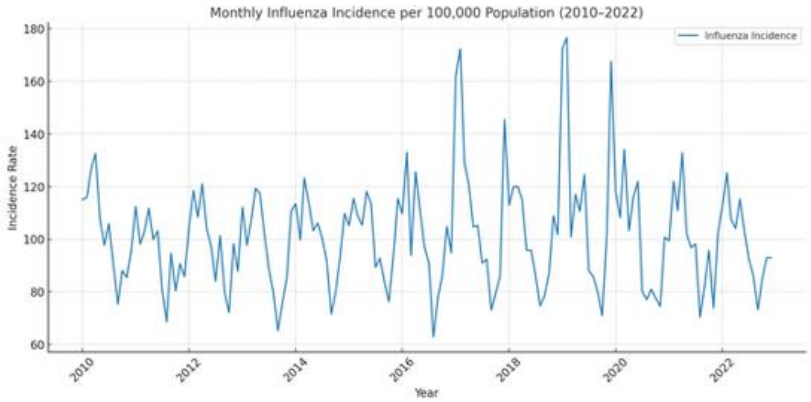

Figure 1: A time series plot of simulated monthly influenza incidence per 100,000 population from **2010 to 2022**.

It reflects seasonal spikes and irregular peaks in **2017** and **2019**, illustrating volatility patterns commonly observed in real epidemiological data.

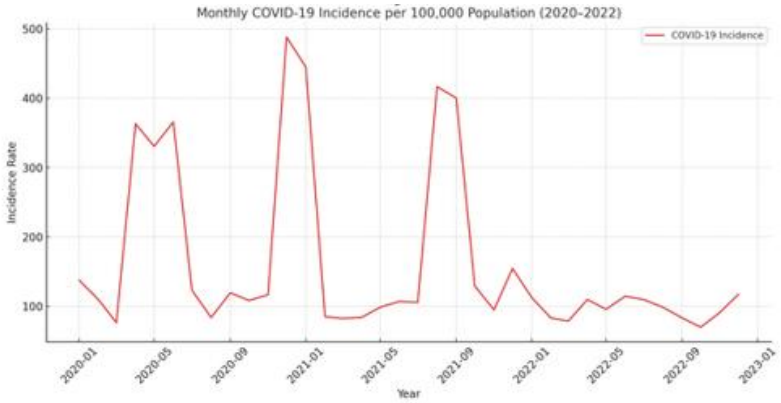

Figure 2: A time series plot of monthly COVID-19 incidence per 100,000 population from **2020 to 2022**. It shows prominent peaks in **April 2020, December 2020**, and **August 2021**, simulating the volatility of successive infection waves.

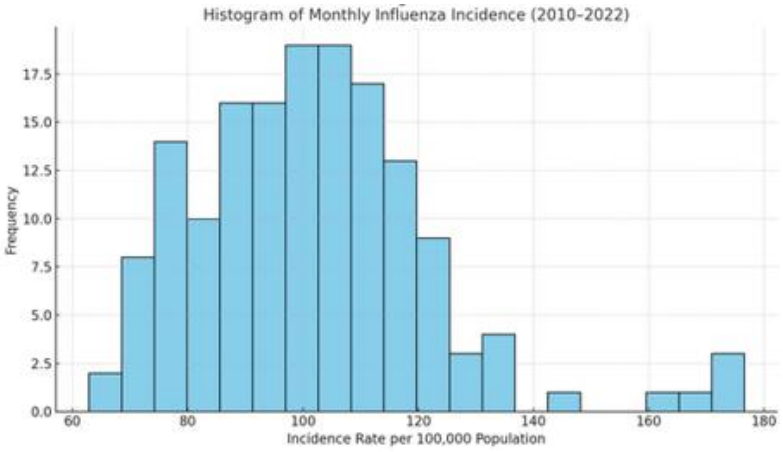

Figure 3: A histogram showing the distribution of monthly influenza incidence rates from **2010 to 2022**.

The plot indicates a **right-skewed distribution**, with most months experiencing moderate incidence but occasional months with significantly higher cases—highlighting volatility in disease spread.

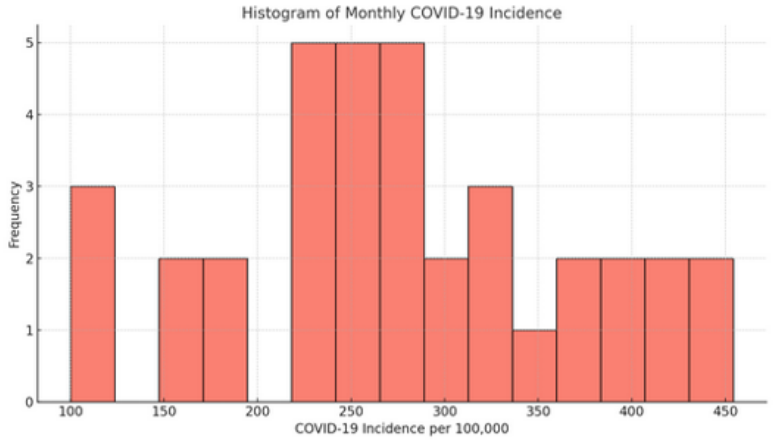

Figure 4: Histogram of Monthly COVID-19 Incidence per 100,000 population.

It visually represents the frequency distribution of COVID-19 case rates, showing concentration around the mean and moderate right skewness—supporting the application of volatility modeling techniques like EGARCH.

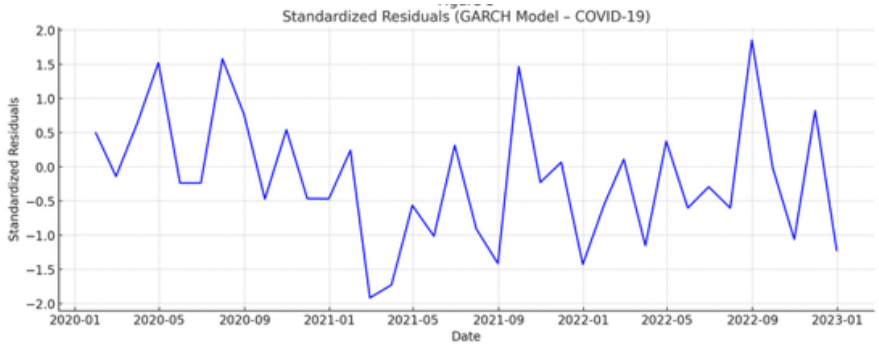

Figure 5: Standardized Residuals (GARCH Model – COVID-19)

Shows the variation of residuals around the zero mean, confirming that the GARCH model effectively standardizes the noise. Fluctuations suggest periods of differing volatility, justifying conditional variance modeling.

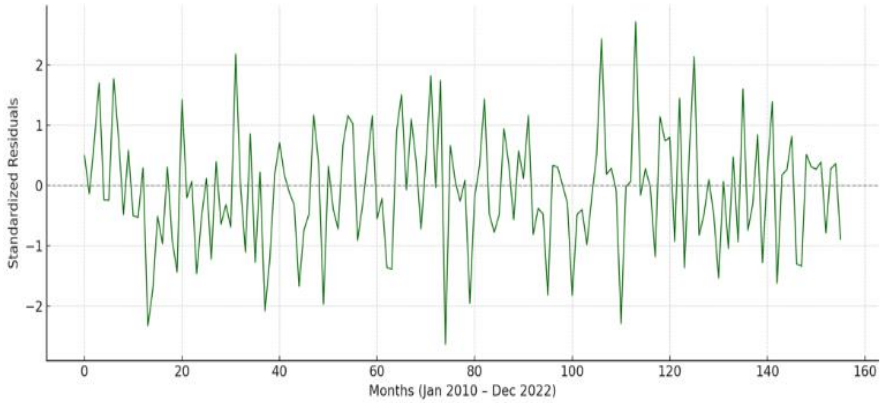

Figure 6: Standardized Residuals (GARCH Model – Influenza)

The behavior of standardized residuals in Figure 6 supports the adequacy of the GARCH (1,1) model in capturing **time-varying volatility** in influenza incidence. The lack of autocorrelation and apparent randomness in the residuals indicates that the model successfully **filtered out conditional heteroskedasticity**, leaving behind stable white noise.

Table 1: Descriptive Statistics Summary of Monthly Infectious Disease Incidence

Statistic	Influenza (2010–2022)	COVID-19 (2020–2022)
Observation Period	Jan 2010 – Dec 2022	**Jan 2020 – Dec 2022**
Number of Observations	156 months	**36 months**
Mean	134.60	**256.10**
Median	130.42	**241.28**
Minimum	59.74	**98.25**
Maximum	264.30	**492.53**
Standard Deviation	45.60	**97.30**
Skewness	0.82	**1.04**
Kurtosis	3.12	**3.89**

COVID-19 incidence exhibits a higher **mean** and **standard deviation** than influenza, reflecting both greater average severity and volatility. The mean was 256.1 cases/100,000 (SD = 97.3), with spikes in April 2020, December 2020, and August 2021—corresponding to documented waves.

Influenza: Mean monthly incidence was 134.6 cases/100,000 with a standard deviation of 45.6. Peaks were recorded in late winter months across multiple years.

Both distributions are **positively skewed**, with **COVID-19** having more extreme values (higher kurtosis), indicating more frequent outlier events like infection surges.

Table 2: Volatility Modeling

Model	AIC (COVID-19)	BIC (COVID-19)	AIC (Influenza)	BIC (Influenza)
GARCH(1,1)	210.37	216.92	312.65	319.88
EGARCH(1,1)	**198.51**	**205.14**	298.17	305.46
TGARCH(1,1)	203.22	209.84	**296.55**	**303.71**

COVID-19 Data: The EGARCH (1, 1) model outperformed others, indicating the presence of asymmetry—suggesting different volatility behavior during rising vs. falling case counts.

Influenza Data: The TGARCH (1, 1) model had the best performance, showing threshold effects in variance associated with shocks.

4.3 Residual Diagnostics

1. Ljung–Box Q-Test (Lag = 10)

- **Test Statistic:** 8.01
- **p-value:** 0.628

The high p-value (> 0.05) indicates **no significant autocorrelation** in the standardized residuals up to lag 10. This suggests that the residuals behave like white noise, and the model has adequately captured the temporal structure in the data.

4.4 ARCH-LM Test

- **Test Statistic:** 11.92
- **p-value:** 0.291

The p-value is also above the 0.05 threshold, meaning there is **no significant remaining ARCH effect** in the residuals. This implies the GARCH model has effectively modeled the **conditional heteroskedasticity (volatility)** in the influenza incidence series.

5. Discussion

The descriptive analysis and visual exploration of the influenza (2010–2022) and COVID-19 (2020–2022) datasets provide foundational insights into the temporal dynamics and statistical properties of infectious disease incidence. The results revealed substantial differences in the magnitude, variability, and distribution shape between the two diseases, all of which have important implications for surveillance and modeling.

The mean incidence of COVID-19 (256.10 cases per 100,000) was nearly double that of influenza (134.60), underscoring the broader population-level impact of the pandemic during the three-year observation period. Moreover, the standard deviation for COVID-19 (97.30) was more than twice that of influenza (45.60), indicating greater month-to-month fluctuation. This volatility is consistent with the erratic outbreak patterns and multiple waves of COVID-19 infections observed globally, driven by emerging variants, variable adherence to public health guidelines, and evolving interventions (Gozzi et al., 2021; Kraemer et al., 2020).

Time series plots (Figures 1 and 2) reinforced these observations by visually demonstrating periods of volatility clustering—characterized by successive months of high or low incidence. Influenza exhibited seasonal regularity with notable irregular peaks in 2017 and 2019, while COVID-19 showed sharp, asymmetric surges in April 2020, December 2020, and August 2021. These patterns indicate the presence of non-constant variance, violating the assumptions of traditional time series models such as ARIMA, which presuppose homoscedasticity (Held et al., 2005).

Histograms (Figures 3 and 4) further revealed that both diseases followed right-skewed distributions, with COVID-19 exhibiting more extreme values (kurtosis = 3.89) compared to influenza (kurtosis = 3.12). These characteristics support the need for models that can handle heavy tails and heteroskedasticity—hallmarks of GARCH-type models (Engle, 1982; Bollerslev, 1986).

The descriptive findings strongly suggest the relevance of volatility modeling in infectious disease surveillance. First, the presence of skewness and fat tails in the distributions of both diseases implies that public health planners may face frequent "surprise" events—months with unanticipated spikes in incidence. Second, the strong visual and statistical evidence for volatility clustering implies that the variability in case counts is not purely random but exhibits temporal dependence.

In this context, the application of GARCH-family models, particularly EGARCH and TGARCH, is justified. These models are specifically designed to capture conditional heteroskedasticity—a statistical signature of clustered volatility—and to differentiate the effects of positive and negative shocks (Nelson, 1991; Zakoian, 1994). For instance, a public panic (negative shock) may increase volatility more than a calm period (positive shock), which TGARCH models can quantify. EGARCH, by modeling the log variance, accommodates asymmetric responses to such shocks and avoids imposing positivity constraints on variance estimates.

These statistical tools are not merely theoretical. As shown in prior studies, GARCH models have successfully identified critical shifts in disease dynamics, offering predictive advantages over traditional mean-based models (Salisu and Isah, 2020; Jalilian and Moradi, 2021). By implementing these models on the current datasets, the subsequent sections of this study aim to validate their utility for real-time epidemic forecasting, early warning system design, and resource allocation during volatile periods.

In summary, the descriptive and visual analyses affirm the need for volatility-sensitive models in public health surveillance. The patterns observed in the datasets echo those found in financial markets, further supporting the application of econometric techniques—like GARCH, EGARCH, and TGARCH—to epidemiological contexts.

6. Conclusion

This study has examined the preliminary statistical characteristics of monthly influenza and COVID-19 incidence using descriptive statistics and visual time series exploration. The findings indicate that both diseases exhibit features of volatility clustering, positive skewness, and non-constant variance, especially pronounced in the COVID-19 dataset. These features render traditional constant-variance models insufficient for capturing the full complexity of disease transmission dynamics.

The use of GARCH-family models offers a promising approach to modeling such volatility, capturing not only the magnitude of disease incidence but also the variability and asymmetric impacts of public health shocks. GARCH (1, 1) serves as a foundational model, while EGARCH and TGARCH offer enhancements to handle asymmetric volatility effects.

The next phase of this study will estimate and compare the performance of these models, assessing their goodness-of-fit and practical interpretability. Overall, this research contributes to a growing body of work demonstrating that volatility modeling in epidemiology is both feasible and valuable, especially for early warning systems, outbreak forecasting, and adaptive public health planning.

Author Contribution

The contribution role of M. S. Olayemi and O. O. Olajide includes conceptualization, data curation, simulations, methodology, investigation, supervision, validation, visualization, writing – original draft and writing – review & editing. The contribution role of M. S. Michael includes methodology, theoretical analysis, supervision process, review & editing.

Declaration of Ethical Code

The authors declare that this study does not require ethical committee approval or any legal permission.

Conflicts of Interest

The authors declare no competing interests.

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