

03_linear_regression

September 29, 2021

1 Stock Price Prediction using the Quantopian Trading Platform

The notebook linear_regression.ipynb contains examples for the prediction of stock prices using OLS with statsmodels and sklearn, as well as ridge and lasso models.

It is designed to run as a notebook on the Quantopian research platform and relies on the factor_library introduced in Chapter 4, Research and Evaluation of Alpha Factors.

1.1 How to run this notebook

This notebook is written for the Quantopian [research environment](#). You can upload it after signing up and execute it on the Quantopian platform to gain access to the datasets.

1.2 Imports

```
[2]: import pandas as pd
import numpy as np
from time import time
import talib
import re
from statsmodels.api import OLS
from sklearn.metrics import mean_squared_error
from scipy.stats import spearmanr
from sklearn.linear_model import LinearRegression, Ridge, RidgeCV, Lasso,
↳LassoCV, LogisticRegression
from sklearn.preprocessing import StandardScaler

from quantopian.research import run_pipeline
from quantopian.pipeline import Pipeline, factors, filters, classifiers
from quantopian.pipeline.data.builtin import USEquityPricing
from quantopian.pipeline.factors import (Latest,
                                          Returns,
                                          AverageDollarVolume,
                                          SimpleMovingAverage,
                                          EWMA,
                                          BollingerBands,
                                          CustomFactor,
                                          MarketCap,
                                          SimpleBeta)
```

```

from quantopian.pipeline.filters import QTradableStocksUS, StaticAssets
from quantopian.pipeline.data.quandl import fred_usdondtd156n as libor
from empyrical import max_drawdown, sortino_ratio

import seaborn as sns
import matplotlib.pyplot as plt

```

1.3 Data Sources

```

[3]: #####
# Fundamentals #
#####

# Morningstar fundamentals (2002 - Ongoing)
# https://www.quantopian.com/help/fundamentals
from quantopian.pipeline.data import Fundamentals

#####
# Analyst Estimates #
#####

# Earnings Surprises - Zacks (27 May 2006 - Ongoing)
# https://www.quantopian.com/data/zacks/earnings_surprises
from quantopian.pipeline.data.zacks import EarningsSurprises
from quantopian.pipeline.factors.zacks import ↵
    ↪BusinessDaysSinceEarningsSurprisesAnnouncement

#####
# Events #
#####

# Buyback Announcements - EventVestor (01 Jun 2007 - Ongoing)
# https://www.quantopian.com/data/eventvestor/buyback_auth
from quantopian.pipeline.data.eventvestor import BuybackAuthorizations
from quantopian.pipeline.factors.eventvestor import BusinessDaysSinceBuybackAuth

# CEO Changes - EventVestor (01 Jan 2007 - Ongoing)
# https://www.quantopian.com/data/eventvestor/ceo_change
from quantopian.pipeline.data.eventvestor import CEOChangeAnnouncements

# Dividends - EventVestor (01 Jan 2007 - Ongoing)
# https://www.quantopian.com/data/eventvestor/dividends
from quantopian.pipeline.data.eventvestor import (
    DividendsByExDate,
    DividendsByPayDate,
    DividendsByAnnouncementDate,
)

```

```

from quantopian.pipeline.factors.eventvestor import (
    BusinessDaysSincePreviousExDate,
    BusinessDaysUntilNextExDate,
    BusinessDaysSinceDividendAnnouncement,
)

# Earnings Calendar - EventVestor (01 Jan 2007 - Ongoing)
# https://www.quantopian.com/data/eventvestor/earnings_calendar
from quantopian.pipeline.data.eventvestor import EarningsCalendar
from quantopian.pipeline.factors.eventvestor import (
    BusinessDaysUntilNextEarnings,
    BusinessDaysSincePreviousEarnings
)

# 13D Filings - EventVestor (01 Jan 2007 - Ongoing)
# https://www.quantopian.com/data/eventvestor/_13d_filings
from quantopian.pipeline.data.eventvestor import _13DFilings
from quantopian.pipeline.factors.eventvestor import ↵
    ↵BusinessDaysSince13DFilingsDate

#####
# Sentiment #
#####

# News Sentiment - Sentdex Sentiment Analysis (15 Oct 2012 - Ongoing)
# https://www.quantopian.com/data/sentdex/sentiment
from quantopian.pipeline.data.sentdex import sentiment

```

1.4 Prepare the Data

We need to select a universe of equities and a time horizon, build and transform alpha factors that we will use as features, calculate forward returns that we aim to predict, and potentially clean our data.

1.4.1 Time horizon

```

[4]: # trading days per period
MONTH = 21
YEAR = 12 * MONTH

```

```

[5]: START = '2014-01-01'
END = '2015-12-31'

```

1.4.2 Universe

We will use equity data for the years 2014 and 2015 from a custom Q100US universe that uses built-in filters, factors, and classifiers to select the 100 stocks with the highest average dollar volume

of the last 200 trading days filtered by additional default criteria (see Quantopian docs linked on GitHub for detail). The universe dynamically updates based on the filter criteria so that, while there are 100 stocks at any given point, there may be more than 100 distinct equities in the sample:

```
[6]: def Q100US():
    return filters.make_us_equity_universe(
        target_size=100,
        rankby=factors.AverageDollarVolume(window_length=200),
        mask=filters.default_us_equity_universe_mask(),
        groupby=classifiers.fundamentals.Sector(),
        max_group_weight=0.3,
        smoothing_func=lambda f: f.downsample('month_start'),
    )
```

```
[7]: # UNIVERSE = StaticAssets(symbols(['MSFT', 'AAPL']))
UNIVERSE = Q100US()
```

1.4.3 Factor Transformations

```
[8]: class AnnualizedData(CustomFactor):
    # Get the sum of the last 4 reported values
    window_length = 260

    def compute(self, today, assets, out, asof_date, values):
        for asset in range(len(assets)):
            # unique asof dates indicate availability of new figures
            _, filing_dates = np.unique(asof_date[:, asset], return_index=True)
            quarterly_values = values[filing_dates[-4:], asset]
            # ignore annual windows with <4 quarterly data points
            if len(~np.isnan(quarterly_values)) != 4:
                out[asset] = np.nan
            else:
                out[asset] = np.sum(quarterly_values)
```

```
[9]: class AnnualAvg(CustomFactor):
    window_length = 252

    def compute(self, today, assets, out, values):
        out[:] = (values[0] + values[-1])/2
```

```
[10]: def factor_pipeline(factors):
    start = time()
    pipe = Pipeline({k: v(mask=UNIVERSE).rank() for k, v in factors.items()},
                    screen=UNIVERSE)
    result = run_pipeline(pipe, start_date=START, end_date=END)
    return result, time() - start
```

1.5 Factor Library

1.5.1 Value Factors

```
[11]: class ValueFactors:
        """Definitions of factors for cross-sectional trading algorithms"""

        @staticmethod
        def PriceToSalesTTM(**kwargs):
            """Last closing price divided by sales per share"""
            return Fundamentals.ps_ratio.latest

        @staticmethod
        def PriceToEarningsTTM(**kwargs):
            """Closing price divided by earnings per share (EPS)"""
            return Fundamentals.pe_ratio.latest

        @staticmethod
        def PriceToDilutedEarningsTTM(mask):
            """Closing price divided by diluted EPS"""
            last_close = USEquityPricing.close.latest
            diluted_eps = AnnualizedData(inputs = [Fundamentals.
→diluted_eps_earnings_reports_asof_date,
                                                    Fundamentals.
→diluted_eps_earnings_reports],
                                         mask=mask)
            return last_close / diluted_eps

        @staticmethod
        def PriceToForwardEarnings(**kwargs):
            """Price to Forward Earnings"""
            return Fundamentals.forward_pe_ratio.latest

        @staticmethod
        def DividendYield(**kwargs):
            """Dividends per share divided by closing price"""
            return Fundamentals.trailing_dividend_yield.latest

        @staticmethod
        def PriceToFCF(mask):
            """Price to Free Cash Flow"""
            last_close = USEquityPricing.close.latest
            fcf_share = AnnualizedData(inputs = [Fundamentals.
→fcf_per_share_asof_date,
                                                    Fundamentals.fcf_per_share],
                                         mask=mask)
            return last_close / fcf_share
```

```

@staticmethod
def PriceToOperatingCashflow(mask):
    """Last Close divided by Operating Cash Flows"""
    last_close = USEquityPricing.close.latest
    cfo_per_share = AnnualizedData(inputs = [Fundamentals.
↪cfo_per_share_asof_date,
                                                Fundamentals.cfo_per_share],
                                    mask=mask)
    return last_close / cfo_per_share

@staticmethod
def PriceToBook(mask):
    """Closing price divided by book value"""
    last_close = USEquityPricing.close.latest
    book_value_per_share = AnnualizedData(inputs = [Fundamentals.
↪book_value_per_share_asof_date,
                                                Fundamentals.
↪book_value_per_share],
                                    mask=mask)
    return last_close / book_value_per_share

@staticmethod
def EVToFCF(mask):
    """Enterprise Value divided by Free Cash Flows"""
    fcf = AnnualizedData(inputs = [Fundamentals.free_cash_flow_asof_date,
                                    Fundamentals.free_cash_flow],
                        mask=mask)
    return Fundamentals.enterprise_value.latest / fcf

@staticmethod
def EVToEBITDA(mask):
    """Enterprise Value to Earnings Before Interest, Taxes, Depreciation and
↪Amortization (EBITDA)"""
    ebitda = AnnualizedData(inputs = [Fundamentals.ebitda_asof_date,
                                    Fundamentals.ebitda],
                        mask=mask)
    return Fundamentals.enterprise_value.latest / ebitda

@staticmethod
def EBITDAYield(mask):
    """EBITDA divided by latest close"""
    ebitda = AnnualizedData(inputs = [Fundamentals.ebitda_asof_date,
                                    Fundamentals.ebitda],
                        mask=mask)
    return USEquityPricing.close.latest / ebitda

```

```
[12]: VALUE_FACTORS = {
    'DividendYield'           : ValueFactors.DividendYield,
    'EBITDAYield'            : ValueFactors.EBITDAYield,
    'EVToEBITDA'             : ValueFactors.EVToEBITDA,
    'EVToFCF'                : ValueFactors.EVToFCF,
    'PriceToBook'            : ValueFactors.PriceToBook,
    'PriceToDilutedEarningsTTM': ValueFactors.PriceToDilutedEarningsTTM,
    'PriceToEarningsTTM'     : ValueFactors.PriceToEarningsTTM,
    'PriceToFCF'             : ValueFactors.PriceToFCF,
    'PriceToForwardEarnings' : ValueFactors.PriceToForwardEarnings,
    'PriceToOperatingCashflow': ValueFactors.PriceToOperatingCashflow,
    'PriceToSalesTTM'        : ValueFactors.PriceToSalesTTM,
}
```

```
[13]: value_factors, t = factor_pipeline(VALUE_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
value_factors.info()
```

/usr/local/lib/python2.7/dist-packages/numpy/lib/arraysetops.py:200:

FutureWarning: In the future, NAT != NAT will be True rather than False.

```
flag = np.concatenate(([True], aux[1:] != aux[:-1]))
```

Pipeline run time 91.43 secs

<class 'pandas.core.frame.DataFrame'>

MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))

Data columns (total 11 columns):

DividendYield	40772 non-null float64
EBITDAYield	49823 non-null float64
EVToEBITDA	49823 non-null float64
EVToFCF	46400 non-null float64
PriceToBook	50343 non-null float64
PriceToDilutedEarningsTTM	50215 non-null float64
PriceToEarningsTTM	48956 non-null float64
PriceToFCF	49133 non-null float64
PriceToForwardEarnings	39607 non-null float64
PriceToOperatingCashflow	50343 non-null float64
PriceToSalesTTM	50362 non-null float64

dtypes: float64(11)

memory usage: 4.6+ MB

1.5.2 Momentum

```
[14]: class MomentumFactors:
    """Custom Momentum Factors"""
    class PercentAboveLow(CustomFactor):
        """Percentage of current close above low
        in lookback window of window_length days
```

```

        """
        inputs = [USEquityPricing.close]
        window_length = 252

        def compute(self, today, assets, out, close):
            out[:] = close[-1] / np.min(close, axis=0) - 1

class PercentBelowHigh(CustomFactor):
    """Percentage of current close below high
    in lookback window of window_length days
    """

    inputs = [USEquityPricing.close]
    window_length = 252

    def compute(self, today, assets, out, close):
        out[:] = close[-1] / np.max(close, axis=0) - 1

    @staticmethod
    def make_dx(timeperiod=14):
        class DX(CustomFactor):
            """Directional Movement Index"""
            inputs = [USEquityPricing.high,
                      USEquityPricing.low,
                      USEquityPricing.close]
            window_length = timeperiod + 1

            def compute(self, today, assets, out, high, low, close):
                out[:] = [talib.DX(high[:, i],
                                   low[:, i],
                                   close[:, i],
                                   timeperiod=timeperiod)[-1]
                           for i in range(len(assets))]

        return DX

    @staticmethod
    def make_mfi(timeperiod=14):
        class MFI(CustomFactor):
            """Money Flow Index"""
            inputs = [USEquityPricing.high,
                      USEquityPricing.low,
                      USEquityPricing.close,
                      USEquityPricing.volume]
            window_length = timeperiod + 1

            def compute(self, today, assets, out, high, low, close, vol):
                out[:] = [talib.MFI(high[:, i],

```



```

        low[:, i],
        close[:, i],
        vol[:, i],
        timeperiod=timeperiod)[-1]
    for i in range(len(assets))]

    return MFI

@staticmethod
def make_oscillator(fastperiod=12, slowperiod=26, matype=0):
    class PPO(CustomFactor):
        """12/26-Day Percent Price Oscillator"""
        inputs = [USEquityPricing.close]
        window_length = slowperiod

        def compute(self, today, assets, out, close_prices):
            out[:] = [talib.PPO(close,
                                fastperiod=fastperiod,
                                slowperiod=slowperiod,
                                matype=matype)[-1]
                       for close in close_prices.T]

    return PPO

@staticmethod
def make_stochastic_oscillator(fastk_period=5, slowk_period=3,
↪slowd_period=3,
                                slowk_matype=0, slowd_matype=0):
    class StochasticOscillator(CustomFactor):
        """20-day Stochastic Oscillator """
        inputs = [USEquityPricing.high,
                  USEquityPricing.low,
                  USEquityPricing.close]
        outputs = ['slowk', 'slowd']
        window_length = fastk_period * 2

        def compute(self, today, assets, out, high, low, close):
            slowk, slowd = [talib.STOCH(high[:, i],
                                         low[:, i],
                                         close[:, i],
                                         fastk_period=fastk_period,
                                         slowk_period=slowk_period,
                                         slowk_matype=slowk_matype,
                                         slowd_period=slowd_period,
                                         slowd_matype=slowd_matype)[-1]
                           for i in range(len(assets))]

            out.slowk[:,], out.slowd[:,] = slowk[-1], slowd[-1]

    return StochasticOscillator

```

```

    @staticmethod
    def make_trendline(timeperiod=252):
        class Trendline(CustomFactor):
            inputs = [USEquityPricing.close]
            """52-Week Trendline"""
            window_length = timeperiod

            def compute(self, today, assets, out, close_prices):
                out[:] = [talib.LINEARREG_SLOPE(close,
                                                timeperiod=timeperiod)[-1]
                          for close in close_prices.T]

        return Trendline

```

```

[15]: MOMENTUM_FACTORS = {
    'Percent Above Low'           : MomentumFactors.PercentAboveLow,
    'Percent Below High'          : MomentumFactors.PercentBelowHigh,
    'Price Oscillator'            : MomentumFactors.make_oscillator(),
    'Money Flow Index'            : MomentumFactors.make_mfi(),
    'Directional Movement Index' : MomentumFactors.make_dx(),
    'Trendline'                   : MomentumFactors.make_trendline()
}

```

```

[16]: momentum_factors, t = factor_pipeline(MOMENTUM_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
momentum_factors.info()

```

```

Pipeline run time 20.68 secs
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 6 columns):
Directional Movement Index    50362 non-null float64
Money Flow Index               50362 non-null float64
Percent Above Low              49536 non-null float64
Percent Below High             49536 non-null float64
Price Oscillator               50355 non-null float64
Trendline                     49536 non-null float64
dtypes: float64(6)
memory usage: 2.7+ MB

```

1.5.3 Efficiency Factors

```

[17]: class EfficiencyFactors:

    @staticmethod
    def CapexToAssets(mask):

```

```

        """Capital Expenditure divided by Total Assets"""
        capex = AnnualizedData(inputs = [Fundamentals.
↪capital_expenditure_asof_date,
                                Fundamentals.capital_expenditure],
                                mask=mask)
        assets = Fundamentals.total_assets.latest
        return - capex / assets

    @staticmethod
    def CapexToSales(mask):
        """Capital Expenditure divided by Total Revenue"""
        capex = AnnualizedData(inputs = [Fundamentals.
↪capital_expenditure_asof_date,
                                Fundamentals.capital_expenditure],
                                mask=mask)
        revenue = AnnualizedData(inputs = [Fundamentals.total_revenue_asof_date,
                                Fundamentals.total_revenue],
                                mask=mask)
        return - capex / revenue

    @staticmethod
    def CapexToFCF(mask):
        """Capital Expenditure divided by Free Cash Flows"""
        capex = AnnualizedData(inputs = [Fundamentals.
↪capital_expenditure_asof_date,
                                Fundamentals.capital_expenditure],
                                mask=mask)
        free_cash_flow = AnnualizedData(inputs = [Fundamentals.
↪free_cash_flow_asof_date,
                                Fundamentals.free_cash_flow],
                                mask=mask)
        return - capex / free_cash_flow

    @staticmethod
    def EBITToAssets(mask):
        """Earnings Before Interest and Taxes (EBIT) divided by Total Assets"""
        ebit = AnnualizedData(inputs = [Fundamentals.ebit_asof_date,
                                Fundamentals.ebit],
                                mask=mask)
        assets = Fundamentals.total_assets.latest
        return ebit / assets

    @staticmethod
    def CFToAssets(mask):
        """Operating Cash Flows divided by Total Assets"""
        cfo = AnnualizedData(inputs = [Fundamentals.
↪operating_cash_flow_asof_date,

```

```

                                Fundamentals.operating_cash_flow],
                                mask=mask)
    assets = Fundamentals.total_assets.latest
    return cfo / assets

    @staticmethod
    def RetainedEarningsToAssets(mask):
        """Retained Earnings divided by Total Assets"""
        retained_earnings = AnnualizedData(inputs = [Fundamentals.
↪retained_earnings_asof_date,
                                Fundamentals.retained_earnings],
                                mask=mask)
        assets = Fundamentals.total_assets.latest
        return retained_earnings / assets

```

```

[18]: EFFICIENCY_FACTORS = {
    'CFO To Assets' :EfficiencyFactors.CFOToAssets,
    'Capex To Assets' :EfficiencyFactors.CapexToAssets,
    'Capex To FCF' :EfficiencyFactors.CapexToFCF,
    'Capex To Sales' :EfficiencyFactors.CapexToSales,
    'EBIT To Assets' :EfficiencyFactors.EBITToAssets,
    'Retained Earnings To Assets' :EfficiencyFactors.RetainedEarningsToAssets
}

```

```

[19]: efficiency_factors, t = factor_pipeline(EFFICIENCY_FACTORS)
    print('Pipeline run time {:.2f} secs'.format(t))
    efficiency_factors.info()

```

```

Pipeline run time 38.54 secs
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 6 columns):
CFO To Assets          50351 non-null float64
Capex To Assets        46997 non-null float64
Capex To FCF           45799 non-null float64
Capex To Sales         46997 non-null float64
EBIT To Assets         46635 non-null float64
Retained Earnings To Assets  50349 non-null float64
dtypes: float64(6)
memory usage: 2.7+ MB

```

1.5.4 Risk Factors

```
[20]: class RiskFactors:

    @staticmethod
    def LogMarketCap(mask):
        """Log of Market Capitalization log(Close Price * Shares Outstanding)"""
        return np.log(MarketCap(mask=mask))

    class DownsideRisk(CustomFactor):
        """Mean returns divided by std of 1yr daily losses (Sortino Ratio)"""
        inputs = [USEquityPricing.close]
        window_length = 252

        def compute(self, today, assets, out, close):
            ret = pd.DataFrame(close).pct_change()
            out[:] = ret.mean().div(ret.where(ret<0).std())

    @staticmethod
    def MarketBeta(**kwargs):
        """Slope of 1-yr regression of price returns against index returns"""
        return SimpleBeta(target=symbols('SPY'), regression_length=252)

    class DownsideBeta(CustomFactor):
        """Slope of 1yr regression of returns on negative index returns"""
        inputs = [USEquityPricing.close]
        window_length = 252

        def compute(self, today, assets, out, close):
            t = len(close)
            assets = pd.DataFrame(close).pct_change()

            start_date = (today - pd.DateOffset(years=1)).strftime('%Y-%m-%d')
            spy = get_pricing('SPY',
                             start_date=start_date,
                             end_date=today.strftime('%Y-%m-%d')).
→reset_index(drop=True)
            spy_neg_ret = (spy
                           .close_price
                           .iloc[-t:]
                           .pct_change()
                           .pipe(lambda x: x.where(x<0)))

            out[:] = assets.apply(lambda x: x.cov(spy_neg_ret)).div(spy_neg_ret.
→var())

    class Vol3M(CustomFactor):
```

```
"""3-month Volatility: Standard deviation of returns over 3 months"""
```

```
inputs = [USEquityPricing.close]
window_length = 63
```

```
def compute(self, today, assets, out, close):
    out[:] = np.log1p(pd.DataFrame(close).pct_change()).std()
```

```
[21]: RISK_FACTORS = {
    'Log Market Cap' : RiskFactors.LogMarketCap,
    'Downside Risk' : RiskFactors.DownsideRisk,
    'Index Beta' : RiskFactors.MarketBeta,
    # 'Downside Beta' : RiskFactors.DownsideBeta,
    'Volatility 3M' : RiskFactors.Vol3M,
}
```

```
[22]: risk_factors, t = factor_pipeline(RISK_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
risk_factors.info()
```

Pipeline run time 46.76 secs

<class 'pandas.core.frame.DataFrame'>

MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to (2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))

Data columns (total 4 columns):

Downside Risk 50362 non-null float64

Index Beta 50079 non-null float64

Log Market Cap 50362 non-null float64

Volatility 3M 50362 non-null float64

dtypes: float64(4)

memory usage: 1.9+ MB

1.5.5 Growth Factors

```
[23]: def growth_pipeline():
    revenue = AnnualizedData(inputs = [Fundamentals.total_revenue_asof_date,
                                       Fundamentals.total_revenue],
                             mask=UNIVERSE)
    eps = AnnualizedData(inputs = [Fundamentals.
    ↪ diluted_eps_earnings_reports_asof_date,
                                       Fundamentals.
    ↪ diluted_eps_earnings_reports],
                          mask=UNIVERSE)

    return Pipeline({'Sales': revenue,
                    'EPS': eps,
                    'Total Assets': Fundamentals.total_assets.latest,
```

```
'Net Debt': Fundamentals.net_debt.latest},
screen=UNIVERSE)
```

```
[24]: start_timer = time()
growth_factors = run_pipeline(growth_pipeline(), start_date=START, end_date=END)

for col in growth_result.columns:
    for month in [3, 12]:
        new_col = col + ' Growth {}'.format(month)
        kwargs = {new_col: growth_factors[col].pct_change(month*MONTH).
↳groupby(level=1).rank()}
        growth_factors = growth_factors.assign(**kwargs)
print('Pipeline run time {:.2f} secs'.format(time() - start_timer))
growth_factors.info()
```

Pipeline run time 23.05 secs

<class 'pandas.core.frame.DataFrame'>

MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))

Data columns (total 12 columns):

EPS	50215 non-null float64
Net Debt	47413 non-null float64
Sales	50351 non-null float64
Total Assets	50362 non-null float64
EPS Growth 3M	50152 non-null float64
EPS Growth 12M	49963 non-null float64
Net Debt Growth 3M	47350 non-null float64
Net Debt Growth 12M	47171 non-null float64
Sales Growth 3M	50288 non-null float64
Sales Growth 12M	50099 non-null float64
Total Assets Growth 3M	50299 non-null float64
Total Assets Growth 12M	50110 non-null float64

dtypes: float64(12)

memory usage: 5.0+ MB

1.5.6 Quality Factors

```
[25]: class QualityFactors:

    @staticmethod
    def AssetTurnover(mask):
        """Sales divided by average of year beginning and year end assets"""

        assets = AnnualAvg(inputs=[Fundamentals.total_assets],
                             mask=mask)
        sales = AnnualizedData([Fundamentals.total_revenue_asof_date,
                                Fundamentals.total_revenue], mask=mask)
```

```

        return sales / assets

    @staticmethod
    def CurrentRatio(mask):
        """Total current assets divided by total current liabilities"""

        assets = Fundamentals.current_assets.latest
        liabilities = Fundamentals.current_liabilities.latest
        return assets / liabilities

    @staticmethod
    def AssetToEquityRatio(mask):
        """Total current assets divided by common equity"""

        assets = Fundamentals.current_assets.latest
        equity = Fundamentals.common_stock.latest
        return assets / equity

    @staticmethod
    def InterestCoverage(mask):
        """EBIT divided by interest expense"""

        ebit = AnnualizedData(inputs = [Fundamentals.ebit_asof_date,
                                         Fundamentals.ebit], mask=mask)

        interest_expense = AnnualizedData(inputs = [Fundamentals.
→interest_expense_asof_date,
                                                    Fundamentals.interest_expense],
→mask=mask)
        return ebit / interest_expense

    @staticmethod
    def DebtToAssetRatio(mask):
        """Total Debts divided by Total Assets"""

        debt = Fundamentals.total_debt.latest
        assets = Fundamentals.total_assets.latest
        return debt / assets

    @staticmethod
    def DebtToEquityRatio(mask):
        """Total Debts divided by Common Stock Equity"""

        debt = Fundamentals.total_debt.latest
        equity = Fundamentals.common_stock.latest
        return debt / equity

```



```

    @staticmethod
    def WorkingCapitalToAssets(mask):
        """Current Assets less Current liabilities (Working Capital) divided by
        ↪Assets"""

        working_capital = Fundamentals.working_capital.latest
        assets = Fundamentals.total_assets.latest
        return working_capital / assets

    @staticmethod
    def WorkingCapitalToSales(mask):
        """Current Assets less Current liabilities (Working Capital), divided
        ↪by Sales"""

        working_capital = Fundamentals.working_capital.latest
        sales = AnnualizedData([Fundamentals.total_revenue_asof_date,
                                Fundamentals.total_revenue], mask=mask)
        return working_capital / sales

class MertonsDD(CustomFactor):
    """Merton's Distance to Default """

    inputs = [Fundamentals.total_assets,
               Fundamentals.total_liabilities,
               libor.value,
               USEquityPricing.close]
    window_length = 252

    def compute(self, today, assets, out, tot_assets, tot_liabilities, r,
    ↪close):
        mertons = []

        for col_assets, col_liabilities, col_r, col_close in zip(tot_assets.
    ↪T, tot_liabilities.T,
                                                                    r.T, close.
    ↪T):
            vol_1y = np.nanstd(col_close)
            numerator = np.log(
                col_assets[-1] / col_liabilities[-1]) + ((252 *
    ↪col_r[-1]) - ((vol_1y ** 2) / 2))
            mertons.append(numerator / vol_1y)

        out[:] = mertons

```

```
[26]: QUALITY_FACTORS = {
    'AssetToEquityRatio' : QualityFactors.AssetToEquityRatio,
    'AssetTurnover' : QualityFactors.AssetTurnover,
    'CurrentRatio' : QualityFactors.CurrentRatio,
    'DebtToAssetRatio' : QualityFactors.DebtToAssetRatio,
    'DebtToEquityRatio' : QualityFactors.DebtToEquityRatio,
    'InterestCoverage' : QualityFactors.InterestCoverage,
    'MertonsDD' : QualityFactors.MertonsDD,
    'WorkingCapitalToAssets' : QualityFactors.WorkingCapitalToAssets,
    'WorkingCapitalToSales' : QualityFactors.WorkingCapitalToSales,
}
```

```
[27]: quality_factors, t = factor_pipeline(QUALITY_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
quality_factors.info()
```

```
Pipeline run time 37.24 secs
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 9 columns):
AssetToEquityRatio      45176 non-null float64
AssetTurnover           50314 non-null float64
CurrentRatio            45680 non-null float64
DebtToAssetRatio        50080 non-null float64
DebtToEquityRatio       48492 non-null float64
InterestCoverage        35250 non-null float64
MertonsDD               50362 non-null float64
WorkingCapitalToAssets  45680 non-null float64
WorkingCapitalToSales   45669 non-null float64
dtypes: float64(9)
memory usage: 3.8+ MB
```

1.5.7 Payout Factors

```
[28]: class PayoutFactors:

    @staticmethod
    def DividendPayoutRatio(mask):
        """Dividends Per Share divided by Earnings Per Share"""

        dps = AnnualizedData(inputs = [Fundamentals.
↪dividend_per_share_earnings_reports_asof_date,
                                   Fundamentals.
↪dividend_per_share_earnings_reports], mask=mask)
```

```

        eps = AnnualizedData(inputs = [Fundamentals.
↪basic_eps_earnings_reports_asof_date,
                                Fundamentals.
↪basic_eps_earnings_reports], mask=mask)
        return dps / eps

    @staticmethod
    def DividendGrowth(**kwargs):
        """Annualized percentage DPS change"""
        return Fundamentals.dps_growth.latest

```

```

[29]: PAYOUT_FACTORS = {
        'Dividend Payout Ratio': PayoutFactors.DividendPayoutRatio,
        'Dividend Growth': PayoutFactors.DividendGrowth
    }

```

```

[30]: payout_factors, t = factor_pipeline(PAYOUT_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
payout_factors.info()

```

```

Pipeline run time 22.46 secs
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 2 columns):
Dividend Growth      40517 non-null float64
Dividend Payout Ratio  39947 non-null float64
dtypes: float64(2)
memory usage: 1.2+ MB

```

1.5.8 Profitability Factors

```

[31]: class ProfitabilityFactors:

        @staticmethod
        def GrossProfitMargin(mask):
            """Gross Profit divided by Net Sales"""

            gross_profit = AnnualizedData([Fundamentals.gross_profit_asof_date,
                                Fundamentals.gross_profit], mask=mask)
            sales = AnnualizedData([Fundamentals.total_revenue_asof_date,
                                Fundamentals.total_revenue], mask=mask)
            return gross_profit / sales

        @staticmethod
        def NetIncomeMargin(mask):
            """Net income divided by Net Sales"""

```

```

        net_income = AnnualizedData([Fundamentals.
↪net_income_income_statement_asof_date,
                                   Fundamentals.net_income_income_statement],
↪mask=mask)
        sales = AnnualizedData([Fundamentals.total_revenue_asof_date,
                                Fundamentals.total_revenue], mask=mask)
        return net_income / sales

```

```

[32]: PROFITABIILTY_FACTORS = {
        'Gross Profit Margin': ProfitabilityFactors.GrossProfitMargin,
        'Net Income Margin': ProfitabilityFactors.NetIncomeMargin,
        'Return on Equity': Fundamentals.roe.latest,
        'Return on Assets': Fundamentals.roa.latest,
        'Return on Invested Capital': Fundamentals.roic.latest
    }

```

```

[33]: profitability_factors, t = factor_pipeline(PAYOUT_FACTORS)
print('Pipeline run time {:.2f} secs'.format(t))
payout_factors.info()

```

```

Pipeline run time 22.56 secs
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 2 columns):
Dividend Growth          40517 non-null float64
Dividend Payout Ratio    39947 non-null float64
dtypes: float64(2)
memory usage: 1.2+ MB

```

```

[34]: # profitability_pipeline().show_graph(format='png')

```

1.6 Build Dataset

1.6.1 Get Returns

We will test predictions for various lookahead periods to identify the best holding periods that generate the best predictability, measured by the information coefficient.

More specifically, we compute returns for 1, 5, 10, and 20 days using the built-in Returns function, resulting in over 50,000 observations for the universe of 100 stocks over two years (that include approximately 252 trading days each)

```

[35]: lookahead = [1, 5, 10, 20]
returns = run_pipeline(Pipeline({'Returns{ }D'.format(i):
↪Returns(inputs=[USEquityPricing.close],

```

```

                                window_length=i+1, mask=UNIVERSE) for i
↪ i in lookahead},
                                screen=UNIVERSE),
                                start_date=START,
                                end_date=END)
return_cols = ['Returns{0}D'.format(i) for i in lookahead]
returns.info()

```

```

<class 'pandas.core.frame.DataFrame'>
MultiIndex: 50362 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 4 columns):
Returns10D    50362 non-null float64
Returns1D     50362 non-null float64
Returns20D    50360 non-null float64
Returns5D     50362 non-null float64
dtypes: float64(4)
memory usage: 1.9+ MB

```

We will use over 50 features that cover a broad range of factors based on market, fundamental, and alternative data. The notebook also includes custom transformations to convert fundamental data that is typically available in quarterly reporting frequency to rolling annual totals or averages to avoid excessive season fluctuations.

Once the factors have been computed through the various pipelines outlined in Chapter 4, Alpha Factors – Research and Evaluation, we combine them using `pd.concat()`, assign index names, and create a categorical variable that identifies the asset for each data point:

```

[36]: data = pd.concat([returns,
                        value_factors,
                        momentum_factors,
                        quality_factors,
                        payout_factors,
                        growth_factors,
                        efficiency_factors,
                        risk_factors], axis=1).sortlevel()
data.index.names = ['date', 'asset']

```

```

[37]: data['stock'] = data.index.get_level_values('asset').map(lambda x: x.asset_name)

```

1.7 Remove columns and rows with less than 80% of data availability

In a next step, we remove rows and columns that lack more than 20 percent of the observations, resulting in a loss of six percent of the observations and three columns:

```

[38]: rows_before, cols_before = data.shape
data = (data
        .dropna(axis=1, thresh=int(len(data)*.8))

```

```

        .dropna(thresh=int(len(data.columns) * .8)))
data = data.fillna(data.median())
rows_after, cols_after = data.shape
print('{:,d} rows and {:,d} columns dropped'.format(rows_before-rows_after,
↪cols_before-cols_after))

```

2,985 rows and 3 columns dropped

At this point, we have 51 features and the categorical identifier of the stock:

```

[39]: data.sort_index(1).info()

<class 'pandas.core.frame.DataFrame'>
MultiIndex: 47377 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 52 columns):
AssetToEquityRatio      47377 non-null float64
AssetTurnover           47377 non-null float64
CF0 To Assets           47377 non-null float64
Capex To Assets         47377 non-null float64
Capex To FCF            47377 non-null float64
Capex To Sales          47377 non-null float64
CurrentRatio            47377 non-null float64
DebtToAssetRatio        47377 non-null float64
DebtToEquityRatio       47377 non-null float64
Directional Movement Index 47377 non-null float64
Dividend Growth         47377 non-null float64
DividendYield           47377 non-null float64
Downside Risk           47377 non-null float64
EBIT To Assets          47377 non-null float64
EBITDAYield             47377 non-null float64
EPS                     47377 non-null float64
EPS Growth 12M          47377 non-null float64
EPS Growth 3M           47377 non-null float64
EVToEBITDA             47377 non-null float64
EVToFCF                47377 non-null float64
Index Beta              47377 non-null float64
Log Market Cap          47377 non-null float64
MertonsDD               47377 non-null float64
Money Flow Index        47377 non-null float64
Net Debt                47377 non-null float64
Net Debt Growth 12M     47377 non-null float64
Net Debt Growth 3M     47377 non-null float64
Percent Above Low       47377 non-null float64
Percent Below High      47377 non-null float64
Price Oscillator        47377 non-null float64
PriceToBook             47377 non-null float64
PriceToDilutedEarningsTTM 47377 non-null float64

```

```

PriceToEarningsTTM      47377 non-null float64
PriceToFCF              47377 non-null float64
PriceToOperatingCashflow 47377 non-null float64
PriceToSalesTTM         47377 non-null float64
Retained Earnings To Assets 47377 non-null float64
Returns10D              47377 non-null float64
Returns1D               47377 non-null float64
Returns20D              47377 non-null float64
Returns5D               47377 non-null float64
Sales                   47377 non-null float64
Sales Growth 12M        47377 non-null float64
Sales Growth 3M         47377 non-null float64
Total Assets            47377 non-null float64
Total Assets Growth 12M 47377 non-null float64
Total Assets Growth 3M  47377 non-null float64
Trendline               47377 non-null float64
Volatility 3M           47377 non-null float64
WorkingCapitalToAssets  47377 non-null float64
WorkingCapitalToSales   47377 non-null float64
stock                   47377 non-null object
dtypes: float64(51), object(1)
memory usage: 19.2+ MB

```

1.8 Data Exploration

For linear regression models, it is important to explore the correlation among the features to identify multicollinearity issues, and to check the correlation between the features and the target. The notebook contains a seaborn clustermap that shows the hierarchical structure of the feature correlation matrix. It identifies a small number of highly correlated clusters.

```
[ ]: g = sns.clustermap(data.drop(['stock'] + return_cols, axis=1).corr())
plt.gcf().set_size_inches((14,14));
```

1.9 Dummy encoding of categorical variables

We need to convert the categorical stock variable into a numeric format so that the linear regression can process it. For this purpose, we use dummy encoding that creates individual columns for each category level and flags the presence of this level in the original categorical column with an entry of 1, and 0 otherwise. The pandas function `get_dummies()` automates dummy encoding. It detects and properly converts columns of type objects as illustrated next. If you need dummy variables for columns containing integers, for instance, you can identify them using the keyword `columns`:

```
[41]: X = pd.get_dummies(data.drop(return_cols, axis=1))
X.info()
```

```

<class 'pandas.core.frame.DataFrame'>
MultiIndex: 47377 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))

```

```
Columns: 182 entries, DividendYield to stock_YELP INC
dtypes: float64(182)
memory usage: 66.1+ MB
```

1.10 Creating forward returns

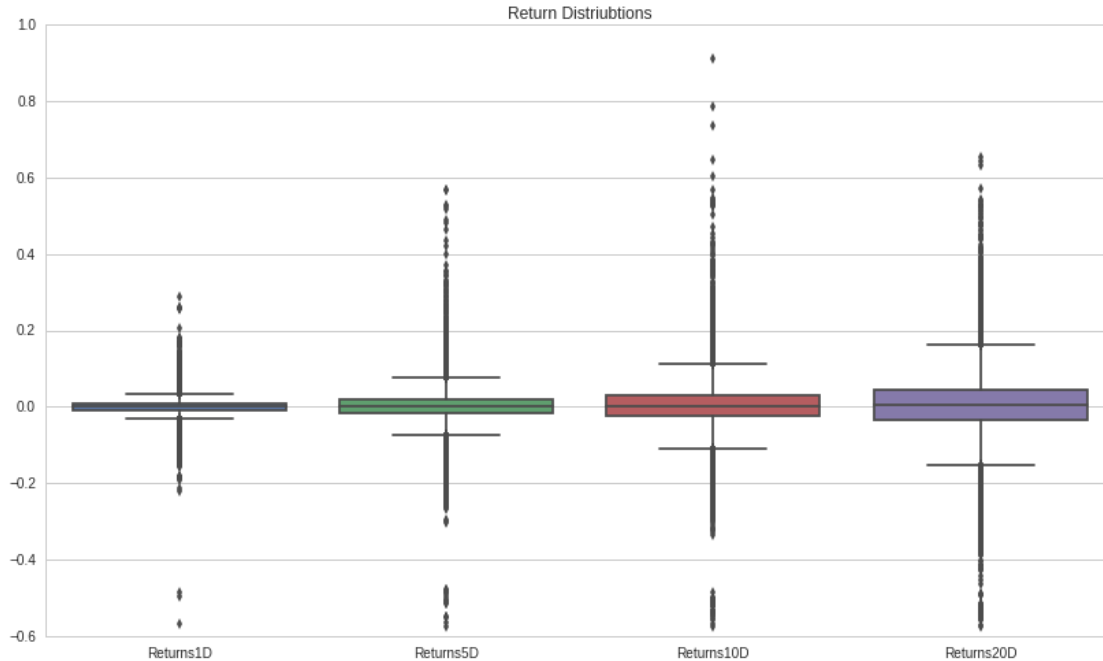
The goal is to predict returns over a given holding period. Hence, we need to align the features with return values with the corresponding return data point 1, 5, 10, or 20 days into the future for each equity. We achieve this by combining the pandas `.groupby()` method with the `.shift()` method as follows:

```
[42]: y = data.loc[:, return_cols]
      shifted_y = []
      for col in y.columns:
          t = int(re.search(r'\d+', col).group(0))
          shifted_y.append(y.groupby(level='asset')['Returns{}'.format(t)].shift(-t).
→to_frame(col))
      y = pd.concat(shifted_y, axis=1)
      y.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 47377 entries, (2014-01-02 00:00:00+00:00, Equity(24 [AAPL])) to
(2015-12-31 00:00:00+00:00, Equity(47208 [GPRO]))
Data columns (total 4 columns):
Returns1D      47242 non-null float64
Returns5D      46706 non-null float64
Returns10D     46036 non-null float64
Returns20D     44696 non-null float64
dtypes: float64(4)
memory usage: 1.8+ MB
```

```
[43]: ax = sns.boxplot(y[return_cols])
      ax.set_title('Return Distriubtions');
```

```
/usr/local/lib/python2.7/dist-packages/seaborn/categorical.py:2171: UserWarning:
The boxplot API has been changed. Attempting to adjust your arguments for the
new API (which might not work). Please update your code. See the version 0.6
release notes for more info.
  warnings.warn(msg, UserWarning)
```

1.11 Linear Regression

1.11.1 Statsmodels

We can estimate a linear regression model using OLS with statsmodels as demonstrated previously. We select a forward return, for example for a 10-day holding period, remove outliers below the 2.5% and above the 97.5% percentiles, and fit the model accordingly:

```
[44]: target = 'Returns1D'
model_data = pd.concat([y[[target]], X], axis=1).dropna()
model_data = model_data[model_data[target].between(model_data[target].quantile(
    ↪0.025),
                                                    model_data[target].quantile(
    ↪0.975))]

model = OLS(endog=model_data[target], exog=model_data.drop(target, axis=1))
trained_model = model.fit()
trained_model.summary()
```

```
[44]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

```

                                OLS Regression Results
=====
Dep. Variable:                Returns1D    R-squared:                0.004
Model:                        OLS         Adj. R-squared:           0.000
Method:                       Least Squares    F-statistic:             1.084
```

Date:	Sun, 09 Sep 2018	Prob (F-statistic):	0.214
Time:	21:17:58	Log-Likelihood:	1.3306e+05
No. Observations:	44878	AIC:	-2.658e+05
Df Residuals:	44703	BIC:	-2.642e+05
Df Model:	174		
Covariance Type:	nonrobust		

			coef	std err	t
P> t	[95.0% Conf. Int.]				

DividendYield			1.249e-06	4.7e-07	2.659
0.008	3.28e-07	2.17e-06			
EBITDAYield			-5.537e-06	9.48e-06	-0.584
0.559	-2.41e-05	1.3e-05			
EVToEBITDA			4.87e-06	8.7e-06	0.560
0.575	-1.22e-05	2.19e-05			
EVToFCF			3.621e-06	1.08e-05	0.334
0.738	-1.76e-05	2.48e-05			
PriceToBook			-5.411e-07	1.03e-05	-0.052
0.958	-2.08e-05	1.97e-05			
PriceToDilutedEarningsTTM			4.561e-06	4.64e-06	0.983
0.326	-4.54e-06	1.37e-05			
PriceToEarningsTTM			6e-08	2.05e-07	0.293
0.770	-3.41e-07	4.61e-07			
PriceToFCF			-9.612e-07	9.07e-06	-0.106
0.916	-1.87e-05	1.68e-05			
PriceToOperatingCashflow			-6.258e-07	6.16e-06	-0.102
0.919	-1.27e-05	1.14e-05			
PriceToSalesTTM			-2.088e-06	5.16e-07	-4.048
0.000	-3.1e-06	-1.08e-06			
Directional Movement Index			-3.169e-07	2.09e-06	-0.152
0.879	-4.4e-06	3.77e-06			
Money Flow Index			-2.768e-06	2.7e-06	-1.025
0.305	-8.06e-06	2.52e-06			
Percent Above Low			2.875e-06	5.17e-06	0.556
0.578	-7.26e-06	1.3e-05			
Percent Below High			-1.786e-06	4.14e-06	-0.431
0.666	-9.9e-06	6.33e-06			
Price Oscillator			9.18e-07	2.92e-06	0.314
0.753	-4.81e-06	6.64e-06			
Trendline			2.007e-06	4.41e-06	0.455
0.649	-6.64e-06	1.07e-05			
AssetToEquityRatio			5.633e-07	3.98e-07	1.414
0.157	-2.17e-07	1.34e-06			
AssetTurnover			-1.27e-05	1.74e-05	-0.731

0.465	-4.68e-05	2.14e-05			
CurrentRatio			3.246e-07	5.2e-07	0.625
0.532	-6.94e-07	1.34e-06			
DebtToAssetRatio			5.697e-07	3.18e-07	1.792
0.073	-5.35e-08	1.19e-06			
DebtToEquityRatio			-5.451e-07	3.69e-07	-1.476
0.140	-1.27e-06	1.79e-07			
MertonsDD			-0.0001	4.64e-05	-2.661
0.008	-0.000	-3.25e-05			
WorkingCapitalToAssets			1.452e-07	6.31e-07	0.230
0.818	-1.09e-06	1.38e-06			
WorkingCapitalToSales			-2.24e-05	2.03e-05	-1.106
0.269	-6.21e-05	1.73e-05			
Dividend Growth			-1.505e-08	1.96e-07	-0.077
0.939	-4e-07	3.69e-07			
EPS			-1.219e-07	3.1e-07	-0.393
0.694	-7.3e-07	4.86e-07			
Net Debt			-1.968e-14	1.12e-14	-1.760
0.078	-4.16e-14	2.23e-15			
Sales			5.85e-15	1.04e-14	0.563
0.574	-1.45e-14	2.62e-14			
Total Assets			-1.665e-14	7.87e-15	-2.116
0.034	-3.21e-14	-1.23e-15			
EPS Growth 3M			-5.625e-08	4.75e-07	-0.118
0.906	-9.87e-07	8.75e-07			
EPS Growth 12M			6.686e-07	4.76e-07	1.405
0.160	-2.64e-07	1.6e-06			
Net Debt Growth 3M			8.433e-08	6.03e-07	0.140
0.889	-1.1e-06	1.27e-06			
Net Debt Growth 12M			4.558e-07	6.14e-07	0.743
0.458	-7.47e-07	1.66e-06			
Sales Growth 3M			2.469e-07	6.4e-07	0.386
0.699	-1.01e-06	1.5e-06			
Sales Growth 12M			-4.861e-07	6.53e-07	-0.745
0.456	-1.77e-06	7.93e-07			
Total Assets Growth 3M			4.535e-07	7.16e-07	0.633
0.527	-9.5e-07	1.86e-06			
Total Assets Growth 12M			-3.477e-07	7.64e-07	-0.455
0.649	-1.84e-06	1.15e-06			
CF0 To Assets			1.731e-05	8.66e-06	1.999
0.046	3.36e-07	3.43e-05			
Capex To Assets			-2.097e-05	1.87e-05	-1.124
0.261	-5.75e-05	1.56e-05			
Capex To FCF			1.29e-06	1.05e-05	0.123
0.902	-1.92e-05	2.18e-05			
Capex To Sales			1.637e-05	2e-05	0.820
0.412	-2.28e-05	5.55e-05			

EBIT To Assets			7.612e-06	8.75e-06	0.870
0.385	-9.55e-06	2.48e-05			
Retained Earnings To Assets			-3.547e-05	1.84e-05	-1.923
0.054	-7.16e-05	6.76e-07			
Downside Risk			4.943e-07	5.32e-06	0.093
0.926	-9.93e-06	1.09e-05			
Index Beta			-8.585e-08	1.09e-07	-0.786
0.432	-3e-07	1.28e-07			
Log Market Cap			1.847e-05	1.86e-05	0.995
0.320	-1.79e-05	5.49e-05			
Volatility 3M			-8.138e-06	4.53e-06	-1.798
0.072	-1.7e-05	7.33e-07			
stock_3D SYSTEMS CORP			0.0157	0.004	3.600
0.000	0.007	0.024			
stock_3M COMPANY			0.0108	0.004	2.823
0.005	0.003	0.018			
stock_ABBOTT LABORATORIES			0.0069	0.003	2.315
0.021	0.001	0.013			
stock_ABBVIE INC			0.0163	0.006	2.916
0.004	0.005	0.027			
stock_ALLERGAN INC			0.0103	0.003	3.563
0.000	0.005	0.016			
stock_ALLERGAN PLC			0.0135	0.004	3.310
0.001	0.006	0.022			
stock_ALTABA INC			0.0161	0.005	3.560
0.000	0.007	0.025			
stock_ALTRIA GROUP INC.			0.0111	0.004	2.847
0.004	0.003	0.019			
stock_AMAZON.COM INC			0.0123	0.005	2.683
0.007	0.003	0.021			
stock_AMERICAN AIRLINES GROUP INC			0.0143	0.005	2.720
0.007	0.004	0.025			
stock_AMERICAN EXPRESS COMPANY			0.0065	0.002	2.656
0.008	0.002	0.011			
stock_AMERICAN INTL GROUP INC			0.0118	0.004	2.850
0.004	0.004	0.020			
stock_AMGEN INC			0.0064	0.003	2.421
0.015	0.001	0.012			
stock_ANADARKO PETROLEUM CORP			0.0077	0.002	3.231
0.001	0.003	0.012			
stock_APACHE CORP			0.0045	0.004	1.262
0.207	-0.003	0.012			
stock_APPLE INC			0.0086	0.004	2.278
0.023	0.001	0.016			
stock_APPLIED MATERIALS INC			0.0075	0.003	2.572
0.010	0.002	0.013			
stock_ARCONIC INC			0.0026	0.002	1.210

0.226	-0.002	0.007			
stock_AT&T INC. COM			0.0103	0.004	2.420
0.016	0.002	0.019			
stock_Alphabet Inc. Cl A			0.0192	0.005	3.528
0.000	0.009	0.030			
stock_BAKER HUGHES INC			0.0078	0.003	2.946
0.003	0.003	0.013			
stock_BANK OF AMERICA CORP			0.0404	0.016	2.532
0.011	0.009	0.072			
stock_BERKSHIRE HATHAWAY INC CL-B			0.0171	0.006	3.069
0.002	0.006	0.028			
stock_BIOGEN INC			0.0120	0.004	3.275
0.001	0.005	0.019			
stock_BOEING CO			0.0053	0.003	1.864
0.062	-0.000	0.011			
stock_BOOKING HOLDINGS INC			0.0153	0.005	3.232
0.001	0.006	0.025			
stock_BRISTOL MYERS SQUIBB COMPANY			0.0097	0.003	3.001
0.003	0.003	0.016			
stock_BROADCOM CORP			0.0134	0.004	3.087
0.002	0.005	0.022			
stock_BROADCOM INC			0.0173	0.006	3.112
0.002	0.006	0.028			
stock_CATERPILLAR INC			0.0042	0.003	1.502
0.133	-0.001	0.010			
stock_CELGENE CORP			0.0091	0.003	2.905
0.004	0.003	0.015			
stock_CHESAPEAKE ENERGY CORP			0.0041	0.005	0.874
0.382	-0.005	0.013			
stock_CHEVRON CORPORATION			0.0137	0.006	2.386
0.017	0.002	0.025			
stock_CISCO SYSTEMS INC			0.0066	0.003	2.363
0.018	0.001	0.012			
stock_CITIGROUP			0.0371	0.014	2.713
0.007	0.010	0.064			
stock_COCA-COLA CO			0.0101	0.004	2.629
0.009	0.003	0.018			
stock_COMCAST CORP			0.0081	0.003	2.917
0.004	0.003	0.013			
stock_CONOCOPHILLIPS			0.0125	0.005	2.566
0.010	0.003	0.022			
stock_COVIDIEN PLC			0.0196	0.005	3.839
0.000	0.010	0.030			
stock_CVS HEALTH CORP			0.0077	0.004	2.122
0.034	0.001	0.015			
stock_DEERE & CO			0.0050	0.003	1.671
0.095	-0.001	0.011			

stock_DELTA AIR LINES INC	0.0141	0.005	2.882
0.004 0.005 0.024			
stock_DIRECTV	0.0114	0.005	2.405
0.016 0.002 0.021			
stock_DOLLAR GENERAL CORP	0.0143	0.005	2.899
0.004 0.005 0.024			
stock_DOW CHEMICAL CO	0.0055	0.003	1.960
0.050 -5.93e-07 0.011			
stock_E.I. Du Pont De Nemours A	0.0060	0.003	2.109
0.035 0.000 0.012			
stock_EBAY INC	0.0166	0.005	3.281
0.001 0.007 0.027			
stock EMC CORPORATION	0.0082	0.003	2.886
0.004 0.003 0.014			
stock_EOG RESOURCES INC	0.0099	0.003	3.577
0.000 0.004 0.015			
stock_EXPRESS SCRIPTS HOLDING CO	0.0034	0.003	1.166
0.244 -0.002 0.009			
stock_EXXON MOBIL CORPORATION	0.0128	0.007	1.936
0.053 -0.000 0.026			
stock_FACEBOOK INC	0.0199	0.006	3.452
0.001 0.009 0.031			
stock_FEDEX CORPORATION	0.0079	0.003	2.618
0.009 0.002 0.014			
stock_FIRST SOLAR INC	0.0180	0.005	3.411
0.001 0.008 0.028			
stock_FORD MOTOR CO(NEW)	0.0057	0.004	1.626
0.104 -0.001 0.013			
stock_FREEPORT-MCMORAN INC	0.0090	0.004	2.333
0.020 0.001 0.017			
stock_GENERAL ELECTRIC CO	0.0165	0.005	3.025
0.002 0.006 0.027			
stock_GENERAL MOTORS CO	0.0131	0.006	2.358
0.018 0.002 0.024			
stock_GILEAD SCIENCES INC	0.0108	0.003	3.141
0.002 0.004 0.017			
stock_GOLDMAN SACHS GROUP INC	0.0317	0.007	4.257
0.000 0.017 0.046			
stock_GOPRO INC	0.0199	0.006	3.550
0.000 0.009 0.031			
stock_HALLIBURTON CO (HOLDING CO)	0.0084	0.003	2.752
0.006 0.002 0.014			
stock_HOME DEPOT INC	0.0070	0.003	2.052
0.040 0.000 0.014			
stock_HP INC	0.0051	0.003	1.624
0.104 -0.001 0.011			
stock_INTEL CORP	0.0087	0.003	2.535

0.011	0.002	0.015			
stock_INTL BUSINESS MACHINES CORP			0.0087	0.004	2.280
0.023	0.001	0.016			
stock_JOHNSON AND JOHNSON			0.0111	0.004	2.834
0.005	0.003	0.019			
stock_JPMORGAN CHASE & CO COM STK			0.0545	0.019	2.818
0.005	0.017	0.092			
stock_KEURIG GREEN MOUNTAIN INC			0.0146	0.004	3.591
0.000	0.007	0.023			
stock_KINDER MORGAN INC			0.0132	0.005	2.470
0.014	0.003	0.024			
stock_LAS VEGAS SANDS CORP			0.0127	0.005	2.488
0.013	0.003	0.023			
stock_LILLY ELI & CO			0.0102	0.004	2.885
0.004	0.003	0.017			
stock_LINKEDIN CORP			0.0197	0.006	3.505
0.000	0.009	0.031			
stock_LOWES COMPANIES INC			0.0075	0.003	2.483
0.013	0.002	0.013			
stock_LYONDELLBASELL INDUSTRIES NV			0.0135	0.005	2.593
0.010	0.003	0.024			
stock_MARATHON PETROLEUM CORP			0.0128	0.006	2.268
0.023	0.002	0.024			
stock_MASTERCARD INCORPORATED			0.0206	0.006	3.731
0.000	0.010	0.031			
stock_MCDONALDS CORP			0.0099	0.004	2.513
0.012	0.002	0.018			
stock_MEDTRONIC PLC			0.0119	0.004	3.390
0.001	0.005	0.019			
stock_MERCK & CO INC			0.0110	0.004	2.966
0.003	0.004	0.018			
stock_METLIFE INC			0.0260	0.008	3.353
0.001	0.011	0.041			
stock_MICHAEL KORS HOLDINGS LTD			0.0214	0.006	3.646
0.000	0.010	0.033			
stock_MICRON TECHNOLOGY INC			0.0102	0.003	3.287
0.001	0.004	0.016			
stock_MICROSOFT CORP			0.0115	0.004	3.028
0.002	0.004	0.019			
stock_MONDELEZ INTERNATIONAL INC			0.0133	0.005	2.875
0.004	0.004	0.022			
stock_MONSANTO COMPANY			0.0153	0.005	3.201
0.001	0.006	0.025			
stock_MORGAN STANLEY			0.0273	0.007	3.884
0.000	0.014	0.041			
stock_MYLAN NV			0.0111	0.003	3.260
0.001	0.004	0.018			

stock_NATIONAL OILWELL VARCO INC.	0.0131	0.005	2.642
0.008 0.003 0.023			
stock_NETFLIX INC	0.0179	0.005	3.555
0.000 0.008 0.028			
stock_NEWMONT MINING CORP (HOLDING COMPANY)	0.0098	0.004	2.773
0.006 0.003 0.017			
stock_NEWS CP - CL A	0.0129	0.004	3.348
0.001 0.005 0.020			
stock_NIKE INC CL-B	0.0104	0.004	2.884
0.004 0.003 0.018			
stock_OCCIDENTAL PETROLEUM CORP	0.0118	0.004	3.153
0.002 0.004 0.019			
stock_ORACLE CORP	0.0118	0.004	3.297
0.001 0.005 0.019			
stock_PANDORA MEDIA INC	0.0235	0.006	3.942
0.000 0.012 0.035			
stock_PENNEY J.C. CO INC (HOLDING COMPANY)	0.0027	0.003	0.905
0.365 -0.003 0.009			
stock_PEPSICO INC	0.0104	0.004	2.533
0.011 0.002 0.018			
stock_PFIZER INC	0.0134	0.004	3.287
0.001 0.005 0.021			
stock_PHILIP MORRIS INTERNATIONAL INC	0.0154	0.006	2.576
0.010 0.004 0.027			
stock_PIONEER NAT RES CO	0.0177	0.004	4.022
0.000 0.009 0.026			
stock_PRECISION CASTPARTS CORP	0.0145	0.004	3.574
0.000 0.007 0.022			
stock_PROCTER & GAMBLE CO	0.0115	0.004	2.722
0.006 0.003 0.020			
stock_QUALCOMM INC	0.0131	0.004	3.223
0.001 0.005 0.021			
stock_REGENERON PHARMACEUTICALS INC	0.0117	0.005	2.380
0.017 0.002 0.021			
stock_SALESFORCE.COM INC	0.0173	0.005	3.443
0.001 0.007 0.027			
stock_SALIX PHARMACEUTICALS LTD	-2.111e-18	7.34e-17	-0.029
0.977 -1.46e-16 1.42e-16			
stock_SANDISK CORP	0.0154	0.004	3.629
0.000 0.007 0.024			
stock_SCHLUMBERGER LTD.	0.0120	0.004	3.003
0.003 0.004 0.020			
stock_SKYWORKS SOLUTIONS INC	0.0191	0.005	3.796
0.000 0.009 0.029			
stock_SOLARCITY CORP	0.0208	0.006	3.549
0.000 0.009 0.032			
stock_SOUTHWEST AIRLINES CO	0.0092	0.003	2.885

0.004	0.003	0.015			
stock_STARBUCKS CORPORATION			0.0147	0.004	3.658
0.000	0.007	0.023			
stock_SUNEDISON INC			0.0183	0.006	3.237
0.001	0.007	0.029			
stock_TARGET CORPORATION			0.0104	0.004	2.349
0.019	0.002	0.019			
stock_TESLA INC			0.0196	0.006	3.520
0.000	0.009	0.031			
stock_TEXAS INSTRUMENTS INC			0.0141	0.004	3.229
0.001	0.006	0.023			
stock_TIME WARNER CABLE INC			0.0140	0.005	2.883
0.004	0.004	0.024			
stock_TIME WARNER INC.			0.0049	0.002	2.324
0.020	0.001	0.009			
stock_TWITTER INC			0.0185	0.006	3.201
0.001	0.007	0.030			
stock_UNION PACIFIC CORPORATION			0.0130	0.004	3.275
0.001	0.005	0.021			
stock_UNITED CONTINENTAL HOLDINGS IN			0.0097	0.005	2.019
0.044	0.000	0.019			
stock_UNITED PARCEL SERVICE INC.CL B			0.0101	0.005	2.184
0.029	0.001	0.019			
stock_UNITED TECHNOLOGIES CORP			0.0113	0.004	2.830
0.005	0.003	0.019			
stock_UNITEDHEALTH GROUP INC			0.0100	0.004	2.453
0.014	0.002	0.018			
stock_VALERO ENERGY CORP (NEW)			0.0099	0.004	2.405
0.016	0.002	0.018			
stock_VERIZON COMMUNICATIONS			0.0116	0.005	2.369
0.018	0.002	0.021			
stock_VISA INC			0.0189	0.005	3.588
0.000	0.009	0.029			
stock_WALGREENS BOOTS ALLIANCE INC			0.0109	0.004	2.732
0.006	0.003	0.019			
stock_WALMART INC			0.0078	0.006	1.208
0.227	-0.005	0.020			
stock_WALT DISNEY CO			0.0102	0.003	3.309
0.001	0.004	0.016			
stock_WELLS FARGO & CO(NEW)			0.0434	0.013	3.348
0.001	0.018	0.069			
stock_WILLIAMS COMPANIES			0.0109	0.004	2.720
0.007	0.003	0.019			
stock_WYNN RESORTS LTD			0.0109	0.005	2.254
0.024	0.001	0.020			
stock_YELP INC			0.0231	0.006	3.978
0.000	0.012	0.034			

```
=====
Omnibus:                41.371    Durbin-Watson:                1.329
Prob(Omnibus):           0.000    Jarque-Bera (JB):           45.849
Skew:                   -0.034    Prob(JB):                   1.11e-10
Kurtosis:               3.141    Cond. No.                   5.40e+21
=====
```

Warnings:

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

[2] The smallest eigenvalue is 1.4e-16. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

"""

The summary is available in the notebook to save some space due to the large number of variables. The diagnostic statistics show that, given the high p-value on the Jarque—Bera statistic, the hypothesis that the residuals are normally distributed cannot be rejected.

However, the Durbin—Watson statistic is low at 1.5 so we can reject the null hypothesis of no autocorrelation comfortably at the 5% level. Hence, the standard errors are likely positively correlated. If our goal were to understand which factors are significantly associated with forward returns, we would need to rerun the regression using robust standard errors (a parameter in `statsmodels.fit()` method), or use a different method altogether such as a panel model that allows for more complex error covariance.

```
[45]: target = 'Returns5D'
model_data = pd.concat([y[[target]], X], axis=1).dropna()
model_data = model_data[model_data[target].between(model_data[target].quantile(
    ↪0.25),
                                                    model_data[target].quantile(
    ↪0.975))]

model = OLS(endog=model_data[target], exog=model_data.drop(target, axis=1))
trained_model = model.fit()
trained_model.summary()
```

```
[45]: <class 'statsmodels.iolib.summary.Summary'>
"""
```

```

                                OLS Regression Results
=====
Dep. Variable:                Returns5D    R-squared:                0.016
Model:                        OLS         Adj. R-squared:           0.012
Method:                    Least Squares    F-statistic:              4.124
Date:                Sun, 09 Sep 2018    Prob (F-statistic):       2.28e-66
Time:                        21:18:00    Log-Likelihood:           95279.
No. Observations:                44370    AIC:                     -1.902e+05
Df Residuals:                    44195    BIC:                     -1.887e+05
Df Model:                        174

```

Covariance Type: nonrobust

			=====		
=====					
			coef	std err	t
P> t	[95.0% Conf. Int.]		-----		

DividendYield			4.504e-06	1.08e-06	4.185
0.000	2.39e-06	6.61e-06			
EBITDAYield			9.323e-06	2.17e-05	0.430
0.667	-3.32e-05	5.19e-05			
EVToEBITDA			1.425e-05	1.98e-05	0.719
0.472	-2.46e-05	5.31e-05			
EVToFCF			2.654e-05	2.47e-05	1.075
0.283	-2.19e-05	7.49e-05			
PriceToBook			1.582e-05	2.36e-05	0.669
0.503	-3.05e-05	6.21e-05			
PriceToDilutedEarningsTTM			5.462e-07	1.06e-05	0.052
0.959	-2.01e-05	2.12e-05			
PriceToEarningsTTM			1.449e-07	4.67e-07	0.310
0.757	-7.71e-07	1.06e-06			
PriceToFCF			-1.94e-05	2.07e-05	-0.939
0.348	-5.99e-05	2.11e-05			
PriceToOperatingCashflow			-4.155e-05	1.42e-05	-2.934
0.003	-6.93e-05	-1.38e-05			
PriceToSalesTTM			-8.975e-06	1.19e-06	-7.530
0.000	-1.13e-05	-6.64e-06			
Directional Movement Index			-4.457e-06	4.75e-06	-0.938
0.348	-1.38e-05	4.86e-06			
Money Flow Index			-5.894e-06	6.16e-06	-0.956
0.339	-1.8e-05	6.19e-06			
Percent Above Low			-1.985e-05	1.18e-05	-1.675
0.094	-4.31e-05	3.38e-06			
Percent Below High			7.651e-06	9.42e-06	0.812
0.417	-1.08e-05	2.61e-05			
Price Oscillator			3.706e-06	6.64e-06	0.558
0.577	-9.31e-06	1.67e-05			
Trendline			1.414e-05	1.01e-05	1.402
0.161	-5.64e-06	3.39e-05			
AssetToEquityRatio			-1.226e-07	8.91e-07	-0.138
0.891	-1.87e-06	1.62e-06			
AssetTurnover			-7.3e-06	3.95e-05	-0.185
0.854	-8.48e-05	7.02e-05			
CurrentRatio			4.11e-07	1.18e-06	0.347
0.728	-1.91e-06	2.73e-06			
DebtToAssetRatio			2.484e-06	7.25e-07	3.427
0.001	1.06e-06	3.9e-06			

DebtToEquityRatio			-5.365e-07	8.37e-07	-0.641
0.521	-2.18e-06	1.1e-06			
MertonsDD			-0.0004	0.000	-3.508
0.000	-0.001	-0.000			
WorkingCapitalToAssets			1.341e-06	1.44e-06	0.932
0.351	-1.48e-06	4.16e-06			
WorkingCapitalToSales			-3.118e-05	4.62e-05	-0.674
0.500	-0.000	5.95e-05			
Dividend Growth			-2.629e-07	4.5e-07	-0.585
0.559	-1.14e-06	6.18e-07			
EPS			2.901e-07	7.04e-07	0.412
0.680	-1.09e-06	1.67e-06			
Net Debt			-8.116e-14	2.56e-14	-3.172
0.002	-1.31e-13	-3.1e-14			
Sales			-5.373e-14	2.4e-14	-2.239
0.025	-1.01e-13	-6.69e-15			
Total Assets			-4.104e-14	1.8e-14	-2.276
0.023	-7.64e-14	-5.7e-15			
EPS Growth 3M			-2.787e-06	1.08e-06	-2.582
0.010	-4.9e-06	-6.72e-07			
EPS Growth 12M			1.257e-06	1.08e-06	1.161
0.246	-8.64e-07	3.38e-06			
Net Debt Growth 3M			2.628e-07	1.37e-06	0.191
0.848	-2.43e-06	2.95e-06			
Net Debt Growth 12M			2.592e-06	1.4e-06	1.858
0.063	-1.43e-07	5.33e-06			
Sales Growth 3M			3.824e-06	1.45e-06	2.634
0.008	9.79e-07	6.67e-06			
Sales Growth 12M			-2.38e-06	1.48e-06	-1.604
0.109	-5.29e-06	5.28e-07			
Total Assets Growth 3M			-6.292e-07	1.63e-06	-0.386
0.699	-3.82e-06	2.56e-06			
Total Assets Growth 12M			-1.46e-06	1.73e-06	-0.842
0.400	-4.86e-06	1.94e-06			
CF0 To Assets			4.634e-05	1.98e-05	2.342
0.019	7.56e-06	8.51e-05			
Capex To Assets			-0.0001	4.26e-05	-3.232
0.001	-0.000	-5.42e-05			
Capex To FCF			3.673e-05	2.39e-05	1.534
0.125	-1.02e-05	8.37e-05			
Capex To Sales			0.0001	4.56e-05	2.247
0.025	1.31e-05	0.000			
EBIT To Assets			8.146e-06	2e-05	0.408
0.683	-3.1e-05	4.73e-05			
Retained Earnings To Assets			-0.0001	4.2e-05	-3.036
0.002	-0.000	-4.51e-05			
Downside Risk			1.166e-05	1.22e-05	0.960

0.337	-1.22e-05	3.55e-05			
Index Beta			-7.363e-07	2.49e-07	-2.958
0.003	-1.22e-06	-2.48e-07			
Log Market Cap			9.103e-05	4.24e-05	2.148
0.032	7.98e-06	0.000			
Volatility 3M			-5.492e-05	1.04e-05	-5.306
0.000	-7.52e-05	-3.46e-05			
stock_3D SYSTEMS CORP			0.0568	0.010	5.697
0.000	0.037	0.076			
stock_3M COMPANY			0.0426	0.009	4.865
0.000	0.025	0.060			
stock_ABBOTT LABORATORIES			0.0264	0.007	3.854
0.000	0.013	0.040			
stock_ABBVIE INC			0.0572	0.013	4.482
0.000	0.032	0.082			
stock_ALLERGAN INC			0.0487	0.007	7.349
0.000	0.036	0.062			
stock_ALLERGAN PLC			0.0543	0.009	5.812
0.000	0.036	0.073			
stock_ALTABA INC			0.0605	0.010	5.857
0.000	0.040	0.081			
stock_ALTRIA GROUP INC.			0.0453	0.009	5.074
0.000	0.028	0.063			
stock_AMAZON.COM INC			0.0513	0.010	4.905
0.000	0.031	0.072			
stock_AMERICAN AIRLINES GROUP INC			0.0490	0.012	4.079
0.000	0.025	0.073			
stock_AMERICAN EXPRESS COMPANY			0.0232	0.006	4.177
0.000	0.012	0.034			
stock_AMERICAN INTL GROUP INC			0.0452	0.009	4.770
0.000	0.027	0.064			
stock_AMGEN INC			0.0266	0.006	4.400
0.000	0.015	0.038			
stock_ANADARKO PETROLEUM CORP			0.0347	0.005	6.387
0.000	0.024	0.045			
stock_APACHE CORP			0.0130	0.009	1.487
0.137	-0.004	0.030			
stock_APPLE INC			0.0471	0.009	5.478
0.000	0.030	0.064			
stock_APPLIED MATERIALS INC			0.0333	0.007	4.965
0.000	0.020	0.046			
stock_ARCONIC INC			0.0090	0.005	1.822
0.068	-0.001	0.019			
stock_AT&T INC. COM			0.0372	0.010	3.817
0.000	0.018	0.056			
stock_Alphabet Inc. Cl A			0.0713	0.012	5.733
0.000	0.047	0.096			

stock_BAKER HUGHES INC	0.0296	0.006	4.920
0.000 0.018 0.041			
stock_BANK OF AMERICA CORP	0.1209	0.037	3.306
0.001 0.049 0.193			
stock_BERKSHIRE HATHAWAY INC CL-B	0.0629	0.013	4.939
0.000 0.038 0.088			
stock_BIOGEN INC	0.0551	0.008	6.605
0.000 0.039 0.071			
stock_BOEING CO	0.0230	0.007	3.524
0.000 0.010 0.036			
stock_BOOKING HOLDINGS INC	0.0600	0.011	5.539
0.000 0.039 0.081			
stock_BRISTOL MYERS SQUIBB COMPANY	0.0405	0.007	5.456
0.000 0.026 0.055			
stock_BROADCOM CORP	0.0564	0.010	5.697
0.000 0.037 0.076			
stock_BROADCOM INC	0.0733	0.013	5.818
0.000 0.049 0.098			
stock_CATERPILLAR INC	0.0139	0.006	2.172
0.030 0.001 0.027			
stock_CELGENE CORP	0.0385	0.007	5.398
0.000 0.025 0.053			
stock_CHESAPEAKE ENERGY CORP	0.0269	0.011	2.555
0.011 0.006 0.048			
stock_CHEVRON CORPORATION	0.0562	0.013	4.283
0.000 0.030 0.082			
stock_CISCO SYSTEMS INC	0.0285	0.006	4.464
0.000 0.016 0.041			
stock_CITIGROUP	0.1090	0.031	3.474
0.001 0.048 0.171			
stock_COCA-COLA CO	0.0384	0.009	4.352
0.000 0.021 0.056			
stock_COMCAST CORP	0.0325	0.006	5.155
0.000 0.020 0.045			
stock_CONOCOPHILLIPS	0.0456	0.011	4.089
0.000 0.024 0.067			
stock_COVIDIEN PLC	0.0743	0.012	6.354
0.000 0.051 0.097			
stock_CVS HEALTH CORP	0.0358	0.008	4.345
0.000 0.020 0.052			
stock_DEERE & CO	0.0115	0.007	1.683
0.092 -0.002 0.025			
stock_DELTA AIR LINES INC	0.0545	0.011	4.896
0.000 0.033 0.076			
stock_DIRECTV	0.0383	0.011	3.558
0.000 0.017 0.059			
stock_DOLLAR GENERAL CORP	0.0508	0.011	4.509

0.000	0.029	0.073			
stock_DOW CHEMICAL CO			0.0234	0.006	3.686
0.000	0.011	0.036			
stock_E.I. Du Pont De Nemours A			0.0204	0.007	3.137
0.002	0.008	0.033			
stock_EBAY INC			0.0611	0.012	5.279
0.000	0.038	0.084			
stock EMC CORPORATION			0.0341	0.007	5.245
0.000	0.021	0.047			
stock_EOG RESOURCES INC			0.0413	0.006	6.573
0.000	0.029	0.054			
stock_EXPRESS SCRIPTS HOLDING CO			0.0177	0.007	2.628
0.009	0.005	0.031			
stock_EXXON MOBIL CORPORATION			0.0677	0.015	4.484
0.000	0.038	0.097			
stock_FACEBOOK INC			0.0762	0.013	5.785
0.000	0.050	0.102			
stock_FEDEX CORPORATION			0.0321	0.007	4.657
0.000	0.019	0.046			
stock_FIRST SOLAR INC			0.0484	0.012	4.004
0.000	0.025	0.072			
stock_FORD MOTOR CO(NEW)			0.0213	0.008	2.647
0.008	0.006	0.037			
stock_FREEPORT-MCMORAN INC			0.0269	0.009	3.063
0.002	0.010	0.044			
stock_GENERAL ELECTRIC CO			0.0556	0.013	4.444
0.000	0.031	0.080			
stock_GENERAL MOTORS CO			0.0485	0.013	3.829
0.000	0.024	0.073			
stock_GILEAD SCIENCES INC			0.0459	0.008	5.868
0.000	0.031	0.061			
stock_GOLDMAN SACHS GROUP INC			0.0965	0.017	5.644
0.000	0.063	0.130			
stock_GOPRO INC			0.0687	0.013	5.377
0.000	0.044	0.094			
stock_HALLIBURTON CO (HOLDING CO)			0.0322	0.007	4.601
0.000	0.018	0.046			
stock_HOME DEPOT INC			0.0336	0.008	4.320
0.000	0.018	0.049			
stock_HP INC			0.0254	0.007	3.507
0.000	0.011	0.040			
stock_INTEL CORP			0.0383	0.008	4.891
0.000	0.023	0.054			
stock_INTL BUSINESS MACHINES CORP			0.0329	0.009	3.784
0.000	0.016	0.050			
stock_JOHNSON AND JOHNSON			0.0431	0.009	4.833
0.000	0.026	0.061			

stock_JPMORGAN CHASE & CO COM STK	0.1531	0.044	3.455
0.001 0.066 0.240			
stock_KEURIG GREEN MOUNTAIN INC	0.0569	0.009	6.135
0.000 0.039 0.075			
stock_KINDER MORGAN INC	0.0427	0.012	3.497
0.000 0.019 0.067			
stock_LAS VEGAS SANDS CORP	0.0494	0.012	4.235
0.000 0.027 0.072			
stock_LILLY ELI & CO	0.0411	0.008	5.097
0.000 0.025 0.057			
stock_LINKEDIN CORP	0.0700	0.013	5.460
0.000 0.045 0.095			
stock_LOWES COMPANIES INC	0.0307	0.007	4.474
0.000 0.017 0.044			
stock_LYONDELLBASELL INDUSTRIES NV	0.0478	0.012	4.043
0.000 0.025 0.071			
stock_MARATHON PETROLEUM CORP	0.0508	0.013	3.939
0.000 0.026 0.076			
stock_MASTERCARD INCORPORATED	0.0778	0.013	6.157
0.000 0.053 0.103			
stock_MCDONALDS CORP	0.0380	0.009	4.236
0.000 0.020 0.056			
stock_MEDTRONIC PLC	0.0482	0.008	6.017
0.000 0.033 0.064			
stock_MERCK & CO INC	0.0425	0.008	5.002
0.000 0.026 0.059			
stock_METLIFE INC	0.0738	0.018	4.162
0.000 0.039 0.109			
stock_MICHAEL KORS HOLDINGS LTD	0.0770	0.013	5.750
0.000 0.051 0.103			
stock_MICRON TECHNOLOGY INC	0.0363	0.007	5.112
0.000 0.022 0.050			
stock_MICROSOFT CORP	0.0468	0.009	5.410
0.000 0.030 0.064			
stock_MONDELEZ INTERNATIONAL INC	0.0519	0.011	4.934
0.000 0.031 0.073			
stock_MONSANTO COMPANY	0.0556	0.011	5.111
0.000 0.034 0.077			
stock_MORGAN STANLEY	0.0829	0.016	5.139
0.000 0.051 0.115			
stock_MYLAN NV	0.0430	0.008	5.515
0.000 0.028 0.058			
stock_NATIONAL OILWELL VARCO INC.	0.0397	0.011	3.525
0.000 0.018 0.062			
stock_NETFLIX INC	0.0690	0.011	6.016
0.000 0.047 0.092			
stock_NEWMONT MINING CORP (HOLDING COMPANY)	0.0312	0.008	3.782

0.000	0.015	0.047			
stock_NEWS CP - CL A			0.0462	0.009	5.253
0.000	0.029	0.063			
stock_NIKE INC CL-B			0.0466	0.008	5.636
0.000	0.030	0.063			
stock_OCCIDENTAL PETROLEUM CORP			0.0420	0.009	4.899
0.000	0.025	0.059			
stock_ORACLE CORP			0.0434	0.008	5.331
0.000	0.027	0.059			
stock_PANDORA MEDIA INC			0.0953	0.014	6.986
0.000	0.069	0.122			
stock_PENNEY J.C. CO INC (HOLDING COMPANY)			0.0163	0.007	2.353
0.019	0.003	0.030			
stock_PEPSICO INC			0.0387	0.009	4.139
0.000	0.020	0.057			
stock_PFIZER INC			0.0498	0.009	5.350
0.000	0.032	0.068			
stock_PHILIP MORRIS INTERNATIONAL INC			0.0577	0.014	4.236
0.000	0.031	0.084			
stock_PIONEER NAT RES CO			0.0716	0.010	7.136
0.000	0.052	0.091			
stock_PRECISION CASTPARTS CORP			0.0510	0.009	5.448
0.000	0.033	0.069			
stock_PROCTER & GAMBLE CO			0.0442	0.010	4.581
0.000	0.025	0.063			
stock_QUALCOMM INC			0.0532	0.009	5.739
0.000	0.035	0.071			
stock_REGENERON PHARMACEUTICALS INC			0.0537	0.011	4.675
0.000	0.031	0.076			
stock_SALESFORCE.COM INC			0.0610	0.011	5.303
0.000	0.038	0.083			
stock_SALIX PHARMACEUTICALS LTD			-4.65e-16	2.62e-15	-0.178
0.859	-5.6e-15	4.67e-15			
stock_SANDISK CORP			0.0624	0.010	6.426
0.000	0.043	0.081			
stock_SCHLUMBERGER LTD.			0.0441	0.009	4.843
0.000	0.026	0.062			
stock_SKYWORKS SOLUTIONS INC			0.0772	0.011	6.749
0.000	0.055	0.100			
stock_SOLARCITY CORP			0.0820	0.013	6.129
0.000	0.056	0.108			
stock_SOUTHWEST AIRLINES CO			0.0430	0.007	5.909
0.000	0.029	0.057			
stock_STARBUCKS CORPORATION			0.0606	0.009	6.590
0.000	0.043	0.079			
stock_SUNEDISON INC			0.0234	0.017	1.401
0.161	-0.009	0.056			

stock_TARGET CORPORATION	0.0356	0.010	3.541
0.000 0.016 0.055			
stock_TESLA INC	0.0720	0.013	5.659
0.000 0.047 0.097			
stock_TEXAS INSTRUMENTS INC	0.0522	0.010	5.206
0.000 0.033 0.072			
stock_TIME WARNER CABLE INC	0.0468	0.011	4.218
0.000 0.025 0.069			
stock_TIME WARNER INC.	0.0227	0.005	4.748
0.000 0.013 0.032			
stock_TWITTER INC	0.0686	0.013	5.194
0.000 0.043 0.094			
stock_UNION PACIFIC CORPORATION	0.0493	0.009	5.446
0.000 0.032 0.067			
stock_UNITED CONTINENTAL HOLDINGS IN	0.0379	0.011	3.469
0.001 0.016 0.059			
stock_UNITED PARCEL SERVICE INC.CL B	0.0366	0.011	3.462
0.001 0.016 0.057			
stock_UNITED TECHNOLOGIES CORP	0.0390	0.009	4.277
0.000 0.021 0.057			
stock_UNITEDHEALTH GROUP INC	0.0455	0.009	4.866
0.000 0.027 0.064			
stock_VALERO ENERGY CORP (NEW)	0.0432	0.009	4.596
0.000 0.025 0.062			
stock_VERIZON COMMUNICATIONS	0.0392	0.011	3.502
0.000 0.017 0.061			
stock_VISA INC	0.0769	0.012	6.389
0.000 0.053 0.100			
stock_WALGREENS BOOTS ALLIANCE INC	0.0444	0.009	4.859
0.000 0.026 0.062			
stock_WALMART INC	0.0554	0.015	3.742
0.000 0.026 0.084			
stock_WALT DISNEY CO	0.0432	0.007	6.119
0.000 0.029 0.057			
stock_WELLS FARGO & CO(NEW)	0.1324	0.030	4.449
0.000 0.074 0.191			
stock_WILLIAMS COMPANIES	0.0472	0.009	5.143
0.000 0.029 0.065			
stock_WYNN RESORTS LTD	0.0410	0.011	3.710
0.000 0.019 0.063			
stock_YELP INC	0.0728	0.013	5.489
0.000 0.047 0.099			
=====			
Omnibus:	71.266	Durbin-Watson:	1.433
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.090
Skew:	-0.067	Prob(JB):	1.82e-17
Kurtosis:	3.154	Cond. No.	3.42e+20

```
=====
```

Warnings:

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

[2] The smallest eigenvalue is 3.44e-14. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
"""
```

```
[46]: target = 'Returns10D'
model_data = pd.concat([y[[target]], X], axis=1).dropna()
model_data = model_data[model_data[target].between(model_data[target].quantile(
    ↪0.25),
                                                    model_data[target].quantile(
    ↪0.975))]

model = OLS(endog=model_data[target], exog=model_data.drop(target, axis=1))
trained_model = model.fit()
trained_model.summary()
```

```
[46]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

OLS Regression Results

```
=====
Dep. Variable:          Returns10D    R-squared:                0.035
Model:                  OLS          Adj. R-squared:           0.031
Method:                 Least Squares  F-statistic:              9.045
Date:                  Sun, 09 Sep 2018  Prob (F-statistic):       5.42e-219
Time:                  21:18:02       Log-Likelihood:           78861.
No. Observations:      43734         AIC:                    -1.574e+05
Df Residuals:          43559         BIC:                    -1.559e+05
Df Model:               174
Covariance Type:       nonrobust
=====
```

```
=====
                                coef    std err          t
P>|t|    [95.0% Conf. Int.]
-----
DividendYield                6.757e-06    1.55e-06     4.370
0.000      3.73e-06  9.79e-06
EBITDAYield                -1.021e-05    3.11e-05    -0.329
0.743     -7.11e-05  5.07e-05
EVToEBITDA                  9.163e-05    2.83e-05     3.233
0.001      3.61e-05    0.000
EVToFCF                     2.372e-05    3.51e-05     0.676
0.499     -4.5e-05  9.25e-05
```

PriceToBook			8.448e-05	3.34e-05	2.533
0.011	1.91e-05	0.000			
PriceToDilutedEarningsTTM			-1.332e-05	1.5e-05	-0.889
0.374	-4.27e-05	1.61e-05			
PriceToEarningsTTM			-6.983e-07	6.67e-07	-1.047
0.295	-2e-06	6.08e-07			
PriceToFCF			-4.525e-06	2.91e-05	-0.155
0.877	-6.16e-05	5.26e-05			
PriceToOperatingCashflow			-8.243e-05	2.02e-05	-4.071
0.000	-0.000	-4.27e-05			
PriceToSalesTTM			-2.324e-05	1.72e-06	-13.493
0.000	-2.66e-05	-1.99e-05			
Directional Movement Index			-2.235e-05	6.75e-06	-3.308
0.001	-3.56e-05	-9.11e-06			
Money Flow Index			4.299e-06	8.77e-06	0.490
0.624	-1.29e-05	2.15e-05			
Percent Above Low			-4.475e-05	1.71e-05	-2.623
0.009	-7.82e-05	-1.13e-05			
Percent Below High			1.295e-05	1.34e-05	0.965
0.335	-1.34e-05	3.93e-05			
Price Oscillator			6.06e-06	9.48e-06	0.640
0.522	-1.25e-05	2.46e-05			
Trendline			2.48e-05	1.44e-05	1.722
0.085	-3.42e-06	5.3e-05			
AssetToEquityRatio			-2.548e-06	1.3e-06	-1.964
0.049	-5.09e-06	-5.59e-09			
AssetTurnover			-0.0001	5.63e-05	-2.054
0.040	-0.000	-5.31e-06			
CurrentRatio			3.392e-06	1.69e-06	2.007
0.045	7.96e-08	6.7e-06			
DebtToAssetRatio			2.605e-06	1.04e-06	2.500
0.012	5.63e-07	4.65e-06			
DebtToEquityRatio			-2.576e-08	1.21e-06	-0.021
0.983	-2.4e-06	2.35e-06			
MertonsDD			-0.0010	0.000	-6.752
0.000	-0.001	-0.001			
WorkingCapitalToAssets			3.97e-06	2.04e-06	1.943
0.052	-3.38e-08	7.97e-06			
WorkingCapitalToSales			-0.0002	6.58e-05	-2.654
0.008	-0.000	-4.56e-05			
Dividend Growth			-9.485e-07	6.45e-07	-1.471
0.141	-2.21e-06	3.16e-07			
EPS			5.254e-07	1e-06	0.525
0.599	-1.43e-06	2.48e-06			
Net Debt			-1.53e-13	3.65e-14	-4.193
0.000	-2.25e-13	-8.15e-14			
Sales			-1.061e-13	3.43e-14	-3.094

0.002	-1.73e-13	-3.89e-14			
Total Assets			-7.923e-14	2.58e-14	-3.068
0.002	-1.3e-13	-2.86e-14			
EPS Growth 3M			-6.126e-06	1.53e-06	-4.002
0.000	-9.13e-06	-3.13e-06			
EPS Growth 12M			2.182e-06	1.53e-06	1.423
0.155	-8.24e-07	5.19e-06			
Net Debt Growth 3M			-1.748e-06	1.95e-06	-0.897
0.370	-5.57e-06	2.07e-06			
Net Debt Growth 12M			5.675e-06	1.98e-06	2.872
0.004	1.8e-06	9.55e-06			
Sales Growth 3M			4.22e-06	2.06e-06	2.051
0.040	1.87e-07	8.25e-06			
Sales Growth 12M			-6.66e-06	2.1e-06	-3.169
0.002	-1.08e-05	-2.54e-06			
Total Assets Growth 3M			-2.435e-07	2.31e-06	-0.105
0.916	-4.77e-06	4.28e-06			
Total Assets Growth 12M			-2.601e-06	2.46e-06	-1.059
0.290	-7.42e-06	2.21e-06			
CF0 To Assets			4.355e-05	2.81e-05	1.551
0.121	-1.15e-05	9.86e-05			
Capex To Assets			-0.0001	6.1e-05	-2.246
0.025	-0.000	-1.74e-05			
Capex To FCF			6.95e-05	3.42e-05	2.030
0.042	2.4e-06	0.000			
Capex To Sales			0.0002	6.51e-05	3.016
0.003	6.87e-05	0.000			
EBIT To Assets			1.444e-05	2.83e-05	0.511
0.610	-4.1e-05	6.99e-05			
Retained Earnings To Assets			-0.0004	6.01e-05	-6.676
0.000	-0.001	-0.000			
Downside Risk			3.345e-05	1.73e-05	1.932
0.053	-4.83e-07	6.74e-05			
Index Beta			-2.09e-06	3.55e-07	-5.886
0.000	-2.79e-06	-1.39e-06			
Log Market Cap			0.0002	6.04e-05	3.147
0.002	7.17e-05	0.000			
Volatility 3M			-8.754e-05	1.47e-05	-5.939
0.000	-0.000	-5.86e-05			
stock_3D SYSTEMS CORP			0.1609	0.014	11.264
0.000	0.133	0.189			
stock_3M COMPANY			0.1423	0.012	11.416
0.000	0.118	0.167			
stock_ABBOTT LABORATORIES			0.0903	0.010	9.116
0.000	0.071	0.110			
stock_ABBVIE INC			0.1833	0.018	10.070
0.000	0.148	0.219			

stock_ALLERGAN INC	0.1434	0.009	15.113
0.000 0.125 0.162			
stock_ALLERGAN PLC	0.1683	0.013	12.648
0.000 0.142 0.194			
stock_ALTABA INC	0.1825	0.015	12.388
0.000 0.154 0.211			
stock_ALTRIA GROUP INC.	0.1533	0.013	12.015
0.000 0.128 0.178			
stock_AMAZON.COM INC	0.1494	0.015	10.035
0.000 0.120 0.179			
stock_AMERICAN AIRLINES GROUP INC	0.1433	0.017	8.373
0.000 0.110 0.177			
stock_AMERICAN EXPRESS COMPANY	0.0785	0.008	9.844
0.000 0.063 0.094			
stock_AMERICAN INTL GROUP INC	0.1021	0.014	7.505
0.000 0.075 0.129			
stock_AMGEN INC	0.0915	0.009	10.550
0.000 0.074 0.108			
stock_ANADARKO PETROLEUM CORP	0.0978	0.008	12.627
0.000 0.083 0.113			
stock_APACHE CORP	0.0568	0.014	4.038
0.000 0.029 0.084			
stock_APPLE INC	0.1309	0.012	10.689
0.000 0.107 0.155			
stock_APPLIED MATERIALS INC	0.1080	0.010	11.289
0.000 0.089 0.127			
stock_ARCONIC INC	0.0422	0.007	5.984
0.000 0.028 0.056			
stock_AT&T INC. COM	0.1122	0.014	8.068
0.000 0.085 0.139			
stock_Alphabet Inc. Cl A	0.2024	0.018	11.450
0.000 0.168 0.237			
stock_BAKER HUGHES INC	0.0945	0.009	11.076
0.000 0.078 0.111			
stock_BANK OF AMERICA CORP	0.2669	0.052	5.090
0.000 0.164 0.370			
stock_BERKSHIRE HATHAWAY INC CL-B	0.1630	0.018	8.968
0.000 0.127 0.199			
stock_BIOGEN INC	0.1688	0.012	14.185
0.000 0.145 0.192			
stock_BOEING CO	0.0769	0.009	8.299
0.000 0.059 0.095			
stock_BOOKING HOLDINGS INC	0.1898	0.015	12.281
0.000 0.159 0.220			
stock_BRISTOL MYERS SQUIBB COMPANY	0.1327	0.011	12.504
0.000 0.112 0.153			
stock_BROADCOM CORP	0.1655	0.014	11.708

0.000	0.138	0.193			
stock_BROADCOM INC			0.2090	0.018	11.611
0.000	0.174	0.244			
stock_CATERPILLAR INC			0.0647	0.009	7.093
0.000	0.047	0.083			
stock_CELGENE CORP			0.1326	0.010	12.974
0.000	0.113	0.153			
stock_CHESAPEAKE ENERGY CORP			0.0682	0.016	4.174
0.000	0.036	0.100			
stock_CHEVRON CORPORATION			0.1637	0.019	8.770
0.000	0.127	0.200			
stock_CISCO SYSTEMS INC			0.0975	0.009	10.689
0.000	0.080	0.115			
stock_CITIGROUP			0.2358	0.045	5.236
0.000	0.148	0.324			
stock_COCA-COLA CO			0.1313	0.013	10.439
0.000	0.107	0.156			
stock_COMCAST CORP			0.0961	0.009	10.691
0.000	0.078	0.114			
stock_CONOCOPHILLIPS			0.1432	0.016	9.039
0.000	0.112	0.174			
stock_COVIDIEN PLC			0.2103	0.017	12.561
0.000	0.177	0.243			
stock_CVS HEALTH CORP			0.1147	0.012	9.823
0.000	0.092	0.138			
stock_DEERE & CO			0.0556	0.010	5.698
0.000	0.036	0.075			
stock_DELTA AIR LINES INC			0.1560	0.016	9.833
0.000	0.125	0.187			
stock_DIRECTV			0.1262	0.015	8.223
0.000	0.096	0.156			
stock_DOLLAR GENERAL CORP			0.1543	0.016	9.600
0.000	0.123	0.186			
stock_DOW CHEMICAL CO			0.0810	0.009	8.981
0.000	0.063	0.099			
stock_E.I. Du Pont De Nemours A			0.0722	0.009	7.789
0.000	0.054	0.090			
stock_EBAY INC			0.1879	0.016	11.397
0.000	0.156	0.220			
stock EMC CORPORATION			0.1141	0.009	12.320
0.000	0.096	0.132			
stock_EOG RESOURCES INC			0.1212	0.009	13.575
0.000	0.104	0.139			
stock_EXPRESS SCRIPTS HOLDING CO			0.0745	0.010	7.775
0.000	0.056	0.093			
stock_EXXON MOBIL CORPORATION			0.1865	0.021	8.679
0.000	0.144	0.229			

stock_FACEBOOK INC	0.2171	0.019	11.586
0.000 0.180 0.254			
stock_FEDEX CORPORATION	0.1002	0.010	10.231
0.000 0.081 0.119			
stock_FIRST SOLAR INC	0.1560	0.017	9.046
0.000 0.122 0.190			
stock_FORD MOTOR CO(NEW)	0.0733	0.011	6.384
0.000 0.051 0.096			
stock_FREEPORT-MCMORAN INC	0.0974	0.013	7.766
0.000 0.073 0.122			
stock_GENERAL ELECTRIC CO	0.1500	0.018	8.332
0.000 0.115 0.185			
stock_GENERAL MOTORS CO	0.1448	0.018	8.032
0.000 0.109 0.180			
stock_GILEAD SCIENCES INC	0.1445	0.011	12.934
0.000 0.123 0.166			
stock_GOLDMAN SACHS GROUP INC	0.2410	0.025	9.822
0.000 0.193 0.289			
stock_GOPRO INC	0.1946	0.018	10.636
0.000 0.159 0.230			
stock_HALLIBURTON CO (HOLDING CO)	0.1050	0.010	10.582
0.000 0.086 0.124			
stock_HOME DEPOT INC	0.1160	0.011	10.522
0.000 0.094 0.138			
stock_HP INC	0.0879	0.010	8.554
0.000 0.068 0.108			
stock_INTEL CORP	0.1170	0.011	10.511
0.000 0.095 0.139			
stock_INTL BUSINESS MACHINES CORP	0.1135	0.012	9.176
0.000 0.089 0.138			
stock_JOHNSON AND JOHNSON	0.1375	0.013	10.821
0.000 0.113 0.162			
stock_JPMORGAN CHASE & CO COM STK	0.3443	0.064	5.416
0.000 0.220 0.469			
stock_KEURIG GREEN MOUNTAIN INC	0.1655	0.013	12.506
0.000 0.140 0.191			
stock_KINDER MORGAN INC	0.1372	0.017	7.888
0.000 0.103 0.171			
stock_LAS VEGAS SANDS CORP	0.1657	0.017	9.963
0.000 0.133 0.198			
stock_LILLY ELI & CO	0.1296	0.011	11.275
0.000 0.107 0.152			
stock_LINKEDIN CORP	0.1981	0.018	10.815
0.000 0.162 0.234			
stock_LOWES COMPANIES INC	0.1054	0.010	10.827
0.000 0.086 0.125			
stock_LYONDELLBASELL INDUSTRIES NV	0.1509	0.017	8.959

0.000	0.118	0.184			
stock_MARATHON PETROLEUM CORP			0.1477	0.018	8.006
0.000	0.112	0.184			
stock_MASTERCARD INCORPORATED			0.2324	0.018	12.916
0.000	0.197	0.268			
stock_MCDONALDS CORP			0.1322	0.013	10.363
0.000	0.107	0.157			
stock_MEDTRONIC PLC			0.1496	0.011	13.103
0.000	0.127	0.172			
stock_MERCK & CO INC			0.1372	0.012	11.332
0.000	0.113	0.161			
stock_METLIFE INC			0.1720	0.025	6.765
0.000	0.122	0.222			
stock_MICHAEL KORS HOLDINGS LTD			0.2136	0.019	11.178
0.000	0.176	0.251			
stock_MICRON TECHNOLOGY INC			0.1122	0.010	11.094
0.000	0.092	0.132			
stock_MICROSOFT CORP			0.1369	0.012	11.104
0.000	0.113	0.161			
stock_MONDELEZ INTERNATIONAL INC			0.1580	0.015	10.549
0.000	0.129	0.187			
stock_MONSANTO COMPANY			0.1725	0.015	11.144
0.000	0.142	0.203			
stock_MORGAN STANLEY			0.2094	0.023	9.058
0.000	0.164	0.255			
stock_MYLAN NV			0.1362	0.011	12.231
0.000	0.114	0.158			
stock_NATIONAL OILWELL VARCO INC.			0.1420	0.016	8.817
0.000	0.110	0.174			
stock_NETFLIX INC			0.2052	0.016	12.512
0.000	0.173	0.237			
stock_NEWMONT MINING CORP (HOLDING COMPANY)			0.0949	0.012	7.982
0.000	0.072	0.118			
stock_NEWS CP - CL A			0.1394	0.013	11.131
0.000	0.115	0.164			
stock_NIKE INC CL-B			0.1440	0.012	12.236
0.000	0.121	0.167			
stock_OCCIDENTAL PETROLEUM CORP			0.1303	0.012	10.690
0.000	0.106	0.154			
stock_ORACLE CORP			0.1384	0.012	11.935
0.000	0.116	0.161			
stock_PANDORA MEDIA INC			0.2348	0.020	11.961
0.000	0.196	0.273			
stock_PENNEY J.C. CO INC (HOLDING COMPANY)			0.0553	0.010	5.558
0.000	0.036	0.075			
stock_PEPSICO INC			0.1325	0.013	9.962
0.000	0.106	0.159			

stock_PFIZER INC	0.1554	0.013	11.701
0.000 0.129 0.181			
stock_PHILIP MORRIS INTERNATIONAL INC	0.2017	0.019	10.405
0.000 0.164 0.240			
stock_PIONEER NAT RES CO	0.1980	0.014	13.850
0.000 0.170 0.226			
stock_PRECISION CASTPARTS CORP	0.1519	0.014	11.190
0.000 0.125 0.179			
stock_PROCTER & GAMBLE CO	0.1412	0.014	10.286
0.000 0.114 0.168			
stock_QUALCOMM INC	0.1585	0.013	12.011
0.000 0.133 0.184			
stock_REGENERON PHARMACEUTICALS INC	0.1549	0.018	8.846
0.000 0.121 0.189			
stock_SALESFORCE.COM INC	0.1797	0.016	10.945
0.000 0.148 0.212			
stock_SALIX PHARMACEUTICALS LTD	1.482e-11	1.92e-11	0.771
0.440 -2.28e-11 5.25e-11			
stock_SANDISK CORP	0.1842	0.014	13.280
0.000 0.157 0.211			
stock_SCHLUMBERGER LTD.	0.1437	0.013	11.126
0.000 0.118 0.169			
stock_SKYWORKS SOLUTIONS INC	0.1829	0.016	11.217
0.000 0.151 0.215			
stock_SOLARCITY CORP	0.2218	0.019	11.593
0.000 0.184 0.259			
stock_SOUTHWEST AIRLINES CO	0.1205	0.010	11.615
0.000 0.100 0.141			
stock_STARBUCKS CORPORATION	0.1770	0.013	13.501
0.000 0.151 0.203			
stock_SUNEDISON INC	0.1297	0.042	3.095
0.002 0.048 0.212			
stock_TARGET CORPORATION	0.1226	0.014	8.556
0.000 0.094 0.151			
stock_TESLA INC	0.2039	0.018	11.215
0.000 0.168 0.240			
stock_TEXAS INSTRUMENTS INC	0.1730	0.014	12.080
0.000 0.145 0.201			
stock_TIME WARNER CABLE INC	0.1446	0.016	9.138
0.000 0.114 0.176			
stock_TIME WARNER INC.	0.0757	0.007	11.026
0.000 0.062 0.089			
stock_TWITTER INC	0.1978	0.019	10.476
0.000 0.161 0.235			
stock_UNION PACIFIC CORPORATION	0.1502	0.013	11.655
0.000 0.125 0.175			
stock_UNITED CONTINENTAL HOLDINGS IN	0.1245	0.016	7.991

0.000	0.094	0.155			
stock_UNITED PARCEL SERVICE INC.CL B			0.1248	0.015	8.288
0.000	0.095	0.154			
stock_UNITED TECHNOLOGIES CORP			0.1288	0.013	9.937
0.000	0.103	0.154			
stock_UNITEDHEALTH GROUP INC			0.1402	0.013	10.559
0.000	0.114	0.166			
stock_VALERO ENERGY CORP (NEW)			0.1296	0.013	9.686
0.000	0.103	0.156			
stock_VERIZON COMMUNICATIONS			0.1198	0.016	7.496
0.000	0.088	0.151			
stock_VISA INC			0.2206	0.017	12.867
0.000	0.187	0.254			
stock_WALGREENS BOOTS ALLIANCE INC			0.1369	0.013	10.559
0.000	0.111	0.162			
stock_WALMART INC			0.1522	0.021	7.225
0.000	0.111	0.194			
stock_WALT DISNEY CO			0.1309	0.010	13.023
0.000	0.111	0.151			
stock_WELLS FARGO & CO(NEW)			0.2969	0.043	6.946
0.000	0.213	0.381			
stock_WILLIAMS COMPANIES			0.1325	0.013	10.104
0.000	0.107	0.158			
stock_WYNN RESORTS LTD			0.1418	0.016	8.999
0.000	0.111	0.173			
stock_YELP INC			0.1947	0.019	10.257
0.000	0.157	0.232			

Omnibus:	0.654	Durbin-Watson:	1.503
Prob(Omnibus):	0.721	Jarque-Bera (JB):	0.669
Skew:	-0.007	Prob(JB):	0.716
Kurtosis:	2.986	Cond. No.	6.39e+16

Warnings:

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

[2] The condition number is large, 6.39e+16. This might indicate that there are strong multicollinearity or other numerical problems.

"""

```
[47]: target = 'Returns20D'
model_data = pd.concat([y[[target]], X], axis=1).dropna()
model_data = model_data[model_data[target].between(model_data[target].quantile(
    ↪0.25),
                                                    model_data[target].quantile(
    ↪0.975))]

```

```

model = OLS(endog=model_data[target], exog=model_data.drop(target, axis=1))
trained_model = model.fit()
trained_model.summary()

```

[47]: <class 'statsmodels.iolib.summary.Summary'>

```

"""
                                OLS Regression Results
=====
Dep. Variable:                Returns20D      R-squared:                0.072
Model:                        OLS             Adj. R-squared:           0.068
Method:                      Least Squares    F-statistic:              19.10
Date:                        Sun, 09 Sep 2018   Prob (F-statistic):       0.00
Time:                        21:18:04         Log-Likelihood:           62705.
No. Observations:            42460            AIC:                     -1.251e+05
Df Residuals:                42288            BIC:                     -1.236e+05
Df Model:                    171
Covariance Type:             nonrobust
=====
=====
                                coef      std err          t
P>|t|      [95.0% Conf. Int.]
-----
DividendYield                1.193e-05    2.23e-06     5.351
0.000      7.56e-06  1.63e-05
EBITDAYield                 -0.0001    4.51e-05    -3.287
0.001      -0.000 -5.98e-05
EVToEBITDA                   0.0003    4.07e-05     7.808
0.000      0.000   0.000
EVToFCF                     -3.67e-06    4.99e-05    -0.074
0.941      -0.000  9.42e-05
PriceToBook                  1.86e-05    4.73e-05     0.393
0.694     -7.41e-05   0.000
PriceToDilutedEarningsTTM    -5.406e-05    2.12e-05    -2.549
0.011     -9.56e-05 -1.25e-05
PriceToEarningsTTM          -8.22e-07    9.41e-07    -0.873
0.382     -2.67e-06  1.02e-06
PriceToFCF                   2.678e-06    4.12e-05     0.065
0.948     -7.8e-05  8.33e-05
PriceToOperatingCashflow     -0.0001    2.91e-05    -4.551
0.000     -0.000 -7.54e-05
PriceToSalesTTM             -4.302e-05    2.5e-06    -17.222
0.000     -4.79e-05 -3.81e-05
Directional Movement Index  -3.389e-05    9.51e-06    -3.566
0.000     -5.25e-05 -1.53e-05
Money Flow Index             2.884e-05    1.23e-05     2.336

```

0.019	4.64e-06	5.3e-05			
Percent Above Low			-7.04e-05	2.47e-05	-2.855
0.004	-0.000	-2.21e-05			
Percent Below High			4.825e-05	1.89e-05	2.559
0.010	1.13e-05	8.52e-05			
Price Oscillator			-5.428e-06	1.33e-05	-0.407
0.684	-3.15e-05	2.07e-05			
Trendline			4.502e-05	2.04e-05	2.204
0.028	4.98e-06	8.51e-05			
AssetToEquityRatio			-8.615e-06	1.86e-06	-4.637
0.000	-1.23e-05	-4.97e-06			
AssetTurnover			-0.0002	8.11e-05	-2.720
0.007	-0.000	-6.16e-05			
CurrentRatio			1.14e-05	2.4e-06	4.756
0.000	6.7e-06	1.61e-05			
DebtToAssetRatio			2.131e-06	1.5e-06	1.421
0.155	-8.08e-07	5.07e-06			
DebtToEquityRatio			4.261e-06	1.74e-06	2.445
0.014	8.45e-07	7.68e-06			
MertonsDD			-0.0013	0.000	-6.145
0.000	-0.002	-0.001			
WorkingCapitalToAssets			5.08e-06	2.89e-06	1.759
0.079	-5.8e-07	1.07e-05			
WorkingCapitalToSales			-0.0004	9.31e-05	-4.593
0.000	-0.001	-0.000			
Dividend Growth			-3.037e-06	9.15e-07	-3.319
0.001	-4.83e-06	-1.24e-06			
EPS			2.228e-06	1.41e-06	1.583
0.113	-5.3e-07	4.99e-06			
Net Debt			-2.368e-13	5.14e-14	-4.609
0.000	-3.37e-13	-1.36e-13			
Sales			-2.182e-13	5.03e-14	-4.341
0.000	-3.17e-13	-1.2e-13			
Total Assets			-2.513e-13	3.73e-14	-6.741
0.000	-3.24e-13	-1.78e-13			
EPS Growth 3M			-1.786e-05	2.15e-06	-8.320
0.000	-2.21e-05	-1.37e-05			
EPS Growth 12M			2.263e-06	2.15e-06	1.053
0.292	-1.95e-06	6.47e-06			
Net Debt Growth 3M			-4.19e-06	2.73e-06	-1.533
0.125	-9.55e-06	1.17e-06			
Net Debt Growth 12M			1.181e-06	2.76e-06	0.428
0.669	-4.23e-06	6.59e-06			
Sales Growth 3M			-7.312e-07	2.88e-06	-0.254
0.800	-6.38e-06	4.92e-06			
Sales Growth 12M			-1.036e-05	2.94e-06	-3.525
0.000	-1.61e-05	-4.6e-06			

Total Assets Growth 3M			7.478e-06	3.24e-06	2.310
0.021	1.13e-06	1.38e-05			
Total Assets Growth 12M			-3.848e-06	3.44e-06	-1.120
0.263	-1.06e-05	2.89e-06			
CFO To Assets			9.296e-05	3.95e-05	2.352
0.019	1.55e-05	0.000			
Capex To Assets			-0.0002	8.77e-05	-1.768
0.077	-0.000	1.68e-05			
Capex To FCF			0.0002	4.86e-05	3.199
0.001	6.03e-05	0.000			
Capex To Sales			0.0003	9.32e-05	2.992
0.003	9.62e-05	0.000			
EBIT To Assets			4.836e-06	4e-05	0.121
0.904	-7.35e-05	8.32e-05			
Retained Earnings To Assets			-0.0010	8.46e-05	-12.222
0.000	-0.001	-0.001			
Downside Risk			-2.381e-05	2.45e-05	-0.972
0.331	-7.18e-05	2.42e-05			
Index Beta			-4.429e-06	5.04e-07	-8.793
0.000	-5.42e-06	-3.44e-06			
Log Market Cap			0.0001	8.62e-05	1.329
0.184	-5.44e-05	0.000			
Volatility 3M			-0.0002	2.08e-05	-7.260
0.000	-0.000	-0.000			
stock_3D SYSTEMS CORP			0.3173	0.020	15.578
0.000	0.277	0.357			
stock_3M COMPANY			0.3182	0.018	17.973
0.000	0.284	0.353			
stock_ABBOTT LABORATORIES			0.2168	0.014	14.970
0.000	0.188	0.245			
stock_ABBVIE INC			0.3427	0.026	13.306
0.000	0.292	0.393			
stock_ALLERGAN INC			0.3183	0.014	23.540
0.000	0.292	0.345			
stock_ALLERGAN PLC			0.3267	0.019	17.361
0.000	0.290	0.364			
stock_ALTABA INC			0.3407	0.021	16.280
0.000	0.300	0.382			
stock_ALTRIA GROUP INC.			0.3366	0.018	18.421
0.000	0.301	0.372			
stock_AMAZON.COM INC			0.2840	0.021	13.457
0.000	0.243	0.325			
stock_AMERICAN AIRLINES GROUP INC			0.2416	0.024	10.047
0.000	0.194	0.289			
stock_AMERICAN EXPRESS COMPANY			0.1996	0.011	17.471
0.000	0.177	0.222			
stock_AMERICAN INTL GROUP INC			0.2697	0.020	13.737

0.000	0.231	0.308			
stock_AMGEN INC			0.2179	0.012	17.559
0.000	0.194	0.242			
stock_ANADARKO PETROLEUM CORP			0.2158	0.011	19.604
0.000	0.194	0.237			
stock_APACHE CORP			0.1494	0.056	2.651
0.008	0.039	0.260			
stock_APPLE INC			0.3383	0.018	19.158
0.000	0.304	0.373			
stock_APPLIED MATERIALS INC			0.2390	0.014	17.579
0.000	0.212	0.266			
stock_ARCONIC INC			0.1068	0.010	10.685
0.000	0.087	0.126			
stock_AT&T INC. COM			0.2514	0.020	12.594
0.000	0.212	0.291			
stock_Alphabet Inc. Cl A			0.4051	0.025	16.157
0.000	0.356	0.454			
stock_BAKER HUGHES INC			0.2139	0.012	17.586
0.000	0.190	0.238			
stock_BANK OF AMERICA CORP			0.7417	0.076	9.797
0.000	0.593	0.890			
stock_BERKSHIRE HATHAWAY INC CL-B			0.3567	0.026	13.681
0.000	0.306	0.408			
stock_BIOGEN INC			0.3593	0.017	21.207
0.000	0.326	0.392			
stock_BOEING CO			0.2107	0.013	15.879
0.000	0.185	0.237			
stock_BOOKING HOLDINGS INC			0.3602	0.022	16.449
0.000	0.317	0.403			
stock_BRISTOL MYERS SQUIBB COMPANY			0.3115	0.015	20.543
0.000	0.282	0.341			
stock_BROADCOM CORP			0.2813	0.020	14.099
0.000	0.242	0.320			
stock_BROADCOM INC			0.3808	0.026	14.895
0.000	0.331	0.431			
stock_CATERPILLAR INC			0.1730	0.013	13.255
0.000	0.147	0.199			
stock_CELGENE CORP			0.2960	0.015	20.285
0.000	0.267	0.325			
stock_CHESAPEAKE ENERGY CORP			-4.999e-14	8.77e-14	-0.570
0.568	-2.22e-13	1.22e-13			
stock_CHEVRON CORPORATION			0.3485	0.027	13.048
0.000	0.296	0.401			
stock_CISCO SYSTEMS INC			0.2298	0.013	17.569
0.000	0.204	0.255			
stock_CITIGROUP			0.6481	0.065	9.957
0.000	0.521	0.776			

stock_COCA-COLA CO			0.2999	0.018	16.645
0.000	0.265	0.335			
stock_COMCAST CORP			0.2309	0.013	17.938
0.000	0.206	0.256			
stock_CONOCOPHILLIPS			0.2784	0.022	12.429
0.000	0.235	0.322			
stock_COVIDIEN PLC			0.3792	0.024	15.807
0.000	0.332	0.426			
stock_CVS HEALTH CORP			0.2568	0.017	15.384
0.000	0.224	0.289			
stock_DEERE & CO			0.1513	0.014	10.763
0.000	0.124	0.179			
stock_DELTA AIR LINES INC			0.2806	0.022	12.572
0.000	0.237	0.324			
stock_DIRECTV			0.2139	0.022	9.864
0.000	0.171	0.256			
stock_DOLLAR GENERAL CORP			0.2719	0.023	11.971
0.000	0.227	0.316			
stock_DOW CHEMICAL CO			0.1912	0.013	14.832
0.000	0.166	0.216			
stock_E.I. Du Pont De Nemours A			0.1633	0.013	12.300
0.000	0.137	0.189			
stock_EBAY INC			0.3558	0.023	15.256
0.000	0.310	0.402			
stock EMC CORPORATION			0.2526	0.013	19.131
0.000	0.227	0.278			
stock_EOG RESOURCES INC			0.2644	0.013	20.854
0.000	0.240	0.289			
stock_EXPRESS SCRIPTS HOLDING CO			0.1640	0.014	11.874
0.000	0.137	0.191			
stock_EXXON MOBIL CORPORATION			0.4155	0.031	13.352
0.000	0.355	0.477			
stock_FACEBOOK INC			0.3934	0.026	14.853
0.000	0.341	0.445			
stock_FEDEX CORPORATION			0.2296	0.014	16.546
0.000	0.202	0.257			
stock_FIRST SOLAR INC			0.3130	0.025	12.617
0.000	0.264	0.362			
stock_FORD MOTOR CO(NEW)			0.1766	0.017	10.680
0.000	0.144	0.209			
stock_FREEPORT-MCMORAN INC			0.1663	0.018	9.357
0.000	0.131	0.201			
stock_GENERAL ELECTRIC CO			0.3810	0.026	14.621
0.000	0.330	0.432			
stock_GENERAL MOTORS CO			0.2661	0.026	10.406
0.000	0.216	0.316			
stock_GILEAD SCIENCES INC			0.3193	0.016	20.030

0.000	0.288	0.351			
stock_GOLDMAN SACHS GROUP INC			0.5289	0.035	14.945
0.000	0.460	0.598			
stock_GOPRO INC			0.3186	0.026	12.297
0.000	0.268	0.369			
stock_HALLIBURTON CO (HOLDING CO)			0.2384	0.014	16.933
0.000	0.211	0.266			
stock_HOME DEPOT INC			0.2761	0.016	17.535
0.000	0.245	0.307			
stock_HP INC			0.2021	0.015	13.749
0.000	0.173	0.231			
stock_INTEL CORP			0.2633	0.016	16.526
0.000	0.232	0.294			
stock_INTL BUSINESS MACHINES CORP			0.2830	0.018	15.965
0.000	0.248	0.318			
stock_JOHNSON AND JOHNSON			0.3200	0.018	17.592
0.000	0.284	0.356			
stock_JPMORGAN CHASE & CO COM STK			0.8913	0.092	9.698
0.000	0.711	1.071			
stock_KEURIG GREEN MOUNTAIN INC			0.3387	0.019	18.109
0.000	0.302	0.375			
stock_KINDER MORGAN INC			0.2413	0.025	9.811
0.000	0.193	0.289			
stock_LAS VEGAS SANDS CORP			0.2950	0.024	12.543
0.000	0.249	0.341			
stock_LILLY ELI & CO			0.2792	0.016	16.965
0.000	0.247	0.311			
stock_LINKEDIN CORP			0.3443	0.026	13.316
0.000	0.294	0.395			
stock_LOWES COMPANIES INC			0.2297	0.014	16.545
0.000	0.202	0.257			
stock_LYONDELLBASELL INDUSTRIES NV			0.2773	0.024	11.680
0.000	0.231	0.324			
stock_MARATHON PETROLEUM CORP			0.2467	0.026	9.411
0.000	0.195	0.298			
stock_MASTERCARD INCORPORATED			0.4555	0.025	17.920
0.000	0.406	0.505			
stock_MCDONALDS CORP			0.2920	0.018	16.033
0.000	0.256	0.328			
stock_MEDTRONIC PLC			0.3192	0.016	19.660
0.000	0.287	0.351			
stock_MERCK & CO INC			0.3003	0.017	17.338
0.000	0.266	0.334			
stock_METLIFE INC			0.3781	0.037	10.338
0.000	0.306	0.450			
stock_MICHAEL KORS HOLDINGS LTD			0.3756	0.027	13.904
0.000	0.323	0.429			

stock_MICRON TECHNOLOGY INC	0.2171	0.014	15.211
0.000 0.189 0.245			
stock_MICROSOFT CORP	0.3047	0.018	17.242
0.000 0.270 0.339			
stock_MONDELEZ INTERNATIONAL INC	0.2891	0.021	13.662
0.000 0.248 0.331			
stock_MONSANTO COMPANY	0.3312	0.022	15.138
0.000 0.288 0.374			
stock_MORGAN STANLEY	0.4563	0.033	13.722
0.000 0.391 0.521			
stock_MYLAN NV	0.2558	0.016	16.113
0.000 0.225 0.287			
stock_NATIONAL OILWELL VARCO INC.	0.2658	0.023	11.681
0.000 0.221 0.310			
stock_NETFLIX INC	0.3875	0.023	16.682
0.000 0.342 0.433			
stock_NEWMONT MINING CORP (HOLDING COMPANY)	0.1446	0.017	8.514
0.000 0.111 0.178			
stock_NEWS CP - CL A	0.2669	0.018	15.067
0.000 0.232 0.302			
stock_NIKE INC CL-B	0.3016	0.017	18.078
0.000 0.269 0.334			
stock_OCCIDENTAL PETROLEUM CORP	0.2756	0.017	15.892
0.000 0.242 0.310			
stock_ORACLE CORP	0.2984	0.017	18.058
0.000 0.266 0.331			
stock_PANDORA MEDIA INC	0.3925	0.028	14.067
0.000 0.338 0.447			
stock_PENNEY J.C. CO INC (HOLDING COMPANY)	0.0737	0.014	5.167
0.000 0.046 0.102			
stock_PEPSICO INC	0.2931	0.019	15.449
0.000 0.256 0.330			
stock_PFIZER INC	0.3336	0.019	17.563
0.000 0.296 0.371			
stock_PHILIP MORRIS INTERNATIONAL INC	0.3844	0.028	13.959
0.000 0.330 0.438			
stock_PIONEER NAT RES CO	0.3579	0.020	17.747
0.000 0.318 0.397			
stock_PRECISION CASTPARTS CORP	0.3008	0.020	14.774
0.000 0.261 0.341			
stock_PROCTER & GAMBLE CO	0.3094	0.020	15.745
0.000 0.271 0.348			
stock_QUALCOMM INC	0.3232	0.019	17.225
0.000 0.286 0.360			
stock_REGENERON PHARMACEUTICALS INC	0.3153	0.043	7.267
0.000 0.230 0.400			
stock_SALESFORCE.COM INC	0.3156	0.023	13.571

0.000	0.270	0.361			
stock_SALIX PHARMACEUTICALS LTD			-5.165e-15	7.41e-15	-0.697
0.486	-1.97e-14	9.37e-15			
stock_SANDISK CORP			0.3350	0.020	17.064
0.000	0.296	0.373			
stock_SCHLUMBERGER LTD.			0.3011	0.018	16.396
0.000	0.265	0.337			
stock_SKYWORKS SOLUTIONS INC			0.3422	0.023	14.843
0.000	0.297	0.387			
stock_SOLARCITY CORP			0.3803	0.027	14.070
0.000	0.327	0.433			
stock_SOUTHWEST AIRLINES CO			0.2513	0.015	16.796
0.000	0.222	0.281			
stock_STARBUCKS CORPORATION			0.3558	0.019	19.139
0.000	0.319	0.392			
stock_SUNEDISON INC			1.713e-16	2.85e-16	0.601
0.548	-3.87e-16	7.3e-16			
stock_TARGET CORPORATION			0.2298	0.020	11.314
0.000	0.190	0.270			
stock_TESLA INC			0.3540	0.026	13.789
0.000	0.304	0.404			
stock_TEXAS INSTRUMENTS INC			0.3573	0.021	17.423
0.000	0.317	0.397			
stock_TIME WARNER CABLE INC			0.2637	0.022	11.821
0.000	0.220	0.307			
stock_TIME WARNER INC.			0.1773	0.010	18.052
0.000	0.158	0.197			
stock_TWITTER INC			0.3333	0.027	12.463
0.000	0.281	0.386			
stock_UNION PACIFIC CORPORATION			0.3164	0.018	17.283
0.000	0.281	0.352			
stock_UNITED CONTINENTAL HOLDINGS IN			0.1975	0.022	8.977
0.000	0.154	0.241			
stock_UNITED PARCEL SERVICE INC.CL B			0.2391	0.021	11.199
0.000	0.197	0.281			
stock_UNITED TECHNOLOGIES CORP			0.2750	0.018	14.928
0.000	0.239	0.311			
stock_UNITEDHEALTH GROUP INC			0.2970	0.019	15.679
0.000	0.260	0.334			
stock_VALERO ENERGY CORP (NEW)			0.2539	0.019	13.356
0.000	0.217	0.291			
stock_VERIZON COMMUNICATIONS			0.2472	0.023	10.825
0.000	0.202	0.292			
stock_VISA INC			0.4192	0.024	17.309
0.000	0.372	0.467			
stock_WALGREENS BOOTS ALLIANCE INC			0.2793	0.018	15.194
0.000	0.243	0.315			

stock_WALMART INC			0.3251	0.031	10.594
0.000	0.265	0.385			
stock_WALT DISNEY CO			0.3131	0.014	21.827
0.000	0.285	0.341			
stock_WELLS FARGO & CO(NEW)			0.7175	0.062	11.586
0.000	0.596	0.839			
stock_WILLIAMS COMPANIES			0.2522	0.019	13.501
0.000	0.216	0.289			
stock_WYNN RESORTS LTD			0.2461	0.022	11.047
0.000	0.202	0.290			
stock_YELP INC			0.3195	0.027	11.882
0.000	0.267	0.372			

Omnibus:	26.157	Durbin-Watson:	1.605
Prob(Omnibus):	0.000	Jarque-Bera (JB):	26.187
Skew:	0.059	Prob(JB):	2.06e-06
Kurtosis:	2.970	Cond. No.	1.95e+19

Warnings:

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

[2] The smallest eigenvalue is 9.91e-12. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

"""

1.12 Linear Models for Prediction: sklearn

Since sklearn is tailored towards prediction, we will evaluate the linear regression model based on its predictive performance using cross-validation.

1.12.1 Custom Time Series Cross-Validation

Our data consists of grouped time series data that requires a custom cross-validation function to provide the train and test indices that ensure that the test data immediately follows the training data for each equity and we do not inadvertently create a look-ahead bias or leakage.

We can achieve this using the following function that returns a generator yielding pairs of train and test dates. The set of train dates that ensure a minimum length of the training periods. The number of pairs depends on the parameter `nfolds`. The distinct test periods do not overlap and are located at the end of the period available in the data. After a test period is used, it becomes part of the training data that grow in size accordingly:

```
[158]: def time_series_split(d=model_data, nfolds=5, min_train=21):
        """Generate train/test dates for nfolds
        with at least min_train train obs
        """
        train_dates = d[:min_train].tolist()
```

```

n = int(len(dates)/(nfolgs + 1)) + 1
test_folds = [d[i:i + n] for i in range(min_train, len(d), n)]
for test_dates in test_folds:
    if len(train_dates) > min_train:
        yield train_dates, test_dates
    train_dates.extend(test_dates)

```

1.12.2 Select Features and Target

We need to select the appropriate return series (we will again use a 10-day holding period) and remove outliers. We will also convert returns to log returns as follows:

```

[49]: target = 'Returns10D'
outliers = .01
model_data = pd.concat([y[[target]], X], axis=1).dropna().reset_index('asset',
↳drop=True)
model_data = model_data[model_data[target].between(*model_data[target].
↳quantile([outliers, 1-outliers]).values)]

model_data[target] = np.log1p(model_data[target])
features = model_data.drop(target, axis=1).columns
dates = model_data.index.unique()

print(model_data.info())

```

```

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 45114 entries, 2014-01-02 to 2015-12-16
Columns: 183 entries, Returns10D to stock_YELP INC
dtypes: float64(183)
memory usage: 63.3 MB
None

```

```

[50]: model_data[target].describe()

```

```

[50]: count      45114.000000
      mean         0.001159
      std         0.045740
      min        -0.157448
      25%        -0.025013
      50%         0.002817
      75%         0.028880
      max         0.146139
      Name: Returns10D, dtype: float64

```

```

[51]: idx = pd.IndexSlice

```

1.13 OLS Linear Regression

We will use 250 folds to generally predict about 2 days of forward returns following the historical training data that will gradually increase in length.

Each iteration obtains the appropriate training and test dates from our custom cross-validation function, selects the corresponding features and targets, and then trains and predicts accordingly.

We capture the root mean squared error as well as the Spearman rank correlation between actual and predicted values:

```
[52]: nfold = 250
lr = LinearRegression()

test_results, result_idx, preds = [], [], pd.DataFrame()
for train_dates, test_dates in time_series_split(dates, nfold=nfold):

    X_train = model_data.loc[idx[train_dates], features]
    y_train = model_data.loc[idx[train_dates], target]
    lr.fit(X=X_train, y=y_train)

    X_test = model_data.loc[idx[test_dates], features]
    y_test = model_data.loc[idx[test_dates], target]
    y_pred = lr.predict(X_test)

    rmse = np.sqrt(mean_squared_error(y_pred=y_pred, y_true=y_test))
    ic, pval = spearmanr(y_pred, y_test)

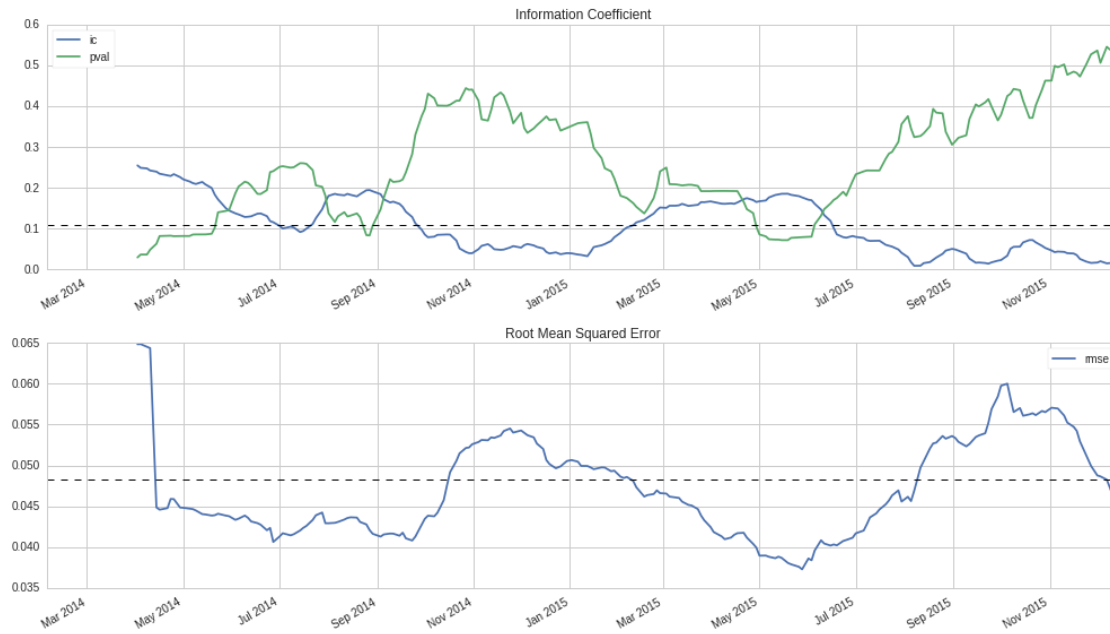
    test_results.append([rmse, ic, pval])
    preds = preds.append(y_test.to_frame('actuals').assign(predicted=y_pred))
    result_idx.append(train_dates[-1])

[53]: test_result = pd.DataFrame(test_results, columns=['rmse', 'ic', 'pval'],
    ↪ index=result_idx)
```

1.13.1 Results

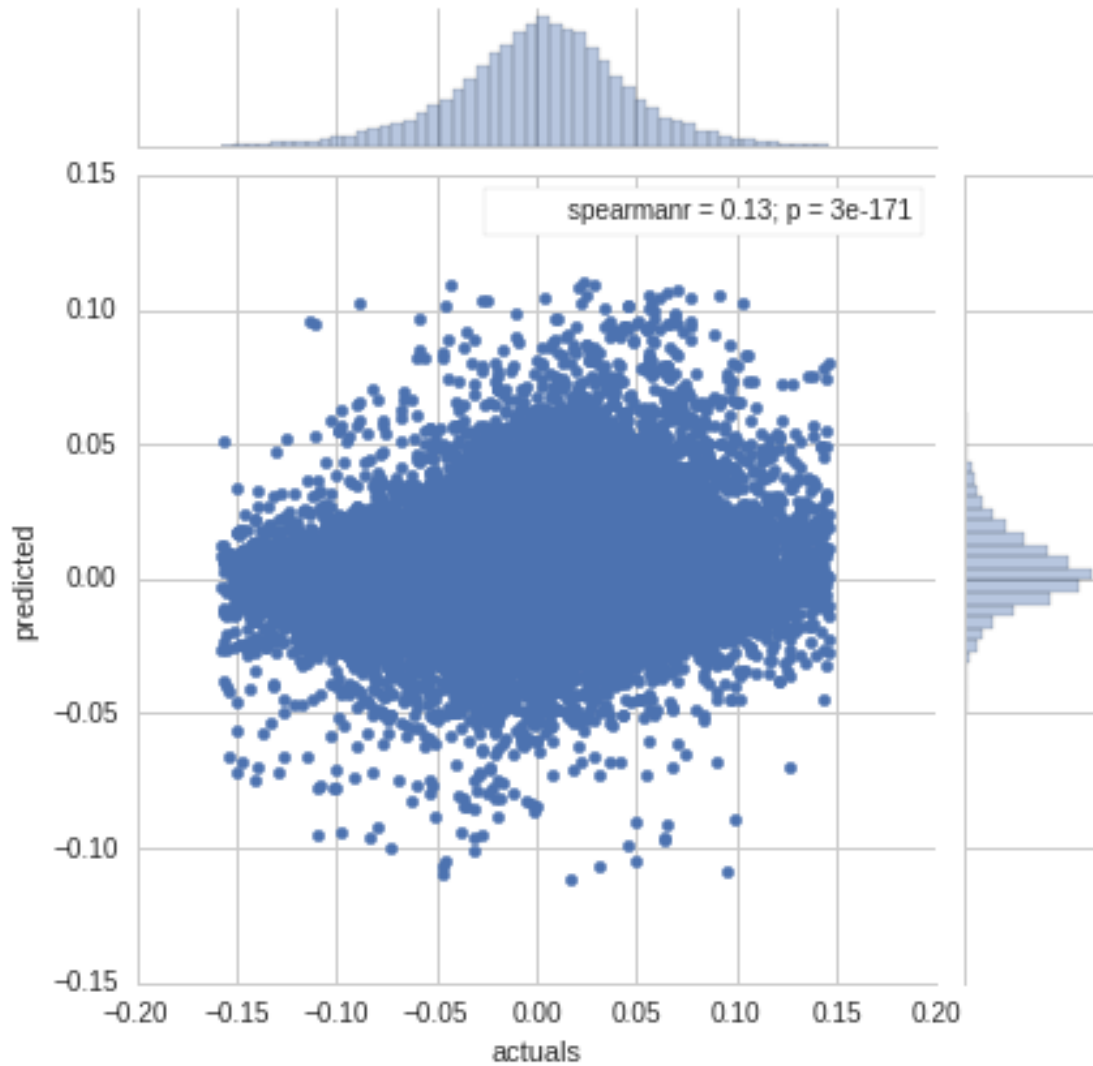
We have captured the test predictions from the 250 folds and can compute both the overall and a 21-day rolling average:

```
[54]: fig, axes = plt.subplots(nrows=2)
rolling_result = test_result.rolling(21).mean()
rolling_result[['ic', 'pval']].plot(ax=axes[0], title='Information Coefficient')
axes[0].axhline(test_result.ic.mean(), lw=1, ls='--', color='k')
rolling_result[['rmse']].plot(ax=axes[1], title='Root Mean Squared Error')
axes[1].axhline(test_result.rmse.mean(), lw=1, ls='--', color='k')
plt.tight_layout();
```



For the entire period, we see that the Information Coefficient measured by the rank correlation of actual and predicted returns is weakly positive and statistically significant:

```
[55]: preds_cleaned = preds[(preds.predicted.between(*preds.predicted.quantile([.001,
↪.999])).values)]
sns.jointplot(x='actuals', y='predicted', data=preds_cleaned,
↪stat_func=spearmanr);
```



1.14 Regularization

For the ridge regression, we need to tune the regularization parameter with the keyword `alpha` that corresponds to the `alpha` we used previously. We will try 21 values from 10^{-5} to 10^5 in logarithmic steps.

1.14.1 Ridge Regression: L2 Penalty

The scale sensitivity of the ridge penalty requires us to standardize the inputs using the `StandardScaler`. Note that we always learn the mean and the standard deviation from the training set using the `.fit_transform()` method and then apply these learned parameters to the test set using the `.transform()` method.

```
[56]: nfold = 250
      alphas = np.logspace(-5, 5, 11)
```



```

scaler = StandardScaler()

ridge_result, ridge_coeffs = pd.DataFrame(), pd.DataFrame()
for i, alpha in enumerate(alphas):
    print i,
    coeffs, test_results = [], []
    lr_ridge = Ridge(alpha=alpha)
    for train_dates, test_dates in time_series_split(dates, nfolds=nfolds):

        X_train = model_data.loc[idx[train_dates], features]
        y_train = model_data.loc[idx[train_dates], target]
        lr_ridge.fit(X=scaler.fit_transform(X_train), y=y_train)
        coeffs.append(lr_ridge.coef_)

        X_test = model_data.loc[idx[test_dates], features]
        y_test = model_data.loc[idx[test_dates], target]
        y_pred = lr_ridge.predict(scaler.transform(X_test))

        rmse = np.sqrt(mean_squared_error(y_pred=y_pred, y_true=y_test))
        ic, pval = spearmanr(y_pred, y_test)

        test_results.append([train_dates[-1], rmse, ic, pval, alpha])
    test_results = pd.DataFrame(test_results, columns=['date', 'rmse', 'ic', 'pval', 'alpha'])
    ridge_result = ridge_result.append(test_results)
    ridge_coeffs[alpha] = np.mean(coeffs, axis=0)

```

0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

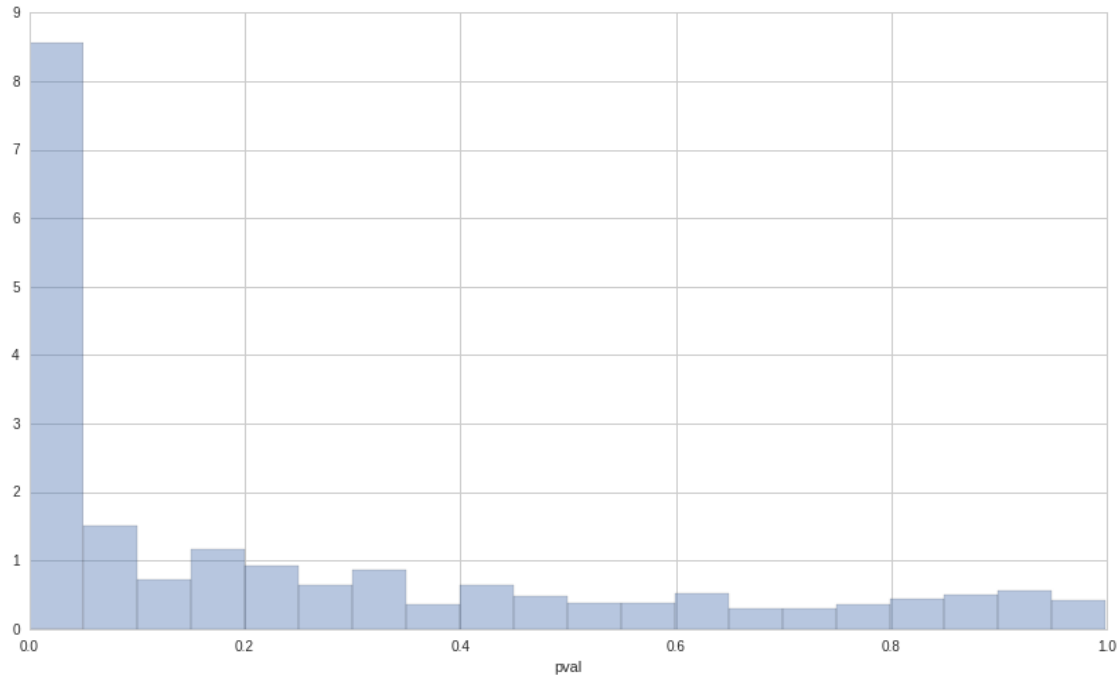
```
[82]: ridge_result.describe()
```

```
[82]:
```

	rmse	ic	pval	alpha
count	4956.000000	4956.000000	4.956000e+03	4.956000e+03
mean	0.046201	0.095743	2.462496e-01	5.291005e+08
std	0.018699	0.148136	2.990978e-01	2.128608e+09
min	0.028501	-0.422446	1.374229e-16	1.000000e-10
25%	0.038269	-0.005162	4.278807e-03	1.000000e-05
50%	0.043257	0.095800	9.506434e-02	1.000000e+00
75%	0.050236	0.201505	4.138598e-01	1.000000e+05
max	0.466332	0.576016	9.991168e-01	1.000000e+10

1.14.2 Significance of Information Coefficients - p-value Distribution

```
[91]: sns.distplot(ridge_result.pval, bins=20, norm_hist=True, kde=False);
```



```
[109]: ridge_result_sig = ridge_result[(ridge_result.pval < .05) & (ridge_result.alpha.
↪between(10**-5, 10**5))]
ridge_result_sig_alpha = ridge_result_sig.groupby('alpha')
```

```
[115]: ridge_coeffs_main = ridge_coeffs.filter(ridge_result_sig.alpha.unique())
```

1.14.3 Ridge Path

We can now plot the information coefficient obtained for each hyperparameter value and also visualize how the coefficient values evolve as the regularization increases. The results show that we get the highest IC value for a value of $\lambda = 10$. For this level of regularization, the right-hand panel reveals that the coefficients have been already significantly shrunk compared to the (almost) unconstrained model with $\lambda = 10^{-5}$:

```
[172]: ridge_result.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 4956 entries, 0 to 235
Data columns (total 5 columns):
date      4956 non-null datetime64[ns, UTC]
rmse      4956 non-null float64
ic         4956 non-null float64
pval      4956 non-null float64
alpha     4956 non-null float64
```

```
dtypes: datetime64[ns, UTC](1), float64(4)
memory usage: 232.3 KB
```

```
[103]: best_ic = ridge_result_sig_alpha['ic'].mean().max()
best_alpha = ridge_result_sig_alpha['ic'].mean().idxmax()
```

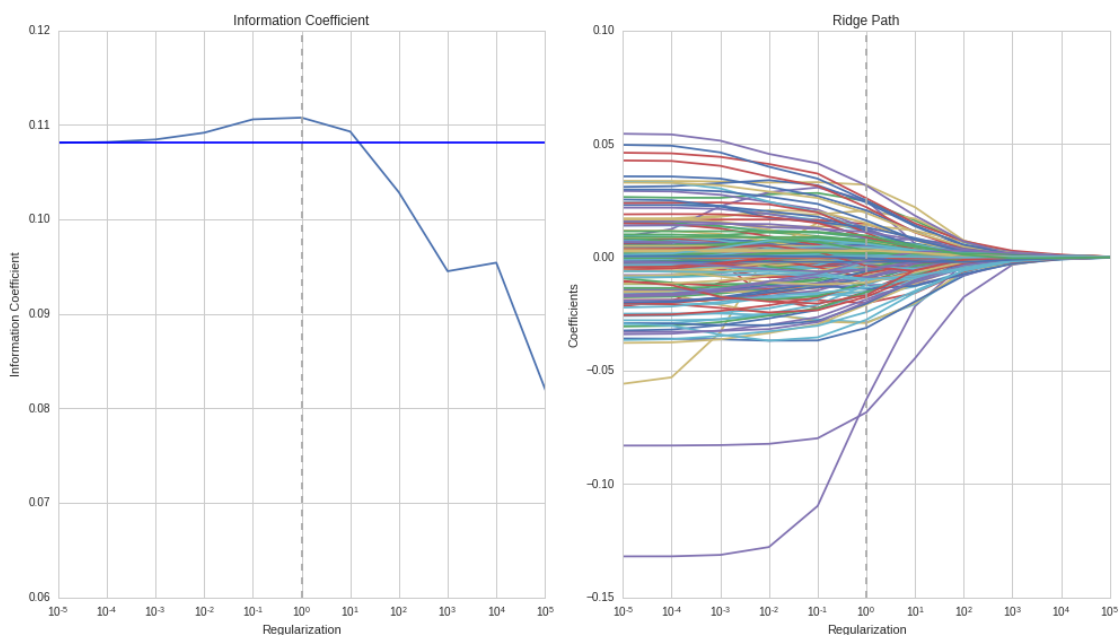
```
[176]:
```

```
[176]: 1.0
```

```
[178]: fig, axes = plt.subplots(ncols=2, sharex=True)

ridge_result.groupby('alpha')['ic'].mean().plot(logx=True, title='Information_
↪Coefficient', ax=axes[0])
axes[0].axhline(ridge_result.groupby('alpha').ic.mean().median())
axes[0].axvline(x=ridge_result.groupby('alpha').ic.mean().idxmax(),
↪c='darkgrey', ls='--')
axes[0].set_xlabel('Regularization')
axes[0].set_ylabel('Information Coefficient')

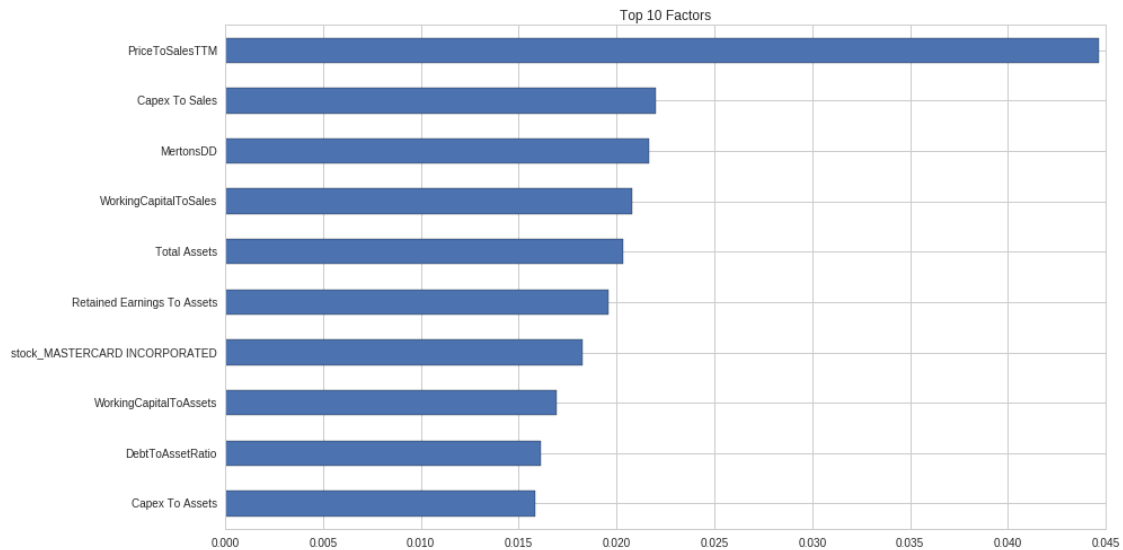
ridge_coeffs_main.T.plot(legend=False, logx=True, title='Ridge Path',
↪ax=axes[1])
axes[1].set_xlabel('Regularization')
axes[1].set_ylabel('Coefficients')
axes[1].axvline(x=ridge_result.groupby('alpha').ic.mean().idxmax(),
↪c='darkgrey', ls='--')
fig.tight_layout();
```



1.14.4 Top 10 Coefficients

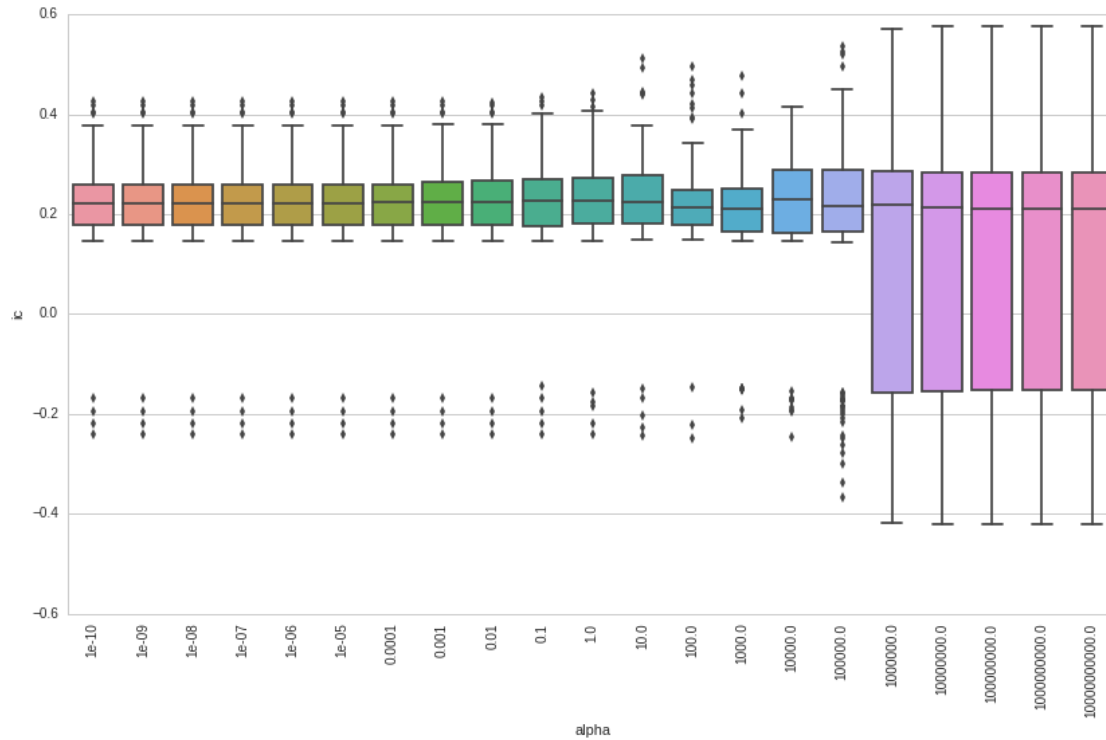
The standardization of the coefficients allows us to draw conclusions about their relative importance by comparing their absolute magnitude. The 10 most relevant coefficients are:

```
[130]: model_coeffs = ridge_coeffs_main.loc[:, best_alpha]
model_coeffs.index = features
model_coeffs.abs().sort_values().tail(10).plot.barh(title='Top 10 Factors');
```



1.14.5 CV Result Distribution

```
[105]: ax = sns.boxplot(y='ic', x='alpha', data=ridge_result_sig)
plt.xticks(rotation=90);
```



1.15 Lasso Regression

The lasso implementation looks very similar to the ridge model we just ran. The main difference is that lasso needs to arrive at a solution using iterative coordinate descent whereas ridge can rely on a closed-form solution:

```
[163]: nfolds = 250
alphas = np.logspace(-8, -2, 13)
scaler = StandardScaler()

lasso_results, lasso_coeffs = pd.DataFrame(), pd.DataFrame()
for i, alpha in enumerate(alphas):
    print i,
    coeffs, test_results = [], []
    lr_lasso = Lasso(alpha=alpha)
    for i, (train_dates, test_dates) in enumerate(time_series_split(dates, u
    ↪ nfolds=nfolds)):
        X_train = model_data.loc[idx[train_dates], features]
        y_train = model_data.loc[idx[train_dates], target]
        lr_lasso.fit(X=scaler.fit_transform(X_train), y=y_train)

        X_test = model_data.loc[idx[test_dates], features]
        y_test = model_data.loc[idx[test_dates], target]
```

```

y_pred = lr_lasso.predict(scaler.transform(X_test))

rmse = np.sqrt(mean_squared_error(y_pred=y_pred, y_true=y_test))
ic, pval = spearmanr(y_pred, y_test)

coeffs.append(lr_lasso.coef_)
test_results.append([train_dates[-1], rmse, ic, pval, alpha])
test_results = pd.DataFrame(test_results, columns=['date', 'rmse', 'ic', 'pval', 'alpha'])
lasso_results = lasso_results.append(test_results)
lasso_coeffs[alpha] = np.mean(coeffs, axis=0)

```

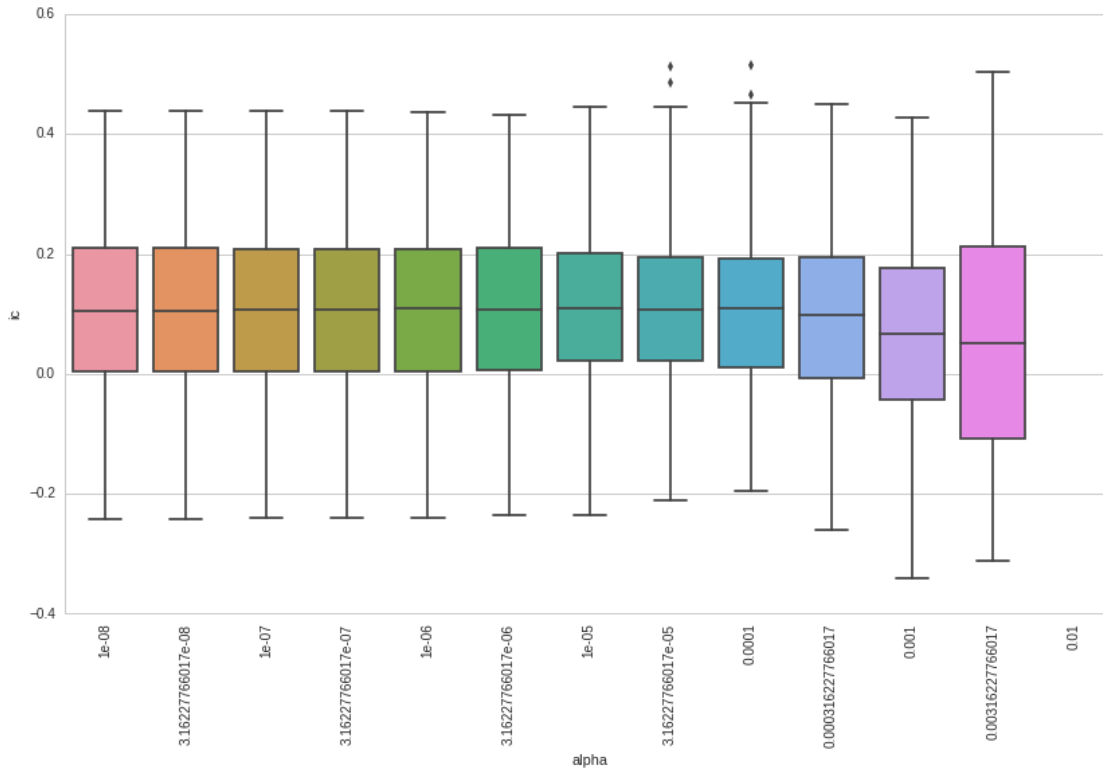
0 1 2 3 4 5 6 7 8 9 10 11 12

```
[164]: lasso_results.groupby('alpha').mean()
```

```
[164]:
```

	rmse	ic	pval
alpha			
1.000000e-08	0.045714	0.108370	0.255438
3.162278e-08	0.045713	0.108384	0.255490
1.000000e-07	0.045710	0.108429	0.255493
3.162278e-07	0.045699	0.108550	0.255804
1.000000e-06	0.045667	0.108794	0.255666
3.162278e-06	0.045572	0.109276	0.254775
1.000000e-05	0.045365	0.110997	0.247775
3.162278e-05	0.045343	0.110751	0.244619
1.000000e-04	0.044766	0.103843	0.248817
3.162278e-04	0.044462	0.095700	0.238646
1.000000e-03	0.044479	0.059093	0.251200
3.162278e-03	0.044529	0.050669	0.190781
1.000000e-02	0.044537	NaN	NaN

```
[165]: ax = sns.boxplot(y='ic', x='alpha', data=lasso_results)
plt.xticks(rotation=90);
```



1.15.1 Cross-validated information coefficient and Lasso Path

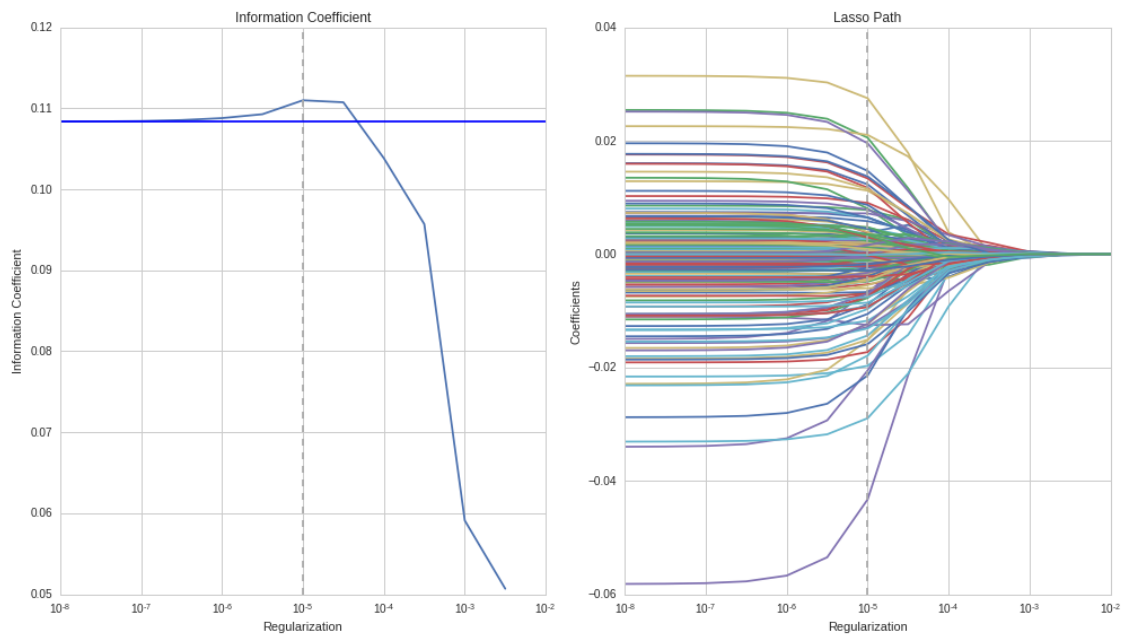
As before, we can plot the average information coefficient for all test sets used during cross-validation. We see again that regularization improves the IC over the unconstrained model, delivering the best out-of-sample result at a level of $\alpha = 10^{-5}$. The optimal regularization value is quite different from ridge regression because the penalty consists of the sum of the absolute, not the squared values of the relatively small coefficient values. We can also see that for this regularization level, the coefficients have been similarly shrunk, as in the ridge regression case:

```
[170]: fig, axes = plt.subplots(ncols=2, sharex=True)

lasso_results.groupby('alpha')['ic'].mean().plot(logx=True, title='Information_
    ↪Coefficient', ax=axes[0])
axes[0].axhline(lasso_results.groupby('alpha')['ic'].mean().median())
axes[0].axvline(x=lasso_results.groupby('alpha')['ic'].mean().idxmax(),
    ↪c='darkgrey', ls='--')
axes[0].set_xlabel('Regularization')
axes[0].set_ylabel('Information Coefficient')

lasso_coeffs.T.plot(legend=False, logx=True, title='Lasso Path', ax=axes[1])
axes[1].set_xlabel('Regularization')
axes[1].set_ylabel('Coefficients')
```

```
axes[1].axvline(x=lasso_results.groupby('alpha')['ic'].mean().idxmax(),
               c='darkgrey', ls='--')
fig.tight_layout();
```



In sum, ridge and lasso will produce similar results. Ridge often computes faster, but lasso also yields continuous features subset selection by gradually reducing coefficients to zero, hence eliminating features.

[]: