Chapter 12

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DSC 530

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Exercise 12-1: The linear model I used in this chapter has the obvious drawback that it is linear, and there is no reason to expect prices to change linearly over time. We can add flexibility to the model by adding a quadratic term, as we did in "Nonlinear Relationships" on page 133. Use a quadratic model to fit the time series of daily prices, and use the model to generate predictions. You will have to write a version of RunLinearModel that runs that quadratic model, but after that you should be able to reuse code from timeseries.py to generate predictions.

```
In [8]: from __future__ import print_function, division
    import pandas
    import numpy as np
    import statsmodels.formula.api as smf
    import thinkplot
    import thinkstats2
    import regression
    import timeseries

In [27]: def RunQuadraticModel(daily):
        daily['years2'] = daily.years**2
            model = smf.ols('ppg ~ years + years2', data = daily)
            results = model.fit()
            return model, results
```

transactions = timeseries.ReadData()

In [28]: transactions = timeseries.ReadData()

daily = dailies[name]

**Df Residuals:** 

**Covariance Type:** 

Df Model:

name = 'high'

dailies = timeseries.GroupByQualityAndDay(transactions) name = 'high' daily = dailies[name]

BIC:

3016.

model, results = RunQuadraticModel(daily) results.summary()

```
model, results = RunQuadraticModel(daily)
           results.summary()
                               OLS Regression Results
Out[28]:
               Dep. Variable:
                                                    R-squared:
                                                                   0.455
                                         ppg
                                        OLS
                                               Adj. R-squared:
                                                                   0.454
                     Model:
                    Method:
                                Least Squares
                                                    F-statistic:
                                                                   517.5
                       Date: Sun, 18 Feb 2024 Prob (F-statistic): 4.57e-164
                                     21:06:44
                                               Log-Likelihood:
                                                                  -1497.4
           No. Observations:
                                        1241
                                                                   3001.
                                                          AIC:
```

 coef
 std err
 t
 P>|t|
 [0.025
 0.975]

 Intercept
 13.6980
 0.067
 205.757
 0.000
 13.567
 13.829

 years
 -1.1164
 0.084
 -13.326
 0.000
 -1.281
 -0.952

 years2
 0.1131
 0.022
 5.060
 0.000
 0.069
 0.157

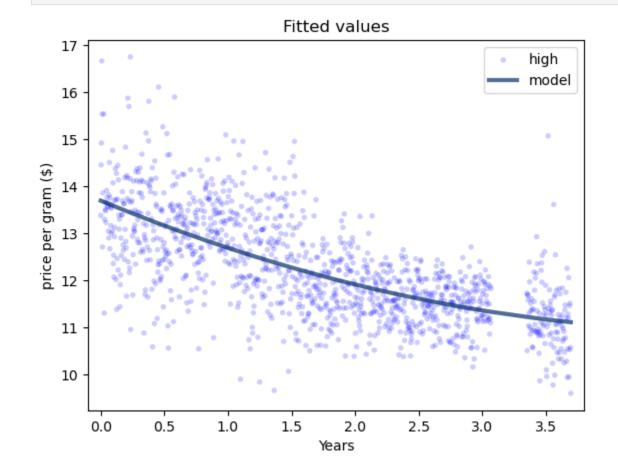
1238

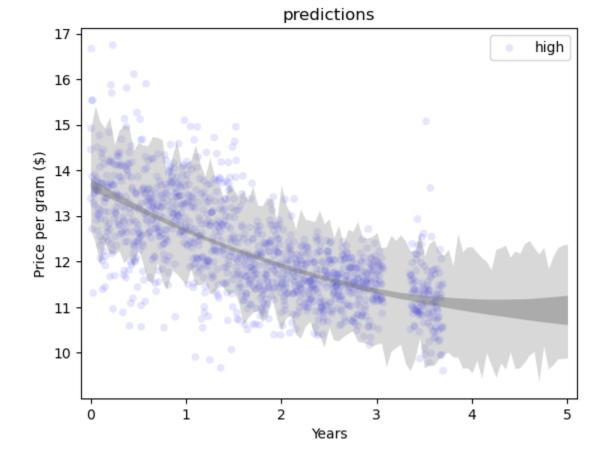
nonrobust

1.885	Durbin-Watson:	49.112	Omnibus:
113.885	Jarque-Bera (JB):	0.000	Prob(Omnibus):
1.86e-25	Prob(JB):	0.199	Skew:
27.5	Cond. No.	4.430	Kurtosis:

## Notes:

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





Exercise 12-2: Write a definition for a class named SerialCorrelationTest that extends HypothesisTest from "Hypothesis Test" on page 102. It should take a series and a lag as data, compute the serial correlation of the series with the given lag, and then compute the p-value of the observed correlation. Use this class to test whether the serial correlation in raw price data is statistically significant. Also test the residuals of the linear model and (if you did the previous exercise), the quadratic model.

```
In [51]: class SerialCorrelationTest(thinkstats2.HypothesisTest):
    def TestStatistic(self, data):
        series, lag = data
        test_stat = abs(thinkstats2.SerialCorr(series, lag))
        return test_stat

    def RunModel(self):
        series, lag = self.data
        permutation = series.reindex(np.random.permutation(series.index))
        return permutation, lag
```

```
In [54]: # test correlation between consecutive prices
series = daily.ppg
test = SerialCorrelationTest((series, 1))
pvalue = test.PValue()
print(test.actual, pvalue)

0.4852293761947382 0.0
```

```
In [56]: # test serial correlation in res of linear mod

_, results = timeseries.RunLinearModel(daily)
series = results.resid
test = SerialCorrelationTest((series, 1))
pvalue = test.PValue()
print(test.actual, pvalue)
```

```
0.07570473767506265 0.009

In [57]: # test serial correlation in res of quadratic mod

_, results = RunQuadraticModel(daily)
series = results.resid
test = SerialCorrelationTest((series, 1))
pvalue = test.PValue()
print(test.actual, pvalue)
```

0.05607308161289924 0.049