Can we predict the future of the cars of the future: A study on predictors of EV car manufacturor stock returns

ECON 623: Dinghai Xu

Andrew Girgis

Introduction: **Motivation** - Literature review

- Passion for financial markets, automotives and the future of EV's(Electric Vehicles)
- New territory: EV's are making a large impact in the market currently with many bills being passed banning production of combustion engines in certain years, forcing many large automotive companies to adopt the BEV(Battery Electric Vehicles) model.
- Can the returns of these new EV startups be predicted using complementary and substitutionary commodities and goods?

Introduction: Motivation - **Literature review**

- Shen, J., Griffith, J., Najand, M., & Sun, L. (2021). Predicting stock and bond market returns with emotions: Evidence from futures markets. Journal of Behavioral Finance, 24(3), 333–344. https://doi.org/10.1080/15427560.2021.1975717 (Shen et al. 2021)
- Li, T., & Sun, X. (2023). Predicting stock market returns using aggregate credit risk. International Review of Economics & Finance, 88, 1087–1103. https://doi.org/10.1016/j.iref.2023.07.039 (Li and Sun 2023)

Introduction: Motivation - **Literature review**

- Cai, Y., & Stander, J. (2019). The threshold GARCH model: Estimation and density forecasting for financial returns*. Journal of Financial Econometrics, 18(2), 395–424. https://doi.org/10.1093/jjfinec/nbz014 (Cai and Stander 2019)
- Hansen, P. R., & Lunde, A. (2001). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.264571 (Hansen and Lunde 2001)

Data - Theory - Model

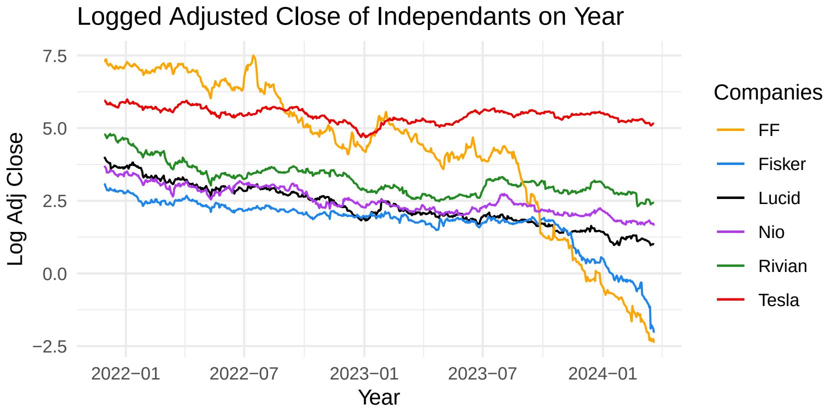


Figure 1: Line plot of the Log Adjusted Close prices of the EV stocks we will be predicting

Data - Theory - Model

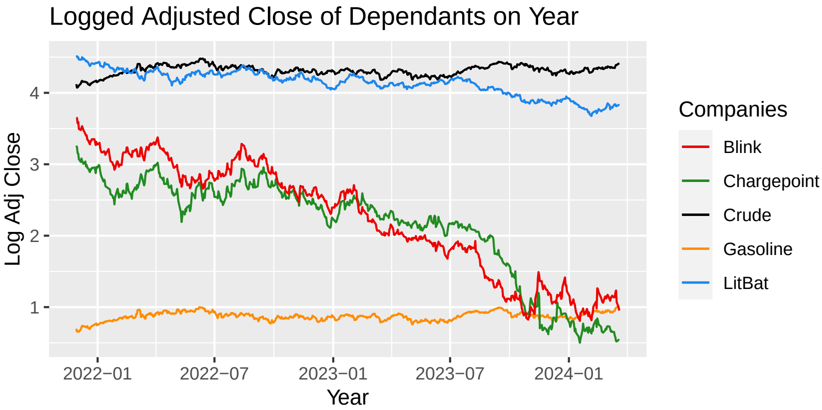
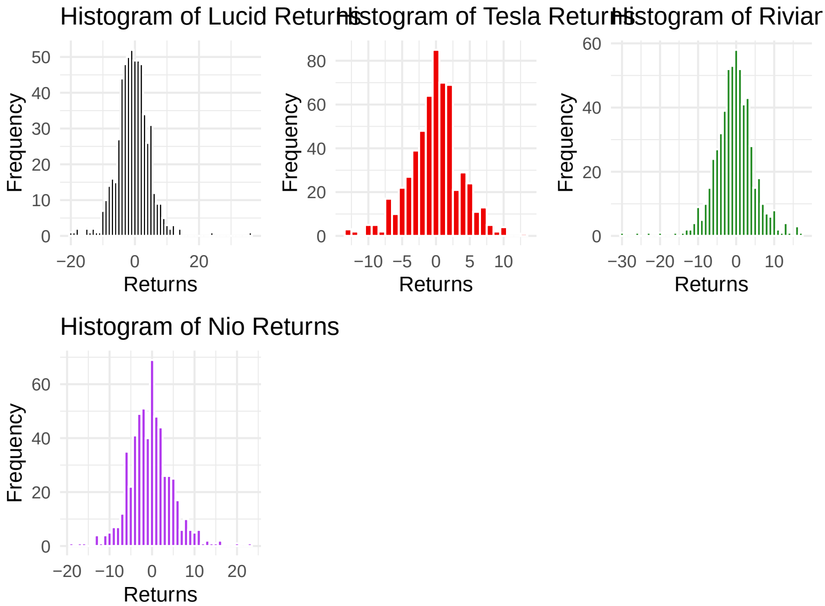


Figure 2: Line plot of the Log Adjusted Close prices of the Dependants we will be using as predictors

Data - Theory - Model



Data - Theory - Model

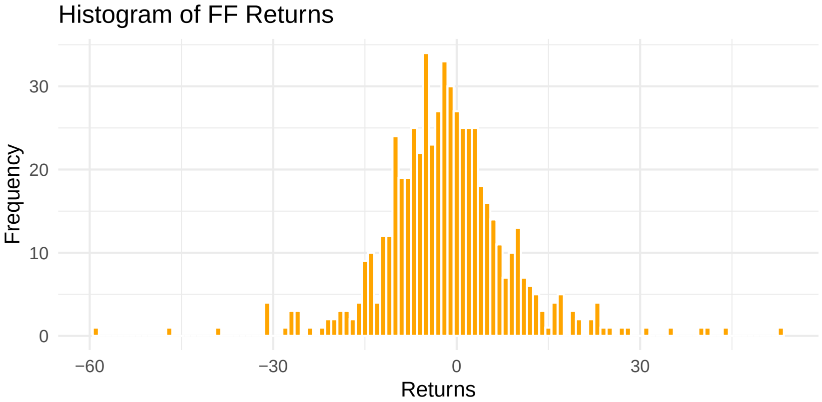


Figure 4: Histogram of Faraday Future returns

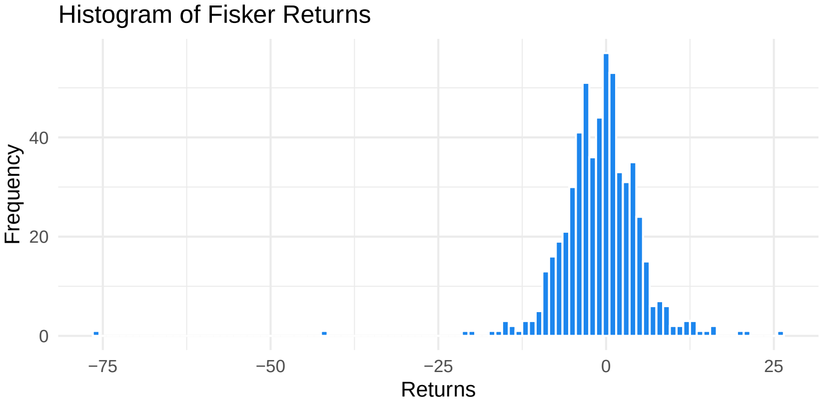
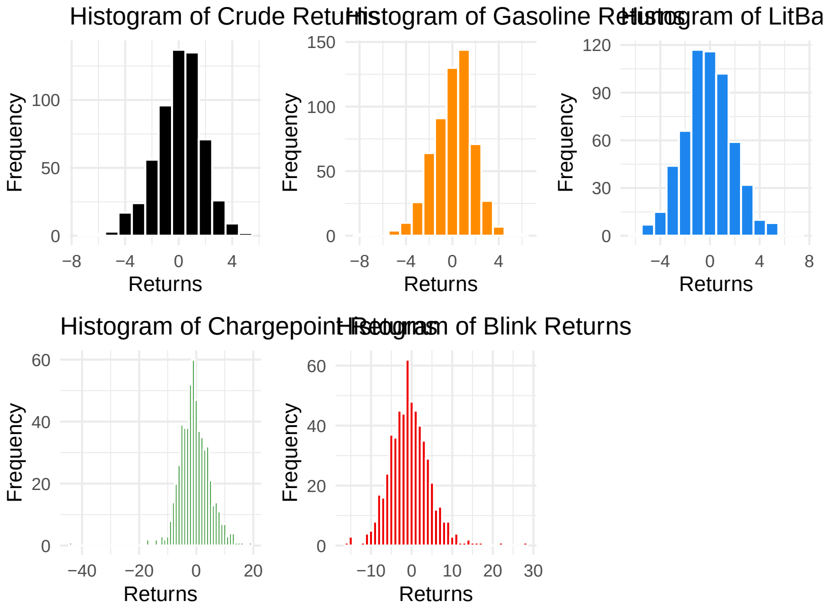


Figure 5: Histogram of Fisker returns

Data - Theory - Model



Data - Theory - Model

Panel A	FF	Fisker	Lucid	Nio	Rivian	Tesla
mean	-1.65	-1.17	-0.51	-0.37	-0.41	-0.14
variance	115.87	65.16	26.16	24.63	27.34	14.14
skewness	0.30	-5.83	0.51	0.37	-0.45	-0.24
kurtosis	7.47	71.99	8.47	4.86	6.45	3.97
Panel B	**FF**	**Fisker**	**Lucid**	**Nio**	**Rivian**	**Tesla**
FF	1.00					
Fisker	0.21	1.00				
Lucid	0.25	0.38	1.00			
Nio	0.26	0.30	0.54	1.00		
Rivian	0.16	0.35	0.67	0.56	1.00	
Tesla	0.21	0.27	0.56	0.52	0.56	1.00

Table 1: Descriptive statistics & correlations of returns of EV stocks

Data - Theory - Model

Panel A	Crude	Gasoline	LitBat	Chargepoint	Blink
mean	0.05	0.05	-0.12	-0.45	-0.44
variance	3.05	2.93	3.83	28.82	25.90
skewness	-0.42	-0.48	0.094	-0.60	0.63
kurtosis	3.67	4.20	3.28	10.21	5.37

Panel B	Crude	Gasoline	LitBat	Chargepoint	Blink
Crude	1.00				
Gasoline	0.94	1.00			
LitBat	0.17	0.19	1.00		
Chargepoint	0.01	0.03	0.49	1.00	
Blink	0.04	0.04	0.50	0.67	1.00

Table 2: Descriptive statistics & correlations of returns of Dependants

Data - **Theory** - Model

- GARCH(1,1)

Mean Equation:

$$r_t = \mu + \epsilon_t$$

Where:
- r_t is the observed return at time t.
- μ is the intercept term or the conditional mean of the return.
- ϵ_t is the error term, assumed to be normally distributed with mean 0.

Data - **Theory** - Model

Variance Equation (GARCH(1,1) with External Regressor):

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 \beta_1 \sigma_{t-1}^2 + \gamma X_{t-1}$$

Where:
- σ_{t-1}^2 is the conditional variance of the return at time t.
- ω is the intercept term.
- α_1 is the parameter associated with the lagged squared error term, representing the ARCH effect.
- β_1 is the parameter associated with the lagged conditional variance, representing the GARCH effect.
- X_{t-1} is the external regressor, representing the lagged returns of the Lithium Battery stock returns.
- γ is the parameter associated with the external regressor.

Data - **Theory** - Model

- VAR(1)

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{n,t} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \dots & A_{nn} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{n,t-1} \end{bmatrix}$$
$$+ \begin{bmatrix} B_{11} & B_{12} & B_{13} \\ B_{21} & B_{22} & B_{23} \\ B_{31} & B_{32} & B_{33} \end{bmatrix} \begin{bmatrix} X_{1,t-1} \\ X_{2,t-1} \\ X_{3,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{n,t} \end{bmatrix}$$

Data - **Theory** - Model

- VAR(1)

where:

- Y_t is a vector representing the returns of Rivian at time t,
- X_{t-1} is a vector representing the lagged returns of the external regressors at time $t-1$,
- A is a coefficient matrix capturing the lagged effects of Rivian returns,
- B is a coefficient matrix capturing the effects of lagged external regressors, and
- ε_t is a vector of error terms at time t.

Data - Theory - **Model**

Finding optimal lags of our VAR model for Rivian returns.

	selection	criteria.1	criteria.2	criteria.3	criteria.4 ...
AIC(n)	1	8.29	8.31	8.33	8.37 ...
HQ(n)	1	8.35	8.42	8.49	8.57 ...
SC(n)	1	8.44	8.59	8.73	8.89 ...
FPE(n)	1	3982.78	4068.04	4151.32	4303.34...

Table 3: Table depicting the optimal number of lags to use in our VAR model for Rivian returns

Finding optimal lags of our VAR model for Tesla returns.

	selection	criteria.1	criteria.2	criteria.3	criteria.4	...
AIC(n)	1	7.65	7.67	7.69	7.71	...
HQ(n)	1	7.71	7.78	7.85	7.91	...
SC(n)	1	7.80	7.94	8.09	8.23	...
FPE(n)	1	2092.56	2139.35	2196.39	2220.36	...

Table 4: Table depicting the optimal number of lags to use in our VAR model for Tesla returns

Inspecting the Granger Causality of our Rivian VAR model.

Granger Causality Test	F-Test	p-value
Rivian does not cause Gas	1.5337	0.2038
Gas does not cause Rivian	1.8225	0.1409
LitBat does not cause Rivian	0.90716	0.4368
CP does not cause Rivian	0.039752	0.9894

Table 5: Granger Causality Test Results for Rivian returns

Data - Theory - **Model**

Inspecting the Granger Causality of our Tesla VAR model.

Granger Causality Test	F-Test	p-value
Tesla does not cause Gas	0.86932	0.4563
Gas does not cause Tesla	2.0865	0.09996
LitBat does not cause Tesla	1.8949	0.1283
CP does not cause Tesla	1.5879	0.1903

Table 6: Granger Causality Test Results for Tesla returns

Model	AIC	BIC
ARMA(0,0) GARCH(1,1)	6.1424	6.1808*
ARMA(1,0) GARCH(1,1)	6.1454	6.1916
ARMA(0,1) GARCH(1,1)	6.1455	6.1916
ARMA(1,1) GARCH(1,1)	6.1471	6.2009
ARMA(0,0) GARCH(2,1)	6.1422*	6.1883
ARMA(1,0) GARCH(2,1)	6.1453	6.1991
ARMA(0,1) GARCH(2,1)	6.1453	6.1991
ARMA(1,1) GARCH(2,1)	6.1473	6.2088
ARMA(0,0) GARCH(2,2)	6.1829	6.2367

Table 7: AIC and BIC of different GARCH models of Rivian returns

Data - Theory - **Model**

Model	AIC	BIC
ARMA(0,0) GARCH(1,1)	5.4993	5.5381
ARMA(1,0) GARCH(1,1)	5.5028	5.5493
ARMA(0,1) GARCH(1,1)	5.5028	5.5493
ARMA(1,1) GARCH(1,1)	5.5025	5.5568
ARMA(0,0) GARCH(2,1)	5.4951	5.5416
ARMA(1,0) GARCH(2,1)	5.4986	5.5528
ARMA(0,1) GARCH(2,1)	5.4986	5.5528
ARMA(1,1) GARCH(2,1)	5.4985	5.5605
ARMA(0,0) GARCH(2,2)	5.4903*	5.5446*

Table 8: AIC and BIC of different GARCH models of Tesla returns

Data - Theory - **Model**

Due to the AIC and BIC of all models being not significantly different from one another I will choose to use the ARMA(0,0) GARCH(1,1) to use the best most simple model with the least extra variables in the model for both the Rivian returns and for the Tesla Returns.

Data Analysis

VAR Forecasts

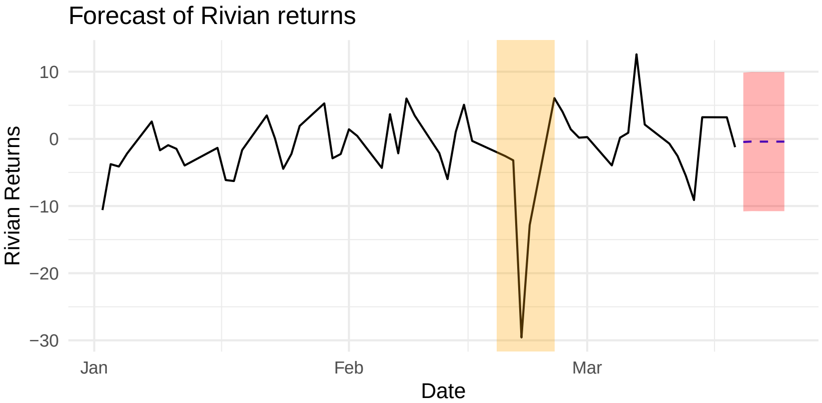


Figure 7: Forecast of Rivian returns with our VAR(1) model

Data Analysis

The period from February 19 to February 26 in Rivian's returns stands out due to a significant decline of approximately 30%. A closer examination on the news during that week revealed that this decline resulted from disappointing 2024 deliveries and earnings reported on February 23. It appears that market expectations were not met, leading to the observed decrease in returns. However, the subsequent rebound in returns might suggest that the initial sell-off reaction was perhaps exaggerated.

Data Analysis

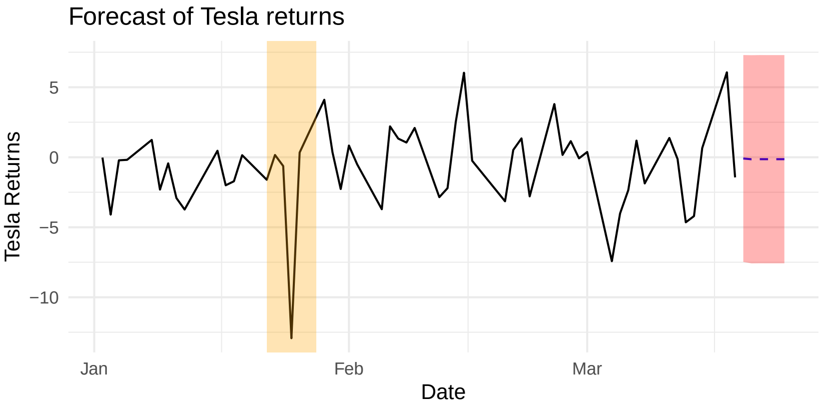


Figure 8: Forecast of Tesla returns with our VAR(1) model

Data Analysis

The period from 2024-01-22 to 2024-01-28 is highlighted in Tesla's returns due to a decline of approximately 12%. After reviewing the news of Tesla's returns on January 25th 2024 I realized the reason for the decrease in the returns was a due to the company reporting earnings that missed expectations with warnings of a slowdown in 2024. Again I believe the subsequent rebound in returns might suggest that the initial sell-off reaction was perhaps exaggerated.

Data Analysis

	Rivian	Tesla
Forecasted Returns MAPE	79.7571	95.56485
Forecasted Volatility MAPE	84.73849	166.2075

Table 9: MAPE values for forecasts of returns and volatility for Rivian and Tesla

Conclusion - Future Research

Upon reviewing the results presented in Table 9, it becomes evident that both the VAR and GARCH models exhibit noticeably high MAPE (Mean Absolute Percentage Error) values. This suggests that the forecasts generated by these models may lack accuracy. Furthermore, the observed high MAPE values indicate a potential lack of explanatory power in the returns of Gasoline, Lithium Battery, and EV Charger producer stocks. While the MAPE for the forecast of Rivian appears to be relatively decent, further research is warranted to ascertain whether this performance holds consistently over the entire lifetime of the stock. Additionally, it's crucial to investigate whether this outcome is an isolated occurrence, given that the stock exhibited lower volatility during the forecast period compared to historical data.

Conclusion - **Future Research**

- Future research endeavors should aim to develop a VAR-GARCH model capable of leveraging stock volatility data to enhance the accuracy of return forecasts.
- Additionally, there is a need to refine the forecasting horizon to shorter periods, such as 1 or 2 days, and evaluate the model's performance on a day-to-day basis to assess its precision with a more focused forecast.
- Exploring the potential explanatory power of the number of active EV car chargers in a region could be a valuable avenue for investigation. This aspect, not fully captured by stock returns alone, suggests the potential benefits of integrating geospatial data into the modeling framework. By incorporating real-time data on active EV chargers, it may be possible to better predict future returns, considering the influence of infrastructure development on consumer behavior towards electric vehicles.

Conclusion - **Future Research**

- Exploring the impact of the implementation of the Federal carbon tax on the returns of an EV startup stock is of particular interest. Although my analysis was constrained by the IPO timing of Rivian, focusing solely on stocks that debuted before the introduction of the Federal carbon tax would allow for a clearer examination of the policy's influence on EV stock returns.
- Additionally, investigating the effects of the Federal rebate for EV cars presents another intriguing avenue for research. Given that this incentive encourages Canadians to purchase EVs, it is reasonable to anticipate a positive impact on the returns of relevant stocks. Exploring this relationship further could provide valuable insights into the dynamics between government policies and EV market performance.

Questions

References I

Cai, Yuzhi, and Julian Stander. 2019. “The Threshold GARCH Model: Estimation and Density Forecasting for Financial Returns*.” *Journal of Financial Econometrics* 18 (2): 395–424. https://doi.org/10.1093/jjfinec/nbz014.

Hansen, Peter Reinhard, and Asger Lunde. 2001. “A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)?” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.264571.

Li, Tangrong, and Xuchu Sun. 2023. “Predicting Stock Market Returns Using Aggregate Credit Risk.” *International Review of Economics &Amp; Finance* 88 (November): 1087–1103. https://doi.org/10.1016/j.iref.2023.07.039.

References II

Shen, Jiancheng, John Griffith, Mohammad Najand, and Licheng Sun. 2021. "Predicting Stock and Bond Market Returns with Emotions: Evidence from Futures Markets." *Journal of Behavioral Finance* 24 (3): 333–44. https://doi.org/10.1080/15427560.2021.1975717.