# Predicting Volatility with Regression

Cindy Xu & Rohan Shukla



# **Volatility is...**

- A measure of how much an asset's price moves over time
- Higher volatility means larger and more frequent price swings
- Lower volatility means smaller and more stable price movements
- Captures risk and uncertainty in financial markets

# There are 2 distinct measures of volatility

#### VIX / Implied Volatility

- Represents the market's expectation of future volatility.
- Based on prices of S&P 500 options.
- Higher VIX = market expects bigger future moves.
- Multiple VIX indices exist, based on different option expiration dates:
  - VIX: 30-day (standard)
  - VIX3M: 3-month
    - VIX6M: 6-month
  - VIX1Y: 1-year
  - Called "implied" because it's inferred from option prices using models like Black-Scholes.

#### **Realized Volatility**

- Measures the actual historical volatility observed in asset returns.
- Calculated using past daily returns over a fixed time window (e.g., 1 month, 1 year).
- No market expectations purely reflects how much asset prices have already moved.



### **Project Overview**

**Goal:** Predict future volatility of the stock market using statistical models.

#### **Research Questions:**

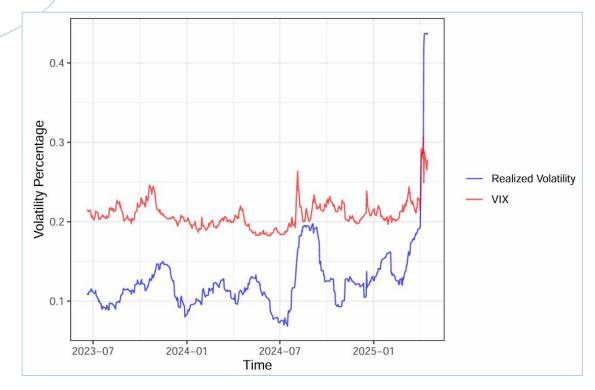
Can we predict future VIX based on only today's realized volatility?

Can we predict future realized volatility based on today's VIX and trailing volatilities?

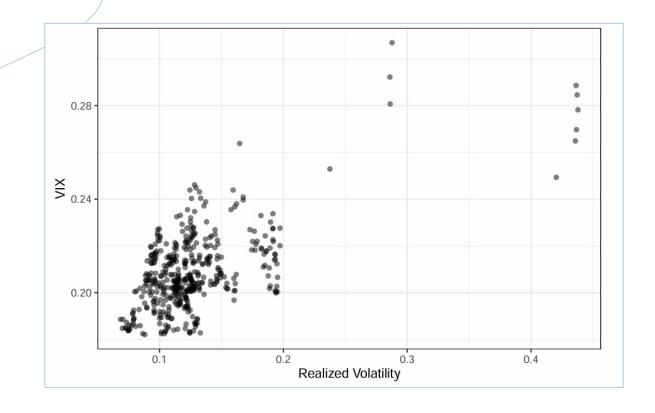


## **Volatility Over Time**

Spans from 6/20/2023 - 4/17/2025



# **VIX vs Realized Volatility**



# Regress VIX on Realized Volatility

Linear Regression

$$\widehat{\mathbb{E}}[Y \mid X] = \widehat{\beta}_0 + \widehat{\beta}_1 X$$

Generalized Additive Model (GAM)

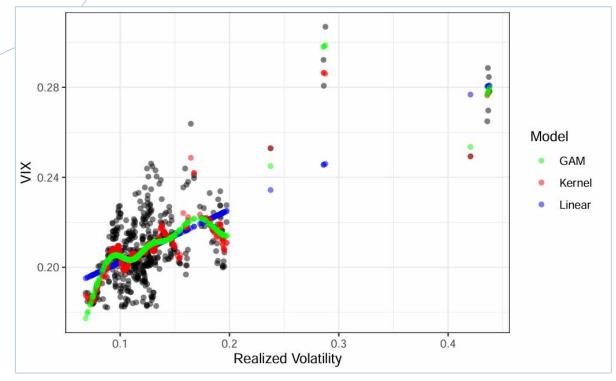
$$\widehat{\mathbb{E}}[Y \mid X] = \widehat{f}(X)$$

Kernel Smoothing

$$\widehat{\mathbb{E}}[Y \mid X = x] = \sum_{i=1}^{n} y_i w(x_i, x)$$

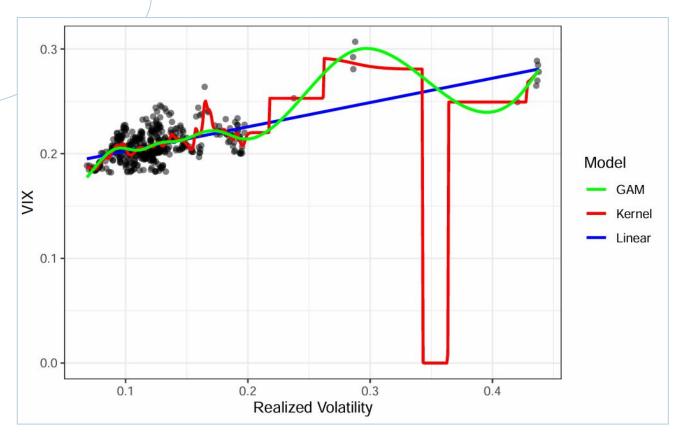
$$= \sum_{i=1}^{n} y_i \frac{K(\frac{x - x_i}{h})}{\sum_{j=1}^{n} K(\frac{x - x_j}{h})}$$

Fitted VIX From Each Model

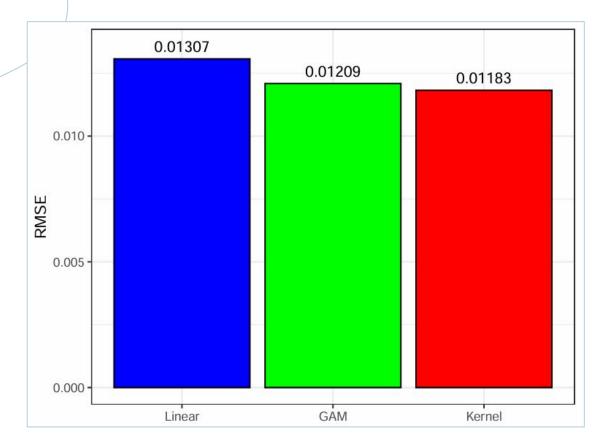


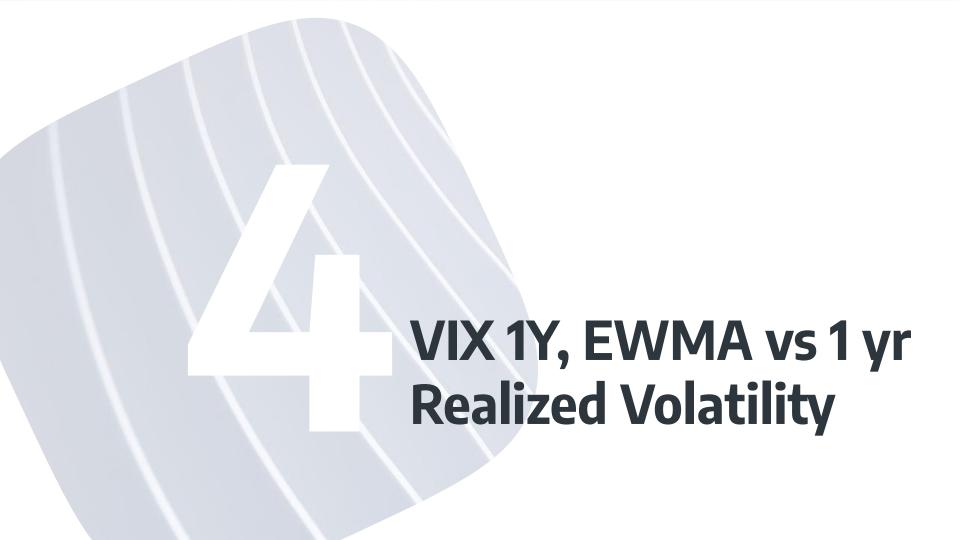
Fitted Curves From Each

Model



# **RMSE Comparison**





# SARIMA and Regression Models

Linear Regression

$$\widehat{\mathbb{E}}[Y \mid X] = \widehat{\beta}_0 + \widehat{\beta}_1 X$$

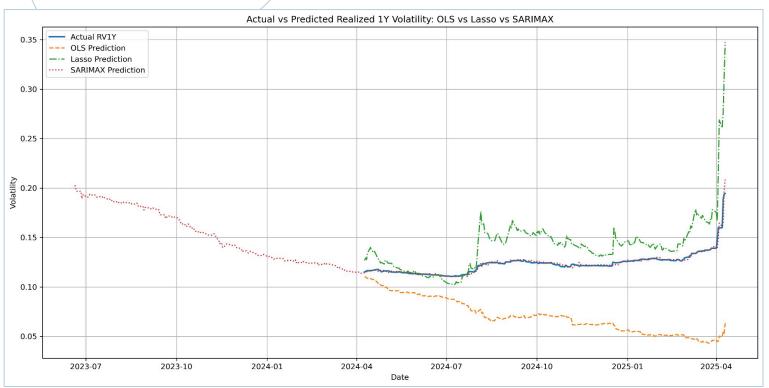
Lasso Regression

$$\widehat{eta} = rg \min_{eta} \left( \sum_{i=1}^n (y_i - eta_0 - eta_1 x_i)^2 + \lambda \sum_{j=1}^p |eta_j| 
ight)$$

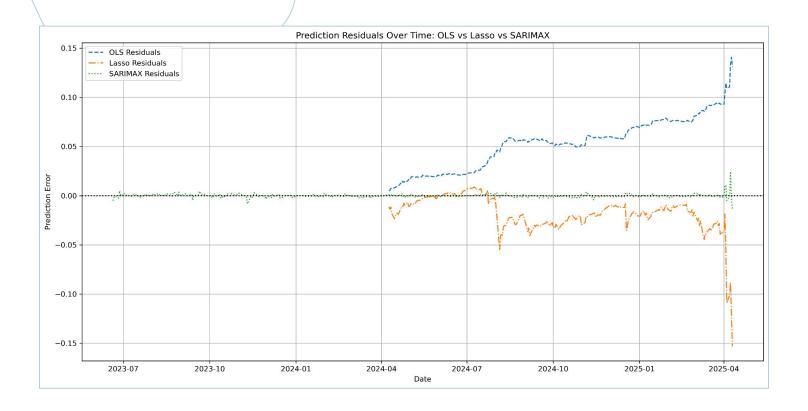
SARIMAX

$$\Phi(B^s)\phi(B)(X_t-\mu)=\Theta(B^s)\theta(B)\epsilon_t$$

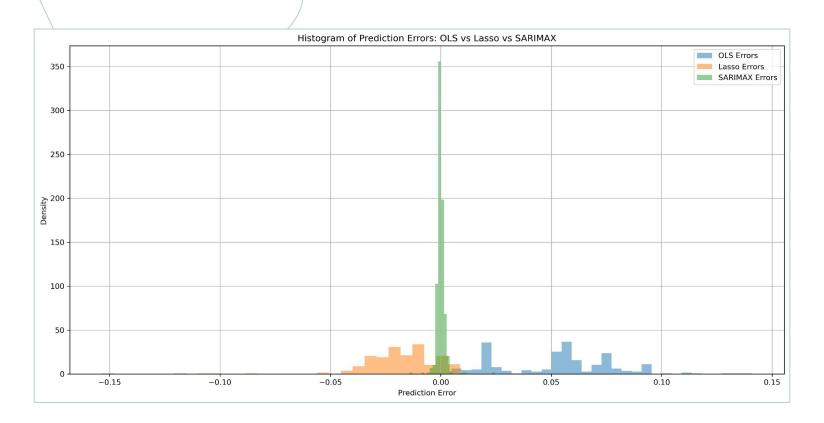
# Actual vs OLS, Lasso, SARIMAX Predicted Volatility



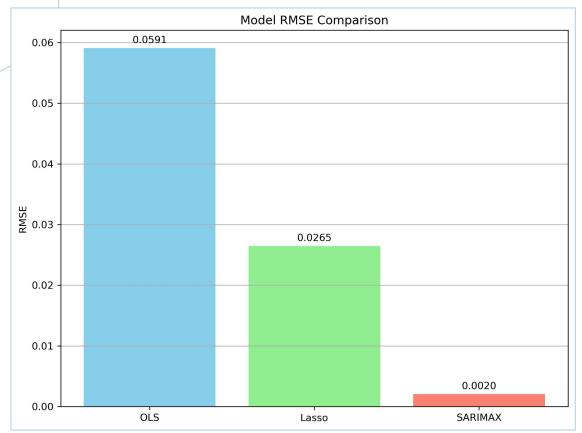
### **Errors: Residuals**



# **Errors: Histograms**



# **RMSE Comparison**



### **Key Takeaways**

- SARIMAX best captures the dynamic behavior of realized 1-year volatility. Lasso improves over standard OLS by reducing multicollinearity and shrinking unnecessary predictors.
- Simple OLS regression fails to capture volatility patterns due to ignoring time dependency.
- We used Time Series Cross-Validation (TimeSeriesSplit) to train the models, ensuring the temporal order was respected and avoiding lookahead bias.

