

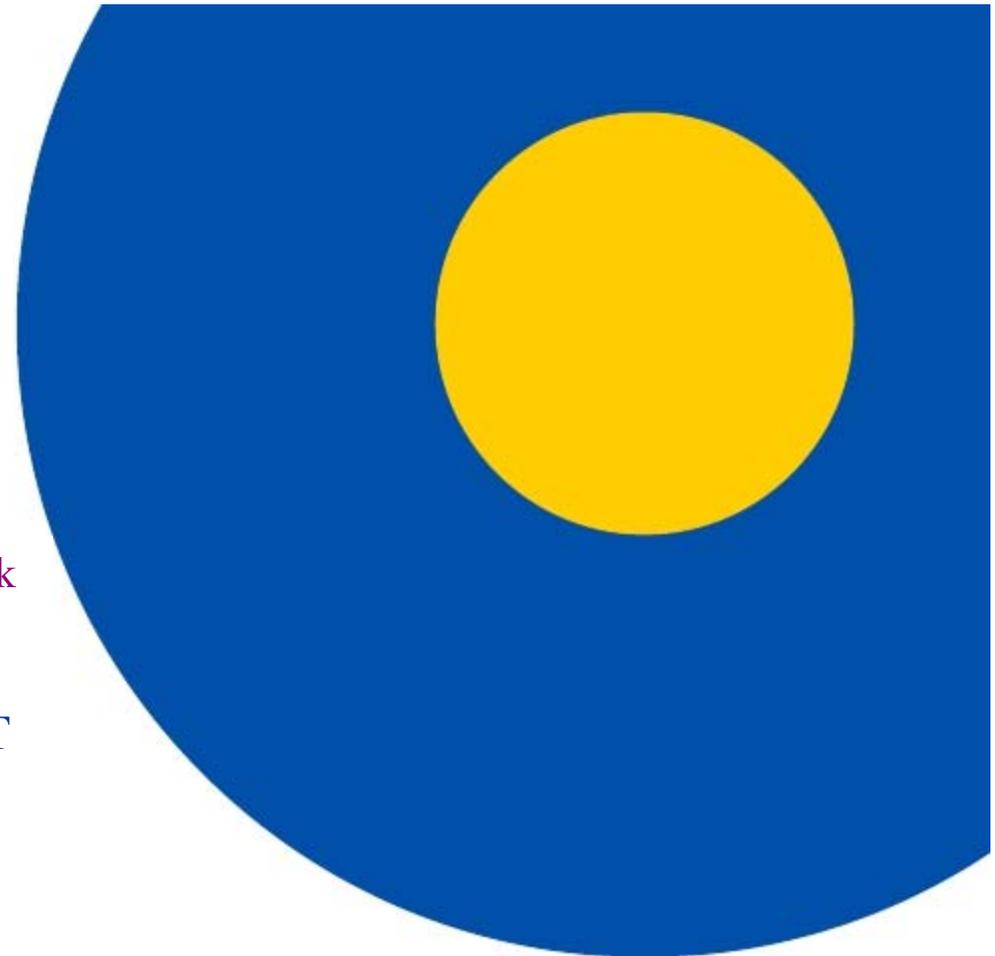


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## **News Sentiment Analysis Using ChatGPT for Bitcoin Price Dynamics**





## Outline of the presentation

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- ⦿ Motivation
- ⦿ Research objectives
- ⦿ Construction of sentiment indicators using ChatGPT
- ⦿ Data, research procedure, applied methods
- ⦿ Empirical results
- ⦿ Conclusions



## Motivation

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- ⦿ The high and still growing popularity of cryptocurrencies → need for tools for analysis and forecasting
- ⦿ High level of investment risk
- ⦿ Promising results of applying ML algorithms in economics and finance
- ⦿ The potential of using LLMs for effective information analysis and market sentiment assessment



## Research Objectives

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- ⦿ Use ChatGPT-4.0 to construct market sentiment indicators for Bitcoin
- ⦿ Verify whether including these indicators in forecasting models can improve the predictions of Bitcoin returns and volatility



## Data

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Time span: January 1, 2021 – March 31, 2024

- ⦿ Bitcoin intraday prices (source: Kraken exchange).
- ⦿ Bitcoin-related news headlines (source: CryptoNews). 113,781 headlines.



## Predicted Variables

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- ⊙ Daily logarithmic returns:

$$r_{d,t} = \ln(P_t/P_{t-1}),$$

where  $P_t$  is the closing price on date  $t$ .

- ⊙ Realized variances:

$$RV_{d,t} = \sum_{k=1}^K r_{k,t}^2,$$

where  $r_{k,t}$  is the intraday return,  $K$  is the number of observations during a day.

We utilize 15-minute price intervals.



## Construction of Sentiment Indicators

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News headlines analyzed independently with respect to three aspects:

- ⦿ Potential short-term price increase/decrease of Bitcoin.
- ⦿ Potential short-term volatility increase/decrease of Bitcoin.
- ⦿ High/low BTC volatility in the short term.



## Query 1: “Potential Price Increase/Decrease”

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Prompt to ChatGPT:

*"Pretend you are a financial expert with cryptocurrency recommendation experience. Elaborate with one short and concise sentence. Can the headline cause a '**price increase**' or '**price decrease**' for Bitcoin in the short term? Answer 'YES' if it is price-increase news, 'NO' if it is price-decrease news, or 'UNKNOWN' if the news is uncertain."*



## Query 2: “Potential Volatility Increase/Decrease”

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Prompt to ChatGPT:

*"Pretend you are a financial expert with cryptocurrency recommendation experience. Elaborate with one short and concise sentence. Can the headline cause a '**volatility increase**' or '**volatility decrease**' for Bitcoin in the short term? Answer 'YES' if it is volatility-increase news, 'NO' if it is volatility-decrease news, or 'UNKNOWN' if the news is uncertain."*



## Query 3: “High/Low Volatility”

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Prompt to ChatGPT:

*"Pretend you are a financial expert with cryptocurrency recommendation experience. Elaborate with one short and concise sentence. Does the headline mean '**high volatility**' or '**low volatility**' for Bitcoin in the short term? Answer 'YES' if it is high-volatility news, 'NO' if it is low-volatility news, or 'UNKNOWN' if the news is uncertain."*



## Construction of Sentiment Indicators $X_P$ , $X_{V1}$ , $X_{V2}$

Calculating sentiment indicators (for a given day):  $X_P$  (Query 1),  $X_{V1}$  (Query 2),  $X_{V2}$  (Query 3):

$$X_P = \frac{\text{number of 'price increase' news} - \text{number of 'price decrease' news}}{\text{total number of news}},$$

$$X_{V1} = \frac{\text{number of 'volatility increase' news} - \text{number of 'volatility decrease' news}}{\text{total number of news}},$$

$$X_{V2} = \frac{\text{number of 'high volatility' news} - \text{number of 'low volatility' news}}{\text{total number of news}}.$$



## Construction of Sentiment Indicators $X_{P-}$ , $X_{P+}$

Additionally, we disaggregate above indicators by creating unidirectional indicators:

- For price change:

$$X_{P+} = \frac{\text{number of 'price increase' news}}{\text{total number of news}},$$

$$X_{P-} = -\frac{\text{number of 'price decrease' news}}{\text{total number of news}}.$$

$$X_P = X_{P+} + X_{P-}$$



## Construction of Sentiment Indicators $X_{V1-}$ , $X_{V1+}$

- For change of volatility:

$$X_{V1+} = \frac{\textit{number of 'volatility increase' news}}{\textit{total number of news}},$$

$$X_{V1-} = -\frac{\textit{number of 'volatility decrease' news}}{\textit{total number of news}}.$$

$$X_{V1} = X_{V1+} + X_{V1-}$$



## Construction of Sentiment Indicators $X_{V2-}$ , $X_{V2+}$

- For level of volatility:

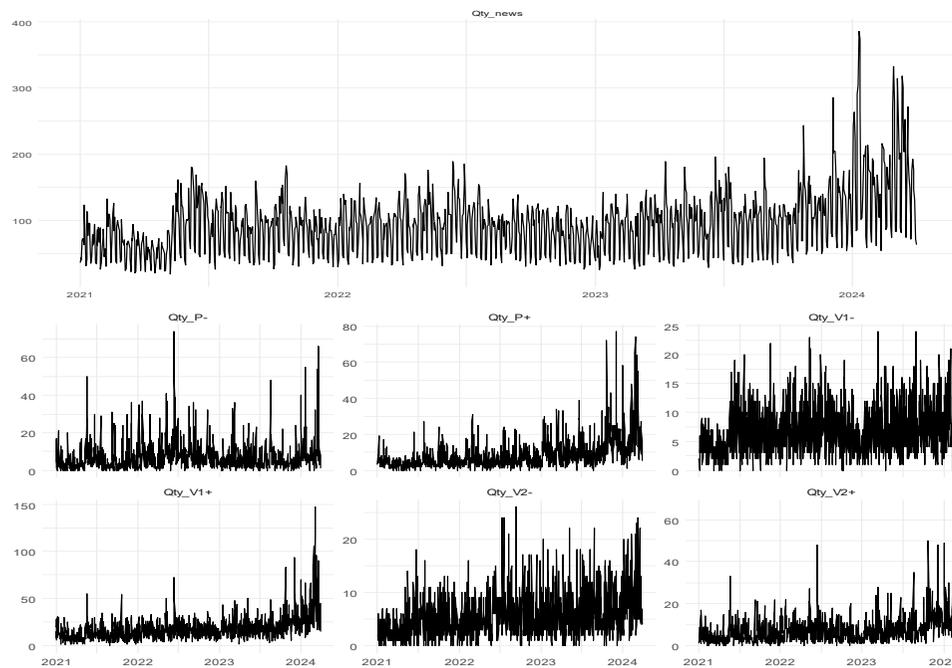
$$X_{V2+} = \frac{\textit{number of 'high volatility' news}}{\textit{total number of news}},$$

$$X_{V2-} = -\frac{\textit{number of 'low volatility' news}}{\textit{total number of news}}.$$

$$X_{V2} = X_{V2+} + X_{V2-}$$



## Daily number of the BTC-related news headlines (total and for individual queries)



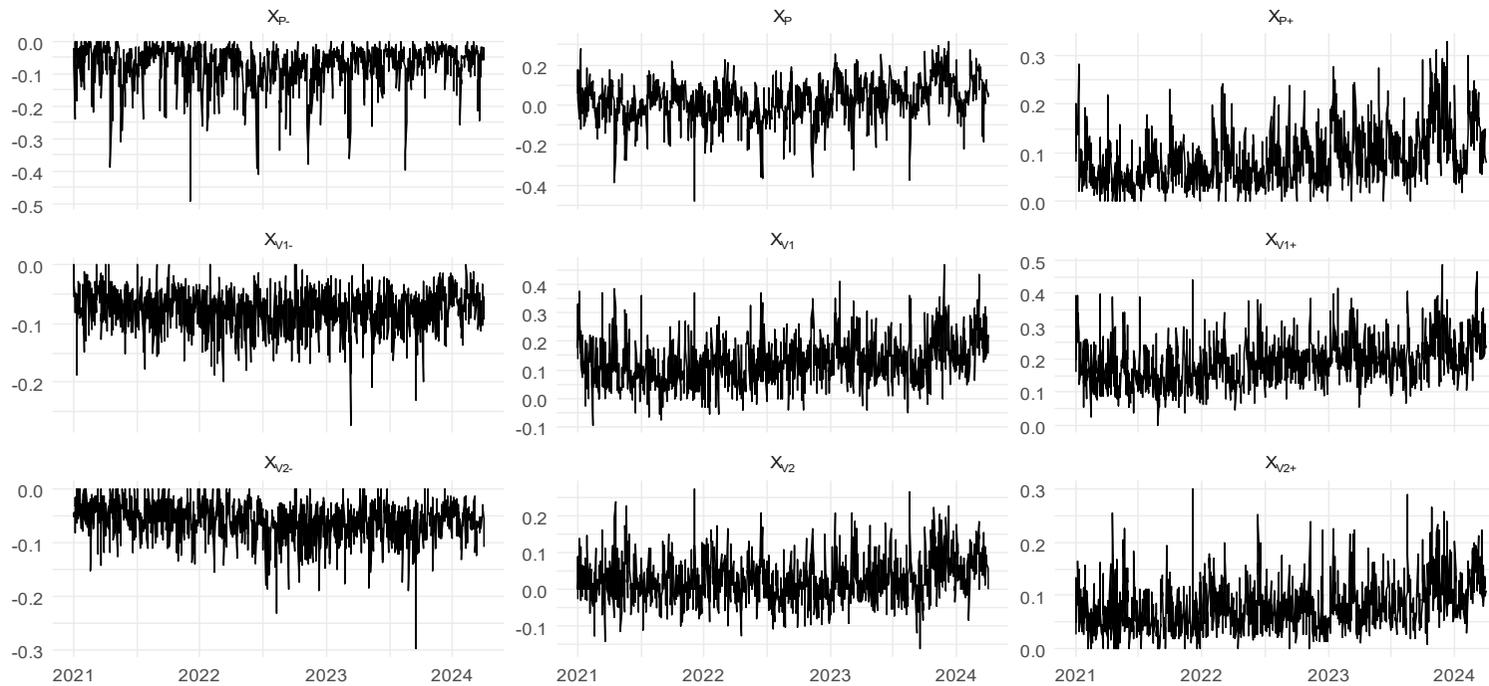


## Summary statistics for daily number of the BTC-related news headlines (total and for individual queries)

Variable	Mean	Minimum	Maximum	Standard deviation	Skewness	Excess kurtosis
Qty_news	95.94	19	386	47.89	1.39	4.25
Qty_P-	7.08	0	74	7.71	2.99	13.81
Qty_P+	9.02	0	77	9.14	2.98	13.23
Qty_V1-	7.26	0	24	4.39	0.78	0.35
Qty_V1+	18.70	0	147	13.59	2.85	14.74
Qty_V2-	5.80	0	26	4.30	1.26	1.98
Qty_V2+	8.16	0	66	7.59	2.80	12.14



## Constructed Indicators





## Summary Statistics of the Investigated Variables

Variable	Mean	Minimum	Maximum	Standard deviation	Skewness	Excess kurtosis
$r_d$	0.748E-03	-0.164	0.147	0.034	-0.265	2.938
$RV_d$	0.130E-02	0.727E-05	0.045	0.002	8.832	118.031
$X_P$	0.020	-0.479	0.316	0.101	-0.505	1.443
$X_{V1}$	0.129	-0.095	0.471	0.082	0.522	0.562
$X_{V2}$	0.025	-0.162	0.274	0.060	0.554	0.751
$X_{P-}$	-0.073	-0.493	0.000	0.064	-1.852	5.161
$X_{P+}$	0.089	0.000	0.329	0.058	1.043	1.030
$X_{V1-}$	-0.077	-0.273	0.000	0.035	-0.653	1.180
$X_{V1+}$	0.192	0.000	0.485	0.070	0.556	0.521
$X_{V2-}$	-0.060	-0.297	0.000	0.035	-1.009	2.663
$X_{V2+}$	0.081	0.000	0.301	0.047	1.001	1.410



## Correlation Analysis Between Indicators

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- ⊙  $X_{V1}$  and  $X_{V2}$  – high correlation (0.582)
- ⊙  $X_{V1+}$  and  $X_{V2+}$  – the highest correlation (0.734)
- ⊙  $X_P$  weakly correlated with  $X_{V1}$  and  $X_{V2}$
- ⊙  $X_{P+}$  highly correlated with  $X_{V1+}$  and  $X_{V2+}$

### *Conclusion:*

- ⊙ The validity of using methods resistant to variable correlation (e.g., LASSO).
- ⊙ Inclusion of two sets of indicators (separately) in the models:

$$X1 = \{X_P, X_{V1}, X_{V2}\}, \quad X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$$



## Empirical Study – Research Procedure

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- ⊙ Two predicted variables:
  - Daily logarithmic returns  $r_{d,t}$ ,
  - Realized variances  $RV_{d,t}$ . We apply a logarithmic transformation  $\ln RV_{d,t}$ , which ensures positive values for the variance estimates.
- ⊙ For each variable (separately):
  - In-sample analysis,
  - Forecast accuracy analysis (out-of-sample analysis).



## I) In-sample Analysis (01.01.2021 – 31.03.2024)

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- ⊙ Calculation of Pearson's linear correlation coefficient between the predicted variables and the sentiment indicators (including its significance).
- ⊙ Granger causality test between the predicted variables and each sentiment indicator (separately) (the Wald test).
- ⊙ Regression model analysis.



## I) Regression Model Analysis – Daily Logarithmic Returns

- ⊙ Benchmark model:

$$r_{d,t} = f(r_{d,t-1})$$

- ⊙ Models augmented with two sets of indicators:

$$X1 = \{X_P, X_{V1}, X_{V2}\}, \quad X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$$

contemporaneous and lagged:

- $r_{d,t} = f(r_{d,t-1}, X_{P,t}, X_{V1,t}, X_{V2,t}),$
- $r_{d,t} = f(r_{d,t-1}, X_{P,t-1}, X_{V1,t-1}, X_{V2,t-1}),$
- $r_{d,t} = f(r_{d,t-1}, X_{P+,t}, X_{P-,t}, X_{V1+,t}, X_{V1-,t}, X_{V2+,t}, X_{V2-,t}),$
- $r_{d,t} = f(r_{d,t-1}, X_{P+,t-1}, X_{P-,t-1}, X_{V1+,t-1}, X_{V1-,t-1}, X_{V2+,t-1}, X_{V2-,t-1}).$



## I) Regression Model Analysis – Realized Variances

⊙ Benchmark model:

$$\ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}),$$

where  $RV_{w,t}$  and  $RV_{m,t}$  are weekly and monthly average realized variances:

$$RV_{w,t} = \frac{RV_{d,t-6} + RV_{d,t-5} + \dots + RV_{d,t}}{7},$$

$$RV_{m,t} = \frac{RV_{d,t-29} + RV_{d,t-28} + \dots + RV_{d,t}}{30}.$$

Inspiration – the HAR model (Corsi, 2009):

$$\ln RV_{d,t} = \gamma_0 + \gamma_1 \ln RV_{d,t-1} + \gamma_2 \ln RV_{w,t-1} + \gamma_3 \ln RV_{m,t-1} + \varepsilon_t$$



## I) Regression Model Analysis – Realized Variances

⊙ Models augmented with two sets of indicators:

$$X1 = \{X_P, X_{V1}, X_{V2}\}, \quad X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$$

contemporaneous and lagged:

$$a) \ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P,t}, X_{V1,t}, X_{V2,t})$$

$$b) \ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P,t-1}, X_{V1,t-1}, X_{V2,t-1})$$

$$c) \ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P+,t}, X_{P-,t}, X_{V1+,t}, X_{V1-,t}, X_{V2+,t}, X_{V2-,t})$$

$$d) \ln RV_{d,t} =$$

$$f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P+,t-1}, X_{P-,t-1}, X_{V1+,t-1}, X_{V1-,t-1}, X_{V2+,t-1}, X_{V2-,t-1})$$



## I) Regression Model Analysis, cont.

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For each of the specified specifications, the following models were constructed:

- ⊙ linear OLS model/HAR model
- ⊙ BMA (Bayesian Model Averaging)
- ⊙ LASSO (Least Absolute Shrinkage and Selection Operator)
- ⊙ SVR (Support Vector Regression)
  - linear kernel
  - Gaussian kernel

Objective – analysis of the significance of variables (sentiment indicators) and comparison of model fit in-sample (MSE, MAE,  $R^2$ , MCS test, SPA test).



## II) Forecast Accuracy Analysis – Daily Logarithmic Returns

Regression models:

- ⊙ Benchmark model:  $r_{d,t} = f(r_{d,t-1})$
- ⊙ Models augmented with two sets of indicators:

$$X1 = \{X_P, X_{V1}, X_{V2}\}, \quad X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$$

only lagged indicators:

- $r_{d,t} = f(r_{d,t-1}, X_{P,t-1}, X_{V1,t-1}, X_{V2,t-1}),$
- $r_{d,t} = f(r_{d,t-1}, X_{P+,t-1}, X_{P-,t-1}, X_{V1+,t-1}, X_{V1-,t-1}, X_{V2+,t-1}, X_{V2-,t-1}).$

For each of the three specifications above, the following models were constructed:

AR (OLS), BMA, LASSO, SVR (linear kernel and Gaussian kernel).



## II) Forecast Accuracy Analysis – Realized Variances

Regression models:

⊙ Benchmark model:  $\ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1})$

⊙ Models augmented with two sets of indicators:

$$X1 = \{X_P, X_{V1}, X_{V2}\}, \quad X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$$

only lagged indicators:

▪  $\ln RV_{d,t} = f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P,t-1}, X_{V1,t-1}, X_{V2,t-1}),$

▪  $\ln RV_{d,t} =$

$$f(\ln RV_{d,t-1}, \ln RV_{w,t-1}, \ln RV_{m,t-1}, X_{P+,t-1}, X_{P-,t-1}, X_{V1+,t-1}, X_{V1-,t-1}, X_{V2+,t-1}, X_{V2-,t-1})$$

For each of the three specifications above, the following models were constructed:

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HAR(OLS), BMA, LASSO, SVR (linear kernel and Gaussian kernel).



## II) Forecasting Procedure

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- ⦿ Forecast horizon – 1 day.
- ⦿ First training sample: 01.01.2021 – 31.07.2022, rolling window
- ⦿ Test sample: 01.08.2022 – 31.03.2024 (609 forecasts of  $r_{d,t}$  and  $RV_{d,t}$ )
- ⦿ For each forecasted value, the models are re-estimated/re-trained
- ⦿ Hyperparameters of LASSO and SVR optimized every 28 days using 10-fold cross-validation (+ grid search)



## Results – In-sample Analysis for $r_{d,t}$

Pearson’s linear correlation coefficient between sentiment indicators and  $r_{d,t}$

Contemporaneous indicators								
$X_{P,t}$	$X_{V1,t}$	$X_{V2,t}$	$X_{P+,t}$	$X_{P-,t}$	$X_{V1+,t}$	$X_{V1-,t}$	$X_{V2+,t}$	$X_{V2-,t}$
0.429 <b>(0.000)</b>	-0.024 (0.404)	-0.021 (0.471)	0.299 <b>(0.000)</b>	0.412 <b>(0.000)</b>	-0.029 (0.315)	-0.006 (0.828)	-0.051 <b>(0.079)</b>	0.034 (0.236)
Lagged indicators								
$X_{P,t-1}$	$X_{V1,t-1}$	$X_{V2,t-1}$	$X_{P+,t-1}$	$X_{P-,t-1}$	$X_{V1+,t-1}$	$X_{V1-,t-1}$	$X_{V2+,t-1}$	$X_{V2-,t-1}$
0.029 (0.313)	0.063 <b>(0.030)</b>	0.033 (0.262)	0.057 <b>(0.051)</b>	-0.005 (0.861)	0.062 <b>(0.033)</b>	-0.002 (0.945)	0.030 (0.305)	-0.051 <b>(0.078)</b>



## Results – In-sample Analysis for $r_{d,t}$

Granger causality between sentiment indicators and  $r_{d,t}$

Indicator	P-value	Lags in VAR model
$X_P$	<b>0.050</b>	1
$X_{V1}$	<b>0.033</b>	1
$X_{V2}$	0.279	1
$X_{P-}$	0.544	1
$X_{P+}$	<b>0.009</b>	1
$X_{V1-}$	0.934	1
$X_{V1+}$	<b>0.037</b>	1
$X_{V2-}$	0.475	1
$X_{V2+}$	0.350	1

P-value for  $H_0$ : „no causality”



## Results – In-sample Analysis for $r_{d,t}$

Estimation results of linear models with indicators  $X1 = \{X_P, X_{V1}, X_{V2}\}$

Model	Contemporaneous indicators X1				
	Const.	$r_{d,t-1}$	$X_{P,t}$	$X_{V1,t}$	$X_{V2,t}$
AR-X1	0.001 (0.591)	-0.252 <b>(0.000)</b>	0.179 <b>(0.000)</b>	-0.028 <b>(0.033)</b>	-0.001 (0.937)
BMA-X1	0.000 (1.000)	-0.251 (1.000)	0.178 (1.000)	-0.017 (0.606)	-0.001 (0.118)
LASSO-X1	0.001	-0.244	0.176	-0.026	0
Model	Lagged indicators X1				
	Const.	$r_{d,t-1}$	$X_{P,t-1}$	$X_{V1,t-1}$	$X_{V2,t-1}$
AR-X1	-0.003 (0.157)	-0.074 <b>(0.021)</b>	0.019 <b>(0.079)</b>	0.025 <b>(0.091)</b>	-0.004 (0.854)
BMA-X1	0.000 (1.000)	-0.002 (0.042)	0.000 (0.018)	0.002 (0.076)	0.000 (0.015)
LASSO-X1	-0.002	-0.056	0.013	0.020	0

31 In parentheses: p-value for AR and PIP (*posterior inclusion probability*) for BMA



## Results – In-sample Analysis for $r_{d,t}$

Estimation results of linear models with indicators  $X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$

	Contemporaneous indicators X2							
	Const.	$r_{d,t-1}$	$X_{P+,t}$	$X_{P-,t}$	$X_{V1+,t}$	$X_{V1-,t}$	$X_{V2+,t}$	$X_{V2-,t}$
AR-X2	0.005 (0.167)	-0.263 (0.000)	0.109 (0.000)	0.241 (0.000)	0.020 (0.327)	-0.031 (0.211)	-0.003 (0.930)	0.034 (0.172)
BMA-X2	0.006 (1.000)	-0.261 (1.000)	0.124 (1.000)	0.228 (1.000)	0.001 (0.051)	-0.001 (0.053)	0.000 (0.034)	0.002 (0.068)
LASSO-X2	0.005	-0.253	0.113	0.232	0.012	-0.024	0	0.028
	Lagged indicators X2							
	Const.	$r_{d,t-1}$	$X_{P+,t-1}$	$X_{P-,t-1}$	$X_{V1+,t-1}$	$X_{V1-,t-1}$	$X_{V2+,t-1}$	$X_{V2-,t-1}$
AR-X2	-0.005 (0.222)	-0.076 (0.019)	0.039 (0.167)	0.004 (0.882)	0.032 (0.180)	-0.008 (0.768)	-0.037 (0.262)	0.023 (0.430)
BMA-X2	0.000 (1.000)	-0.001 (0.026)	0.001 (0.032)	0.000 (0.005)	0.001 (0.040)	0.000 (0.005)	0.000 (0.008)	0.000 (0.006)
LASSO-X2	-0.003	-0.045	0.024	0	0.011	0	0	0.002

In parentheses: p-value for AR and t (posterior inclusion probability) for BMA



## Results – In-sample Analysis for $r_{d,t}$

### Model fit analysis – contemporaneous indicators

Model	MSE×10 <sup>3</sup>	Rank	P-value	MAE×10 <sup>2</sup>	Rank	P-value	R <sup>2</sup>	Rank
AR	1.149	12	0.000	2.332	12	0.000	0.003	12
LASSO	1.152	13	0.000	2.335	13	0.000	0.000	14
SVR-G	1.149	11	0.000	2.332	11	0.000	0.003	11
SVR-L	1.152	14	0.000	2.339	14	0.000	0.003	13
AR-X1	0.874	7	0.026	2.196	10	0.000	0.242	7
BMA-X1	0.874	9	0.024	2.193	8	0.000	0.241	9
LASSO-X1	0.874	8	0.030	2.193	9	0.000	0.242	8
SVR-G-X1	0.857	2	0.039	2.129	2	0.084	0.261	2
SVR-L-X1	0.887	10	0.018	2.163	3	0.001	0.240	10
AR-X2	0.857	3	0.071	2.173	6	0.000	0.256	3
BMA-X2	0.860	5	0.039	2.176	7	0.000	0.254	5
LASSO-X2	0.857	4	0.039	2.170	5	0.000	0.256	4
SVR-G-X2	<b>0.830</b>	1	1.000*	<b>2.107</b>	1	1.000*	<b>0.287</b>	1
SVR-L-X2	0.870	6	0.034	2.164	4	0.001	0.250	6

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level



## Results – In-sample Analysis for $r_{d,t}$

### Model fit analysis – lagged indicators

Model	MSE×10 <sup>3</sup>	Rank	P-value	MAE×10 <sup>2</sup>	Rank	P-value	R <sup>2</sup>	Rank
AR	1.149	8	0.455*	2.332	5	0.450*	0.003	12
LASSO	1.152	12	0.194*	2.335	10	0.245*	0.000	14
SVR-G	1.149	7	0.400*	2.332	4	0.450*	0.003	11
SVR-L	1.153	13	0.284*	2.339	13	0.175*	0.003	13
AR-X1	1.142	2	0.761*	2.336	12	0.245*	0.009	3
BMA-X1	1.151	9	0.560*	2.334	7	0.342*	0.007	7
LASSO-X1	1.142	3	0.761*	2.333	6	0.342*	0.009	4
SVR-G-X1	1.144	4	0.761*	<b>2.326</b>	1	1.000*	0.009	2
SVR-L-X1	1.146	6	0.761*	2.328	2	0.456*	0.006	8
AR-X2	<b>1.140</b>	1	1.000*	2.341	14	0.095	<b>0.011</b>	1
BMA-X2	1.152	10	0.362*	2.334	9	0.342*	0.007	6
LASSO-X2	1.145	5	0.761*	2.331	3	0.450*	0.009	5
SVR-G-X2	1.153	14	0.105*	2.335	11	0.245*	0.004	10
SVR-L-X2	1.152	11	0.374*	2.334	8	0.342*	0.005	9

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level



## Results – In-sample Analysis for $r_{d,t}$

### SPA test

Compared models	Contemporaneous indicators		Lagged indicators	
	MSE	MAE	MSE	MAE
	P-value	P-value	P-value	P-value
AR vs. AR-X1	<b>0.000</b>	<b>0.001</b>	<b>0.092</b>	0.696
AR vs. AR-X2	<b>0.000</b>	<b>0.000</b>	<b>0.086</b>	0.863
AR vs. BMA-X1	<b>0.000</b>	<b>0.001</b>	0.665	0.669
AR vs. BMA-X2	<b>0.000</b>	<b>0.000</b>	0.676	0.672
LASSO vs. LASSO-X1	<b>0.000</b>	<b>0.001</b>	<b>0.077</b>	0.413
LASSO vs. LASSO-X2	<b>0.000</b>	<b>0.000</b>	<b>0.034</b>	0.194
SVR-G vs. SVR-G-X1	<b>0.000</b>	<b>0.000</b>	<b>0.084</b>	0.155
SVR-G vs. SVR-G-X2	<b>0.000</b>	<b>0.000</b>	0.748	0.743
SVR-L vs. SVR-L-X1	<b>0.000</b>	<b>0.000</b>	<b>0.024</b>	<b>0.017</b>
SVR-L vs. SVR-L-X2	<b>0.000</b>	<b>0.000</b>	0.468	0.277

35 P-value for the SPA test. A value lower than  $\alpha = 0.1$  indicates the superiority of the second model.



## Results – In-sample Analysis for $\ln RV_{d,t}$

Pearson’s linear correlation coefficient between sentiment indicators and  $\ln RV_{d,t}$

Contemporaneous indicators								
$X_{P,t}$	$X_{V1,t}$	$X_{V2,t}$	$X_{P+,t}$	$X_{P-,t}$	$X_{V1+,t}$	$X_{V1-,t}$	$X_{V2+,t}$	$X_{V2-,t}$
-0.245 <b>(0.000)</b>	0.039 (0.180)	0.178 <b>(0.000)</b>	-0.140 <b>(0.000)</b>	-0.254 <b>(0.000)</b>	0.016 (0.577)	0.029 (0.318)	0.112 <b>(0.000)</b>	0.167 <b>(0.000)</b>
Lagged indicators								
$X_{P,t-1}$	$X_{V1,t-1}$	$X_{V2,t-1}$	$X_{P+,t-1}$	$X_{P-,t-1}$	$X_{V1+,t-1}$	$X_{V1-,t-1}$	$X_{V2+,t-1}$	$X_{V2-,t-1}$
-0.195 <b>(0.000)</b>	0.007 (0.805)	0.105 <b>(0.000)</b>	-0.159 <b>(0.000)</b>	-0.155 <b>(0.000)</b>	-0.017 (0.558)	0.013 (0.655)	0.039 (0.176)	0.146 <b>(0.000)</b>



## Results – In-sample Analysis for $\ln RV_{d,t}$

Granger causality between sentiment indicators and  $\ln RV_{d,t}$

Indicator	P-value	Lags in VAR model
$X_P$	<b>0.095</b>	14
$X_{V1}$	<b>0.000</b>	14
$X_{V2}$	<b>0.000</b>	14
$X_{P-}$	<b>0.000</b>	14
$X_{P+}$	0.178	14
$X_{V1-}$	0.271	21
$X_{V1+}$	<b>0.000</b>	14
$X_{V2-}$	<b>0.029</b>	14
$X_{V2+}$	<b>0.000</b>	14

P-value for  $H_0$ : „no causality”



## Results – In-sample Analysis for $\ln RV_{d,t}$

Estimation results of linear models with indicators  $X1 = \{X_P, X_{V1}, X_{V2}\}$

Model	Contemporaneous indicators X1						
	Const.	$\ln RV_{d,t-1}$	$\ln RV_{w,t-1}$	$\ln RV_{m,t-1}$	$X_{P,t}$	$X_{V1,t}$	$X_{V2,t}$
HAR-X1	-0.703 (0.000)	0.389 (0.000)	0.312 (0.000)	0.240 (0.000)	-1.003 (0.000)	0.553 (0.106)	2.224 (0.000)
BMA-X1	-0.706 (1.000)	0.387 (1.000)	0.317 (1.000)	0.232 (0.999)	-0.995 (0.999)	0.217 (0.392)	2.476 (1.000)
LASSO-X1	-0.706	0.389	0.313	0.240	-1.000	0.548	2.220
Model	Lagged indicators X1						
	Const.	$\ln RV_{d,t-1}$	$\ln RV_{w,t-1}$	$\ln RV_{m,t-1}$	$X_{P,t-1}$	$X_{V1,t-1}$	$X_{V2,t-1}$
HAR-X1	-0.542 (0.009)	0.415 (0.000)	0.378 (0.000)	0.157 (0.003)	-0.042 (0.858)	0.229 (0.514)	-0.328 (0.496)
BMA-X1	-0.623 (1.000)	0.415 (1.000)	0.404 (1.000)	0.115 (0.737)	-0.002 (0.036)	0.002 (0.039)	-0.012 (0.045)
LASSO-X1	-0.690	0.406	0.375	0.146	0	0	0

38 In parentheses: p-value for HAR and PIP (*posterior inclusion probability*) for BMA



## Results – In-sample Analysis for $\ln RV_{d,t}$

Estimation results of linear models with indicators  $X2 = \{X_{P+}, X_{P-}, X_{V1+}, X_{V1-}, X_{V2+}, X_{V2-}\}$

Model	Contemporaneous indicators X2									
	Const.	$\ln RV_{d,t-1}$	$\ln RV_{w,t-1}$	$\ln RV_{m,t-1}$	$X_{P+,t}$	$X_{P-,t}$	$X_{V1+,t}$	$X_{V1-,t}$	$X_{V2+,t}$	$X_{V2-,t}$
HAR-X2	-0.557 (0.006)	0.375 (0.000)	0.320 (0.000)	0.289 (0.000)	3.203 (0.000)	-4.355 (0.000)	-2.104 (0.000)	1.159 (0.067)	2.149 (0.004)	0.521 (0.418)
BMA-X2	-0.613 (1.000)	0.375 (1.000)	0.325 (1.000)	0.289 (1.000)	3.214 (1.000)	-4.336 (1.000)	-1.900 (0.961)	0.520 (0.435)	1.823 (0.846)	0.114 (0.196)
LASSO-X2	-0.595	0.375	0.320	0.286	2.969	-4.172	-1.876	1.073	2.062	0.463
Model	Lagged indicators X2									
	Const.	$\ln RV_{d,t-1}$	$\ln RV_{w,t-1}$	$\ln RV_{m,t-1}$	$X_{P+,t-1}$	$X_{P-,t-1}$	$X_{V1+,t-1}$	$X_{V1-,t-1}$	$X_{V2+,t-1}$	$X_{V2-,t-1}$
HAR-X2	-0.588 (0.006)	0.425 (0.000)	0.372 (0.000)	0.149 (0.007)	-0.922 (0.173)	0.762 (0.185)	0.682 (0.226)	-0.465 (0.484)	0.051 (0.948)	-0.157 (0.817)
BMA-X2	-0.663 (1.000)	0.416 (1.000)	0.417 (1.000)	0.096 (0.612)	-0.009 (0.025)	0.005 (0.021)	0.000 (0.020)	-0.008 (0.020)	-0.007 (0.023)	-0.002 (0.018)
LASSO-X2	-0.721	0.404	0.374	0.142	0	0	0	0	0	0

39 In parentheses: p-value for HAR and PIP (*posterior inclusion probability*) for BMA



## Results – In-sample Analysis for $\ln RV_{d,t}$

### Model fit analysis – contemporaneous indicators

Model	MSE×10 <sup>3</sup>	Rank	P-value	MAE×10 <sup>2</sup>	Rank	P-value	R <sup>2</sup>	Rank
HAR	0.430	13	0.057	0.678	12	0.006	0.342	13
BMA	0.429	12	0.054	0.678	14	0.003	0.342	12
LASSO	0.430	14	0.057	0.678	13	0.004	0.342	14
SVR-G	0.427	11	0.066	0.683	15	0.002	0.338	15
SVR-L	0.447	15	0.051	0.673	11	0.008	0.343	11
HAR-X1	0.380	7	0.207*	0.652	8	0.018	0.421	8
BMA-X1	0.383	9	0.057	0.654	10	0.013	0.416	10
LASSO-X1	0.380	8	0.152*	0.652	9	0.015	0.421	9
SVR-G-X1	0.358	2	0.432*	<b>0.615</b>	1	1.000*	0.465	3
SVR-L-X1	0.385	10	0.251*	0.647	7	0.021	0.428	7
HAR-X2	0.360	3	0.412*	0.644	5	0.021	0.462	4
BMA-X2	0.363	6	0.304*	0.642	3	0.024	0.456	6
LASSO-X2	0.360	4	0.340*	0.644	4	0.021	0.462	5
SVR-G-X2	0.360	5	0.412*	0.641	2	0.021	<b>0.469</b>	1
SVR-L-X2	<b>0.347</b>	1	1.000*	0.647	6	0.021	0.466	2

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level



## Results – In-sample Analysis for $\ln RV_{d,t}$

### Model fit analysis – lagged indicators

Model	MSE×10 <sup>3</sup>	Rank	P-value	MAE×10 <sup>2</sup>	Rank	P-value	R <sup>2</sup>	Rank
HAR	0.430	8	0.503*	0.678	8	0.273*	0.342	11
BMA	0.429	7	0.503*	0.678	10	0.273*	0.342	8
LASSO	0.430	9	0.466*	0.678	9	0.273*	0.342	12
SVR-G	0.427	2	0.503*	0.683	14	0.252*	0.338	14
SVR-L	0.447	14	0.033	0.673	3	0.273*	0.343	7
HAR-X1	0.429	6	0.503*	0.678	7	0.273*	0.343	6
BMA-X1	0.429	5	0.503*	0.679	11	0.273*	0.343	4
LASSO-X1	0.433	10	0.219*	0.677	6	0.273*	0.342	10
SVR-G-X1	0.441	12	0.094	0.673	2	0.293*	0.341	13
SVR-L-X1	<b>0.417</b>	1	1.000*	0.696	15	0.252*	0.336	15
HAR-X2	0.429	4	0.503*	0.679	12	0.273*	0.343	5
BMA-X2	0.428	3	0.503*	0.679	13	0.273*	0.344	3
LASSO-X2	0.436	11	0.167*	0.676	5	0.273*	0.342	9
SVR-G-X2	0.445	13	0.033	<b>0.671</b>	1	1.000*	<b>0.347</b>	1
SVR-L-X2	0.450	15	0.033	0.674	4	0.273*	0.344	2

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level



## Results – In-sample Analysis for $\ln RV_{d,t}$

### SPA test

Compared models	Contemporaneous indicators		Lagged indicators	
	MSE	MAE	MSE	MAE
	P-value	P-value	P-value	P-value
HAR vs. HAR-X1	<b>0.033</b>	<b>0.003</b>	<b>0.067</b>	0.167
HAR vs. HAR-X2	<b>0.027</b>	<b>0.002</b>	0.240	0.665
BMA vs. BMA-X1	<b>0.034</b>	<b>0.004</b>	0.114	0.803
BMA vs. BMA-X2	<b>0.025</b>	<b>0.001</b>	0.121	0.823
LASSO vs. LASSO-X1	<b>0.033</b>	<b>0.003</b>	0.952	0.130
LASSO vs. LASSO-X2	<b>0.027</b>	<b>0.002</b>	0.956	0.155
SVR-G vs. SVR-G-X1	<b>0.024</b>	<b>0.000</b>	0.946	<b>0.046</b>
SVR-G vs. SVR-G-X2	<b>0.026</b>	<b>0.001</b>	0.956	<b>0.056</b>
SVR-L vs. SVR-L-X1	<b>0.023</b>	<b>0.011</b>	<b>0.076</b>	0.922
SVR-L vs. SVR-L-X2	<b>0.027</b>	<b>0.061</b>	0.917	0.586

42 P-value for the SPA test. A value lower than  $\alpha = 0.1$  indicates the superiority of the second model.



## In-sample Analysis – Conclusions

- ⊙ **For  $r_{d,t}$ :** The correlation analysis, the Granger causality test, and the significance of regressors in the extended AR, BMA, and LASSO models indicate that most **sentiment indicators related to the expected change in BTC price** (i.e.,  $X_P, X_{P+}, X_{P-}$ ) have a **significant influence** on BTC returns.

BTC returns are only minimally affected by the indicators related to **expected volatility**.

- ⊙ **For  $\ln RV_{d,t}$ :** The correlation analysis, the Granger causality test, and the significance of regressors in the extended HAR, BMA, and LASSO models indicate that most sentiment indicators **significantly influence** BTC volatility.

The impact of the indicator related to the expected change in BTC price is negative, which aligns with the leverage effect observed in other financial time series, such as stocks or fiat currencies.



## In-sample Analysis – Conclusions

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- ⊙ Including contemporaneous sentiment indicators **improves the accuracy** (MSE, MAE,  $R^2$ ) of all models (AR/HAR, BMA, LASSO, and SVR) in-sample.

This conclusion is less clear for lagged indicators, as the improvement in estimation quality is observed only in some models.



## In-sample Analysis – Conclusions

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- ⊙ **For  $r_{d,t}$ :** The SVR model with a Gaussian kernel performs best among return models with **contemporaneous** variables representing the sentiment indicators.

It is impossible to identify a significantly better model for models extended with the **lagged** explanatory indicators.

- ⊙ **For  $\ln RV_{d,t}$ :** For both contemporaneous or lagged indicators, no single model emerges as superior.



## Results – Out-of-sample Analysis for $r_{d,t}$

### Forecast accuracy analysis (lagged variables)

Model	MSE×10 <sup>4</sup>	Rank	P-value	MAE×10 <sup>2</sup>	Rank	P-value	R <sup>2</sup>	Rank
AR	6.616	6	0.940*	<b>1.713</b>	1	1.000*	0.002	10
LASSO	6.613	5	0.940*	1.716	6	0.679*	0.002	8
SVR-G	7.421	14	0.066	1.741	10	0.121*	<b>0.027</b>	1
SVR-L	6.774	13	0.066	1.753	11	0.000	0.000	14
AR-X1	6.622	7	0.940*	1.720	8	0.478*	0.001	12
BMA-X1	6.611	3	0.940*	1.715	4	0.826*	0.002	6
LASSO-X1	<b>6.609</b>	1	1.000*	1.714	2	0.925*	0.002	7
SVR-G-X1	6.694	10	0.254*	1.725	9	0.250*	0.001	13
SVR-L-X1	6.773	12	0.374*	1.761	13	0.009	0.003	3
AR-X2	6.675	9	0.827*	1.757	12	0.002	0.002	9
BMA-X2	6.610	2	0.940*	1.715	3	0.917*	0.003	5
LASSO-X2	6.611	4	0.940*	1.715	5	0.726*	0.003	4
SVR-G-X2	6.650	8	0.702*	1.718	7	0.578*	0.003	2
SVR-L-X2	6.751	11	0.066	1.762	14	0.000	0.001	11

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level.



## Results – Out-of-sample Analysis for $r_{d,t}$

### SPA test

Compared models	MSE	MAE
	P-value	P-value
AR vs. AR-X1	0.557	0.780
AR vs. AR-X2	0.760	0.500
AR vs. BMA-X1	0.417	0.652
AR vs. BMA-X2	0.414	0.636
LASSO vs. LASSO-X1	0.288	0.163
LASSO vs. LASSO-X2	0.404	0.377
SVR-G vs. SVR-G-X1	0.139	0.215
SVR-G vs. SVR-G-X2	0.125	0.147
SVR-L vs. SVR-L-X1	0.479	0.665
SVR-L vs. SVR-L-X2	0.400	0.699

P-value for the SPA test. A value lower than  $\alpha = 0.1$  indicates the superiority of the second model.



## Results – Out-of-sample Analysis for $\ln RV_{d,t}$

### Forecast accuracy analysis (lagged variables)

Model	MSE $\times 10^4$	Rank	P-value	MAE $\times 10^2$	Rank	P-value	$R^2$	Rank
HAR	7.061	9	0.502*	3.732	2	0.912*	0.177	11
BMA	7.036	7	0.559*	3.739	5	0.777*	0.178	7
LASSO	7.056	8	0.559*	<b>3.731</b>	1	1.000*	0.177	10
SVR-G	7.100	14	0.559*	3.738	4	0.912*	0.175	12
SVR-L	7.065	10	0.559*	3.735	3	0.912*	0.178	9
HAR-X1	6.982	4	0.559*	3.753	9	0.658*	0.185	4
BMA-X1	6.937	2	0.948*	3.746	6	0.658*	<b>0.189</b>	1
LASSO-X1	<b>6.935</b>	1	1.000*	3.746	7	0.658*	<b>0.189</b>	2
SVR-G-X1	7.100	13	0.413*	3.803	14	0.322*	0.172	14
SVR-L-X1	7.066	11	0.502*	3.799	13	0.285*	0.178	8
HAR-X2	7.092	12	0.413*	3.780	12	0.574*	0.172	13
BMA-X2	7.003	6	0.559*	3.748	8	0.628*	0.182	6
LASSO-X2	6.992	5	0.559*	3.753	10	0.658*	0.183	5
SVR-G-X2	7.376	15	0.217*	3.822	15	0.396*	0.142	15
SVR-L-X2	6.978	3	0.312*	3.757	11	0.355*	0.188	3

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P-value for MCS test. Symbol \* indicates that the model belongs to MCS at the 0.90 confidence level.



## Results – Out-of-sample Analysis for $\ln RV_{d,t}$

### SPA test

Compared models	MSE	MAE
	P-value	P-value
HAR vs. HAR-X1	0.311	0.760
HAR vs. HAR-X2	0.543	0.912
BMA vs. BMA-X1	0.205	0.690
BMA vs. BMA-X2	0.259	0.865
LASSO vs. LASSO-X1	0.210	0.749
LASSO vs. LASSO-X2	0.304	0.827
SVR-G vs. SVR-G-X1	0.575	0.509
SVR-G vs. SVR-G-X2	0.838	0.932
SVR-L vs. SVR-L-X1	0.408	0.920
SVR-L vs. SVR-L-X2	0.614	0.908

P-value for the SPA test. A value lower than  $\alpha = 0.1$  indicates the superiority of the second model.



## Out-of-sample Analysis – Conclusion

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- ⦿ Models incorporating sentiment indicators **do not produce significantly more accurate out-of-sample forecasts** compared to models without these variables. This finding is consistent with the **efficient market hypothesis**, which assumes that prices immediately reflect all available information.



Thank you for your attention

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