Unveiling Dynamics in EU Carbon Emissions Futures

A Comprehensive Analysis with Interlinked Financial Indices

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Overview of the Paper

- Goal: Examine the dynamics in EU carbon emissions futures
  - Long-term stochastic and volatile patterns (2013/01/01-2023/12/01)
  - Establish short-term relationship with Tesla stock prices (2020/01/01-2023/12/01)
- Datasets used:
  - EU carbon emissions futures (CFI2Z3)
  - Tesla stock (TSLA)
  - Brent oil futures
  - Dow Jones U.S. Oil & Gas Index (DJUSEN)
  - S&P Dow Jones Indices (S&P500)

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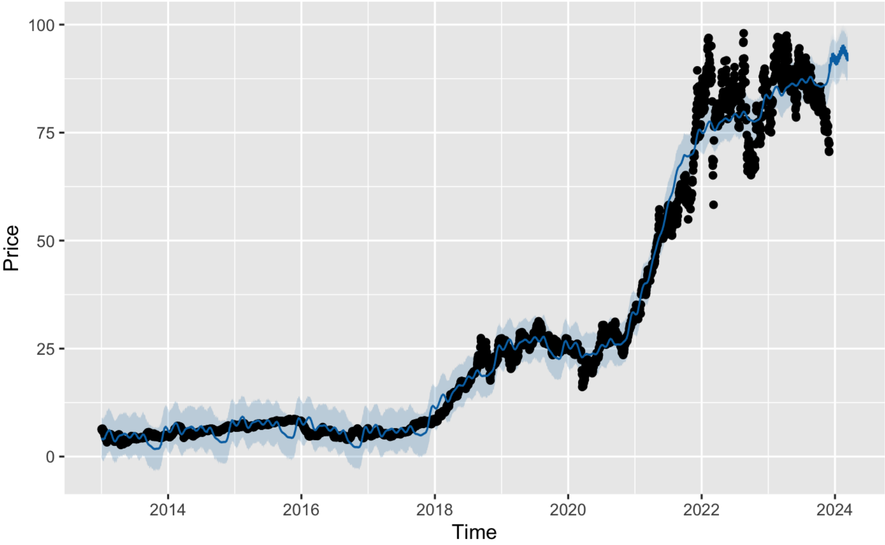
Introduction to Prophet

- Time-series forecasting model developed by Facebook (Meta).
- Define $Y_t = g(t) + s(t) + h(t) + \epsilon_t$, where Y_t is the predicted value at time t, $g(t)$ is the trend, $s(t)$ is the seasonality, $h(t)$ is the holiday effect, and ϵ_t is the error term.
  - Define $g(t) := \sum_{i=1}^{n}(k_i \cdot I(t \geq \tau_i))$ as a piecewise linear model with changepoints, where k_i is the slope of the trend between changepoints τ_i and $I(t \geq \tau_i)$ is an indicator function.
  - Define $s(t) := s_{yearly}(t) + s_{weekly}(t)$.
    - Handles seasonality through Fourier series expansion, specifically: $s_{yearly}(t) = \sum_{i=1}^{n}(a_i \cdot cos(\frac{2\pi it}{p}) + b_i \cdot sin(\frac{2\pi it}{p}))$ for p as the period and $s_{weekly}(t) = \sum_{i=1}^{n}(c_i \cdot cos(\frac{2\pi it}{7}) + d_i \cdot sin(\frac{2\pi it}{7}))$.

Prophet Forecasting



Prophet Performance Metrics

	horizon	mse	rmse	mae	mape	mdape	smape	coverage
1	10 days	44.58054	6.676866	4.211846	0.1305795	0.1104775	0.1319389	0.3306329
2	11 days	44.84171	6.696395	4.260533	0.1339213	0.1141489	0.1355290	0.3293413
3	12 days	45.06999	6.713418	4.272120	0.1373568	0.1206375	0.1391424	0.3265868
4	13 days	47.43316	6.887174	4.377205	0.1425713	0.1240495	0.1442525	0.3113772
5	14 days	50.13136	7.080350	4.499246	0.1464885	0.1286582	0.1481812	0.2926799
6	15 days	50.87282	7.132519	4.522070	0.1483203	0.1286582	0.1498330	0.2860162

Main Takeaways from Prophet

- From forecasting graph: good fit up to 2022 (especially the growth from 2020 to 2022), but fails to capture data after 2022.
- From performance metrics: we observe an increase in the forecast horizon leads to an increase in the forecast error, which implies that Prophet is better when forecasting over a shorter period and long-term forecasts are usually more volatile.
- Inclination towards HFT (High-Frequency Trading).
- Motivation for short-term analysis.

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Granger Causality Test

- Granger causality test refers to a statistical hypothesis test used to determine whether one time series helps to predict another.
- We can use $TSLA_{t-6}$ to predict $Carbon_t$.

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Granger causality test

Model 1: Carbon_ts ~ Lags(Carbon_ts, 1:6) + Lags(tsla_ts, 1:6)
Model 2: Carbon_ts ~ Lags(Carbon_ts, 1:6)
  Res.Df Df     F  Pr(>F)
1    194
2    200 -6 2.187 0.04586 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Linear Regression

$$\begin{aligned} Carbon_t = 9.348537 &+ 0.946187 \times Carbon_{t-1} + 0.032055 \times TSLA_t \\ &- 0.015963 \times TSLA_{t-6} - 0.103238 \times Brent_t \\ &+ 0.021104 \times DJUSEN_t - 0.003461 \times S\&P500_t \end{aligned}$$

```
Time series regression with "ts" data:
Start = 1(7), End = 1(213)

Call:
dynlm(formula = Carbon_ts ~ L(Carbon_ts, 1) + tsla_ts + L(tsla_ts,
    6) + brent_ts + DJUSEN_ts + sp500_ts)

Residuals:
    Min      1Q  Median      3Q     Max
-4.9218 -1.2180  0.0269  1.3230  4.4920

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      9.348537   6.490565   1.440 0.151338
L(Carbon_ts, 1)  0.946187   0.026655  35.497  < 2e-16 ***
tsla_ts          0.032055   0.008550   3.749 0.000232 ***
L(tsla_ts, 6)   -0.015963   0.006771  -2.358 0.019361 *
brent_ts        -0.103238   0.067675  -1.526 0.128713
DJUSEN_ts        0.021104   0.010504   2.009 0.045866 *
sp500_ts        -0.003461   0.001451  -2.385 0.018023 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.826 on 200 degrees of freedom
Multiple R-squared:  0.896,     Adjusted R-squared:  0.8929
F-statistic: 287.3 on 6 and 200 DF,  p-value: < 2.2e-16
```

Introduction of PCA

- **Definition**: ML technique that extracts important features and reduces noise by transforming high-dimensional datasets into low-dimensional ones.
- **Procedure**: (1) Data Normalization $\Rightarrow$ (2) Covariance Matrix $\Rightarrow$ (3) Eigenvalue Decomposition $\Rightarrow$ (4) Select Principal Components (top k eigenvectors corresponding to the largest k eigenvalues) $\Rightarrow$ (5) Apply Projection $Y = ZW_k$, where Z is the normalized matrix and W_k is the matrix of selected eigenvectors, so Y is the reduced dimensionality dataset.
- **Comments**: PCA generally gives difficult interpretation, but is good for testing how much error we can reduce.

PCA Results

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Importance of components:
                          PC1    PC2    PC3    PC4     PC5      PC6
Standard deviation     1.7267 1.3512 0.9881 0.3842 0.26240 7.17e-16
Proportion of Variance 0.4969 0.3043 0.1627 0.0246 0.01148 0.00e+00
Cumulative Proportion  0.4969 0.8012 0.9639 0.9885 1.00000 1.00e+00

Call:
lm(formula = Carbon_ts ~ PC1 + PC2 + PC3, data = pc_data)

Residuals:
     Min       1Q   Median       3Q      Max
-1.00232 -0.30502 -0.00133  0.34184  0.77645

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 85.80418    0.02806 3058.18   <2e-16 ***
PC1          0.66383    0.01629   40.76   <2e-16 ***
PC2         -1.02548    0.02081  -49.27   <2e-16 ***
PC3          5.25804    0.02846  184.73   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4095 on 209 degrees of freedom
Multiple R-squared:  0.9946,    Adjusted R-squared:  0.9945
F-statistic: 1.274e+04 on 3 and 209 DF,  p-value: < 2.2e-16
```

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Conclusion

For EU carbon emissions futures:

- Long-term instability is recognized.
- Short-term relationship with Tesla and its lags are recognized.
- Future work: discover more relationships with green tech stock prices, especially with their lags.

Thank you!