Predicting Bitcoin Price Movements Using Public Sentiment

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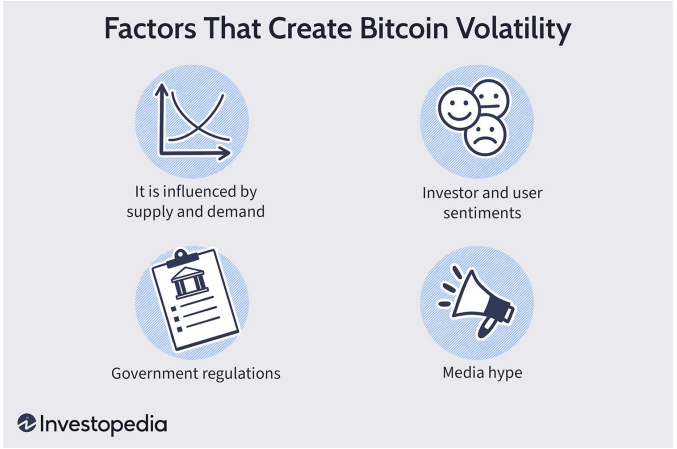
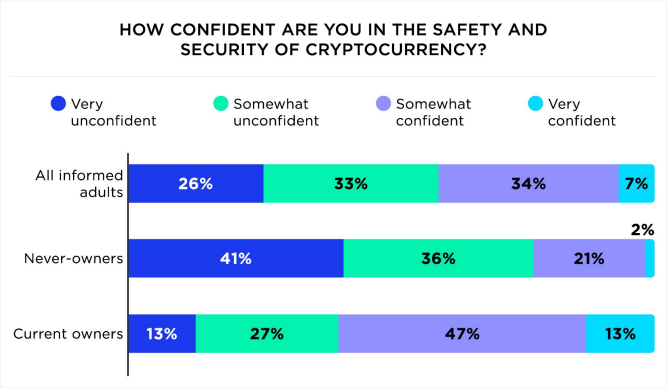
Motivation: Bitcoin and Sentiment

- Bitcoin are highly volatile and largely driven by retail participation, unlike traditional financial assets
- Information, attention, and public sentiment may play a large role in price formation.



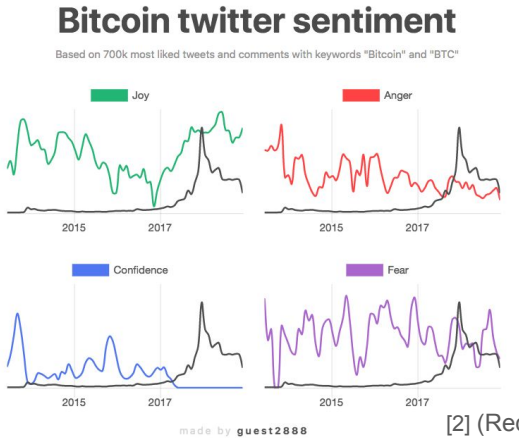
[4] (Reiff, 2025)



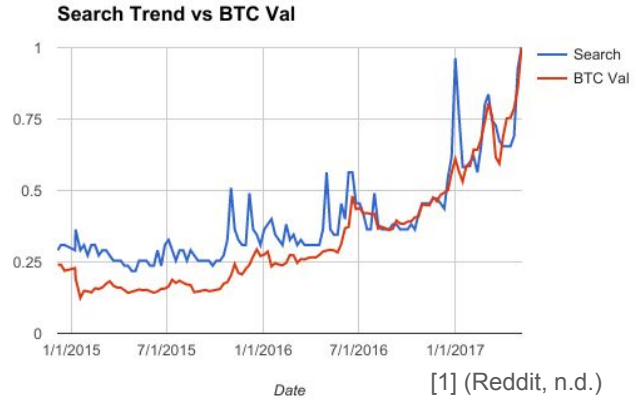
[5] (Cruz & Petrino, 2025)

Motivation: Bitcoin and Sentiment

- Twitter and Reddit are major platforms where crypto discussions, hype, fear, and rumors spread rapidly.
- Google search volume reflect levels of investor attention and interest in Bitcoin



[2] (Reddit, n.d.)



[1] (Reddit, n.d.)

[3] (Reddit, n.d.)

Motivation: Bitcoin and Sentiment

- Prior research suggest sentiment can influence markets, but findings are mixed across:
  - Different time horizons,
  - Different sentiment sources
  - Different market outcomes such as return v.s. volatility
- Comparing multiple sentiment sources
- Analyzing both price movements and volatility
- Focusing on short-term dynamics

Bitcoin Price Prediction Using Sentiment Analysis and Empirical Mode Decomposition

Serdar Arslan[1]

Accepted: 6 March 2024 / Published online: 28 May 2024
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[6] (Arslan, 2024)

Examining Cryptocurrency Price Movements and Twitter Sentiment Using VADER and Econometric Models

Publisher: IEEE

Cite This | PDF

Sky Nurimba ; Riyanto Jayadi ; Tanty Oktavia ; Takaaki Hosoda **All Authors**

[7] (Nurimba et al., 2025)

The Sentiment Augmented GARCH-LSTM Hybrid Model for Value-at-Risk Forecasting

Dániel Léber[1] · Balázs Egyed[1]

Accepted: 23 June 2025
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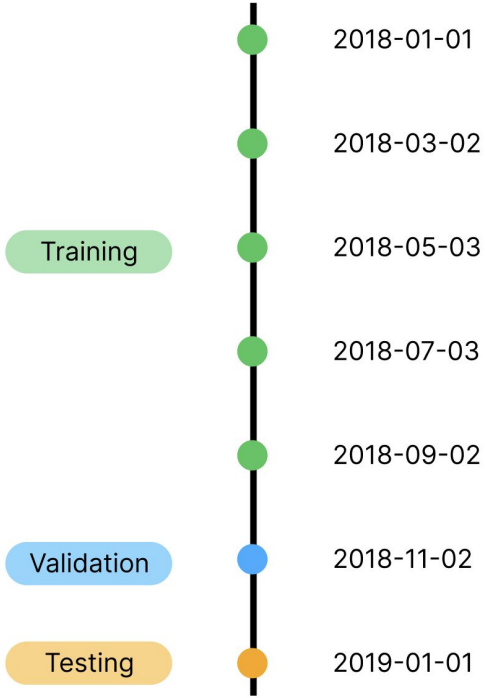
[8] (Léber & Egyed, 2025)

Research Question & Hypothesis

1. **Does Twitter sentiment about Bitcoin have predictive power for short-term price movements at different time horizons during 2018–2019?**
   - *Hypothesis: Higher sentiment leads to higher subsequent Bitcoin returns at both daily and 5-minute horizons.*
2. **Does Reddit sentiment correlate with Bitcoin volatility in short time intervals (1-minute/ 10-minutes/next-day) during 2018-2019?**
   - *Hypothesis: Increasing negative sentiment leads to increased volatility.*
3. **Does Google search activity related to Bitcoin predict short-term market momentum or volatility?**
   - *Hypothesis (volatility): Spikes in "Bitcoin" Google search volume are followed by increase in bitcoin volatility within 24 hours.*
   - *Hypothesis (momentum): Spikes in "Bitcoin" Google search volume are followed by positive bitcoin momentum.*
4. **Does daily sentiment disagreement predict Bitcoin price instability for the next day.**
   - *Hypothesis: Higher sentiment disagreement predic unstable Bitcoin price volatility*

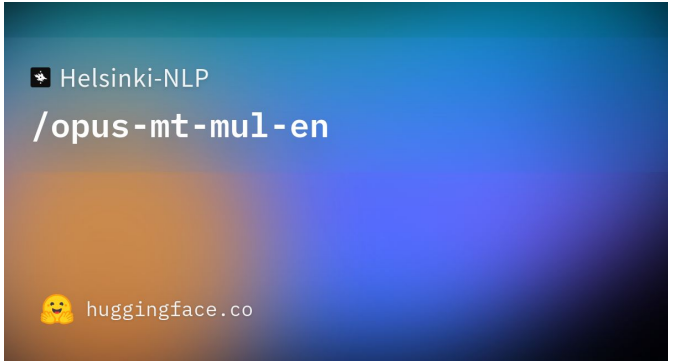
Data

- Online Kaggle datasets
  - **Twitter**: Bitcoin tweets - 16M
  - **Reddit**: Reddit Comments Containing “Bitcoin” 2009 to 2019
  - **BTC**: Bitcoin Historical Data
- For Google Search using **Google Trends**
- Limit time frame to **1 Jan 2018 - 1 Jan 2019**
- Separated into 6 parts:
  - Training dataset: part 1 - 4
  - Validation dataset: part 5
  - Testing dataset part 6
- 1.2M Tweets
- 890K Reddit



Data

- **Translate** content:
  - based on model **Helsinki-NLP/opus-mt-mul-en**
  - Multilingual translation model trained on the Tatoeba Translation Challenge dataset from OPUS
- Evaluate **sentiment score**:
  - based on model **cardiffnlp/Twitter-roBERTa-base-sentiment**
  - trained on 58M tweets and finetuned for sentiment analysis with TweetEval benchmark.
- Run parallel on A100 GPU with Google Colab for 25 hours in total



What this study

does claim

- Identifies statistical relationship between sentiment and Bitcoin returns and volatility
- Compares multiple sentiment sources
- Evaluates short-term predictive usefulness
- Provides empirical evidence statistical test

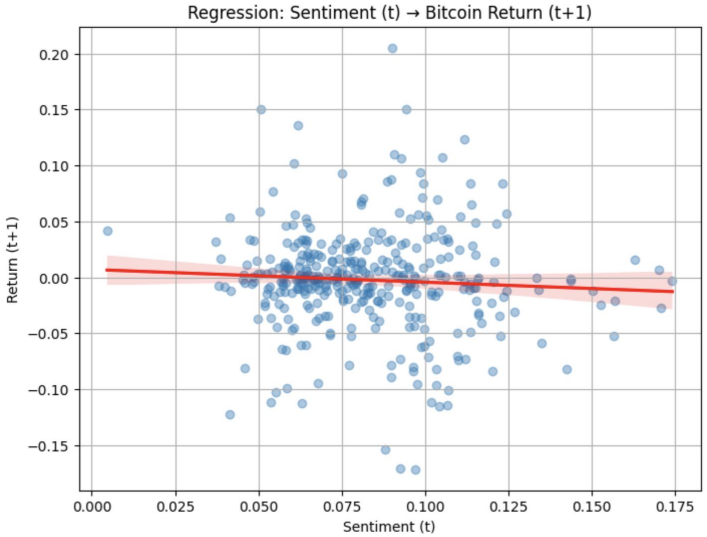
does NOT claim

- Causality relationships
- Guaranteed profitable trading strategies
- Long-term price forecasting
- Perfect sentiment measurement

Research Question 1

Research Question 1

Does Twitter sentiment about Bitcoin have predictive power for short-term price movements at different time horizons during 2018–2019?



Hypothesis: Higher sentiment leads to higher subsequent Bitcoin returns at both daily and 5-minute horizons.

Focus: short-term predictability

Two horizons: next-day vs 5-minute

Method

Data preparation

Sentiment Aggregation by Daily / 5-minutes horizon

Bitcoin returns

$$Return_t = \ln(P_t/P_{t-1})$$

Sentiment

$$Sentiment_{t-1}$$

Pearson correlation

$$\rho = (\mathrm{Cov}(Sentiment_{t-1}, Return_t))/\ \sigma Sentiment\ \sigma\ Return$$

Rolling correlation (stability over time)

OLS regression

$$Return_t = \alpha + \beta \cdot Sentiment_{t-1} + \varepsilon t$$

Daily Results

Pearson correlation:

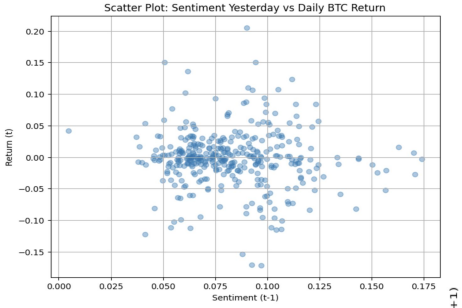
p= −0.062

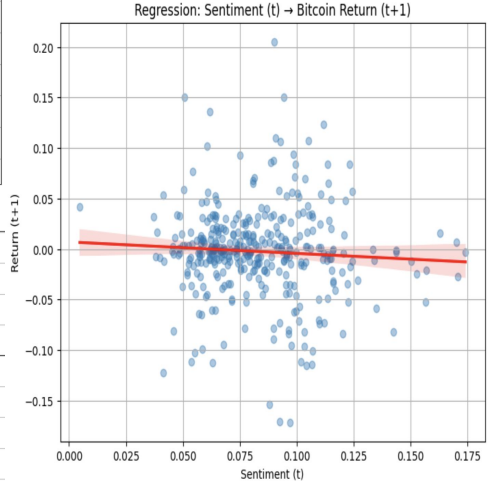
OLS regression:

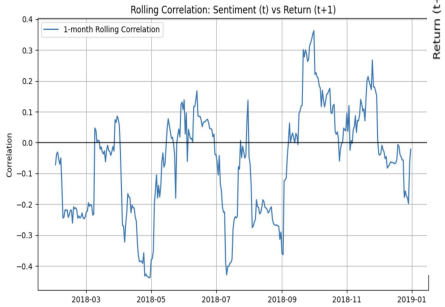
β = −0.114
p = 0.238
R^2 = 0.004
N = 364

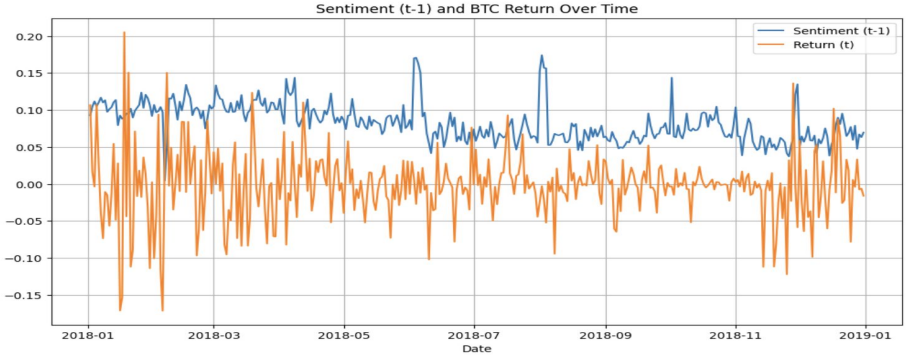
The negative coefficient suggests a very weak inverse relationship between sentiment and next-day returns. The effect is not statistically significant and explains less than 0.5% of return variation.

The scatter plots show no clear linear pattern.
At the same time, daily rolling correlations move back and forth between positive and negative values.









5-Minute Results

Pearson correlation:

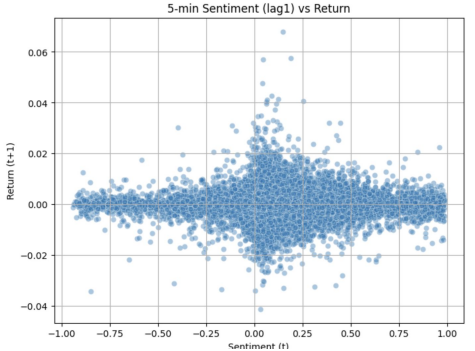
p= 0.0014

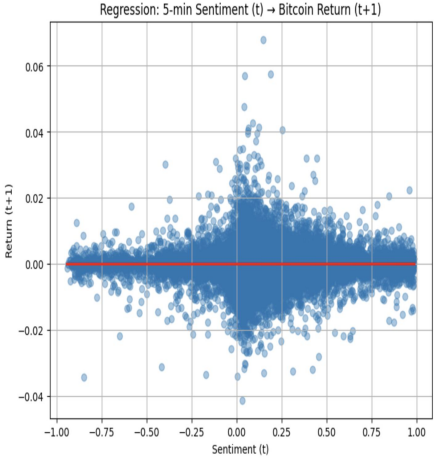
OLS regression:

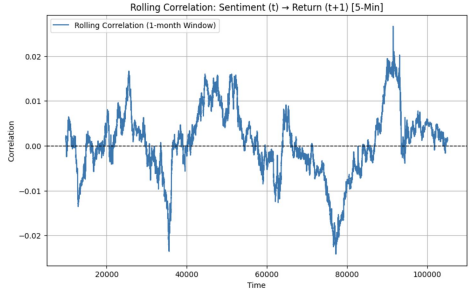
β ≈ 0
p = 0.686
R^2 = 0.000
N = 82,111

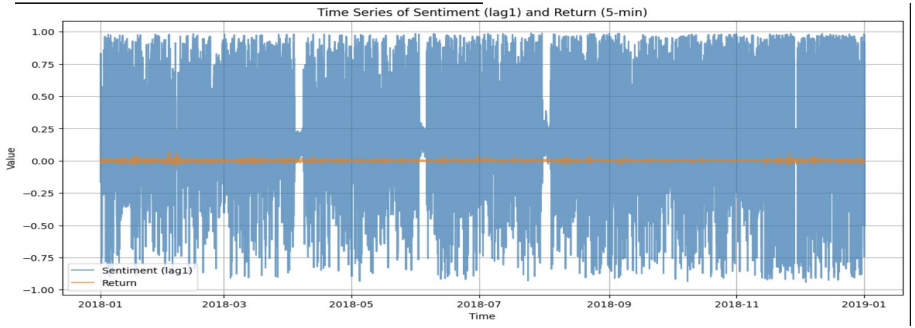
Sentiment shows almost no relationship with 5-minute returns. The regression line is essentially flat, and the model explains virtually none of the variation in prices.

Rolling correlations stay very close to zero.
Any sentiment effects at the 5-minute level are short-lived and quickly drowned out by market noise.

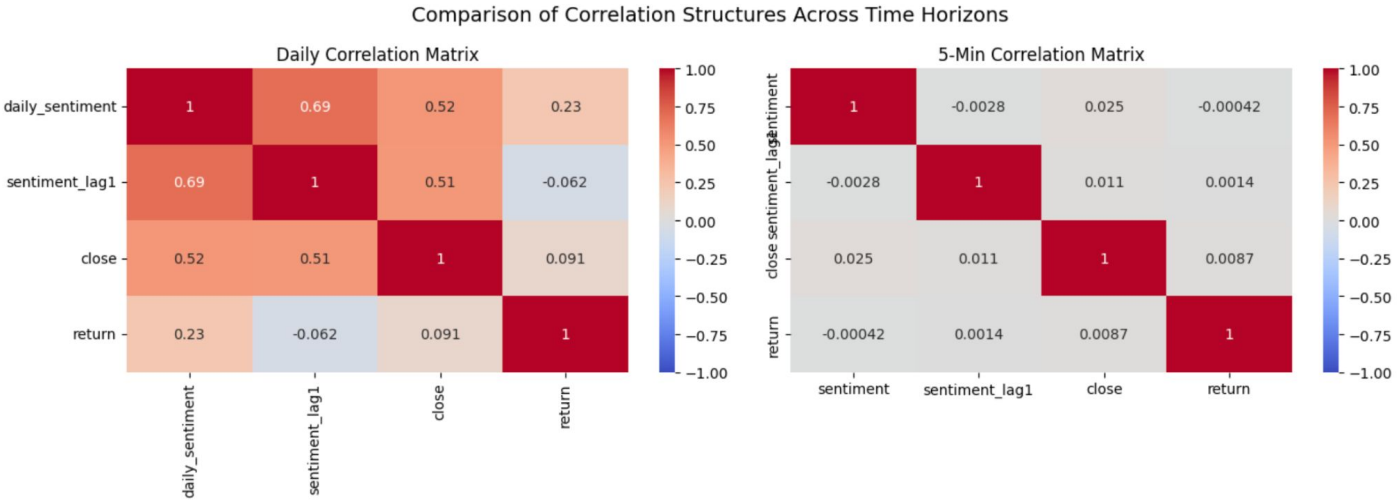


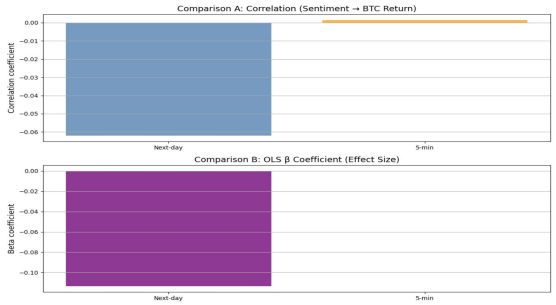






Direct Comparison





- Small and insignificant
- Daily: weak negative effect
- 5-min: weak positive effect
- Both are extremely close to zero

Even with much more high-frequency data, sentiment still explains virtually none of the price variation.

Conclusion & Interpretation

- Twitter sentiment has very limited predictive power for Bitcoin returns
- Results are consistent across time scales

Interpretation:

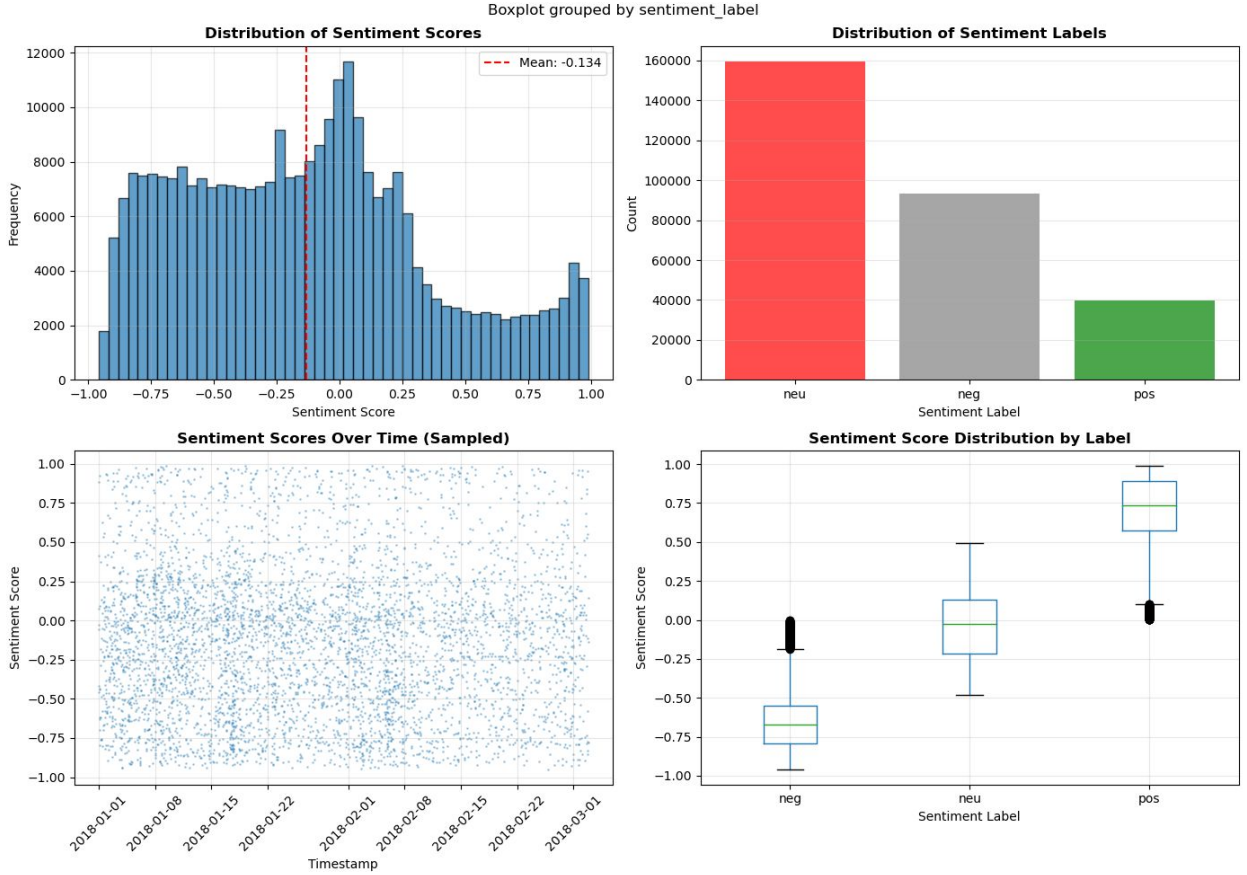
- Market reacts too fast or too noisily
- Public sentiment is quickly absorbed into prices
- Bitcoin behaves close to an efficient market

Research Question 2

Research Question 2

Question: Does Reddit sentiment correlate with Bitcoin volatility in short time intervals (1-minute/ 10-minutes/next-day) during 2018-2019?

Hypothesis: Increasing negative sentiment leads to increased volatility.



Mathematical Explanation

Volatility definitions (realized volatility)

Let returns be: $r_t = \log(P_t) - \log(P_{t-1})$

1-minute volatility: $RV_t^{(1m)} = |r_t|$

10-minute volatility: $RV_t^{(10m)} = \sqrt{\sum_{i=0}^{9} r_{t-i}^2}$

Daily volatility: $RV_t^{(1d)} = \sqrt{\sum_{i \in \text{day } t} r_i^2}$

Models (OLS regression)

Baseline model (no sentiment):

$$RV_t = \alpha + \beta_1 RV_{t-1} + \varepsilon_t$$

Model with sentiment:

$$RV_t = \alpha + \beta_1 RV_{t-1} + \beta_2 \text{Sent}_t + \varepsilon_t$$

Decision rule
If:

$$\beta_2 \neq 0$$

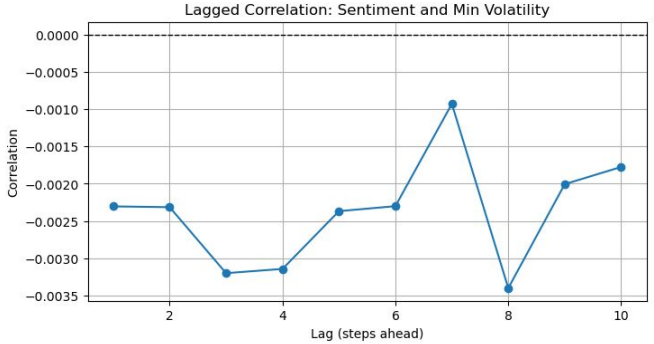
and/or:

$$\Delta R^2 > 0$$

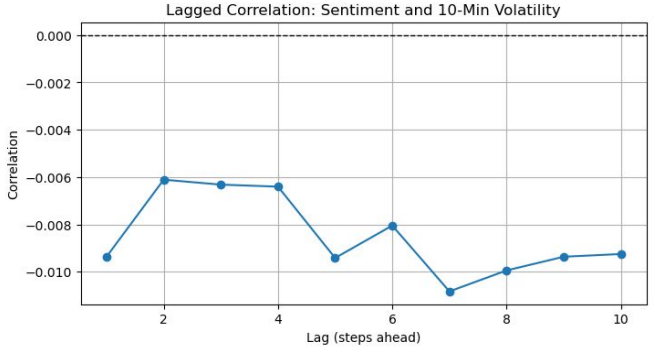
then sentiment helps predict volatility

Results

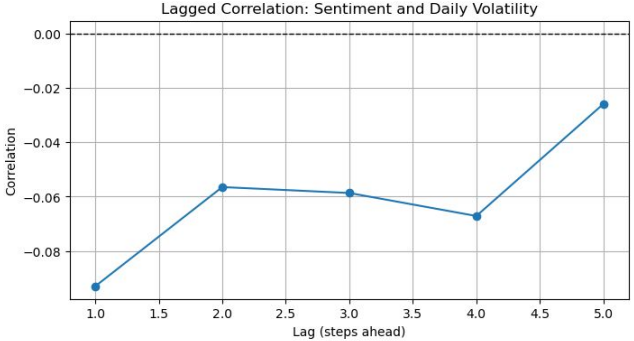
Baseline R^2: 0.1593583425682341
Sentiment R^2: 0.1593591456486223
ΔR^2: 8.030803881897697e-07
Sentiment coefficient:
-2.5612265794087943e-06
P-value for sentiment:
0.4785743383953841



Baseline R^2: 0.5012128412601853
Sentiment R^2: 0.501224425049817
ΔR^2: 1.1583789631730568e-05
Sentiment coefficient:
-6.340448914716828e-05
P-value for sentiment:
0.26925106650601555



Baseline R^2: 0.7055577240074085
Sentiment R^2: 0.7131832486547959
ΔR^2: 0.007625524647387416
Sentiment coefficient:
-0.07824001500312314
P-value for sentiment:
0.0021007390478738007



Takeaways

- Reddit sentiment does not correlate with volatility at very short horizons (1-min / 10-min)
- Next-day volatility -> sentiment becomes statistically significant, with a small but consistent negative relationship
- Negative sentiment tends to be followed by higher volatility
- Suggests sentiment might act more like a market mood signal

Research Question 3

Research question 3

RQ3: Does Google search activity related to Bitcoin predict short-term market momentum or volatility?

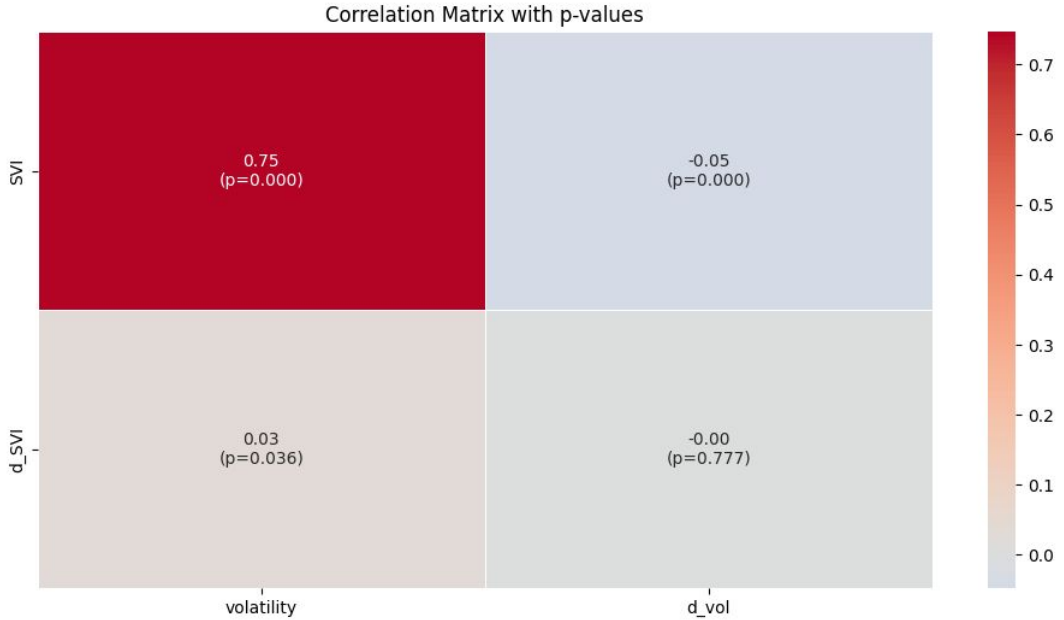
Motivation: Interest in Bitcoin market is directly reflected in google search volume, making it relevant for testing its influence on short-term price behaviour.

Hypothesis (volatility): Spikes in "Bitcoin" Google search volume are followed by increase in bitcoin volatility within 24 hours.

Hypothesis (momentum): Spikes in "Bitcoin" Google search volume are followed by positive bitcoin momentum.

Correlation: Search Volume ↔Volatility

- Volatility is calculated by standard deviation of the bitcoin price in a 24 hour window.
- Strong correlation: SVI ↔ Volatility (0.75)



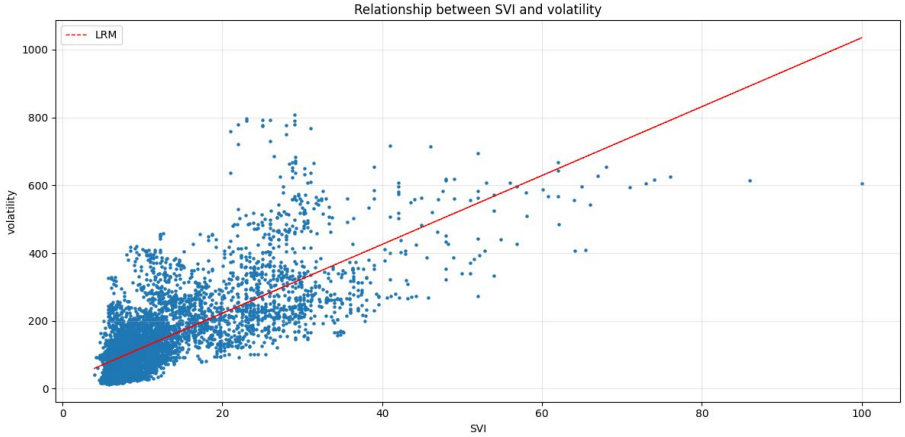
OLS Model (SVI → volatility)

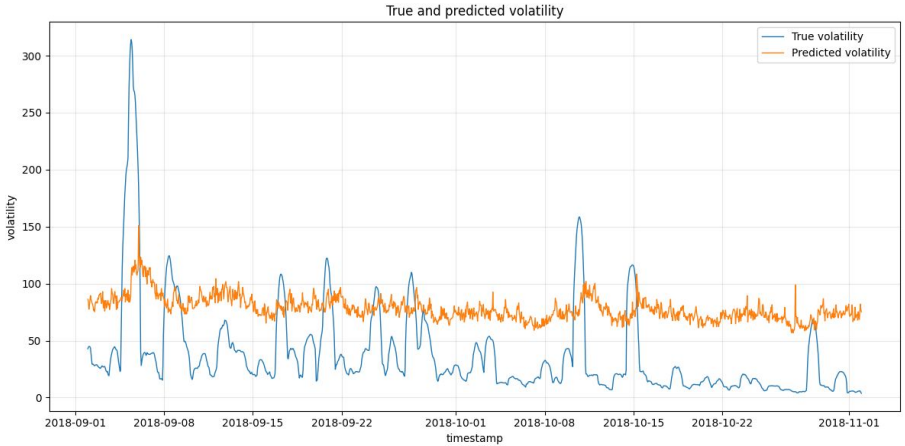
Ordinary least squares model (regression):

- H_0: There is no predictive power
  - $\text{mean}(L^{model}_t - L^{bench}_t) \geq 0$
- H_1: There is predictive power -
  - $\text{mean}(L^{model}_t - L^{bench}_t) < 0$

$\text{Benchmark}_t = v_{t-1}$

Confidence interval is computed by bootstrapping $L^{model}_t - L^{bench}$ instances. In this case: **[2819.50, 3258.35]**





Correlation: Search Volume ↔ Momentum

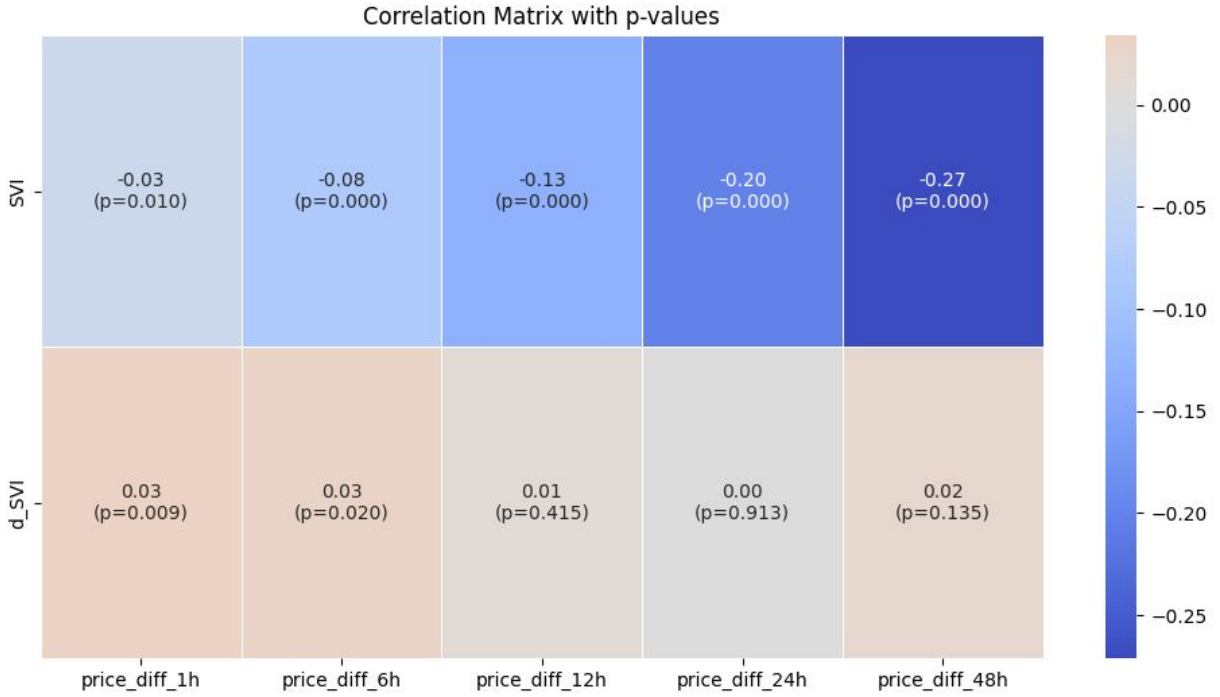
- Momentum is calculated by:

$$M = Price_t - Price_{t-x}$$

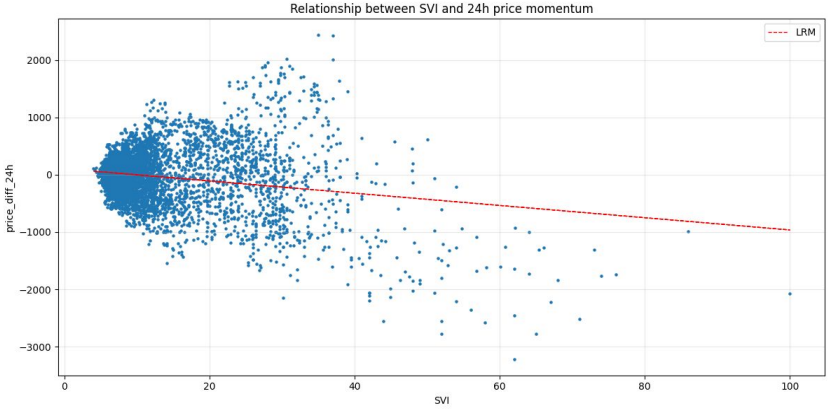
- X = {1, 6, 12, 24, 48}

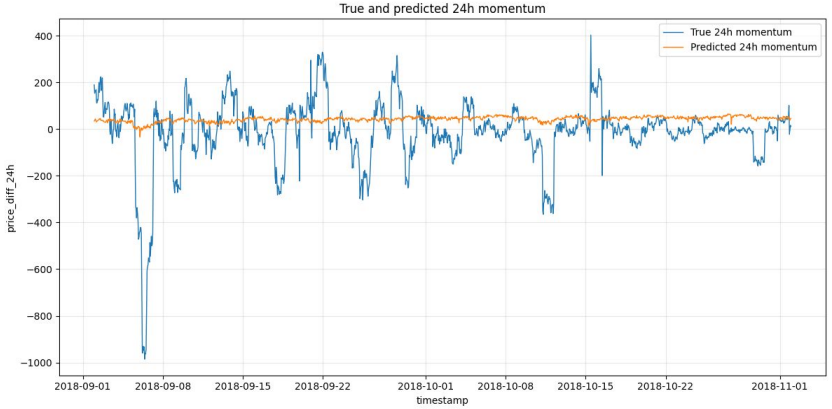
(SVI ↔24h momentum): -0.27

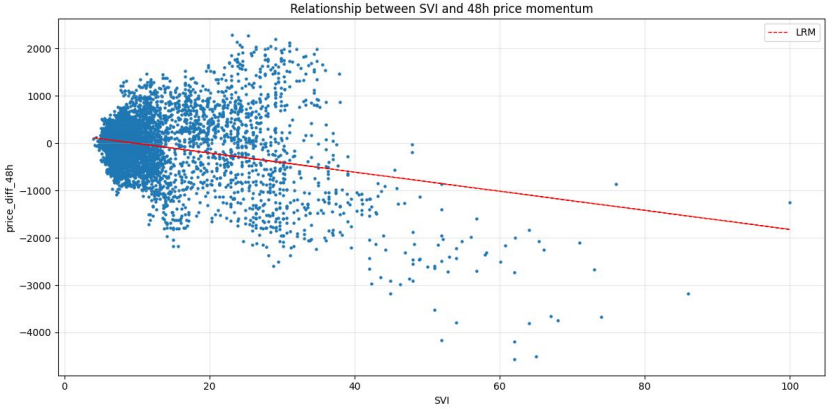
(SVI ↔48h momentum): -0.20

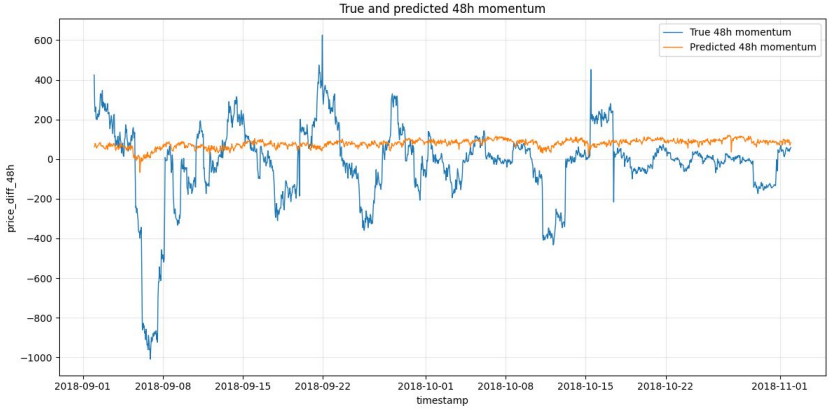


OLS Model (SVI → 24h, SVI → 48h)









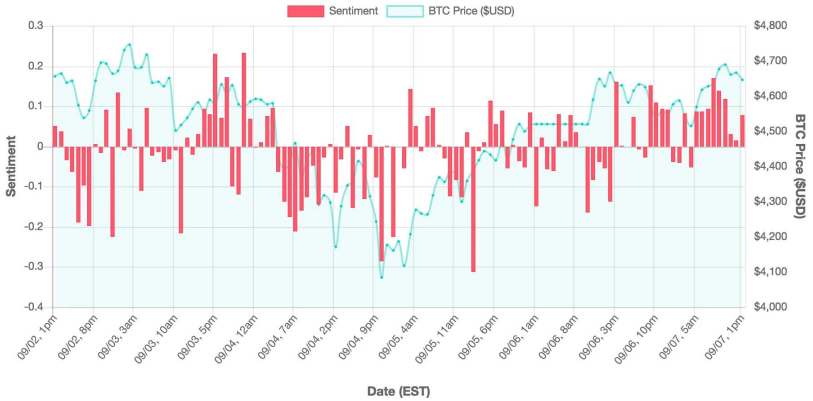
Takeaways

- Moderate positive correlation between search volume index and volatility
- Computed linear models do not provide a good prediction of Bitcoin price behaviour

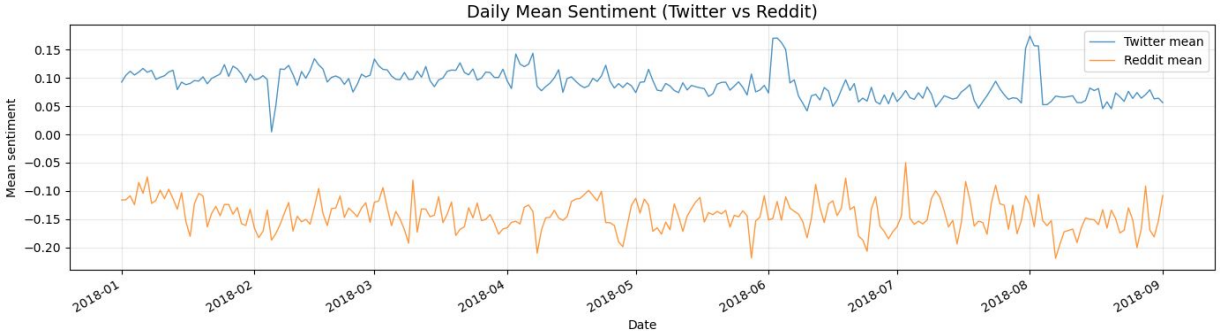
Research Question 4

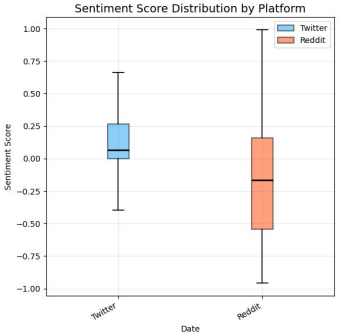
Research Question 4

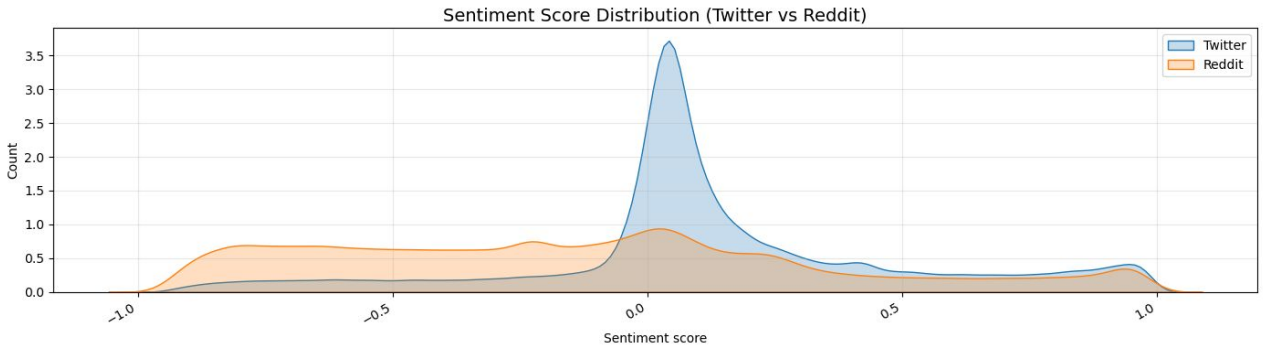
- **RQ 4**: Does daily sentiment disagreement predict Bitcoin price instability for the next day.
- **Motivation**:
  - Averages can hide conflict
  - Disagreement captures how divided public opinion is
- **Hypothesis**: Higher sentiment disagreement predic unstable Bitcoin price volatility

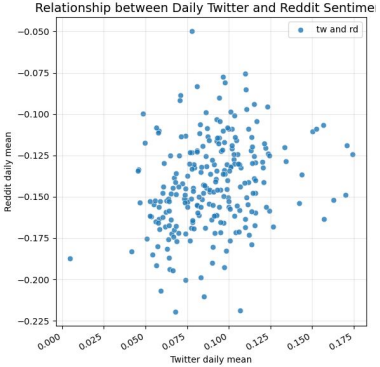


Exploratory Data Analysis on Sentiment Disagreement



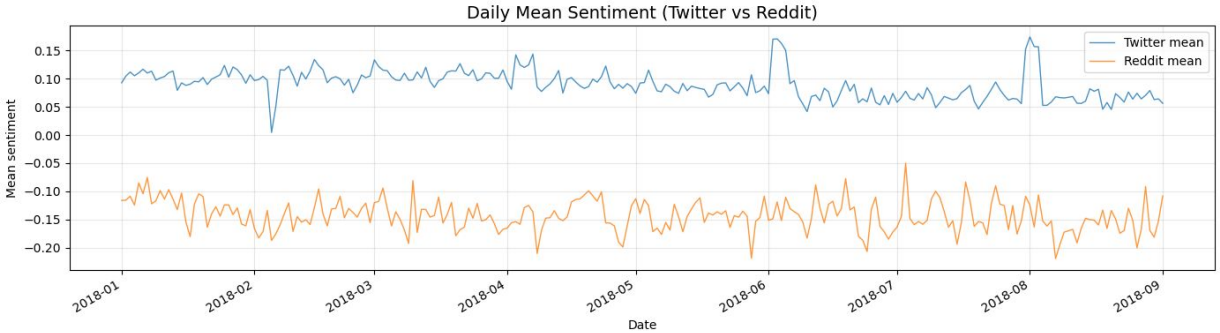


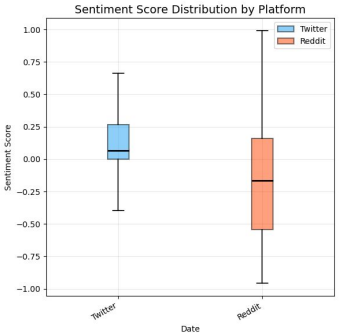




Conclusion from EDA

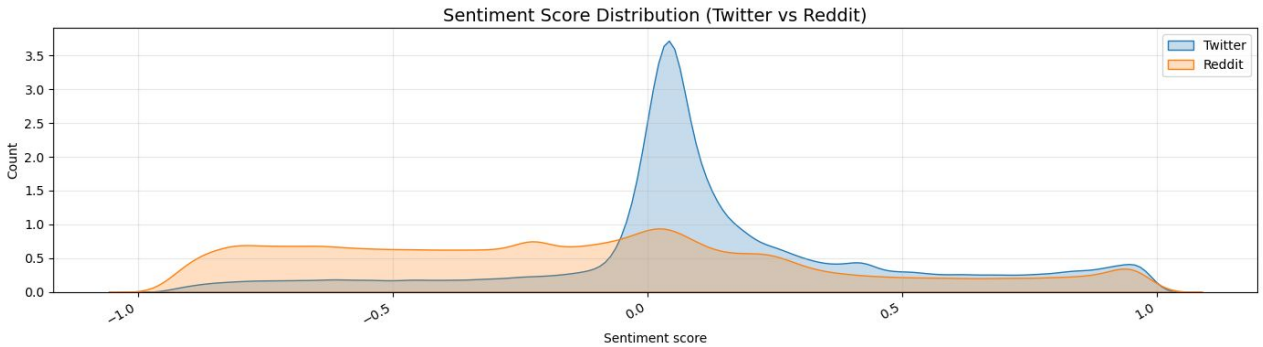
- Overall sentiment levels are very different between platforms
  - Twitter tends to be positive, while Reddit tends to be negative on average
- Sentiment variability is higher on Reddit
  - More emotional variability, polarized and expressive.

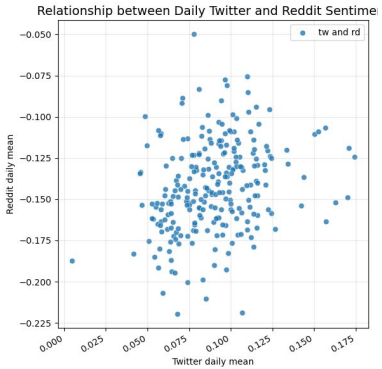




Conclusion from EDA

- Relationship between platforms is weak but positive
  - Correlation around 0.27, the platforms move together slightly
- Distribution shape differences reflect community culture
  - Twitter is dominated by neutral or slightly positive short post -> tighter distribution around 0
  - Reddit content is longer, more opinions, and critical -> broader distribution and negative central tendency.





10 Sentiment Disagreement Features

- $s_{i,t}$ **Sentiment score** of each text in each day.
- Daily **Median Absolute Deviation**: Continuous score dispersion based on the median
- Daily **Mean Gap**: Cross-platform disagreement between Twitter and Reddit
- Daily **Variance**
- Daily **Standard Deviation**
- Daily **Interquartile Range**: capture variation while ignoring extremes
- **7 Day Rolling** disagreement features

$$D_t^{\mathrm{MAD}} = \mathrm{median}\Big(\left|s_{i,t} - \mathrm{median}(s_{i,t})\right|\Big)$$

$$D_t^{\Delta\mu} = \left|\mu_t^{tw} - \mu_t^{rd}\right|$$

$$D_t^{\mathrm{var}} = \mathrm{Var}(s_{i,t})$$

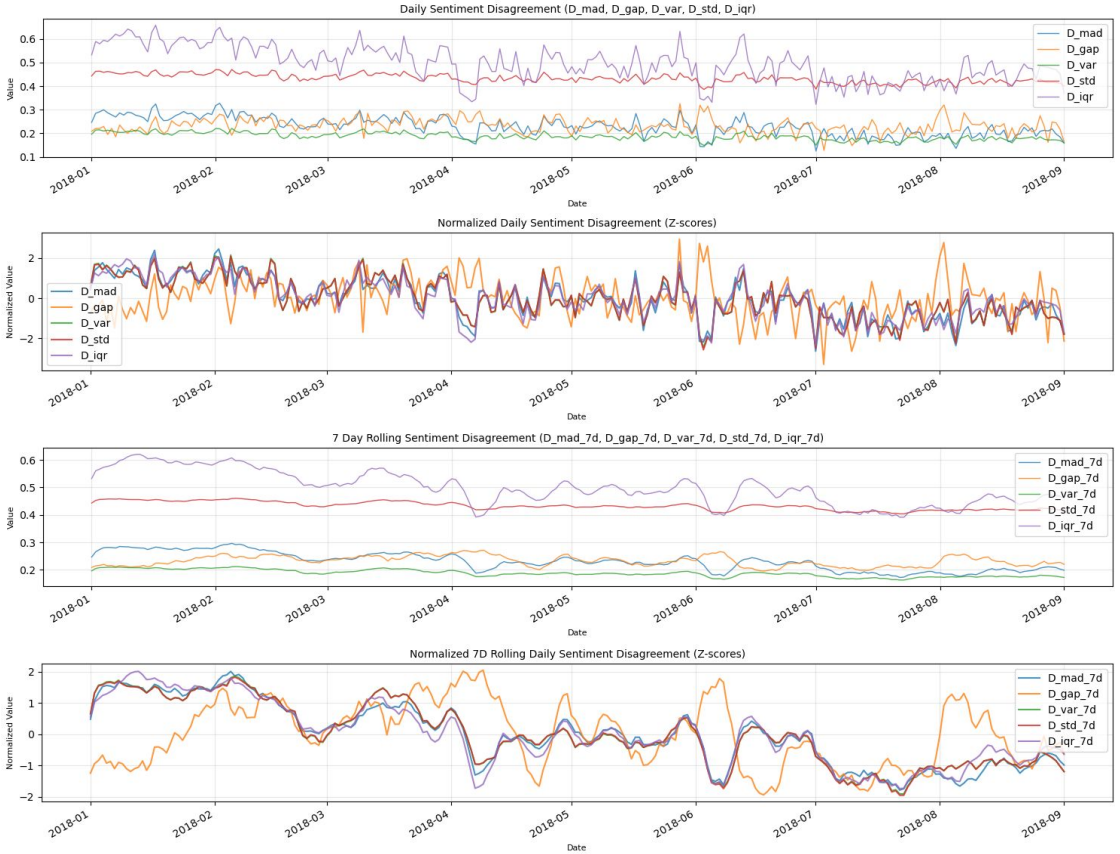
$$D_t^{\mathrm{std}} = \sqrt{\mathrm{Var}(s_{i,t})}$$

$$D_t^{\mathrm{IQR}} = Q_{0.75}(s_{i,t}) - Q_{0.25}(s_{i,t})$$

$$D_t^{(7\mathrm{d})} = \frac{1}{7}\sum_{r=t-6}^{t} D_r$$

Visualization: Daily Sentiment Disagreement

- Overall sentiment disagreement declines over time
- Robust measure confirm the trend (MAD, IQR)
- Platform sentiment diverges at times (GAP)



Compute Price Instability

- **Close-to-close log return**: measure of relative price change
- **Realized Volatility**: computed from intraday data, captures total price variation
- **Parkinson Volatility**: range-based daily volatility estimator that uses the high and low, reflect how wide the price range was.
- **Absolute Daily Log return**: the absolute value of close-to-close daily log return.

$$r_t = \log\left(\frac{C_t}{C_{t-1}}\right)$$

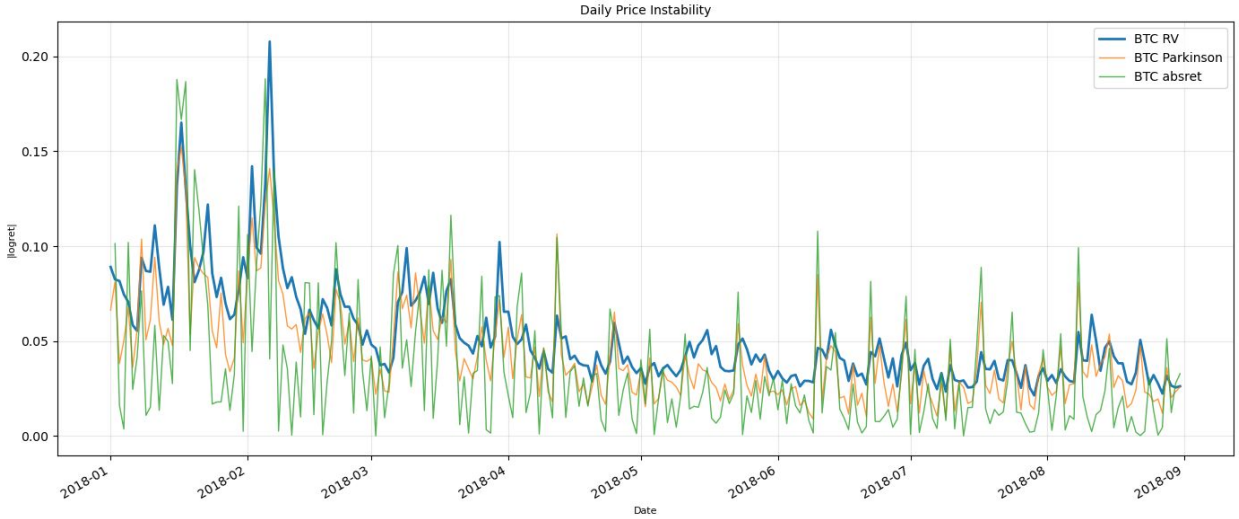
$$RV_t = \sqrt{\sum_{i \in t} r_i^2}$$

$$\sigma_t^{\text{Parkinson}} = \sqrt{\frac{1}{4\ln 2}\left(\ln\frac{H_t}{L_t}\right)^2}$$

$$\text{absret\_daily} = |\ln(C_t) - \ln(C_{t-1})|$$

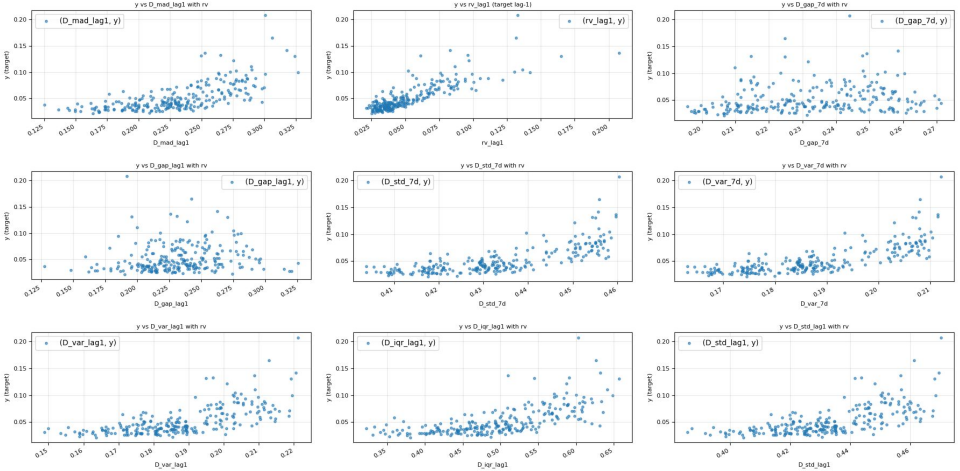
Visualization: Price Instability

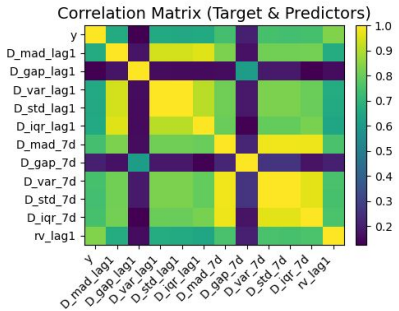
- We mainly focus on **Realized Volatility (RV)**
- Uses all intraday information with 1 minute bars.
- Lower noise implies more stable and informative volatility.
- Capture full path of price fluctuations



Combine Into A Training Dataset

- Daily volatility target y: RV
- Lagged daily disagreement features, to avoid look-ahead bias
- Persistence control: rv_lag1 = yesterday's RV, captures volatility clustering as the AR(1) baseline.
- **"Given yesterday's sentiment and volatility, predict today's RV"**





Training Model

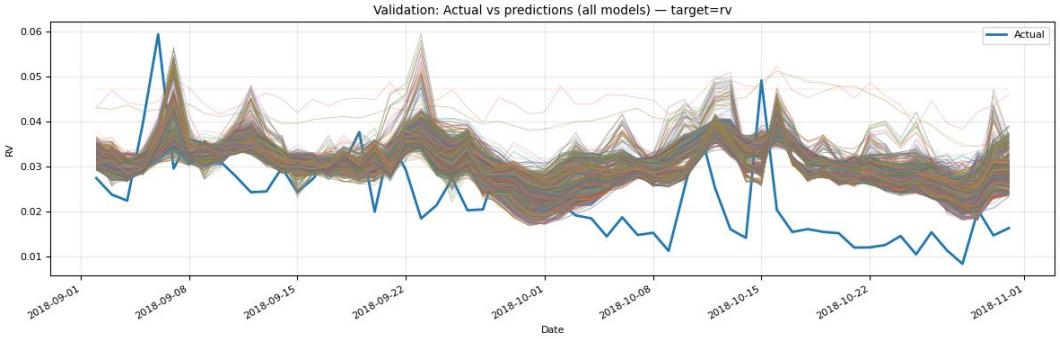
1. Generate model space based on feature sets:
   - 2048 model combinations
   - For example:
     - AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D
     - AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D
2. Build regression matrices
   - Construct matrix X for train and validation from selected predictors.
   - OLS is solved via the matrix form

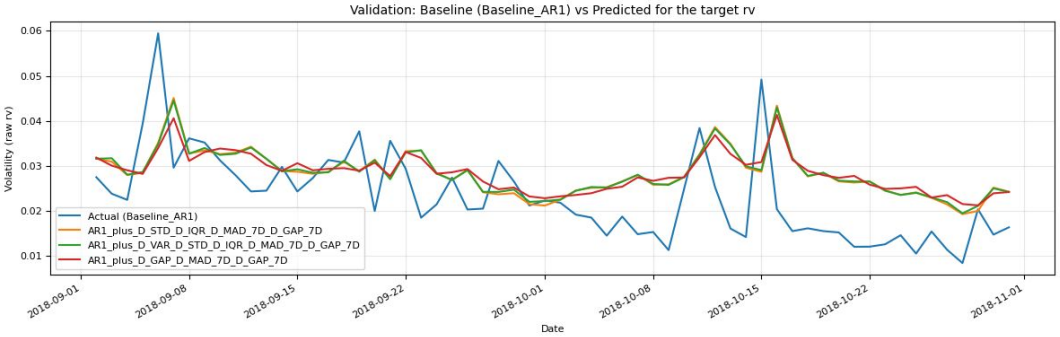
$$\hat{\beta} = (X^\top X)^{-1} X^\top y$$

3. Fit OLS with time-series robust uncertainty
   - Fit on the training dataset using **statsmodels.OLS().fit(cov_type="HAC", maxlags=7)**
   - **HAC(Newey-West)** keeps coefficients the same, but fixes standard errors for **autocorrelation + heteroskedasticity**
     - Standard OLS assumes regression error are independent and homoskedastic
     - Autocorrelation in standard OLS cause standard error are too small implies false significance.
     - HAC changes the covariance matrix that allows correlated residual up to *maxlags*, and time-varying variance
4. Predict on validation using the mode

Model Validation

- Error functions:
  - **Root Mean Square Error (RMSE)**: penalizes large error, good measure overall accuracy
  - **Mean Absolute Error**: measure typical prediction error, less sensitive to outliers.
- Validated using the validation set.



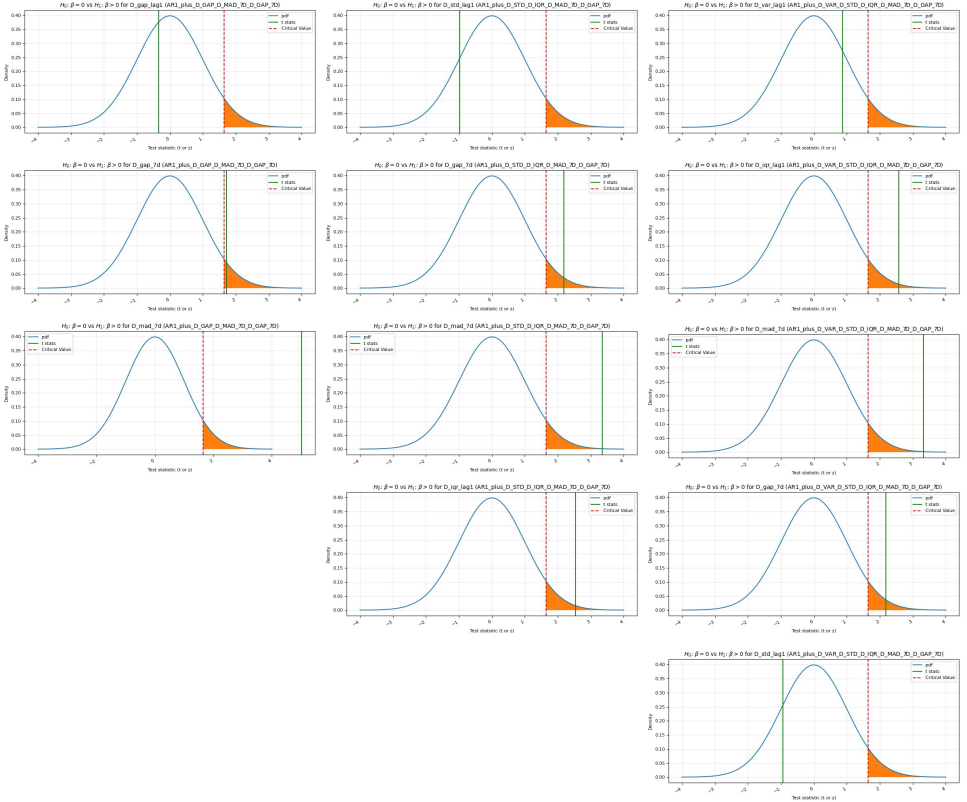



```
=== Best Models on Validation Set ===
RMSE (raw scale)     → AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D  (value = 0.010210)
RMSE (log scale)     → AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D  (value = 0.444736)
MAE  (raw scale)     → AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D  (value = 0.008572)
MAE  (log scale)     → AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D  (value = 0.363641)
=====================================
```

Hypothesis Test

- Perform hypothesis test on single regression coefficient from the statistical mode
- **Null Hypothesis**: Sentiment disagreement is not associated and has no effect with Bitcoin price instability $H_0 : \beta = 0$
- **Alternative Hypothesis**: Higher sentiment disagreement predict higher Bitcoin price instability $H_1 : \beta > 0$

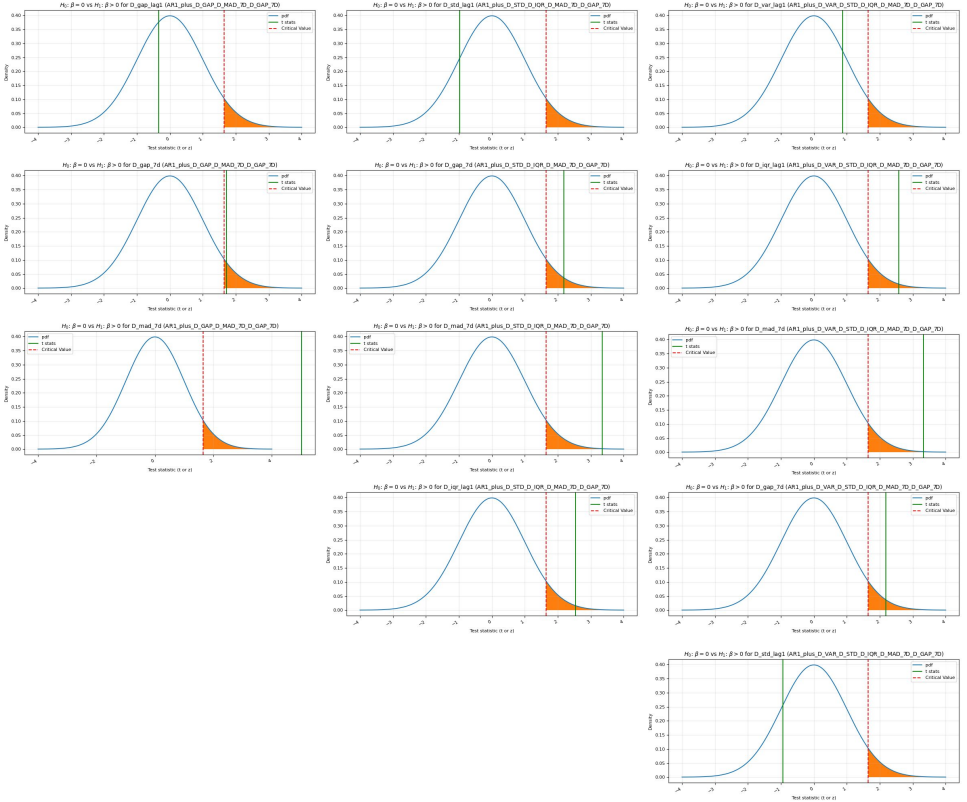
model	term	beta	t	p	alpha	reject
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_mad_7d	4.9905	5.023	2.54e-07	0.05	✅
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_gap_7d	1.5603	1.718	0.0429	0.05	✅
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_gap_lag1	-0.1494	-0.346	0.6352	0.05	❌
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_std_lag1	-1.8672	-0.976	0.8355	0.05	❌
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_iqr_lag1	1.3557	2.536	0.0056	0.05	✅
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_mad_7d	3.4938	3.346	0.0004	0.05	✅
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_gap_7d	1.6877	2.184	0.0145	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_var_lag1	33.0473	0.876	0.1905	0.05	❌
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_std_lag1	-30.2859	-0.944	0.8274	0.05	❌
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_mad_7d	3.5063	3.328	0.0004	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_gap_7d	1.7124	2.180	0.0146	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_iqr_lag1	1.3765	2.570	0.0051	0.05	✅



Hypothesis Test

- **Reject H0** for several key sentiment-disagreement features, as they are **positive** and **p<0.05**
- Important features:
  - D_MAD_7d
  - D_GAP_7d
  - D_IQR_lag_1
- Higher sentiment disagreement is associated and predict higher next-day instability

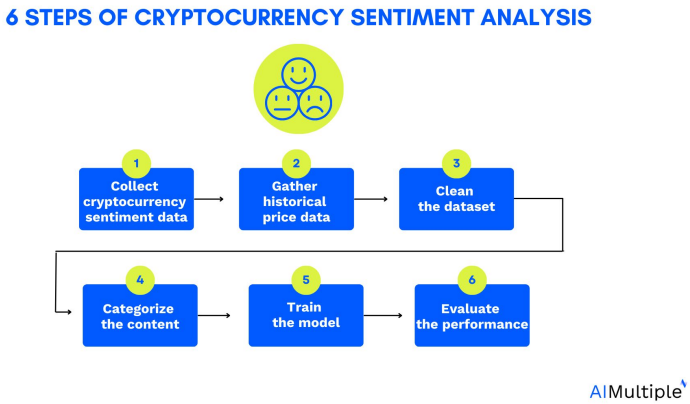
model	term	beta	t	p	alpha	reject
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_mad_7d	4.9905	5.023	2.54e-07	0.05	✅
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_gap_7d	1.5603	1.718	0.0429	0.05	✅
AR1_plus_D_GAP_D_MAD_7D_D_GAP_7D	D_gap_lag1	-0.1494	-0.346	0.6352	0.05	❌
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_std_lag1	-1.8672	-0.976	0.8355	0.05	❌
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_iqr_lag1	1.3557	2.536	0.0056	0.05	✅
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_mad_7d	3.4938	3.346	0.0004	0.05	✅
AR1_plus_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_gap_7d	1.6877	2.184	0.0145	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_var_lag1	33.0473	0.876	0.1905	0.05	❌
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_std_lag1	-30.2859	-0.944	0.8274	0.05	❌
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_mad_7d	3.5063	3.328	0.0004	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_gap_7d	1.7124	2.180	0.0146	0.05	✅
AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D	D_iqr_lag1	1.3765	2.570	0.0051	0.05	✅



Research Question 5

Research Question 5

- **RQ5**: Can Sentiment from Twitter, Reddit, Google Trends, and Disagreement improve next-day BTC return prediction vs a price-only baseline?
- **Hypothesis**: A predictive model including sentiment features achieves better accuracy than a model using only past Bitcoin prices.

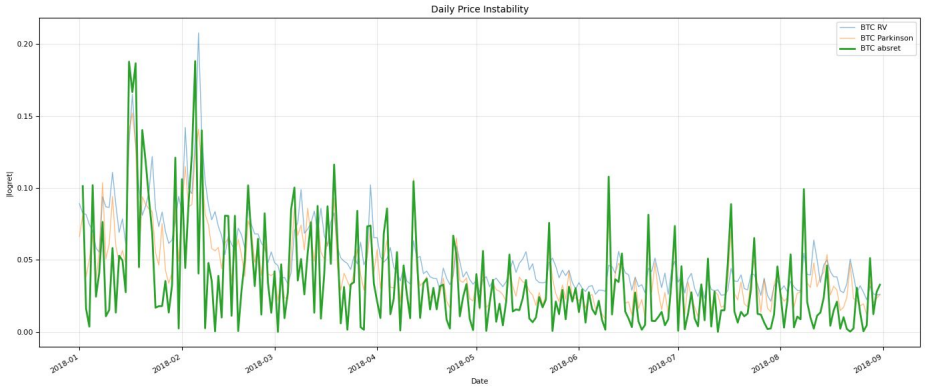


Target: Absolute Log Return

- **Absolute Daily Log return**: the absolute value of close-to-close daily log return.
- Measures price movement magnitude, not direction
- Captures volatility clustering
- Stronger signal than signed returns
- Standard proxy for short-horizon risk

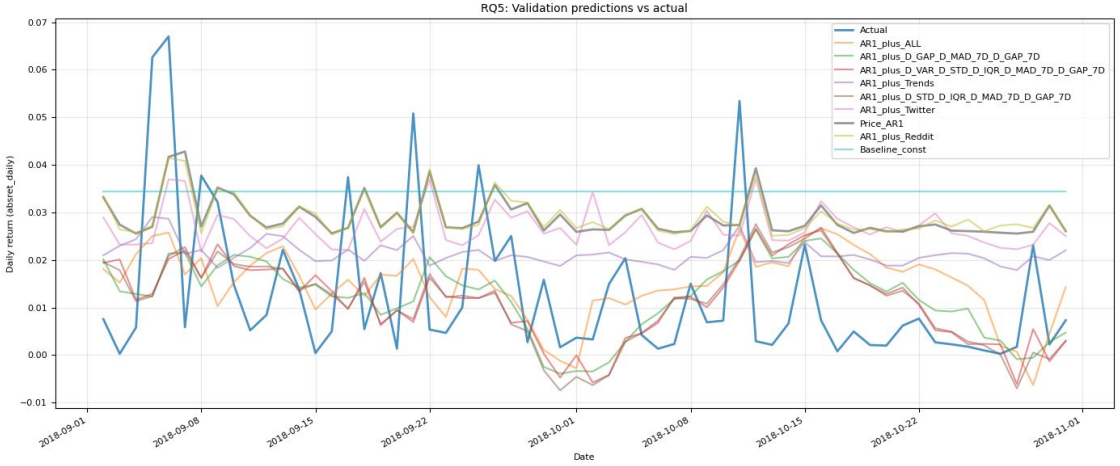
$$r_t = \log\left(\frac{C_t}{C_{t-1}}\right)$$

$$\text{absret\_daily} = |\ln(C_t) - \ln(C_{t-1})|$$

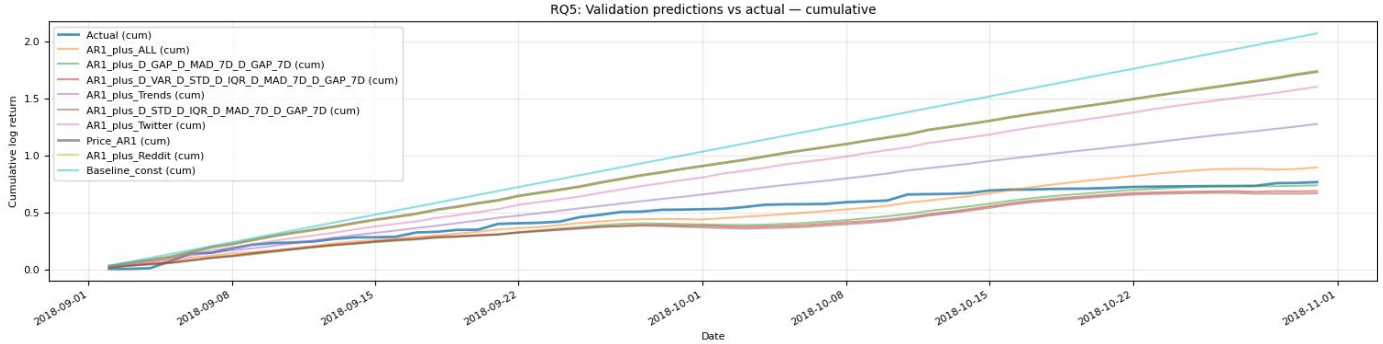


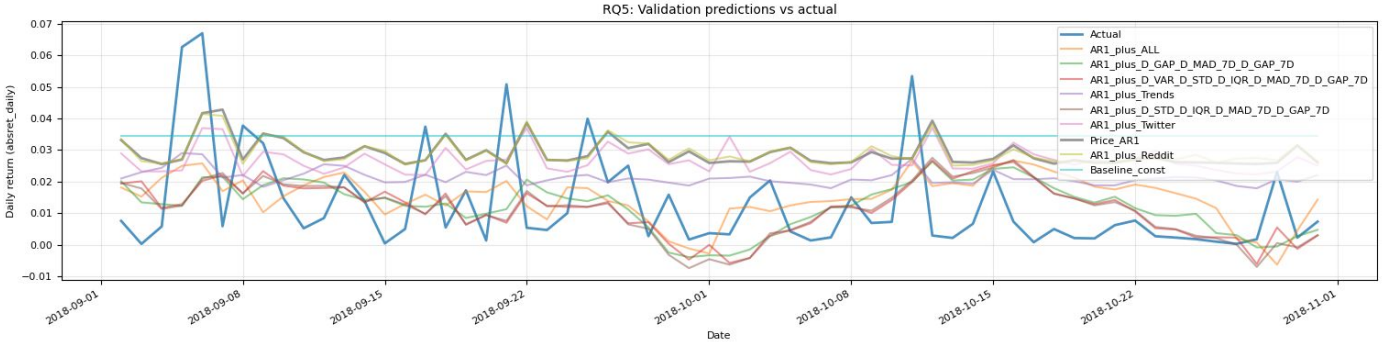
Baseline Model

- **Price_AR1: Lagged Absolute Daily Log Return**
- Captures volatility persistence
- Strong benchmark for risk prediction
- Sentiment must beat this to add value



Best Model based on Error Functions





Best RMSE: 'AR1_plus_ALL', 'rmse': 0.0151, 'mae': 0.0123
Best MAE : 'AR1_plus_D_VAR_D_STD_D_IQR_D_MAD_7D_D_GAP_7D', 'rmse': 0.0164, 'mae': 0.012

Reference

1. *“Bitcoin” Google Search Trend vs Bitcoin Value [OC]*. (n.d.). Reddit. https://www.reddit.com/r/dataisbeautiful/comments/6aiked/bitcoin_google_search_trend_vs_bitcoin_value_oc/
2. *Bitcoin Twitter sentiment (based on 700k tweets & comments)*. (n.d.). Reddit. https://www.reddit.com/r/dataisbeautiful/comments/a5jzy0/bitcoin_twitter_sentiment_based_on_700k_tweets/
3. *Reddit crypto sentiment vs price of Bitcoin*. (n.d.). Reddit. https://www.reddit.com/r/dataisbeautiful/comments/kv15y2/oc_reddit_crypto_sentiment_vs_price_of_bitcoin/
4. Reiff, N. (2025, October 30). *Why Bitcoin’s price is so volatile: Key factors explained*. Investopedia. https://www.investopedia.com/articles/investing/052014/why-bitcoins-value-so-volatile.asp
5. Cruz, B., & Petrino, G. (2025, November 21). *2025 Cryptocurrency Adoption and Consumer Sentiment Report*. Security.org. https://www.security.org/digital-security/cryptocurrency-annual-consumer-report/
6. Arslan, S. (2024). Bitcoin price prediction using sentiment analysis and empirical mode decomposition. *Computational Economics*, *65*(4), 2227–2248. https://doi.org/10.1007/s10614-024-10588-3
7. Nurimba, S., Jayadi, R., Oktavia, T., & Hosoda, T. (2025). Examining Cryptocurrency Price Movements and Twitter Sentiment Using VADER and Econometric Models. *IEEE*, 1–7. https://doi.org/10.1109/iccit65724.2025.11167099
8. Léber, D., & Egyed, B. (2025). The sentiment augmented GARCH-LSTM hybrid model for Value-at-Risk forecasting. *Computational Economics*. https://doi.org/10.1007/s10614-025-11042-8

Q&A