04_statistical_inference_of_stock_returns_with_statsmodels

September 29, 2021

1 Statistical inference of stock returns with linear regression

1.1 Imports & Settings

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
%matplotlib inline

import pandas as pd

from statsmodels.api import OLS, add_constant, graphics
from statsmodels.graphics.tsaplots import plot_acf
from scipy.stats import norm

import seaborn as sns
import matplotlib.pyplot as plt
```

[3]:
```
sns.set_style('whitegrid')
idx = pd.IndexSlice
```

1.2 Load Data

[4]:
```
with pd.HDFStore('data.h5') as store:
    data = (store['model_data']
            .dropna()
            .drop(['open', 'close', 'low', 'high'], axis=1))
```

1.2.1 Select Investment Universe

[5]:
```
data = data[data.dollar_vol_rank<100]
```

[6]:
```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 109675 entries, ('AAL', Timestamp('2013-07-25 00:00:00')) to ('ZTS',
Timestamp('2014-12-04 00:00:00'))
Data columns (total 65 columns):
```

```
 #    Column                 Non-Null Count   Dtype
---   ------                 --------------   -----
 0    volume                 109675 non-null  float64
 1    dollar_vol             109675 non-null  float64
 2    dollar_vol_1m          109675 non-null  float64
 3    dollar_vol_rank        109675 non-null  float64
 4    rsi                    109675 non-null  float64
 5    bb_high                109675 non-null  float64
 6    bb_low                 109675 non-null  float64
 7    atr                    109675 non-null  float64
 8    macd                   109675 non-null  float64
 9    return_1d              109675 non-null  float64
 10   return_5d              109675 non-null  float64
 11   return_10d             109675 non-null  float64
 12   return_21d             109675 non-null  float64
 13   return_42d             109675 non-null  float64
 14   return_63d             109675 non-null  float64
 15   return_1d_lag1         109675 non-null  float64
 16   return_5d_lag1         109675 non-null  float64
 17   return_10d_lag1        109675 non-null  float64
 18   return_21d_lag1        109675 non-null  float64
 19   return_1d_lag2         109675 non-null  float64
 20   return_5d_lag2         109675 non-null  float64
 21   return_10d_lag2        109675 non-null  float64
 22   return_21d_lag2        109675 non-null  float64
 23   return_1d_lag3         109675 non-null  float64
 24   return_5d_lag3         109675 non-null  float64
 25   return_10d_lag3        109675 non-null  float64
 26   return_21d_lag3        109675 non-null  float64
 27   return_1d_lag4         109675 non-null  float64
 28   return_5d_lag4         109675 non-null  float64
 29   return_10d_lag4        109675 non-null  float64
 30   return_21d_lag4        109675 non-null  float64
 31   return_1d_lag5         109675 non-null  float64
 32   return_5d_lag5         109675 non-null  float64
 33   return_10d_lag5        109675 non-null  float64
 34   return_21d_lag5        109675 non-null  float64
 35   target_1d              109675 non-null  float64
 36   target_5d              109675 non-null  float64
 37   target_10d             109675 non-null  float64
 38   target_21d             109675 non-null  float64
 39   year_2014              109675 non-null  uint8
 40   year_2015              109675 non-null  uint8
 41   year_2016              109675 non-null  uint8
 42   year_2017              109675 non-null  uint8
 43   month_2                109675 non-null  uint8
 44   month_3                109675 non-null  uint8
 45   month_4                109675 non-null  uint8
```

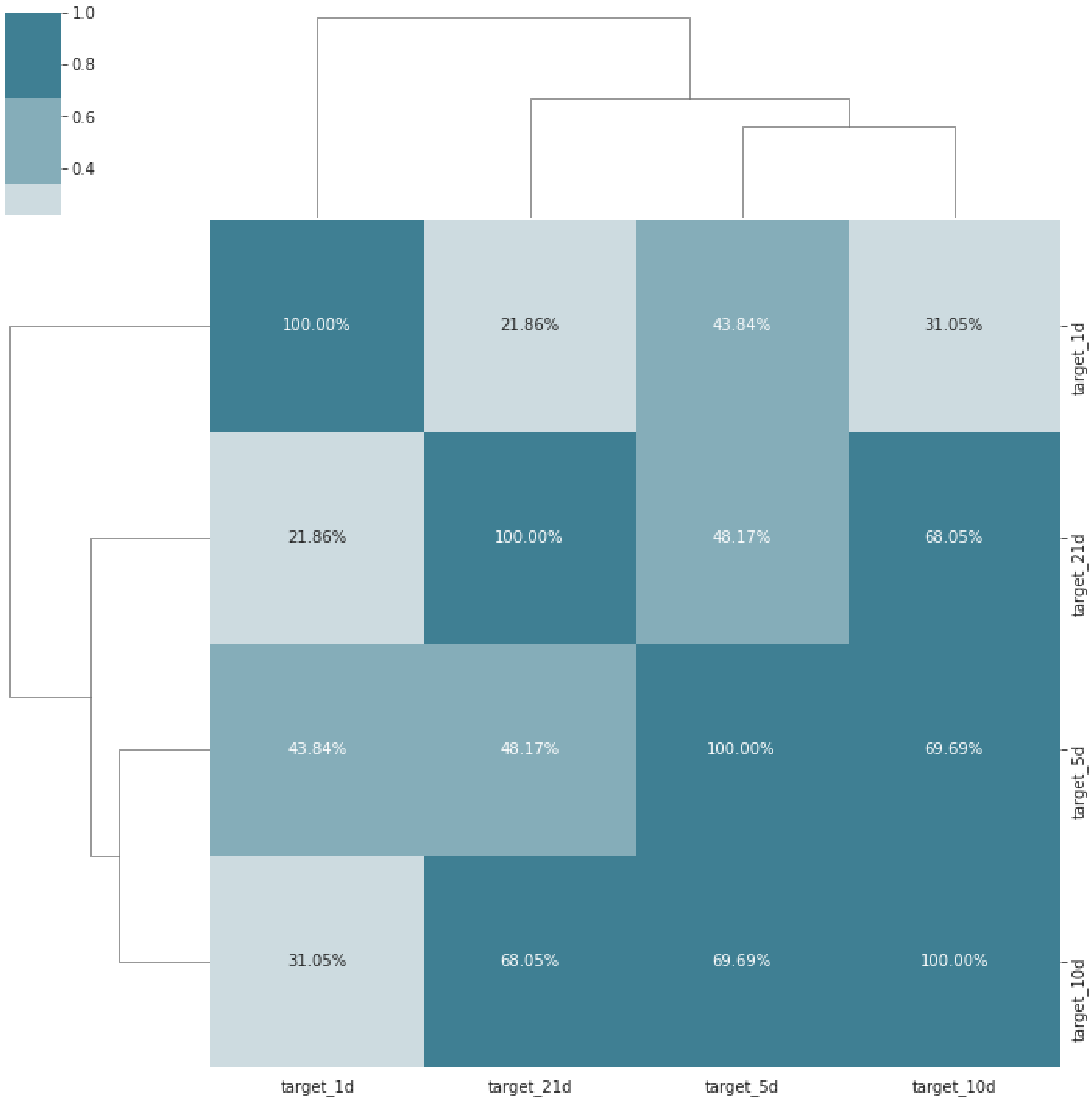
```
 46   month_5                  109675 non-null  uint8
 47   month_6                  109675 non-null  uint8
 48   month_7                  109675 non-null  uint8
 49   month_8                  109675 non-null  uint8
 50   month_9                  109675 non-null  uint8
 51   month_10                 109675 non-null  uint8
 52   month_11                 109675 non-null  uint8
 53   month_12                 109675 non-null  uint8
 54   capital_goods            109675 non-null  uint8
 55   consumer_durables        109675 non-null  uint8
 56   consumer_non-durables    109675 non-null  uint8
 57   consumer_services        109675 non-null  uint8
 58   energy                   109675 non-null  uint8
 59   finance                  109675 non-null  uint8
 60   health_care              109675 non-null  uint8
 61   miscellaneous            109675 non-null  uint8
 62   public_utilities         109675 non-null  uint8
 63   technology               109675 non-null  uint8
 64   transportation           109675 non-null  uint8
dtypes: float64(39), uint8(26)
memory usage: 36.5+ MB
```

1.2.2 Create Model Data

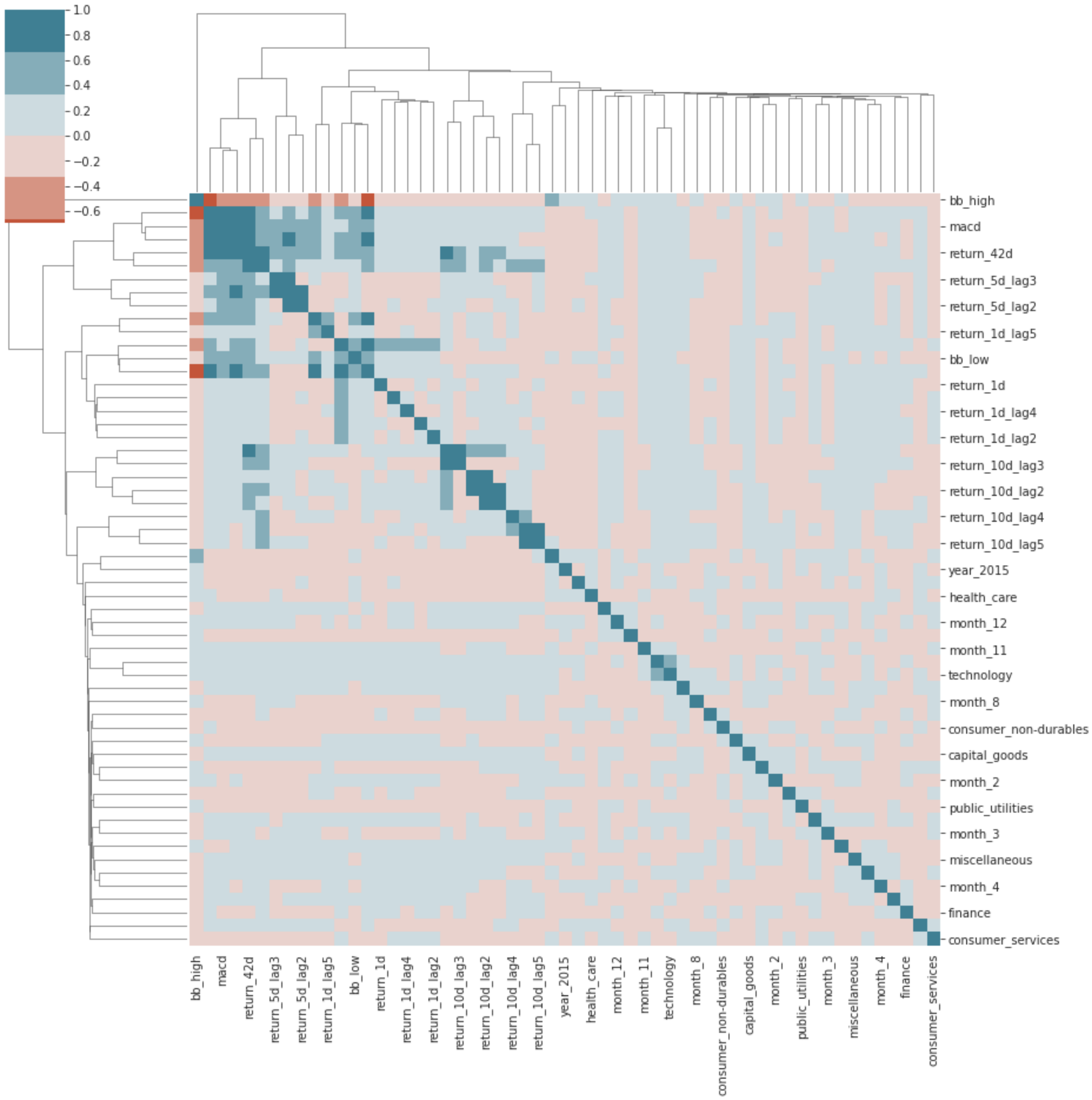
[7]:
```
y = data.filter(like='target')
X = data.drop(y.columns, axis=1)
X = X.drop(['dollar_vol', 'dollar_vol_rank', 'volume', 'consumer_durables'],␣
↪axis=1)
```

1.3 Explore Data

[8]:
```
sns.clustermap(y.corr(), cmap=sns.diverging_palette(h_neg=20, h_pos=220),␣
↪center=0, annot=True, fmt='.2%');
```



[9]:
```
sns.clustermap(X.corr(), cmap=sns.diverging_palette(h_neg=20, h_pos=220),
    center=0);
plt.gcf().set_size_inches((14, 14))
```



[10]:
```
corr_mat = X.corr().stack().reset_index()
corr_mat.columns=['var1', 'var2', 'corr']
corr_mat = corr_mat[corr_mat.var1!=corr_mat.var2].sort_values(by='corr',␣
↪ascending=False)
```

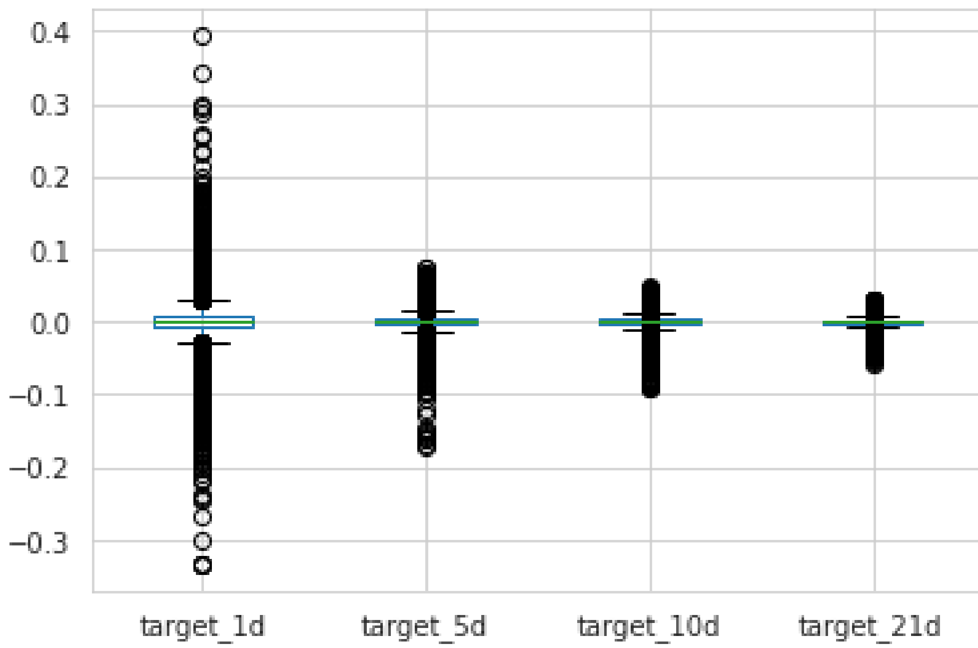
[11]:
```
corr_mat.head().append(corr_mat.tail())
```

[11]:

	var1	var2	corr
581	return_42d	return_63d	0.835634
637	return_63d	return_42d	0.835634
286	macd	rsi	0.817113
62	rsi	macd	0.817113
518	return_21d	macd	0.793893

```
515  return_21d      bb_high -0.632777
122     bb_high  return_10d -0.693640
458  return_10d      bb_high -0.693640
59          rsi      bb_high -0.696555
115     bb_high          rsi -0.696555
```

[12]:
```
y.boxplot();
```



1.4 Linear Regression for Statistical Inference: OLS with statsmodels

1.4.1 Ticker-wise standardization

`statsmodels` warns of high design matrix condition numbers. This can arise when the variables are not standardized and the Eigenvalues differ due to scaling. The following step avoids this warning.

[13]:
```
sectors = X.iloc[:, -10:]
X = (X.drop(sectors.columns, axis=1)
      .groupby(level='ticker')
      .transform(lambda x: (x - x.mean()) / x.std())
     .join(sectors)
     .fillna(0))
```

1.4.2 1-Day Returns

[14]:
```
target = 'target_1d'
model = OLS(endog=y[target], exog=add_constant(X))
trained_model = model.fit()
print(trained_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              target_1d   R-squared:                       0.010
Model:                            OLS   Adj. R-squared:                  0.009
Method:                 Least Squares   F-statistic:                     19.03
Date:                Thu, 15 Apr 2021   Prob (F-statistic):          9.43e-189
Time:                        15:03:16   Log-Likelihood:             2.8852e+05
No. Observations:              109675   AIC:                        -5.769e+05
Df Residuals:                  109617   BIC:                        -5.764e+05
Df Model:                          57
Covariance Type:            nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
const                    -0.0002      0.000     -0.793      0.428      -0.001
0.000
dollar_vol_1m            -0.0004   6.88e-05     -5.214      0.000      -0.000
-0.000
rsi                       0.0002      0.000      0.978      0.328      -0.000
0.001
bb_high                   0.0002      0.000      0.927      0.354      -0.000
0.001
bb_low                    0.0006      0.000      2.940      0.003       0.000
0.001
atr                   -3.752e-05   7.44e-05     -0.504      0.614      -0.000
0.000
macd                     -0.0004      0.000     -1.835      0.066      -0.001
2.96e-05
return_1d                 0.0029      0.000      9.684      0.000       0.002
0.003
return_5d                -0.0019      0.001     -2.015      0.044      -0.004
-5.08e-05
return_10d               -0.0064      0.001     -6.443      0.000      -0.008
-0.004
return_21d                0.0028      0.000      6.242      0.000       0.002
0.004
return_42d               -0.0036      0.001     -5.995      0.000      -0.005
-0.002
```

return_63d	-0.0019	0.000	-4.241	0.000	-0.003	-0.001
return_1d_lag1	0.0027	0.000	8.998	0.000	0.002	0.003
return_5d_lag1	0.0048	0.001	7.033	0.000	0.003	0.006
return_10d_lag1	-0.0010	0.001	-0.896	0.370	-0.003	0.001
return_21d_lag1	0.0029	0.000	7.667	0.000	0.002	0.004
return_1d_lag2	0.0027	0.000	9.177	0.000	0.002	0.003
return_5d_lag2	0.0009	0.001	1.141	0.254	-0.001	0.002
return_10d_lag2	8.065e-05	0.001	0.097	0.923	-0.002	0.002
return_21d_lag2	0.0003	0.000	0.857	0.392	-0.000	0.001
return_1d_lag3	0.0027	0.000	8.973	0.000	0.002	0.003
return_5d_lag3	0.0015	0.001	1.919	0.055	-3.15e-05	0.003
return_10d_lag3	0.0005	0.000	3.457	0.001	0.000	0.001
return_21d_lag3	-0.0002	5.55e-05	-3.739	0.000	-0.000	-9.88e-05
return_1d_lag4	0.0030	0.000	9.976	0.000	0.002	0.004
return_5d_lag4	0.0006	0.001	1.057	0.290	-0.001	0.002
return_10d_lag4	0.0004	0.000	3.845	0.000	0.000	0.001
return_21d_lag4	4.323e-05	5.5e-05	0.786	0.432	-6.46e-05	0.000
return_1d_lag5	-8.924e-05	6.19e-05	-1.441	0.149	-0.000	3.21e-05
return_5d_lag5	0.0001	0.001	0.241	0.810	-0.001	0.001
return_10d_lag5	0.0007	9.95e-05	7.235	0.000	0.001	0.001
return_21d_lag5	9.403e-05	5.48e-05	1.716	0.086	-1.34e-05	0.000
year_2014	-0.0004	8.38e-05	-4.430	0.000	-0.001	-0.000
year_2015	-0.0006	9.15e-05	-6.804	0.000	-0.001	-0.000
year_2016	-0.0005	8.95e-05	-5.113	0.000	-0.001	-0.000

```
year_2017               -0.0002   8.83e-05     -2.024      0.043      -0.000
-5.66e-06
month_2                  0.0010   7.21e-05     14.079      0.000       0.001
0.001
month_3                  0.0003   7.44e-05      4.637      0.000       0.000
0.000
month_4                  0.0005   7.36e-05      7.053      0.000       0.000
0.001
month_5                  0.0005   7.25e-05      6.741      0.000       0.000
0.001
month_6                  0.0004   7.34e-05      5.696      0.000       0.000
0.001
month_7                  0.0006   7.63e-05      8.415      0.000       0.000
0.001
month_8               6.821e-05    7.7e-05      0.886      0.375   -8.26e-05
0.000
month_9                  0.0004   7.59e-05      5.017      0.000       0.000
0.001
month_10                 0.0007    7.8e-05      8.524      0.000       0.001
0.001
month_11                 0.0006    7.6e-05      7.697      0.000       0.000
0.001
month_12                 0.0004   7.42e-05      5.153      0.000       0.000
0.001
capital_goods            0.0010      0.000      2.714      0.007       0.000
0.002
consumer_non-durables    0.0007      0.000      1.793      0.073   -6.33e-05
0.001
consumer_services        0.0008      0.000      2.234      0.025    9.29e-05
0.001
energy                   0.0003      0.000      0.913      0.361      -0.000
0.001
finance                  0.0009      0.000      2.533      0.011       0.000
0.002
health_care              0.0007      0.000      2.065      0.039    3.51e-05
0.001
miscellaneous            0.0011      0.000      2.565      0.010       0.000
0.002
public_utilities         0.0003      0.000      0.749      0.454      -0.001
0.001
technology               0.0011      0.000      3.285      0.001       0.000
0.002
transportation           0.0010      0.000      2.426      0.015       0.000
0.002
==============================================================================
Omnibus:                    29139.970   Durbin-Watson:                   2.010
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          2800989.218
Skew:                          -0.105   Prob(JB):                         0.00
```

```
Kurtosis:                      27.757   Cond. No.                         80.7
==============================================================================

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

1.4.3 5-Day Returns

[15]:
```python
target = 'target_5d'
model = OLS(endog=y[target], exog=add_constant(X))
trained_model = model.fit()
print(trained_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              target_5d   R-squared:                       0.031
Model:                            OLS   Adj. R-squared:                  0.031
Method:                 Least Squares   F-statistic:                     61.86
Date:                Thu, 15 Apr 2021   Prob (F-statistic):               0.00
Time:                        15:03:16   Log-Likelihood:             3.7883e+05
No. Observations:              109675   AIC:                        -7.575e+05
Df Residuals:                  109617   BIC:                        -7.570e+05
Df Model:                          57
Covariance Type:            nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
const                    -0.0005      0.000     -3.412      0.001      -0.001
-0.000
dollar_vol_1m            -0.0003   3.02e-05     -8.790      0.000      -0.000
-0.000
rsi                       0.0005   8.43e-05      5.477      0.000       0.000
0.001
bb_high                   0.0010   9.88e-05     10.353      0.000       0.001
0.001
bb_low                   -0.0004   9.46e-05     -4.550      0.000      -0.001
-0.000
atr                     -9.8e-05   3.27e-05     -2.999      0.003      -0.000
-3.4e-05
macd                     -0.0004      0.000     -3.880      0.000      -0.001
-0.000
return_1d                 0.0010      0.000      7.468      0.000       0.001
0.001
return_5d                 0.0012      0.000      2.947      0.003       0.000
```

```
0.002
return_10d             -0.0038        0.000       -8.639       0.000       -0.005
-0.003
return_21d              0.0021        0.000       10.714       0.000        0.002
0.003
return_42d             -0.0024        0.000       -9.124       0.000       -0.003
-0.002
return_63d             -0.0017        0.000       -8.800       0.000       -0.002
-0.001
return_1d_lag1          0.0009        0.000        7.281       0.000        0.001
0.001
return_5d_lag1          0.0035        0.000       11.632       0.000        0.003
0.004
return_10d_lag1         0.0007        0.000        1.546       0.122       -0.000
0.002
return_21d_lag1         0.0020        0.000       11.876       0.000        0.002
0.002
return_1d_lag2          0.0010        0.000        7.493       0.000        0.001
0.001
return_5d_lag2       -6.79e-06        0.000       -0.020       0.984       -0.001
0.001
return_10d_lag2        -0.0003        0.000       -0.918       0.359       -0.001
0.000
return_21d_lag2         0.0006        0.000        4.309       0.000        0.000
0.001
return_1d_lag3          0.0010        0.000        7.844       0.000        0.001
0.001
return_5d_lag3          0.0001        0.000        0.397       0.691       -0.001
0.001
return_10d_lag3         0.0005      6.4e-05        8.171       0.000        0.000
0.001
return_21d_lag3        -0.0002     2.44e-05       -7.933       0.000       -0.000
-0.000
return_1d_lag4          0.0010        0.000        7.887       0.000        0.001
0.001
return_5d_lag4          0.0007        0.000        2.443       0.015        0.000
0.001
return_10d_lag4      4.558e-05     4.51e-05        1.012       0.312    -4.27e-05
0.000
return_21d_lag4      8.989e-05     2.41e-05        3.724       0.000     4.26e-05
0.000
return_1d_lag5       1.138e-05     2.72e-05        0.419       0.675    -4.19e-05
6.46e-05
return_5d_lag5          0.0005        0.000        1.848       0.065    -2.91e-05
0.001
return_10d_lag5         0.0004     4.37e-05        8.446       0.000        0.000
0.000
return_21d_lag5         0.0002      2.4e-05        7.811       0.000        0.000
```

						0.000
year_2014	-0.0003	3.68e-05	-9.407	0.000	-0.000	-0.000
year_2015	-0.0005	4.02e-05	-13.632	0.000	-0.001	-0.000
year_2016	-0.0003	3.93e-05	-8.157	0.000	-0.000	-0.000
year_2017	-0.0002	3.88e-05	-4.454	0.000	-0.000	-9.67e-05
month_2	0.0009	3.16e-05	27.541	0.000	0.001	0.001
month_3	0.0001	3.27e-05	3.949	0.000	6.5e-05	0.000
month_4	0.0003	3.23e-05	9.721	0.000	0.000	0.000
month_5	0.0005	3.18e-05	14.481	0.000	0.000	0.001
month_6	0.0002	3.22e-05	7.201	0.000	0.000	0.000
month_7	0.0004	3.35e-05	13.321	0.000	0.000	0.001
month_8	3.574e-05	3.38e-05	1.058	0.290	-3.05e-05	0.000
month_9	0.0003	3.33e-05	7.745	0.000	0.000	0.000
month_10	0.0004	3.42e-05	12.425	0.000	0.000	0.000
month_11	0.0005	3.33e-05	13.788	0.000	0.000	0.001
month_12	0.0001	3.26e-05	4.388	0.000	7.91e-05	0.000
capital_goods	0.0011	0.000	6.699	0.000	0.001	0.001
consumer_non-durables	0.0009	0.000	5.179	0.000	0.001	0.001
consumer_services	0.0009	0.000	6.038	0.000	0.001	0.001
energy	0.0004	0.000	2.488	0.013	8.11e-05	0.001
finance	0.0010	0.000	6.510	0.000	0.001	0.001
health_care	0.0008	0.000	5.240	0.000	0.000	0.001
miscellaneous	0.0012	0.000	6.354	0.000	0.001	0.002
public_utilities	0.0003	0.000	1.864	0.062	-1.77e-05	0.001
technology	0.0011	0.000	7.760	0.000	0.001	

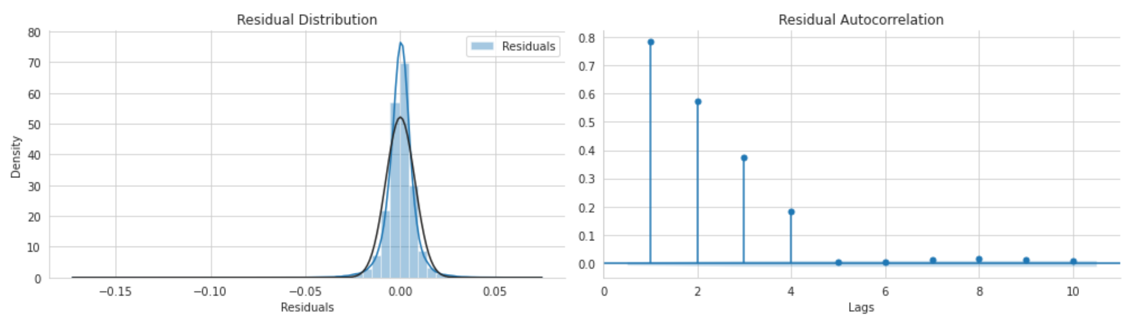
```
0.001
transportation           0.0010      0.000      5.920      0.000       0.001
0.001
==============================================================================
Omnibus:                43640.257   Durbin-Watson:                   0.436
Prob(Omnibus):              0.000   Jarque-Bera (JB):          2362450.641
Skew:                      -1.138   Prob(JB):                         0.00
Kurtosis:                  25.623   Cond. No.                         80.7
==============================================================================

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

Obtain the residuals

[16]:
```
preds = trained_model.predict(add_constant(X))
residuals = y[target] - preds
```

[17]:
```
fig, axes = plt.subplots(ncols=2, figsize=(14,4))
sns.distplot(residuals, fit=norm, ax=axes[0], axlabel='Residuals',␣
 ↪label='Residuals')
axes[0].set_title('Residual Distribution')
axes[0].legend()
plot_acf(residuals, lags=10, zero=False, ax=axes[1], title='Residual␣
 ↪Autocorrelation')
axes[1].set_xlabel('Lags')
sns.despine()
fig.tight_layout();
```



1.4.4 10-Day Returns

[18]:
```
target = 'target_10d'
model = OLS(endog=y[target], exog=add_constant(X))
trained_model = model.fit()
print(trained_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              target_10d   R-squared:                       0.043
Model:                             OLS   Adj. R-squared:                  0.042
Method:                  Least Squares   F-statistic:                     85.38
Date:                 Thu, 15 Apr 2021   Prob (F-statistic):               0.00
Time:                         15:03:18   Log-Likelihood:             4.1892e+05
No. Observations:               109675   AIC:                        -8.377e+05
Df Residuals:                   109617   BIC:                        -8.372e+05
Df Model:                           57
Covariance Type:             nonrobust
================================================================================
=========
                            coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
const                    -0.0004    9.5e-05     -3.922      0.000      -0.001
-0.000
dollar_vol_1m            -0.0001    2.1e-05     -6.800      0.000      -0.000
-0.000
rsi                       0.0002   5.85e-05      2.759      0.006    4.67e-05
0.000
bb_high                   0.0006   6.85e-05      9.273      0.000       0.001
0.001
bb_low                   -0.0002   6.56e-05     -2.847      0.004      -0.000
-5.82e-05
atr                      -0.0002   2.27e-05     -7.328      0.000      -0.000
-0.000
macd                     -0.0001   7.22e-05     -1.908      0.056      -0.000
3.76e-06
return_1d                 0.0005   9.01e-05      6.046      0.000       0.000
0.001
return_5d               5.98e-05      0.000      0.212      0.832      -0.000
0.001
return_10d               -0.0008      0.000     -2.741      0.006      -0.001
-0.000
return_21d                0.0017      0.000     11.902      0.000       0.001
0.002
return_42d               -0.0025      0.000    -13.475      0.000      -0.003
-0.002
return_63d               -0.0014      0.000    -10.322      0.000      -0.002
-0.001
return_1d_lag1            0.0005   8.98e-05      5.980      0.000       0.000
0.001
return_5d_lag1            0.0013      0.000      6.090      0.000       0.001
0.002
return_10d_lag1           0.0009      0.000      2.615      0.009       0.000
```

```
0.002
return_21d_lag1        0.0017      0.000     14.947      0.000       0.002
0.002
return_1d_lag2         0.0005   8.99e-05      5.956      0.000       0.000
0.001
return_5d_lag2      6.813e-05      0.000      0.294      0.769      -0.000
0.001
return_10d_lag2        0.0002      0.000      0.690      0.490      -0.000
0.001
return_21d_lag2        0.0002   9.01e-05      2.768      0.006    7.28e-05
0.000
return_1d_lag3         0.0005   9.03e-05      6.066      0.000       0.000
0.001
return_5d_lag3      9.299e-06      0.000      0.040      0.968      -0.000
0.000
return_10d_lag3        0.0005   4.44e-05     12.279      0.000       0.000
0.001
return_21d_lag3       -0.0001   1.69e-05     -6.699      0.000      -0.000
-8.02e-05
return_1d_lag4         0.0006   9.08e-05      6.278      0.000       0.000
0.001
return_5d_lag4         0.0002      0.000      1.250      0.211      -0.000
0.001
return_10d_lag4        0.0002   3.13e-05      7.472      0.000       0.000
0.000
return_21d_lag4     9.467e-05   1.67e-05      5.653      0.000    6.18e-05
0.000
return_1d_lag5     -1.792e-05   1.89e-05     -0.950      0.342   -5.49e-05
1.9e-05
return_5d_lag5         0.0002      0.000      1.064      0.287      -0.000
0.001
return_10d_lag5        0.0003   3.03e-05     10.693      0.000       0.000
0.000
return_21d_lag5        0.0001   1.67e-05      8.453      0.000       0.000
0.000
year_2014             -0.0004   2.55e-05    -13.817      0.000      -0.000
-0.000
year_2015             -0.0006   2.79e-05    -20.441      0.000      -0.001
-0.001
year_2016             -0.0002   2.73e-05     -9.022      0.000      -0.000
-0.000
year_2017             -0.0002   2.69e-05     -7.333      0.000      -0.000
-0.000
month_2                0.0006    2.2e-05     28.394      0.000       0.001
0.001
month_3             4.204e-05   2.27e-05      1.855      0.064   -2.37e-06
8.65e-05
month_4                0.0002   2.24e-05      8.025      0.000       0.000
```

```
0.000
month_5                   0.0003   2.21e-05     14.300      0.000       0.000
0.000
month_6                   0.0002   2.24e-05      7.894      0.000       0.000
0.000
month_7                   0.0002   2.32e-05      8.109      0.000       0.000
0.000
month_8                -6.35e-05   2.34e-05     -2.709      0.007      -0.000
-1.76e-05
month_9                4.795e-05   2.31e-05      2.075      0.038    2.66e-06
9.32e-05
month_10                  0.0003   2.37e-05     14.479      0.000       0.000
0.000
month_11                  0.0002   2.31e-05     10.264      0.000       0.000
0.000
month_12              -3.354e-05   2.26e-05     -1.485      0.138   -7.78e-05
1.07e-05
capital_goods             0.0010      0.000      8.686      0.000       0.001
0.001
consumer_non-durables     0.0007      0.000      6.399      0.000       0.001
0.001
consumer_services         0.0007      0.000      7.209      0.000       0.001
0.001
energy                    0.0003      0.000      2.736      0.006    8.26e-05
0.001
finance                   0.0009      0.000      8.318      0.000       0.001
0.001
health_care               0.0006      0.000      6.168      0.000       0.000
0.001
miscellaneous             0.0012      0.000      8.854      0.000       0.001
0.001
public_utilities          0.0002      0.000      1.618      0.106   -4.39e-05
0.000
technology                0.0010      0.000      9.984      0.000       0.001
0.001
transportation            0.0010      0.000      7.928      0.000       0.001
0.001
==============================================================================
Omnibus:                    38454.440   Durbin-Watson:                   0.233
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1111784.823
Skew:                          -1.087   Prob(JB):                         0.00
Kurtosis:                      18.446   Cond. No.                         80.7
==============================================================================

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

1.4.5 Monthly Returns

[19]:
```
target = 'target_21d'
model = OLS(endog=y[target], exog=add_constant(X))
trained_model = model.fit()
print(trained_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             target_21d   R-squared:                       0.059
Model:                            OLS   Adj. R-squared:                  0.058
Method:                 Least Squares   F-statistic:                     119.7
Date:                Thu, 15 Apr 2021   Prob (F-statistic):               0.00
Time:                        15:03:18   Log-Likelihood:             4.6155e+05
No. Observations:              109675   AIC:                        -9.230e+05
Df Residuals:                  109617   BIC:                        -9.224e+05
Df Model:                          57
Covariance Type:            nonrobust
================================================================================
=========
                   coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
---------
const           -0.0003   6.44e-05     -4.358      0.000      -0.000
-0.000
dollar_vol_1m -4.008e-05   1.42e-05     -2.820      0.005   -6.79e-05
-1.22e-05
rsi           2.026e-05   3.97e-05      0.511      0.609   -5.75e-05
9.8e-05
bb_high          0.0002   4.65e-05      3.684      0.000    8.01e-05
0.000
bb_low           0.0002   4.45e-05      4.367      0.000       0.000
0.000
atr             -0.0002   1.54e-05    -12.330      0.000      -0.000
-0.000
macd            -0.0003   4.89e-05     -5.137      0.000      -0.000
-0.000
return_1d        0.0003   6.11e-05      4.853      0.000       0.000
0.000
return_5d       -0.0005      0.000     -2.575      0.010      -0.001
-0.000
return_10d      -0.0003      0.000     -1.332      0.183      -0.001
0.000
return_21d       0.0018   9.41e-05     18.701      0.000       0.002
0.002
return_42d      -0.0018      0.000    -14.314      0.000      -0.002
-0.002
```

return_63d	-0.0012	9.31e-05	-12.676	0.000	-0.001	-0.001
return_1d_lag1	0.0003	6.09e-05	5.014	0.000	0.000	0.000
return_5d_lag1	0.0003	0.000	2.387	0.017	6.01e-05	0.001
return_10d_lag1	9.985e-05	0.000	0.445	0.656	-0.000	0.001
return_21d_lag1	0.0017	7.93e-05	21.339	0.000	0.002	0.002
return_1d_lag2	0.0003	6.09e-05	5.494	0.000	0.000	0.000
return_5d_lag2	7.005e-05	0.000	0.446	0.655	-0.000	0.000
return_10d_lag2	0.0001	0.000	0.716	0.474	-0.000	0.000
return_21d_lag2	0.0005	6.11e-05	7.894	0.000	0.000	0.001
return_1d_lag3	0.0004	6.12e-05	5.956	0.000	0.000	0.000
return_5d_lag3	0.0001	0.000	0.696	0.486	-0.000	0.000
return_10d_lag3	0.0001	3.01e-05	4.171	0.000	6.65e-05	0.000
return_21d_lag3	-8.503e-05	1.15e-05	-7.415	0.000	-0.000	-6.26e-05
return_1d_lag4	0.0004	6.16e-05	6.187	0.000	0.000	0.001
return_5d_lag4	5.046e-05	0.000	0.401	0.688	-0.000	0.000
return_10d_lag4	3.895e-05	2.12e-05	1.838	0.066	-2.59e-06	8.05e-05
return_21d_lag4	0.0001	1.14e-05	13.100	0.000	0.000	0.000
return_1d_lag5	3.351e-06	1.28e-05	0.262	0.793	-2.17e-05	2.84e-05
return_5d_lag5	-9.804e-06	0.000	-0.080	0.936	-0.000	0.000
return_10d_lag5	6.256e-06	2.05e-05	0.305	0.761	-3.4e-05	4.65e-05
return_21d_lag5	-3.545e-05	1.13e-05	-3.134	0.002	-5.76e-05	-1.33e-05
year_2014	-0.0003	1.73e-05	-17.088	0.000	-0.000	-0.000
year_2015	-0.0006	1.89e-05	-29.827	0.000	-0.001	-0.001
year_2016	-0.0002	1.85e-05	-9.707	0.000	-0.000	-0.000

```
year_2017              -0.0002   1.82e-05    -10.028      0.000      -0.000
-0.000
month_2              8.855e-05   1.49e-05      5.950      0.000    5.94e-05
0.000
month_3                -0.0001   1.54e-05     -9.594      0.000      -0.000
-0.000
month_4                -0.0001   1.52e-05     -7.960      0.000      -0.000
-9.11e-05
month_5              2.356e-05    1.5e-05      1.574      0.116   -5.78e-06
5.29e-05
month_6              -1.92e-05   1.52e-05     -1.266      0.206   -4.89e-05
1.05e-05
month_7                -0.0003   1.57e-05    -18.369      0.000      -0.000
-0.000
month_8                -0.0002   1.59e-05    -14.877      0.000      -0.000
-0.000
month_9                -0.0002   1.57e-05    -11.661      0.000      -0.000
-0.000
month_10             6.676e-05   1.61e-05      4.147      0.000    3.52e-05
9.83e-05
month_11               -0.0001   1.57e-05     -7.393      0.000      -0.000
-8.52e-05
month_12               -0.0004   1.53e-05    -25.897      0.000      -0.000
-0.000
capital_goods           0.0008   7.57e-05     11.198      0.000       0.001
0.001
consumer_non-durables   0.0007   7.84e-05      8.618      0.000       0.001
0.001
consumer_services       0.0006   7.01e-05      8.933      0.000       0.000
0.001
energy                  0.0002   7.22e-05      2.652      0.008    4.99e-05
0.000
finance                 0.0008   7.37e-05     10.794      0.000       0.001
0.001
health_care             0.0005   6.89e-05      7.493      0.000       0.000
0.001
miscellaneous           0.0012   9.02e-05     12.969      0.000       0.001
0.001
public_utilities        0.0001   8.71e-05      1.241      0.215   -6.26e-05
0.000
technology              0.0009   6.95e-05     13.417      0.000       0.001
0.001
transportation          0.0009   8.24e-05     11.165      0.000       0.001
0.001
==============================================================================
Omnibus:                    40182.050   Durbin-Watson:                   0.129
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           848232.085
Skew:                          -1.254   Prob(JB):                         0.00
```

```
Kurtosis:                      16.391   Cond. No.                         80.7
==============================================================================

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