

# exploration

August 19, 2024

## 0.0.1 Key observations on these relationships

- Data utilized for training: 4 years worth half-hourly national demand and prices sourced from UK historical demand page and elexon
- Data was also scaled using minmax scaler to maintain a sensible matrix for inversion
- Note that this is an exploratory analysis whose intention is to figure out if there is a sensible linear model which can fit properties like prices and intraday volatility against demand. To simplify things, I only used the national demand which can be extended with other factors like Interconnector flows, capacity etc for a more extensive approach
- Starting off, the time series regression do make sense as the ADF test says that we are not having unit roots in residuals implying that the residuals aren't random walks.
- While the  $R^2$  scores are low, AIC/BIC are negative implying a fair amount of positive likelihood (Regression stats are available)
- Some preprocessing I did was to remove trend/seasonality from demand / prices / vol as they had very low DW statistic implying lot of residual autocorrelation. To make forecasts on forecasted demand in future, one can remove trend/seasonality, predict using the model and add these properties back. My intention was to focus on a more generic relationship between demands and clearing prices as rest of the signals are systematic noise
- Considering the demand created by EV / residential heating, we can formulate  $D_{adj} = D + f(EV, Res_{heat})$  which can mean that the prices would increase when a certain amount of the demand is driven orthogonally from the existing demand values
- However, a thing which was strange was that the overall ND was reducing over time which felt counterintuitive but could be due to the amount of outflow happening through interconnectors
- As for intraday volatility, unless  $f(EV, Res_{heat})$  follows a very volatile model, I wouldn't expect it to increase as much compared to that of prices due to the low demand loading.
- A much more extensive analysis can be performed when only certain hours are shocked instead of all hours, which can effect prices significantly but would expect the impact to be lower for intraday vol as its a metric across the whole day which would lead to averaged out effect
- Summarizing, in short term, I would expect the prices and vols to increase, prices specifically but vol not as much. As someone who trades short term power, I would think cobblestone does get impacted by this in auctions and should adjust theoretical prices accordingly to maximize profits
- Below pages have plots which you can refer to, only two online resources I used were <https://www.nationalgrideso.com/data-portal/historic-demand-data> for demand data and elexon for prices

## 0.0.2 Extensions

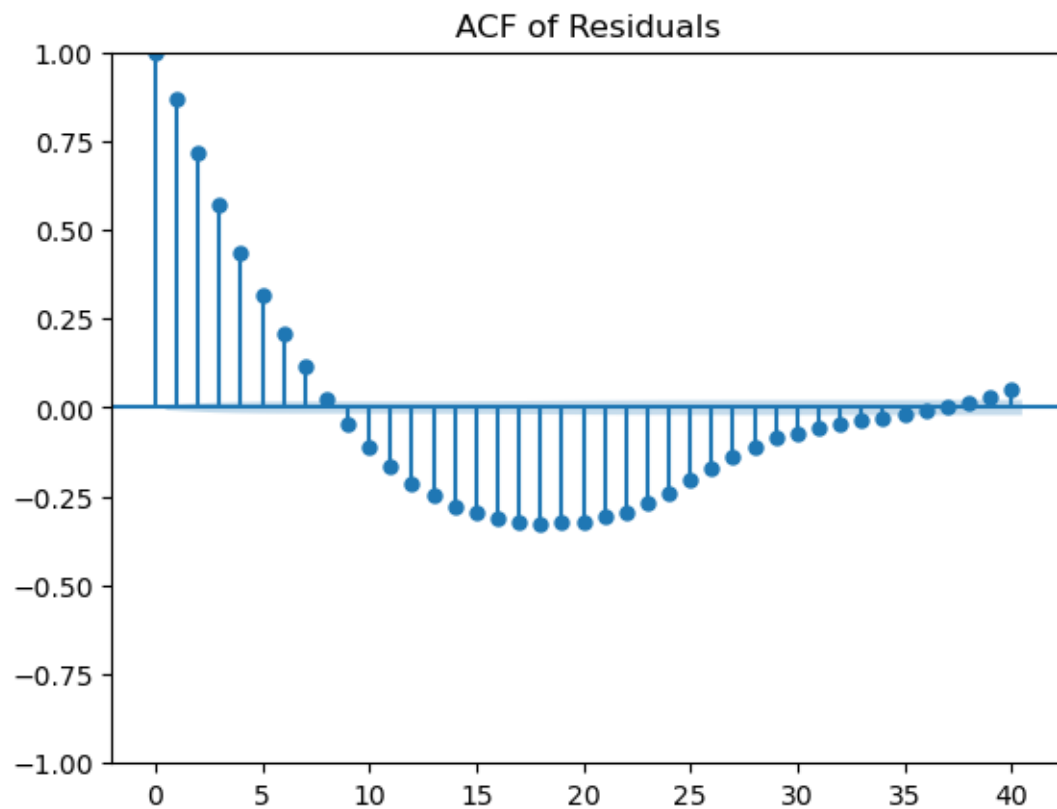
- Slightly complicated model for demand on EV / heating would be better to work with. I have tried to find some relevant material under the time constraint but most of the research seemed to focus on psychological aspect of EV taking off which involved forms/surveys
- Maybe we can draw a parallel to US adoptions and see if any inference can be made. I initially was opposed to doing this as the demographics are very different
- Obviously linear regression isn't the best model to pinpoint the impact but is a very good starter to get an idea of impact direction and magnitude. We can try using a random forest/XGBoost by decomposing trend/seasonality, use various components of demand and make a complex model which can accurately estimate the price/vol impact. I stuck to OLS because of the interpretability

## 0.0.3 Analysis

OLS Regression Results						
=====						
Dep. Variable:	y	R-squared:	0.088			
Model:	OLS	Adj. R-squared:	0.088			
Method:	Least Squares	F-statistic:	6058.			
Date:	Mon, 19 Aug 2024	Prob (F-statistic):	0.00			
Time:	19:23:31	Log-Likelihood:	1.6119e+05			
No. Observations:	62451	AIC:	-3.224e+05			
Df Residuals:	62449	BIC:	-3.224e+05			
Df Model:	1					
Covariance Type:	nonrobust					
=====						
	coef	std err	t	P> t	[0.025	0.975]
-----						
const	0.2274	0.000	895.216	0.000	0.227	0.228
x1	0.0393	0.001	77.834	0.000	0.038	0.040
=====						
Omnibus:	96830.375	Durbin-Watson:	0.265			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	223875298.180			
Skew:	9.275	Prob(JB):	0.00			
Kurtosis:	295.731	Cond. No.	8.52			
=====						

Notes:

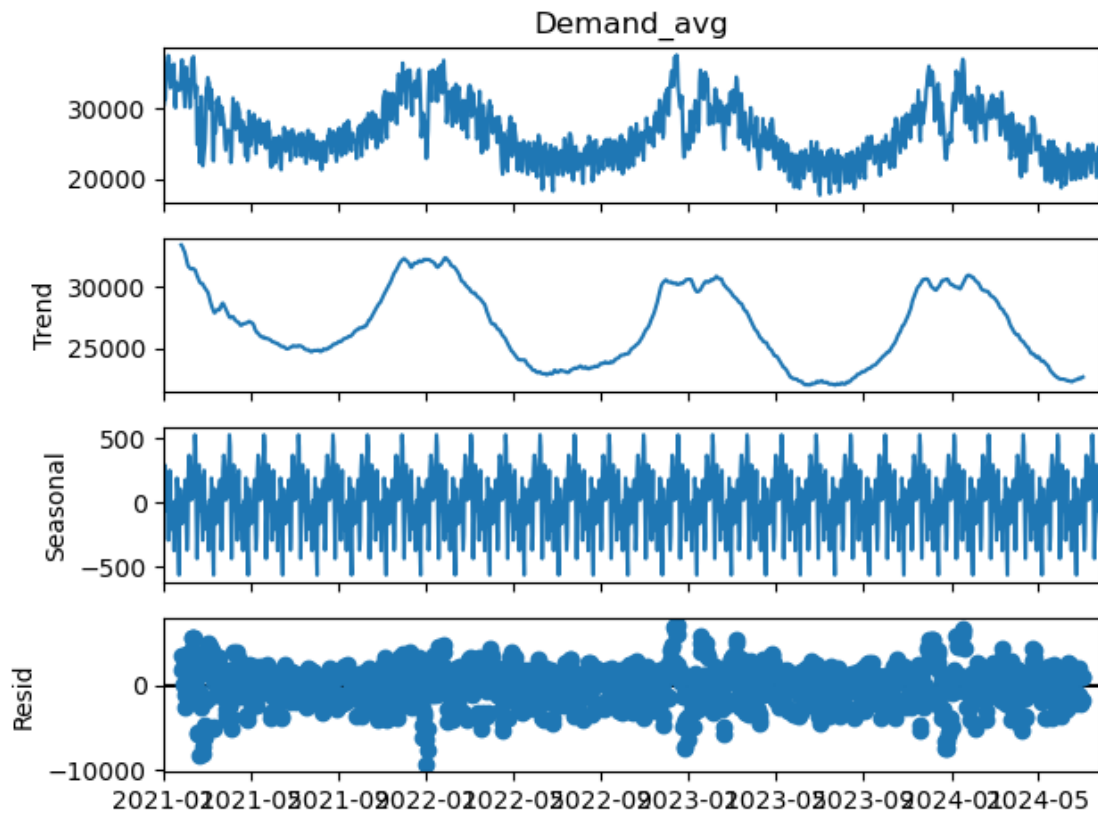
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



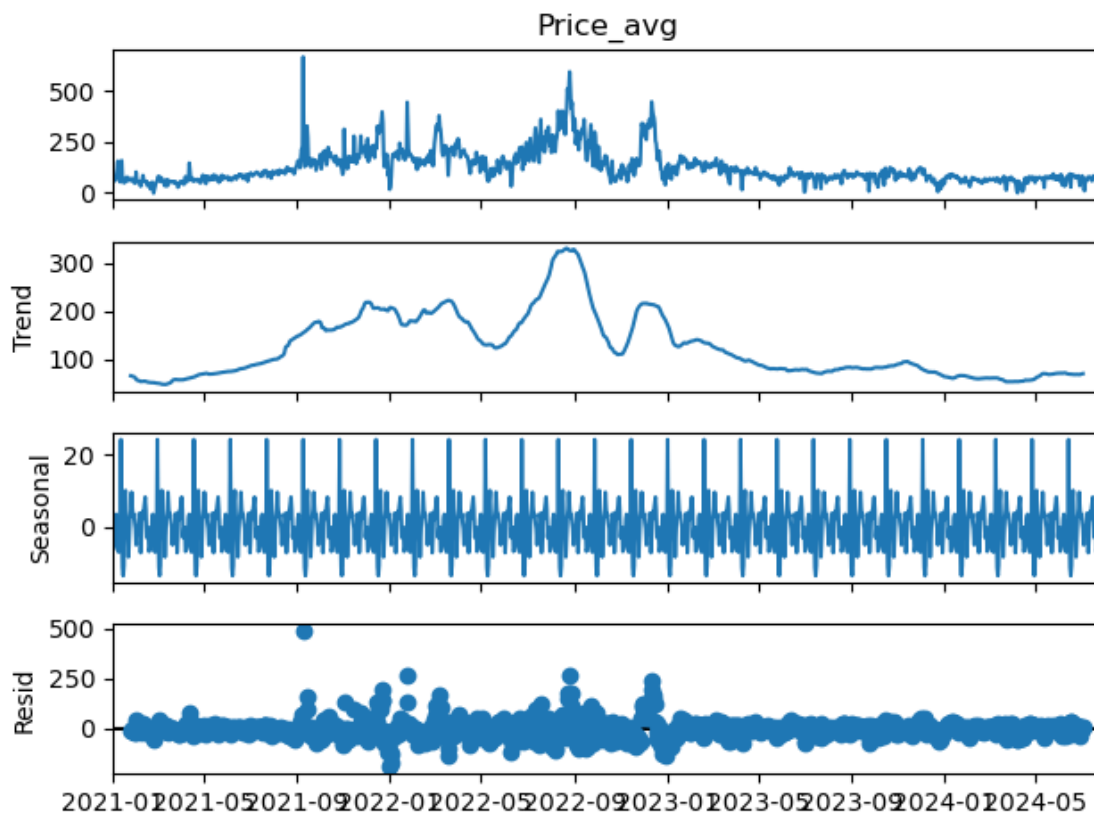
ADF Statistic: -54.84722149994893  
p-value: 0.0

#### 0.0.4 On data grouped to a daily granularity

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<Figure size 300x300 with 0 Axes>



### OLS Regression Results

```

=====
Dep. Variable:          y      R-squared:          0.264
Model:                  OLS    Adj. R-squared:       0.263
Method:                 Least Squares  F-statistic:       448.3
Date:                   Mon, 19 Aug 2024  Prob (F-statistic): 2.63e-85
Time:                   19:23:39  Log-Likelihood:    1879.2
No. Observations:      1255     AIC:              -3754.
Df Residuals:          1253     BIC:              -3744.
Df Model:               1
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.1539	0.006	24.700	0.000	0.142	0.166
x1	0.2242	0.011	21.174	0.000	0.203	0.245

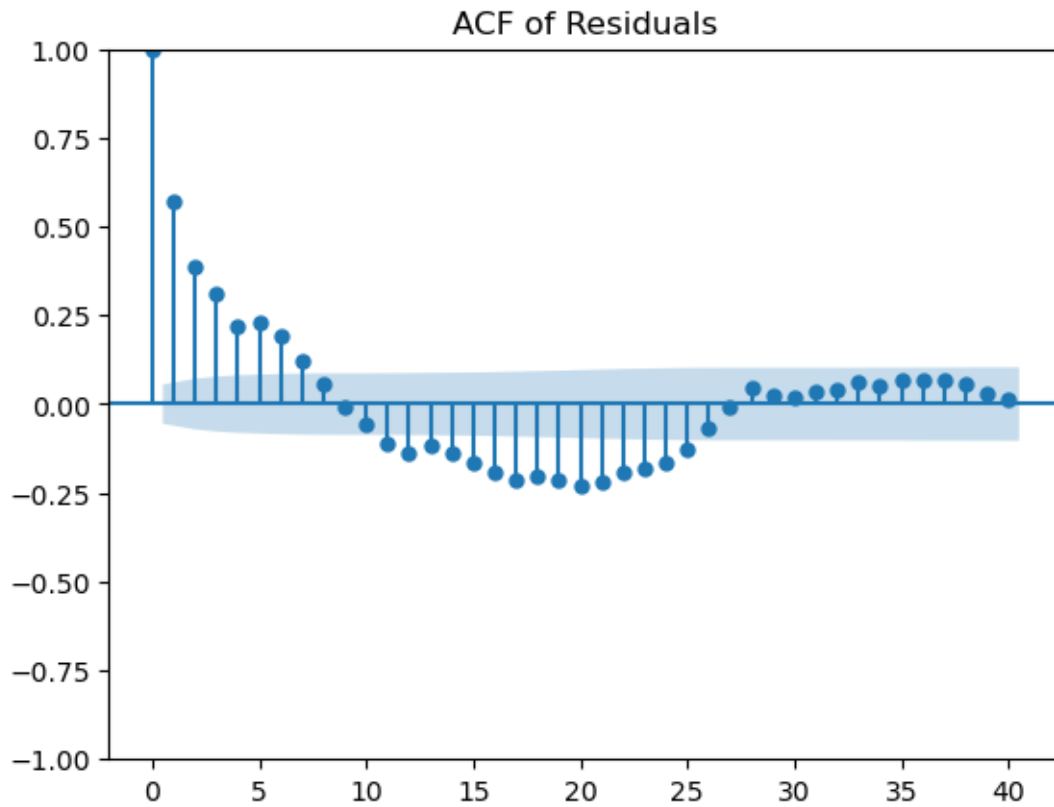
```

=====
Omnibus:                916.523  Durbin-Watson:        0.857
Prob(Omnibus):           0.000   Jarque-Bera (JB):     37376.043
Skew:                    2.903   Prob(JB):              0.00
Kurtosis:                29.097  Cond. No.              9.21
=====

```

Notes:

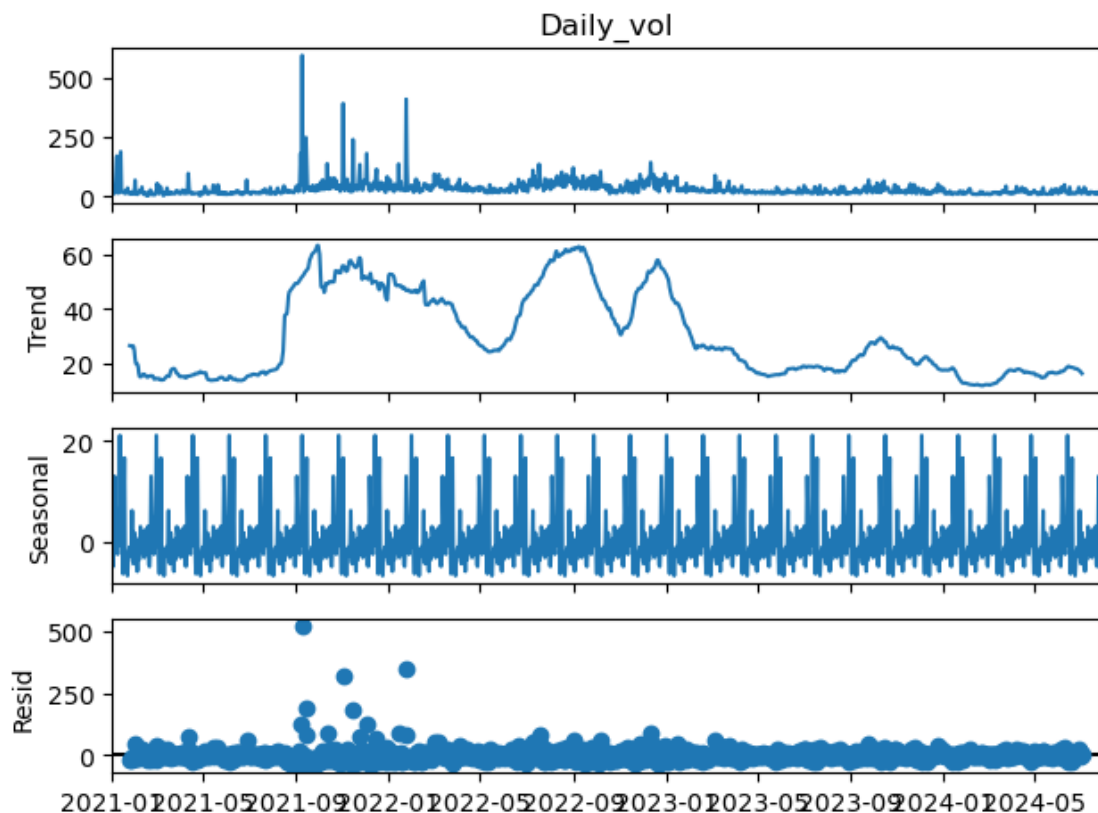
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



ADF Statistic: -10.844320876688789

p-value: 1.5865945477557885e-19

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#### OLS Regression Results

```

=====
Dep. Variable:                y      R-squared:                0.008
Model:                        OLS    Adj. R-squared:           0.007
Method:                        Least Squares    F-statistic:              10.14
Date:                          Mon, 19 Aug 2024    Prob (F-statistic):       0.00149
Time:                          19:23:41    Log-Likelihood:           2041.1
No. Observations:              1255    AIC:                      -4078.
Df Residuals:                  1253    BIC:                      -4068.
Df Model:                      1
Covariance Type:               nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	0.0609	0.005	11.115	0.000	0.050	0.072
x1	0.0296	0.009	3.185	0.001	0.011	0.048

```

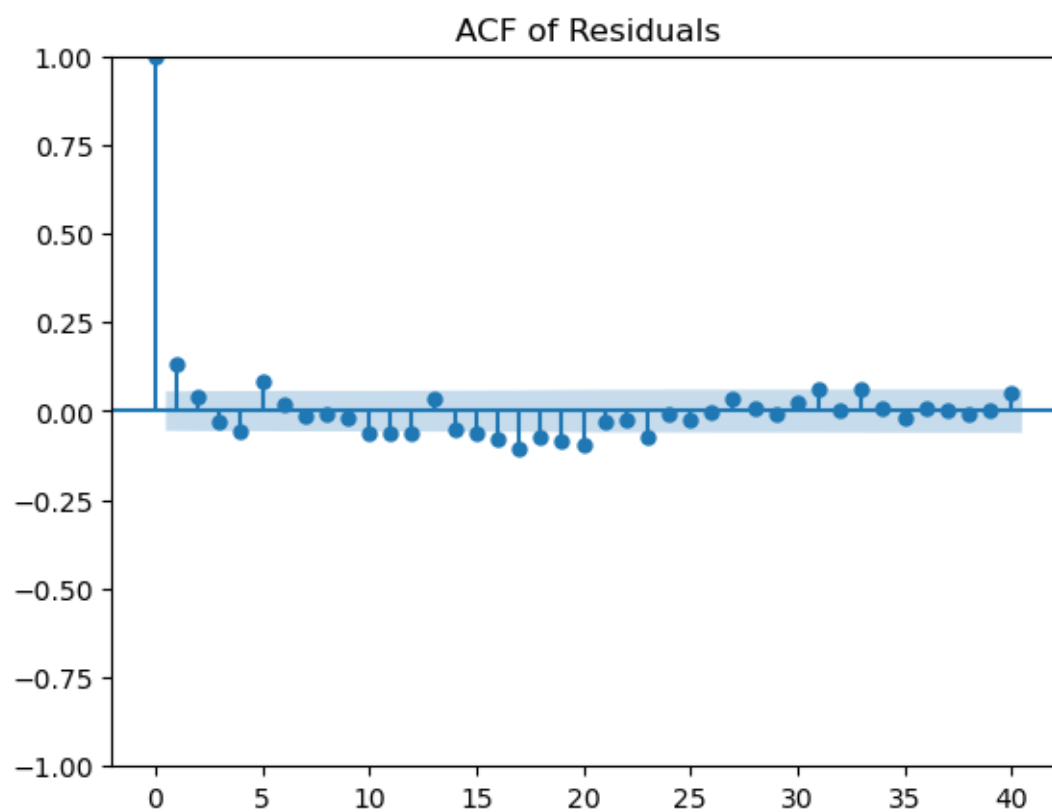
=====
Omnibus:                      1978.384    Durbin-Watson:              1.737
Prob(Omnibus):                 0.000    Jarque-Bera (JB):           1181154.179
Skew:                          9.534    Prob(JB):                   0.00
Kurtosis:                     152.078    Cond. No.:                   9.21
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Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.



ADF Statistic: -11.90660994033187

p-value: 5.417569099155691e-22