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Predictive Modelling of Health Expenditure in Italy: Using GARCH Techniques

Dr. Shyam Charan Barma

Head (Assistant Professor), Department of Economics, Kalipada Ghosh Tarai Mahavidyalaya (Under University of North Bengal, W.B, India)

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ABSTRACT

This study analyses Italy's monthly data about health expenditure from January 2012 to October 2022, sourced from International Financial Statistics (IMF). Augmented Dickey-Fuller (ADF) tests confirm the series is non-stationary at levels, exhibiting random walk behaviour, but achieves stationarity after first differencing, indicating integration of order one [Et ~ I(1)]. Regression analysis reveals a significant 12-month lagged effect, where a 1% increase in prior health expenditure growth raises the current growth rate by 0.19%, reflecting annual seasonality (e.g., fiscal budgets, winter health costs). The constant term indicates a robust 4.26% monthly growth rate, driven by Italy's aging population, rising medical costs, and universal healthcare system (SSN), consistent with 8–9% of GDP spending. ARIMA forecasting shows a 0.284% increase in current growth per 1% prior growth, while GARCH(1,1) modelling indicates a marginally significant 0.169% effect from 5-month lagged growth and persistent volatility from shocks like COVID-19. The small value of R^2 and insignificant F-stat. value suggested unmodeled factors (e.g., GDP, inflation) drive variability. The 2012–2022 period, marked by economic recovery and the pandemic, underscores volatility, necessitating refined models and flexible budgeting for Italy's healthcare system.

Keywords: Stationarity, ADF Test, ACF, PACF, Angel-Granger Cointegration, ARIMA, ARCH, GARCH. JEL Classification: H51, H52, H53, H75, I15, I150, I180

INTRODUCTION:

The healthcare system in Italy is renowned for its universal coverage and high-quality services. Over the period from 1980 to 2022, Italy's health expenditure and the development of healthcare facilities have undergone significant transformations influenced by economic, demographic, and policy changes. This essay examines the evolution of health expenditure and facilities in Italy, focusing on key trends, challenges, and policy responses during this period. The 1980s marked a period of consolidation for Italy's National Health Service (Servizio Sanitario Nazionale, SSN), established in 1978. Health expenditure during this decade grew steadily as the government aimed to ensure universal access to healthcare services. Public health spending increased as a percentage of GDP, reflecting the government's commitment to building a robust healthcare infrastructure. However, the system faced challenges such as regional disparities in service quality and efficiency.In the 1990s, Italy implemented several reforms aimed at enhancing the efficiency and effectiveness of the SSN. The most significant reform was the 1992 legislation, which decentralized healthcare administration to regional governments. This shift aimed to address regional disparities and promote more efficient allocation of resources. Despite these efforts, the decade also saw growing concerns about rising healthcare costs, driven by an aging population and increasing demand for healthcare services.The early 2000s were characterized by efforts to contain healthcare costs while improving service quality. The introduction of the National Health Plan in 2001 set priorities for the healthcare system, including reducing hospital beds, promoting primary care, and improving preventive services. Health expenditure continued to rise, but at a slower pace, due to cost-containment measures such as budget caps for regional health authorities and the promotion of generic drugs. Despite these measures, regional disparities in health expenditure and service quality persisted.The global financial crisis of 2008 had a significant impact on Italy's economy, leading to austerity measures that affected healthcare funding. Between 2010 and 2015, public health expenditure as a percentage of GDP decreased, prompting concerns about the sustainability of the SSN. Austerity measures included cuts to healthcare budgets, reductions in hospital beds, and increased co-payments for services. These measures led to increased pressure on healthcare facilities and staff, as well as longer waiting times for patients.The COVID-19 pandemic, which began in 2020, posed unprecedented challenges to Italy's healthcare system. The initial outbreak in Lombardy exposed weaknesses in the system, including insufficient ICU capacity and inadequate protective equipment for healthcare workers. In response, the government increased health expenditure significantly to strengthen the healthcare infrastructure, enhance testing and tracing capabilities, and support the rollout of vaccination programs. The pandemic underscored the need for a resilient healthcare system capable of responding to public health emergencies.

Development of Healthcare Facilities

From the 1980s to the 1990s, Italy invested heavily in expanding and modernizing healthcare facilities. New hospitals were built, and existing ones were upgraded to improve service delivery. The decentralization of healthcare administration in the 1990s aimed to enhance regional healthcare infrastructure and address disparities in access and quality of care. However, this period also highlighted the challenges of coordinating healthcare services across regions with varying levels of resources and expertise. The 2000s saw significant technological advancements in healthcare facilities. Investments in medical technology, such as MRI machines, CT scanners, and minimally invasive surgical equipment, improved diagnostic and treatment capabilities. Specialized healthcare centres were established to provide advanced care for complex conditions. Despite these advancements, the uneven distribution of facilities and resources across regions remained a challenge. During the 2010s, Italy faced the dual challenges of an aging population and budget constraints. To address these challenges, the healthcare system increasingly focused on primary care and community-based services. Initiatives such as the Casa della Salute (Health House) model aimed to integrate primary care, specialist services, and social care under one roof, enhancing coordination and access to care. Telemedicine and digital health technologies also gained traction, offering new ways to deliver healthcare services more efficiently. The Covid-19 pandemic highlighted the critical importance of resilient healthcare facilities. Italy's healthcare system faced immense pressure, particularly in the early months of the pandemic. The government responded by rapidly increasing ICU capacity, converting non-healthcare facilities into temporary hospitals, and mobilizing additional healthcare workers. Investments in telemedicine and digital health solutions accelerated, enabling remote consultations and monitoring to reduce the burden on hospitals. The pandemic underscored the need for flexible and adaptable healthcare facilities capable of responding to emergencies.

REVIEW OF LITERATURE:

John Bryant, Audrey Teasdale, Martin Tobias, Jit Cheung and Mhairi McHugh (2004) they explained through the simulation model assesses population ageing's impact on New Zealand's government health expenditures (acute and long-term care) from 1951 to 2051. Ageing, including disability and proximity to death, increases the elderly's expenditure share from 29% to 63%. However, non-demographic factors (e.g., treatment expansion, wage increases) drive most expenditure growth. Restraining expenditure to 6-12% of GDP requires significantly lower non-demographic growth rates.

Paraskevi Klazoglou and Nikolaos Dritsakis (2018) they developed an ARIMA (0,1,1) model using the Box–Jenkins method to forecast US health expenditure from 1970 to 2015. The model minimizes the difference between predicted and observed values, employing static one-step ahead forecasting for accurate projections. It effectively captures structural trends and innovations, providing a robust tool for predicting health expenditure dynamics.

Ulf-G. Gerdtham, Bengt Jönsson (2000) they suggested the comparative analyses of aggregate health expenditure across countries, highlighting the role of institutional regimes and explanatory variables. The regression analyses using cross-section and panel data identify aggregate income as the primary driver, with income elasticity often exceeding unity, suggesting healthcare as a luxury good. Primary care gatekeepers and capitation systems reduce expenditure compared to fee-for-service. Future research needs stronger macroeconomic theory and updated, unified empirical studies.

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Section: I

Test of Stationary of health expenditure through Correlogram Study:

The nature of stationarity and integrability of health expenditure have been enquired into through the study of their respective correlograms. The Figure 1 present correlograms of health expenditure at level and at first difference respectively. Again Figure 2 present the correlograms of the health expenditure series at level and at first difference respectively.

Figure:1 Correlogram of Health Expenditure at Level Data

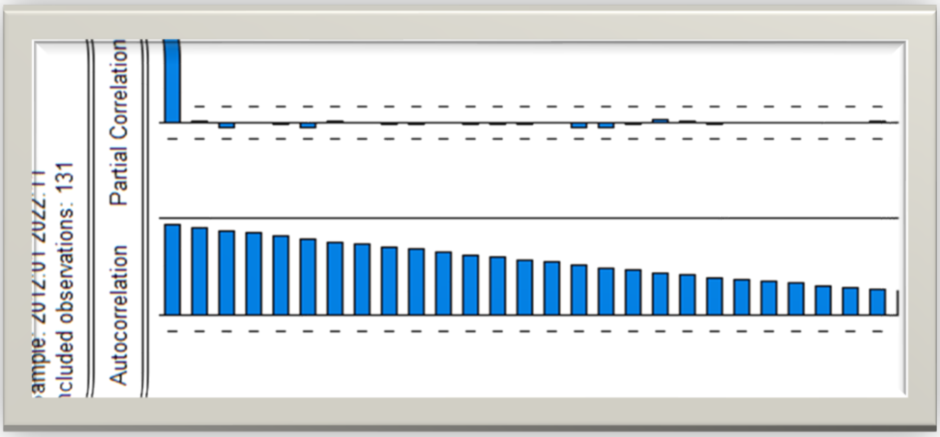

Figure:2 Correlogram of Health Expenditure at 1st Difference Data

Findings from The Figures 1 And 2

(A) It is observed from the correlogram of health expenditure given by the Figure 1 that

- the *ACF* of health expenditure displays a long ladder-like dying out pattern of solid spikes as the lag length increases.
- the *PACF* contains only one significant spike (even at 1% level) at lag one and all other lags contain very insignificant spikes.

All these features of the correlogram confirm the *non-stationarity* of the health expenditure series at level.

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(B) The integrability of health expenditure series is being enquired into through the examination of the correlogram of health expenditure series at first difference as given by the Figure 2.

It is observed from the Figure 2 that for the first differenced filtered series of health expenditure.

- the *ACF* is marked by the absence of any dying out pattern of spikes.
- no singularly significant large spike appears at the first lag of the corresponding *PACF*.

These features of the correlogram, as given in the Figure 2, confirm that the first differenced series of health expenditure is stationary. Consequently, health expenditure series is I (1).

Augmented Dickey Fuller Unit Root Test

In order to test for the existence of unit roots, and to determine the degree of differencing necessary to induce stationarity, the *Augmented Dickey-Fuller test* is used.

The results of the *Augmented Dickey-Fuller test* (ADF) determine the form in which the data should be applied in any econometric analyses. The test is based on the following equations:

$$\Delta e_t = \alpha_1 + \gamma_1 e_{t-1} + \delta_{1t} \sum_{i=1}^{k} \Delta e_{t-1} + \varepsilon_{1t} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where $\Delta e_t = (e_t - e_{t-1})$ $\qquad \varepsilon_{1t} \sim iidN(0, \sigma_{\varepsilon t}^2)$

Table:1

Results of the Augmented Dickey Fuller (Unit Root Test)

(Automatic based on SIC, MAXLAG=12) [Sample:- 2012:I -2022:XI]

Country	Variable	ADF Test Stat.	Prob* Value	Mackinnon Critical Value			Remarks
				1%	5%	10%	
Italy	E_t	2.189	0.999	-3.481	-2.884	-2.579	Non-Stationary
	$\boldsymbol{\Delta E_t}$	-11.309	**0.000**	-3.481	-2.884	-2.579	**Stationary**

Where E_t stands for Health Expenditure at level and ΔE_t stands for Health Expenditure at 1st difference.

Review of the Findings:

The findings in our study through ADF Unit Root Tests and through the examinations of relevant correlograms of the variables confirm that over the period 2012: I - 2022: XI.

- health expenditure series is non-stationary at level and therefore, exhibit random walk processes.
- The health expenditure series attain stationarity upon filtering through first differencing Consequently, the series is integrated of order one i.e, $E_t \sim I(1)$.

ARIMA Model:

ARIMA is a popular time series forecasting method that combines three components:

1. Autoregressive (AR)

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2. Integrated (I)
3. Moving Average (MA)

ARIMA models are denoted as ARIMA (p, d, q) where we consider

I. p is the number of lag observations included in the model (AR part).
II. d is the number of times that the raw observations are differenced (I part).
III. q is the size of the moving average window (MA part).

Now AR(p) model is

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots \dots \dots \dots . \dots \alpha_p y_{t-p} + \varepsilon_t \dots\dots\dots\dots\dots\dots (2)$$

I(d)differencing:

$$y_t^{'} = y_t - y_{t-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

(Repeated d times if d>1)

MA(q) Model:

$$y_t = \epsilon_t + \theta_t \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots \dots \dots \dots \dots . . + \theta_q \epsilon_{t-q} \dots\dots\dots\dots\dots\dots (4)$$

So the ARIMA(p, d, q)model can be written as

$$y_t^{'} = \emptyset_1 y_{t-1}^{'} + \emptyset_2 y_{t-2}^{'} + \cdots \dots \dots \dots . + \emptyset_p y_{t-p}^{'} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots \dots \dots . \theta_q \epsilon_{t-q} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

Where $y_t^{'}$ is differenced series.

Section: II

Estimated model: AR(12) structure of health expenditure is

$$\Delta E_t = \alpha_1 + \alpha_2 \Delta E_{t-12} + \varepsilon_t \dots\dots\dots\dots\dots (6)$$

Estimated model of the equation (6)

$$\Delta \boldsymbol{E}_t \;=\; \alpha_1 \;+\; \beta_t \Delta \boldsymbol{E}_{t-12} \dots\dots\dots\dots\dots\dots\dots\dots (7)$$

Coefficient	0.033	0.191
t- Stat.	**4.011**	**2.331**
S.E.	0.008	0.082
Prob.	0.000	0.021

R^2 = 0.045 Adj R^2 = 0.036 AIC = -2.094

SIC = -2.048 S. E of Regression = 0 .084 F- stat. = 5.436

Prob(F- stat.) = 0.021 SSR = 0.822 D .W. stat. = 1.918

Findings from the AR (12) model: This variable represents the health expenditure from 12 months prior. The positive coefficient indicates a significant positive relationship between health expenditure in the current period and that from twelve month ago. A 1-unit increase in health expenditure from the twelve-month results in a 0.191

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unit increase in the current period. The value of R^2 indicates that approximately 4.48% of the variance in health expenditure is explained by the model. Similarly, the Adj. R^2 value indicates that the number of predictors in the model, suggesting a slightly lower explanatory power. When we consider the degrees of freedoms of regression implies that the standard error of the regression, indicating the average distance that the observed values fall from the regression line. The SSR indicates that the Measure of the discrepancy between the data and the estimation model. The values of Log Likelihood suggested that a higher value indicates a better fit of the model to the data.

Again, the value of AIC indicates that used for model selection; lower values indicate a better model fit and for SIC Similar to AIC but penalizes for the number of parameters; used for model selection. Both F-stat. and Prob(F-stat.) indicates that the model is statistically significant at the 5% level. Similarly, D.W stat. values means that there is no autocorrelation of health expenditure of Italian Economy.

Figure: 3

Correlogram of Residual

It is observed from the correlogram of residual series is given by the figure 3 that

I. the *ACF* of the residual series is free from any dying out pattern of spikes, and

II. the *PACF* of the series is marked by the absence of any singularly significant spike at lag one.

III. Here the residual series is stationary at level i.e residual is I(0).

and these observations testify for MA(0) structure for ΔE_t. ARIMA (12,1,0) forecasts for E_t. The estimated model becomes

$$\Delta E_t = \alpha_1 + \alpha_2 \Delta E_{t-12} + \gamma_{3\delta_t} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots(8)$$

ARIMA(12,1,0) model as given by the equation (8) has been used for generating one period ahead forecast for E_t. The time plots of health expenditure (E_t) and the corresponding ARIMA forecast (δ_t) are being presented through the figure 4. E_t is found to be coincident with δ_t over the period concerned.

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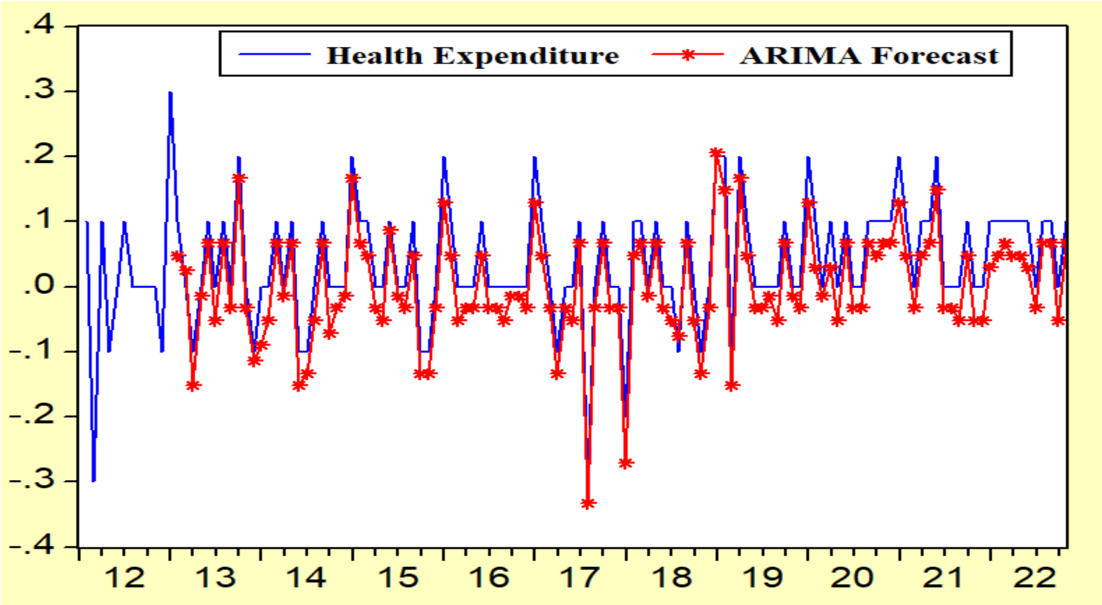
Figure:4

ARIMA (12.1.0) forecasting of Health Expenditure



The graph illustrates the ARIMA forecasting of health expenditure in Italy from 2012 to 2022. Time Period (X-axis**)** covers the years from 2012 to 2022, marking the timeline over which the health expenditure data and the ARIMA forecasts are plotted. Expenditure Level (Y-axis) indicates the level of health expenditure, ranging from -0.4 to 0.4. The scale is likely normalized or differenced, a common practice in time-series forecasting to stabilize variance and better identify patterns.

Here Health Expenditure (solid Line**)** represents the actual health expenditure in Italy over the time period. It shows the real data, highlighting the fluctuations, peaks, and dips in spending. ARIMA Forecast (dotted line**)** represent the forecasted values using the ARIMA (Auto Regressive Integrated Moving Average) model. ARIMA is a widely used statistical method for time-series forecasting, particularly for data that shows trends and seasonality. The model predicts future data points based on past observations.

Explanation of ARIMA Forecasting for Health Expenditure in Italy:

From the above ARIMA forecasting model, we observed that

1. Actual Values indicated by a solid line, showing the real health expenditure over time.
2. Forecasted Values represented by a dashed or dotted line, showing the predicted health expenditure based on the model.
3. Trend Compared the overall trend of the actual values with the forecasted values. They should follow a similar path, indicating that the model has captured the trend well.
4. The ARIMA forecasts (red stars) generally follow the blue line representing actual expenditure. This suggests that the model captures the overall trends and cyclical patterns present in the data.
5. The ARIMA model does a good job of tracking the health expenditure, there are periods where the forecast slightly deviates from the actual data and from the above figure-4, we observed that the forecast data almost coincide with actual data of health expenditure for the period from 2012 to 2022 in Italy.
6. The expenditure data shows significant volatility, with sharp rises and falls. The ARIMA model attempts to capture these changes but is limited in fully predicting extreme fluctuations, such as sudden spikes or drops around 2018 and 2020.
7. Both the actual data and ARIMA forecast stabilize, with fewer pronounced fluctuations, indicating a more consistent trend in health expenditure within the period from period 2021 to 2022.

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Section: III

The ARCH Model:

ARCH (Autoregressive Conditional Heteroskedasticity) is used to model time series data with changing variance (heteroskedasticity), where periods of high volatility are followed by high volatility and periods of low volatility are followed by low volatility.

We know ARCH equations are

The Mean equation is

$$y_t = \mu + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where is the y_t is observed time series, μ is the mean ε_t is the error term

The Variance equation is

$$\varepsilon_t = \sigma_t z_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

where z_t is white noise with zero mean and σ_t *is* unit variance.

Conditional variance

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots\ldots\ldots\ldots + \alpha_q \varepsilon_{t-q}^2 \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where $\alpha_0 > 0$ *and* $\alpha_i \geq 0$ *for* $i = 1,2,3, \ldots\ldots\ldots\ldots\ldots\ldots, q$

The Estimated equation of ARCH model is

$$\sigma_t^2 = 0.005 + 0.264\, \varepsilon_{t-5}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

t-Stat. **3.496** **2.833**

S.E. 0.001 0.093

P-Value 0.001 0.005

$R^2 = 0.070$ Adj. $R^2 = 0.062$

F-Stat. = 8.028 D.W. Stat. = 1.995

The coefficient of residual lag 5 of health expenditure indicates that a one-unit increase in the residual of health expenditure lagged by 5 periods is associated with a 0.264 increase in the current residual. The coefficient is statistically significant (p-value = 0.005), indicating that past residuals have a meaningful impact on current residuals. The value of R^2 suggested that there is only about 7.04% of the variation in the residual of health expenditure is explained by the lagged residual of health expenditure in the model and values of R^2 is relatively low which suggesting that the other factors not included in the model may explain most of the variation and Adj. R^2 value indicated that there is slightly lower than R^2, reflecting the inclusion of lagged variables and their limited explanatory power. Similarly, F-stat value is significant (p-value = 0.005), indicating that the model as a whole is statistically significant and D.W Stat value is close to 2, suggesting that there is no significant autocorrelation in the residuals.

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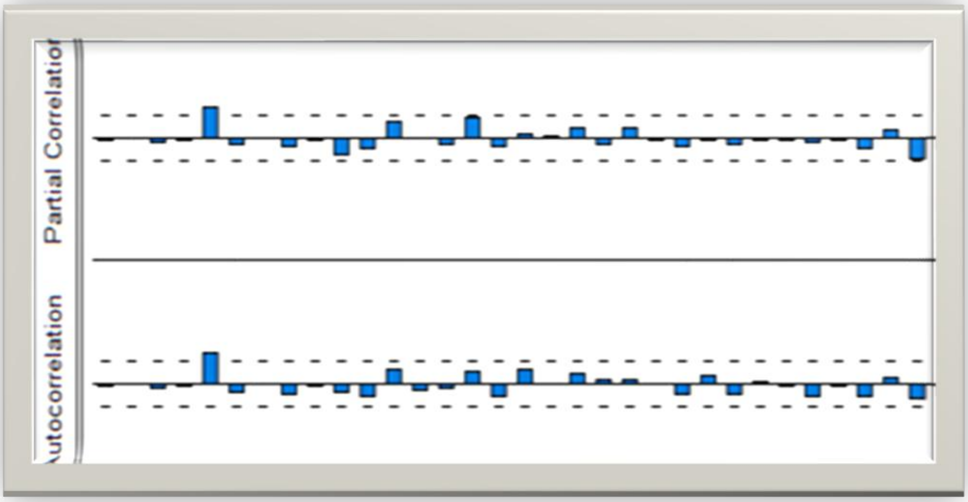
Figure: 4 Correlogram of Residual in ARCH Model



It is observed from the figure - 4 that

- the *ACF* is marked by the absence of any dying out pattern of spikes.
- no singularly significant large spike appears at the first lag of the corresponding *PACF*.

So, we observed that these features of the correlogram, as given in the Figure - 4, confirm that the first differenced series of residual value of health expenditure is stationary.

This suggests that health expenditure residuals exhibit a persistent trend or integrated behavior (I(1)), meaning shocks or changes in expenditure levels tend to have lasting effects rather than reverting quickly to a mean. The significant coefficient at lag 5 (0.264, p=0.005) in what appears to be an autoregressive (AR) model implies a cyclical or periodic dependence every five periods.

Section: IV

GARCH Model:

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) extends the ARCH model by including lagged conditional variances in the variance equation, allowing for a more flexible representation of time-varying volatility.

In GARCH model also there are three equations the mean and variance equation are same as in ARCH that have mentioned in equations no 9 and 10 but the conditional equation is different,

conditional equation

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots \ldots \ldots \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots \ldots \ldots \ldots + \beta_p \sigma_{t-p}^2 \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where $\alpha_0 > 0 \; and \; \alpha_i \geq 0 \;\; for \;\; i = 1,2,3, \ldots \ldots \ldots \ldots \ldots \ldots, q, \;\; \beta_j \geq 0 \;\; for \; j = 1,2,3, \ldots \ldots \ldots \ldots p$

These ARIMA, ARCH and GARCH models are the fundamental in time series analysis and forecasting, particularly in finance, economics we so try to understanding and predicting time-dependent data of health expenditure in the economy of Italy.

The Estimated Mean equation of GARCH (1,1) model is

$$E_t = \quad 0.042 + 0.283 \text{ ARIMA(F)}_{t-12} + 0.169 GARCH(F)_{t-5} \ldots\ldots\ldots\ldots (14)$$

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P-Value 0.000 0.002 0.055

Where ARIMA(F) stands for Autoregressive Integrated Moving Average Forecasting and GARCH(F) means Generalized Autoregressive Conditional Heteroskedasticity Forecasting and

$\varepsilon_t = z_1\sqrt{h_t}$ means error term with $z_t \sim N(0,1)$.

Here we see that coefficient of constant term is highly significant with p-value is 0.000 . Similarly, coefficient of ARIMA(F) and GARCH(F) are also significant.

The Variance equation is

$$h_t = \alpha_0 + \sum_{i=1}^{q} a_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \ldots\ldots\ldots\ldots\ldots\ldots(15)$$

h_t = conditional variance at time t

$\alpha_0 > 0$: Constant term, $\alpha_i \geq 0$: coefficient of lag squared error (ARCH terms)

$\beta_j \geq 0$: coefficient of lag conditional variances (GARCH terms)

The sum $\sum \alpha_i + \sum \beta_j < 1$ ensure stationarity of the variance process.

The estimated Variance Equation of GARCH(1,1) of equation (15) is

$$h_t = 0.002 - 0.0104\, \epsilon^2_{t-1} + 1.034 h_{t-1} - 0.043 E_t + 0.041 ARIMA(F)_t - 0.002 GARCH(F)_t \ldots(16)$$

P-value 0.001 0.034 0.000 0.259 0.001 0.946

$R^2 = 0.069$ Adj $R^2 = -0.008$ D.W. stat.= 1.888 AIC = -2.185 Mean = 0.040 S.D. = 0.086

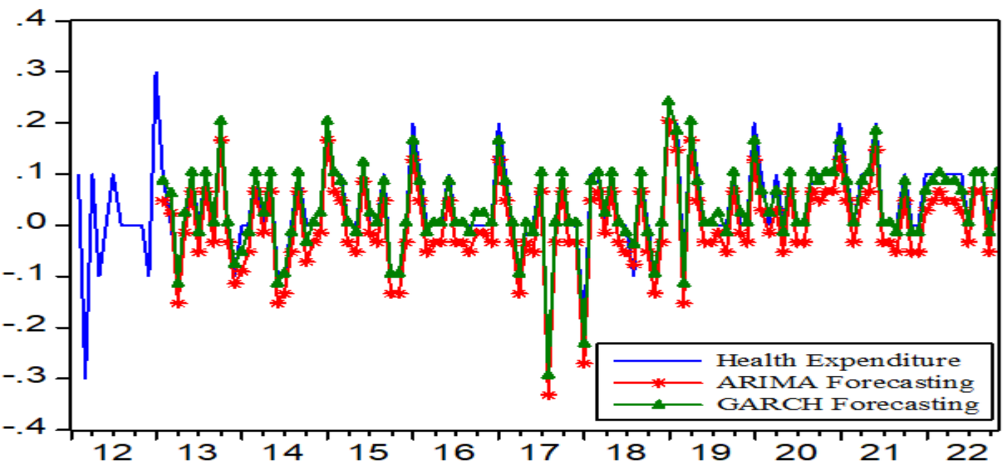
Where h_t: Conditional variance of ϵ_t, capturing volatility in health expenditure growth.

ϵ^2_{t-1} : Squared residual from the previous period (ARCH term).

h_{t-1}: Lagged conditional variance (GARCH term).

So, we see that the coefficient of constant term is significant. Similarly, coefficient of ARCH(1), GARCH(1,1) ARIMA forecasting value are also significant. The low value of R^2 indicated that the mean equation explains little variation in health expenditure in the economy of Italy and negative value of Adj R^2 suggested that the poor fit after adjusting for degrees of freedom. Similerly, the value of D.W stat. is close to 2 which implies that no significant residual autocorrelation. Mean and Standard Deviation explained that the health expenditure has a 4.06% average monthly growth and high volatility (8.59%).

Figure:6 GARCH Forecasting about Health Expenditure



In the above figure -6 we examined that a time series plot comparing the actual health expenditure in Italy with the forecasts generated by two models: ARIMA (Auto Regressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity).We explained brief explanation of these models and their relevance to health expenditure forecasting:

In the Figure - 6 indicated that the ARIMA forecast line shows red with star markers attempts to predict the health expenditure based on its past values. ARIMA models are useful when the time series has patterns or trends, but not necessarily large, sudden fluctuations. Similarly, GARCH forecasting was typically used for financial time series, especially when there is volatility clustering periods of swings followed by relative calm. Both the forecasts model we see that there have been mean and variance series, which helps capture sudden spikes or drops.

GARCH forecasting (shown in green with triangle markers) captures the volatility or variability in health expenditure over time. It might be useful if health expenditure has periods of high volatility, possibly due to sudden policy changes, pandemics, or economic shifts and the blue line represents the actual health expenditure data. The fluctuations seen may reflect various factors such as government spending, changes in healthcare needs, or economic conditions. So, we see that both ARCH and GARCH forecasting represent the general trend but doesn't capture the volatility as effectively. The GARCH forecast (green triangles) better aligns with periods of high volatility, indicating it might be more effective in capturing sudden spikes and dips.

Summary Conclusions and Policy Implication in the Economy of Italy:

The coefficient of constant term indicated that the 4.26% monthly growth rate implies strong structural increases in Italy's health expenditure, driven by an aging population, rising medical costs, and the universal healthcare system (Servizio Sanitario Nazionale, SSN). This aligns with Italy's healthcare spending (8–9% of GDP). The value of coefficient of ARIMA forecasting indicated that a 1% increase in growth 12 months prior raises current growth by 0.284%, indicating annual seasonality (e.g., fiscal budgets, winter health costs). This reflects predictable cycles in healthcare spending. In case of short term, we see that the value for GARCH forecasting implies 1% increase in growth 5 months prior raises current growth by 0.169%, marginally significant. The high GARCH coefficient indicates persistent volatility, meaning shocks (e.g., COVID-19 costs in 2020–2021) have long-lasting effects on expenditure variability.

The significant value for ARIMA forecasting in the variance equation suggests that forecasting signals influence volatility. The sample period from 2012 to 2022 includes Italy's economic recovery and the COVID-19 pandemic, which likely increased expenditure volatility.

Policy Implications: The 4.26% baseline growth and 12-month persistence suggest predictable increases, useful for planning annual healthcare budgets. We used the lagged expenditure data (12- and 5-month lags) to forecast spending, ensuring sufficient allocations for seasonal peaks. The high GARCH value persistence indicates sustained volatility, especially post-COVID-19, requiring flexible budgets for unexpected shocks. There should be create a contingency funds and use GARCH-based volatility forecasts to prepare for high-risk periods (e.g., pandemics, policy shifts). The negative ARCH coefficient and low value of R^2 suggested that misspecification. Missing variables (e.g., GDP, inflation) likely drive expenditure growth.

Increasing public investment in healthcare infrastructure can mitigate projected cost increases due to population aging—potentially by allocating a larger share of GDP through targeted taxes or efficiency-enhancing reforms. In both economic and health policy circles, differentiated budgetary responses—such as ring-fencing health funds during recessions—can protect vulnerable populations and essential services. Furthermore, linking health expenditure to broader macroeconomic objectives, such as GDP growth or EU recovery funds, would improve the predictive power of models beyond simple lagged effects, thereby fostering long-term sustainable development.

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