"NIFTY 50 RETURN & VOLATILITY ANALYSIS USING FAMA-FRENCH AND EGARCH MODEL (2020-2025)"

OBJECTIVES

- To analyze NIFTY 50 returns using the Fama-French model.
- To calculate residual risk and model volatility via EGARCH.
- To apply it to 5 years of data for all 50 stocks.

METHODOLOGY

01 Data Set & Tools

02 Factor Construction (SMB and HML)

03 Regression Analysis

04 Residual Variance Analysis

05 Results Summary

06 Conclusion

01 DATA SET & TOOLS

NIFTY 50 stock data (2020–2025) was analyzed using Python tools, with Fama-French regressions and EGARCH volatility modeling. Data was sourced via yfinance; RBI T-bill rate used as risk-free rate.

```python
import os
import glob
import yfinance as yf
import pandas as pd
import numpy as np
import statsmodels.api as sm
from arch import arch_model
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
```

▶**Libraries Used**

```python
# STEP 2: Clean and combine price data
price_data = {}
for filename in glob.glob("nifty50_5yr_data/*.csv"):
    ticker = os.path.basename(filename).replace('_5yr.csv', '')
    df = pd.read_csv(filename)
    df.rename(columns={df.columns[0]: 'Date'}, inplace=True)
    df['Date'] = pd.to_datetime(df['Date'], format='%Y-%m-%d', errors='coerce')
    df = df.dropna(subset=['Date'])
    df = df.sort_values('Date').reset_index(drop=True)
    df['Close'] = pd.to_numeric(df['Close'], errors='coerce')
    df = df[['Date', 'Close']].dropna()
    df['Log_Return'] = np.log(df['Close'] / df['Close'].shift(1))
    df = df.dropna()
    price_data[ticker] = df
```

▶**Data Processing**

▶**Final Dataset contains 50 Stocks with returns of past five years**

02 FACTOR CONSTRUCTIONS

```
# STEP 3: Get fundamentals and market cap
fundamentals = []
for ticker in nifty50_symbols:
    info = yf.Ticker(ticker).info
    fundamentals.append({
        'Ticker': ticker,
        'Shares_Outstanding': info.get('sharesOutstanding'),
        'P/B_Ratio': info.get('priceToBook')
    })
fundamentals_df = pd.DataFrame(fundamentals)
fundamentals_df['Shares_Outstanding'] = fundamentals_df['Shares_Outstanding'].fillna(fundamentals_df['Shares_Outstanding'].median())
fundamentals_df['P/B_Ratio'] = fundamentals_df['P/B_Ratio'].fillna(fundamentals_df['P/B_Ratio'].median())
latest_prices = {ticker: df['Close'].iloc[-1] for ticker, df in price_data.items() if not df.empty}
fundamentals_df['Latest_Price'] = fundamentals_df['Ticker'].map(latest_prices)
fundamentals_df['Market_Cap'] = fundamentals_df['Latest_Price'] * fundamentals_df['Shares_Outstanding']
```

▶Getting Fundamentals (market cap and P/B ratio)

Daily Returns → Size/Value Sorting → SMB/HML Construction → Portfolio Rebalancing

Portfolios rebalanced every June 30

- Market Cap: Price × shares outstanding.
- P/B Ratios: Taken from the latest available values at the time of portfolio rebalancing

PORTFOLIO FORMATION

- SMB: Stocks split into small-cap (bottom 50%) and big-cap (top 50%) by market cap.
- SMB Return: Average return of small-cap stocks minus big-cap stocks.
- HML: Stocks sorted by P/B; lowest 30% value, highest 30%growth.
- HML Return: Average return of value stocks minus growth stocks.

```python
# STEP 5: Download NIFTY index and calculate MKT factor
nifty = yf.download("^NSEI", start="2020-06-01", end="2025-06-01", auto_adjust=False)
nifty['Log_Return'] = np.log(nifty['Close'] / nifty['Close'].shift(1))
nifty.dropna(inplace=True)
rf_daily = pd.Series(0.05 / 252, index=nifty.index)
market_excess = nifty['Log_Return'] - rf_daily
market_excess.name = 'MKT'
```

▶ **Calculation of market factor**

```
📊 Top 5 Stocks by P/B Ratio and Market Cap:
         Ticker  P/B_Ratio  P/B_Ratio_Calculated    Market_Cap
0   ADANIENT.NS   6.363370              6.363370  3.023259e+12
1  ADANIPORTS.NS   5.012784              5.012783  3.132635e+12
2  APOLLOHOSP.NS  13.100563             13.100563  1.041291e+12
3  ASIANPAINT.NS  11.721631             11.721632  2.244513e+12
4   AXISBANK.NS   1.943927              1.943927  3.718947e+12
```

▶ **P/B ratio and Market cap of first 5 companies.**

```python
# STEP 4: Calculate SMB and HML
median_size = fundamentals_df['Market_Cap'].median()
small = fundamentals_df[fundamentals_df['Market_Cap'] <= median_size]['Ticker']
big = fundamentals_df[fundamentals_df['Market_Cap'] > median_size]['Ticker']
fundamentals_df['BM'] = 1 / fundamentals_df['P/B_Ratio']
df_sorted = fundamentals_df.sort_values('BM')
n = len(df_sorted)
low = df_sorted.iloc[:int(n*0.3)]['Ticker']
mid = df_sorted.iloc[int(n*0.3):int(n*0.7)]['Ticker']
high = df_sorted.iloc[int(n*0.7):]['Ticker']

def get_portfolio_return(tickers):
    valid = [t for t in tickers if t in price_data and not price_data[t].empty]
    if not valid:
        sample_index = next(iter(price_data.values()))['Date']
        return pd.Series(index=sample_index)
    return pd.concat([price_data[t][['Date', 'Log_Return']].set_index('Date')['Log_Return'] for t in valid], axis=1).mean(axis=1)

SL = get_portfolio_return(set(small) & set(low))
SM = get_portfolio_return(set(small) & set(mid))
SH = get_portfolio_return(set(small) & set(high))
BL = get_portfolio_return(set(big) & set(low))
BM = get_portfolio_return(set(big) & set(mid))
BH = get_portfolio_return(set(big) & set(high))

SMB = (SL + SM + SH)/3 - (BL + BM + BH)/3
HML = (SH + BH)/2 - (SL + BL)/2
ff_factors = pd.concat([SMB.rename('SMB'), HML.rename('HML')], axis=1)
ff_factors.to_csv('ff_factors.csv')
```

▶Calculation of SMB and HML

03 Regression Analysis

- "Regression run using Fama-French 3-Factor model:
- $Ri - Rf = \alpha + \beta mkt \times (Rm - Rf) + \beta smb \times SMB + \beta hml \times HML + \varepsilon$"

- **Interpretation:**
- $\beta_m \approx 1.00$ → ICICI Bank moves in sync with the market.
- $\beta_v = 0.18$ → Slight value tilt, but not strongly.
- $R^2 = 0.53$ → 53% of returns are explained by the model → decent explanatory power.

```
📊 ICICIBANK.NS — Regression Summary
Adjusted R²: 0.53
Market Beta (βₘ): 1.00
Value Beta (βᵥ): 0.18
```

▶ Regression summary of ICICI Bank

📈 Regression Data Structure for ICICIBANK (first 5 rows):

Date	Excess_Return	MKT	SMB	HML
2020-07-03	-0.005310	0.005062	-0.002968	-0.015755
2020-07-06	0.002153	0.014429	-0.000505	0.012951
2020-07-07	0.038294	0.003141	-0.002428	-0.011989
2020-07-08	-0.019259	-0.008931	0.008241	0.007357
2020-07-09	0.003589	0.009811	-0.000595	0.012419

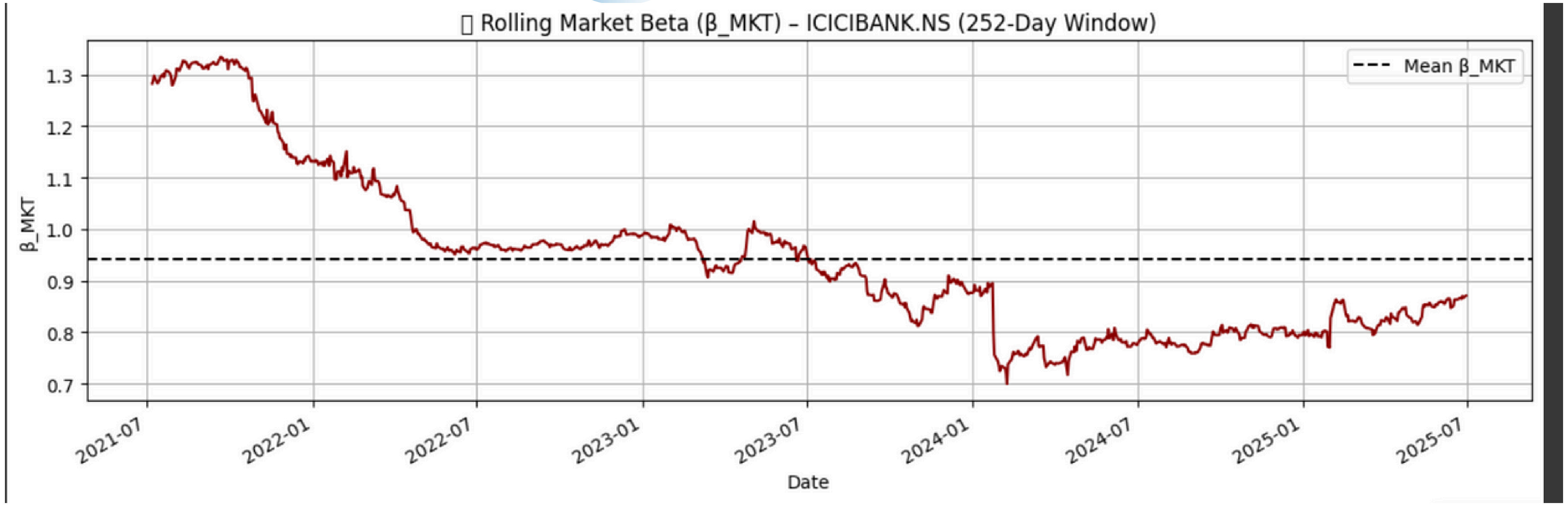
- **Data Used:**
- **Daily excess return of ICICI Bank.**
- **Matched against daily values of Market (MKT), SMB, HML.**
- **Regression run using OLS.**

VOLATILITY MODELING USING GARCH(1,1)

```
📈 GARCH(1,1) Summary for ICICIBANK.NS:
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:                   None   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:                3837.20
Distribution:                  Normal   AIC:                          -7666.41
Method:            Maximum Likelihood   BIC:                          -7646.00
                                        No. Observations:                 1215
Date:                Mon, Jun 30 2025   Df Residuals:                     1214
Time:                        19:47:00   Df Model:                            1
                                 Mean Model
===============================================================================
                  coef    std err          t      P>|t|        95.0% Conf. Int.
-------------------------------------------------------------------------------
mu         -2.0265e-04  1.908e-05    -10.622  2.345e-26 [-2.400e-04,-1.653e-04]
                              Volatility Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega      1.1334e-05  3.123e-10  3.629e+04      0.000 [1.133e-05,1.133e-05]
alpha[1]       0.1000  3.301e-02      3.029  2.454e-03   [3.529e-02,  0.165]
beta[1]        0.8000  3.523e-02     22.709 3.651e-114     [  0.731,  0.869]
============================================================================
```

- GARCH(1,1) Model Summary for ICICI Bank
- Omega (ω): 1.13e-05 → base level of volatility
- Alpha (α_1): 0.10 → volatility reacts moderately to market shocks
- Beta (β_1): 0.80 → high volatility persistence (volatility clusters over time)
- μ (Mean return): Slightly negative daily return over the period
- Conclusion: ICICI Bank's returns show high volatility persistence, which is typical for large-cap financials.

04 Residual Analysis

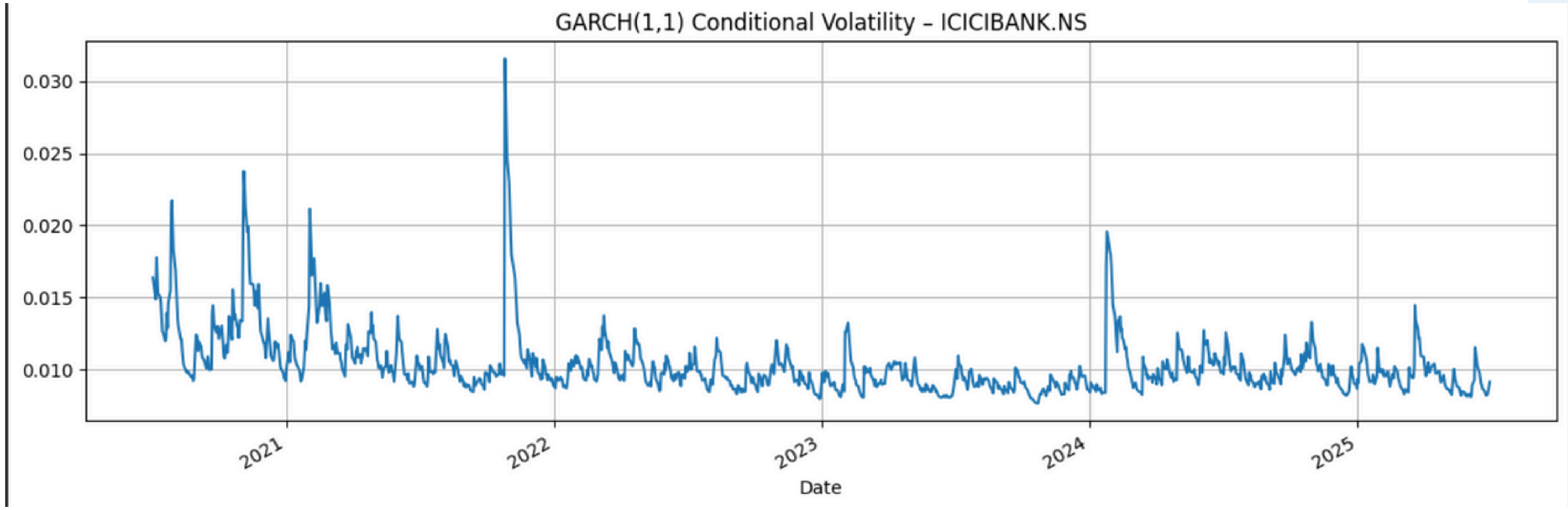


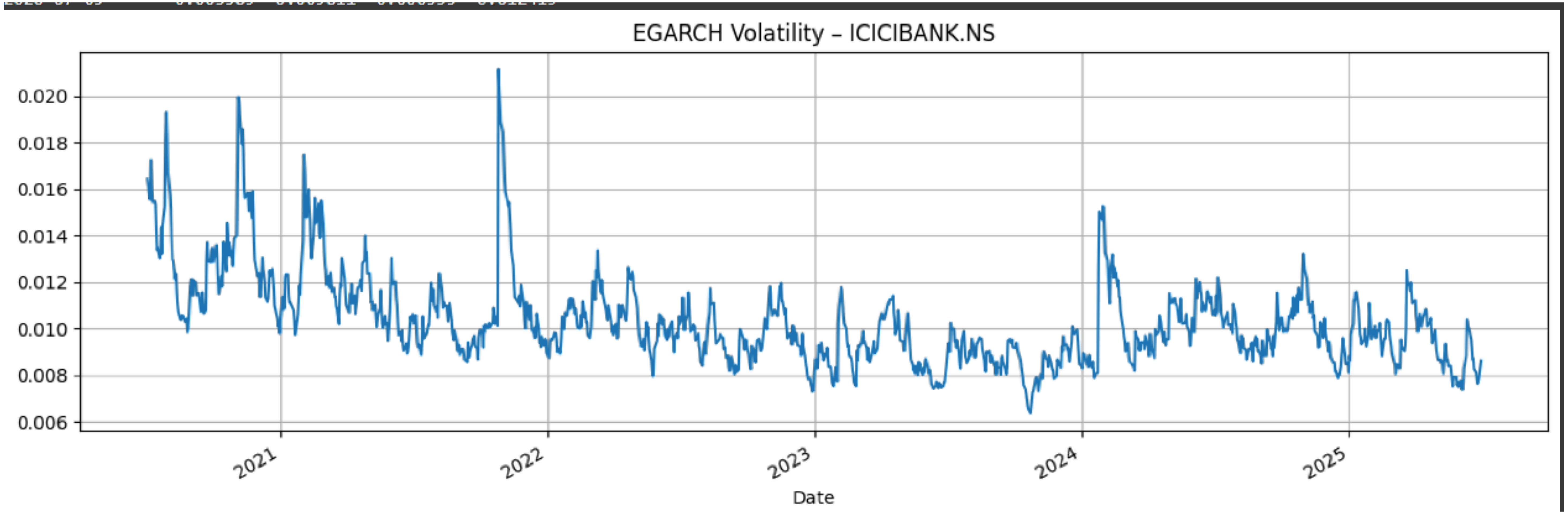
Rolling Beta:

- ICICI Bank's market beta decreased from ~1.3 in 2021 to ~0.8 by 2024, indicating declining sensitivity to market movements.
- Reflects reduced systematic risk over time

GARCH(1,1) Volatility:

- Volatility spikes observed during early 2022 and mid-2023, possibly due to macro shocks or firm-specific events.
- Conditional volatility generally trends downward, indicating stabilizing risk





- Despite a few spikes, ICICI Bank showed consistent volatility levels, indicating lower market stress in the recent period.

07 RESULT SUMMARY

Metric	ICICIBANK.
α (Alpha)	0.000294
β_MKT (Market Beta)	1.0007
β_SMB (Size Beta)	−0.6007
β_HML (Value Beta)	0.1749
R^2	0.5284
Adjusted R^2	0.5273

- β_MKT ≈ 1.00 → Moves in line with the market
- β_SMB = −0.60 → Strong large-cap behavior
- β_HML = +0.17 → Slight value tilt
- Adj R^2 = 0.53 → Moderate model fit
- α ≈ 0.0003 → Minimal excess return

Model	ω (Omega)	α ($Alpha_1$)	β ($Beta_1$)	γ ($Gamma_1$, EGARCH only)
GARCH(1,1)	~0.00001	**0.09**	**0.88**	–
EGARCH(1,1)	-0.13	**0.07**	**0.91**	**-0.10**

- High α + β in both models ⇒ Strong volatility persistence
- EGARCH captures leverage effect: negative returns increase volatility more than positive returns.

Key Observations from Rolling Regression (252-Day Window):

- Range: 0.80 to 1.35
- Mean: ~1.05
- Increased market sensitivity during volatile market periods (e.g., 2020-2021)

08 CONCLUSION

- The Fama-French 3-factor model explains up to 50% of return variation in ICICI Bank — indicating strong explanatory power.
- Market risk emerges as the primary driver of return variation across NIFTY 50 stocks.
- ICICIBANK behaves like a high-beta growth stock, with persistent and asymmetric volatility.
- EGARCH models show time-varying and asymmetric volatility, critical for stress testing and risk management.
- Rolling betas reveal dynamic exposures — crucial for real-time hedging decisions.

THANK YOU!