Comprehensive Explanation of the Project: Calculating Residual Variance Using Fama-French Model

Objective

To quantify **firm-specific (idiosyncratic) risk** in RELIANCE.NS by:

- 1. Decomposing stock returns using the Fama-French three-factor model.
- 2. Calculating residual variance unexplained by market, size, or value factors.
- 3. Analyzing time-varying volatility through rolling regression and GARCH models.

Step-by-Step Methodology

1. Data Collection & Cleaning

- Sources:
 - 5 years of daily prices for Nifty 50 stocks (using yfinance).
 - Shares outstanding and P/B ratios for fundamental analysis.

• Processing:

```
# Handle missing fundamentals
shares_outstanding_df.fillna(shares_outstanding_df.median(), inplace=True)
pb_ratios_df.fillna(pb_ratios_df.median(), inplace=True)
```

- Key Checks:
 - Drops stocks with incomplete price histories.
 - Ensures no missing values in returns data.
- Output: 50 stocks with 1,260 days of clean data (2020–2025).

2. Factor Construction (SMB & HML)

- Annual Rebalancing:
 - Portfolios rebuilt every June 30 using:
 - Market Cap = Price × Shares Outstanding.
 - **P/B Ratios** = Value metric.
- Portfolio Formation:
 - SMB (Size Factor):

```
small_stocks = market_caps[market_caps <= median_mcap].index</pre>
```

```
smb = small_cap_returns.mean(axis=1) - big_cap_returns.mean(axis=1)
```

```
high_value_stocks = pb_sorted.iloc[:int(n*0.3)].index
hml = high_value_returns.mean(axis=1) - low_value_returns.mean(axis=1)
```

• Market Factor: Nifty 50 returns minus risk-free rate (5% annual T-bill \rightarrow daily rate: $(1+0.05)^{1/365}-1$).

3. Regression Analysis

• Fama-French Model:

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \beta_s \text{SMB} + \beta_v \text{HML} + \epsilon$$

• Code Implementation:

```
model = sm.OLS(excess_returns, sm.add_constant(factors_df)).fit()
residuals = model.resid
```

- Output:
 - Adj. $R^2=0.43$ (43% of returns explained).
 - ullet Betas: Market ($eta_m=0.99$), Value ($eta_v=0.22$).

4. Residual Variance Analysis

• Rolling Variance (252-day window):

```
rolling_variances = []
for start in range(len(residuals) - 252 + 1):
    window = residuals.iloc[start:start+252]
    rolling_variances.append(window.var())
```

- Result: Spikes during events (e.g., 2023 variance surged 180% to 0.00042).
- GARCH(1,1) Model:

$$\sigma_t^2 = \omega + lpha \epsilon_{t-1}^2 + eta \sigma_{t-1}^2$$

```
garch = arch_model(residuals, vol='Garch', p=1, q=1).fit(disp='off')
```

- Output: $\alpha = 0.15$, $\beta = 0.82$ \rightarrow Persistence = 0.97.
- EGARCH(1,1) Model:

$$\log(\sigma_t^2) = \omega + lpha rac{|\epsilon_{t-1}|}{\sigma_{t-1}} + \gamma rac{\epsilon_{t-1}}{\sigma_{t-1}} + eta \log(\sigma_{t-1}^2)$$

• **Output**: Leverage effect ($\gamma = -0.08$).

Key Results

Metric	Value	Interpretation
Adj. R^2	0.43	43% of returns explained by factors
Baseline Residual Var	0.00014	Low idiosyncratic risk
Max Rolling Variance	0.00042	180% surge during corporate events
GARCH Persistence	0.97	High volatility clustering
EGARCH Leverage	$\gamma = -0.08$	Negative shocks increase volatility 30% more

Conclusion & Applications

- Idiosyncratic Risk: 57% of RELIANCE.NS risk is firm-specific (unexplained by factors).
- Actionable Insights:
 - **Hedging Trigger**: When rolling variance > 90th percentile (0.00025).
 - Portfolio Construction: Avoid stocks with volatile residuals in low-risk portfolios.
- **Methodology Strength**: Combines Fama-French regression with time-varying volatility models.

Execution Workflow

1. Data Pipeline:

Automated data collection → cleaning → returns calculation.

2. Factor Engineering:

Annual rebalancing of SMB/HML portfolios.

3. Modeling:

Regression → residual extraction → volatility modeling.

4. Visualization:

• Rolling variance plots, GARCH volatility charts.

Why This Matters

- Isolates firm-specific risk missed by traditional models.
- Provides dynamic risk signals for traders and portfolio managers.
- Framework applicable to any stock/portfolio.

For implementation details, refer to the <u>full code</u>.