Oil Price Volatility

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Introduction

In a commodity trading market the price level is expected to be tied to the system dynamics. Volatility, the variation in price over time, reflects uncertainty in the supply, demand, and delivery of the commodity being traded. This research paper aims to answer a simply posed question: "does oil price volatility scale with price?"; i.e., can we expect to observe larger price swings when the price is near \$100/barrel vs \$20/barrel?

If oil price volatility reflects uncertainty about supply and demand dynamics, it isn't immediately clear whether we should expect volatility to depend on price level. Higher oil prices are associated with "tightness" in the supply market, meaning there is little excess capacity to increase production. However, factors such as storage dynamics, the ability of producers to increase production fast enough to bring more oil to market in response to high prices ("rebalancing"), and market speculation complicate this picture and mean it must be studied empirically.

If it is found that oil price volatility is dependent on price level, the relationship may follow a scaling formula. For instance, if we can expect volatility of \$1/barrel when oil is at \$20/barrel, can we expect volatility of \$5/barrel at \$100/barrel price levels via a simple linear scaling rule? Three methods are presented in this research paper to answer this question: (1) regression modeling of price and volatility, (2) viewing volatility within oil price regimes, and (3) using multivariate

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) modeling.

Note that in this research paper *oil price* is used to specifically mean spot-traded crude oil. This represents only one component of the oil markets, and most of the actual oil price is determined by futures and long term delivery contracts (need cite). This research paper is concerned with understanding the energy system using pricing information. In this way, it differs from much of the published research in that it is not concerned with forecasting prices or volatility. Nor is it addressing exogeneous system elements such as equity markets or interest rates, though the literature shows that the crude oil market and larger economic indicators are intertwined (add cite). Instead, it contributes to our understanding of the system dynamics of an essential energy commodity.

Exploratory Data Analysis

Data Source

The data source is the West Texas Intermediate (WTI) nominal (i.e. not inflation adjusted) daily spot price record from the U.S. Energy Information Administration. The WTI series was filtered to the date range January 2, 1986 through December 30, 2016.

| Date Range	Price Range
Min. :1986-01-03	Min. : 10.25
1st Qu.:1993-09-01	1st Qu.: 19.38
Median :2001-06-11	Median : 28.01
Mean :2001-06-19	Mean : 42.87
3rd Qu.:2009-03-31	3rd Qu.: 63.47
Max. :2016-12-30	Max. :145.31

Returns and Volatility

In this research paper, volatility is characterized two ways: (1) 5-day historic volatility and (2) 30-day historic volatility. In addition, the relationship between the returns themselves and price

level is investigated. Single-period returns were calculated as:
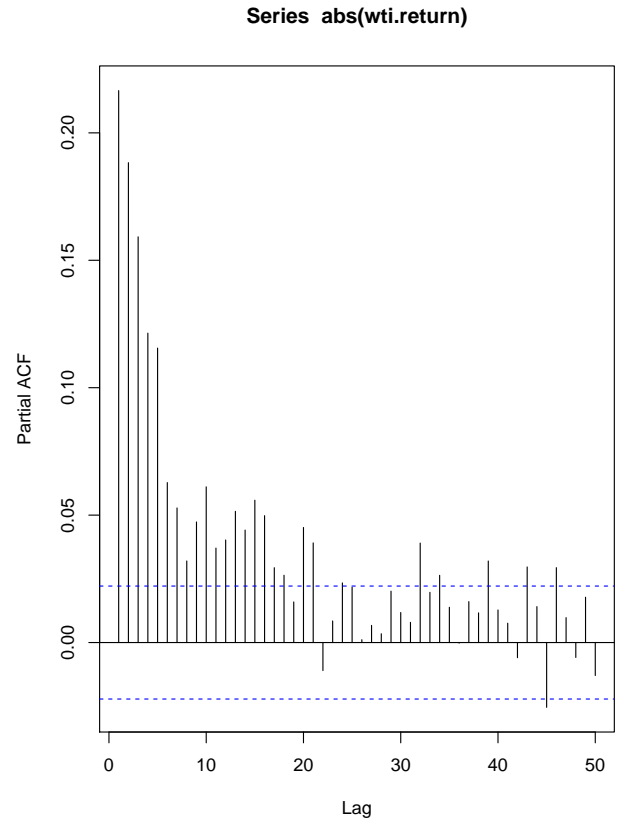
$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

and in some sections, their absolute values are used.

WTI Price Series

WTI Return Series

WTI 30–day Historic Volatility

WTI 5–day Historic Volatility
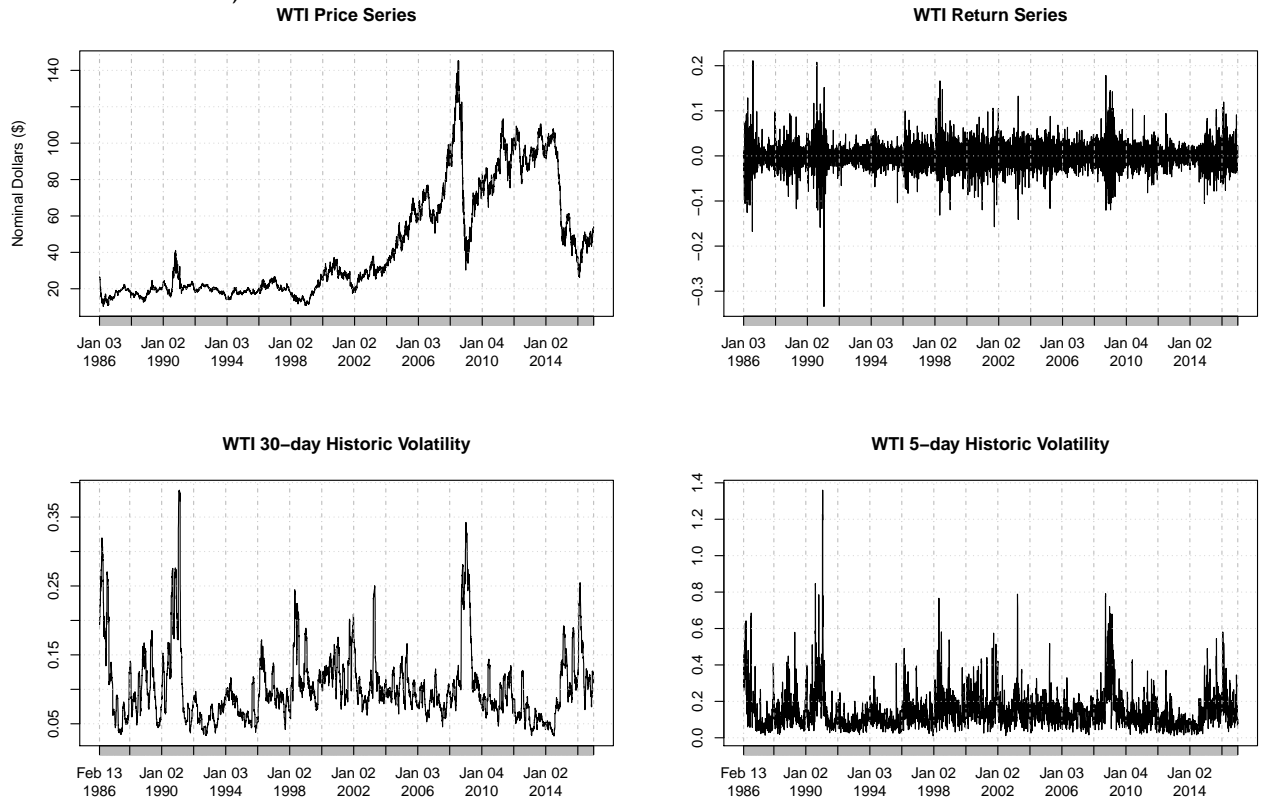
Ase seen in Figure 1, most of the series from 1986 through 2004 contains prices between $10/barrel and $40/barrel. This results in a price series with left skew and a long right tail. These distribution characteristics are common in financial time series. The return series displays the

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Oil Prices Density Plot

Oil Returns Density Plot
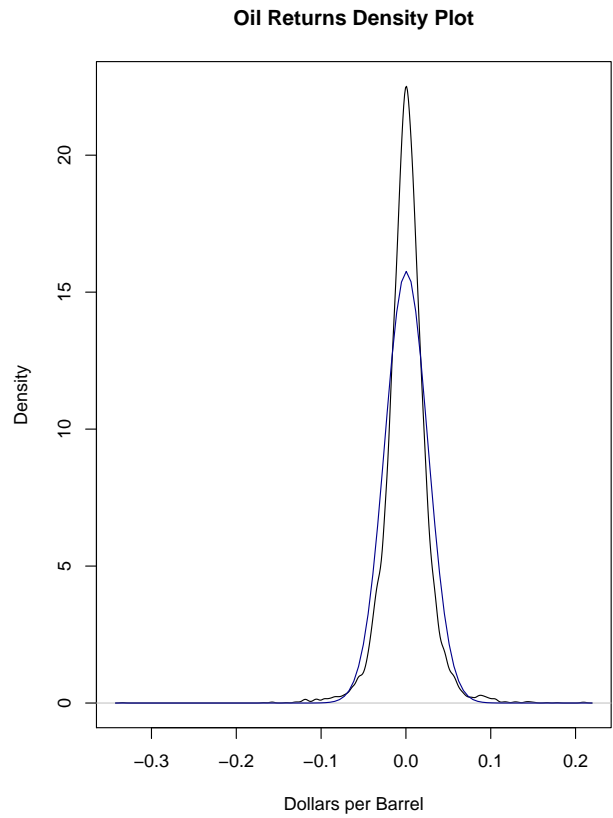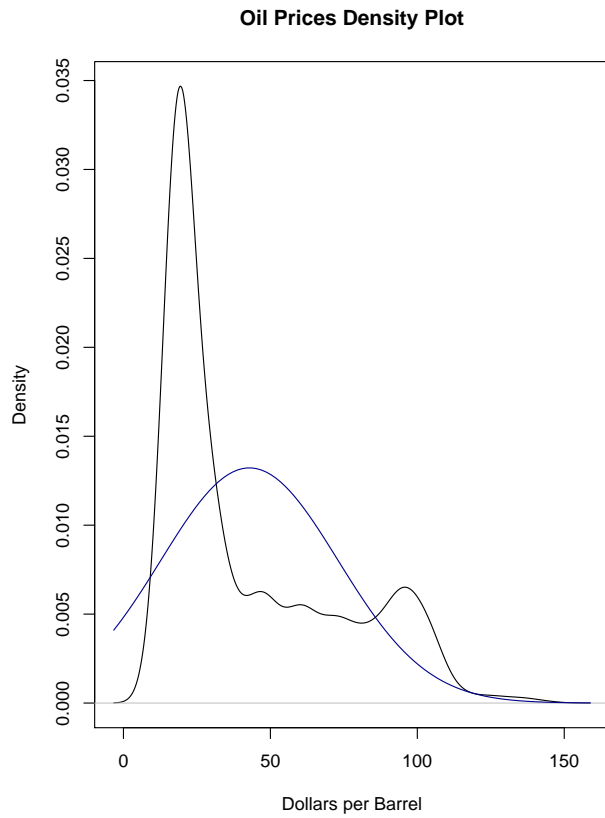
Times series exploration

Series abs(wti.return)

Series abs(wti.return)
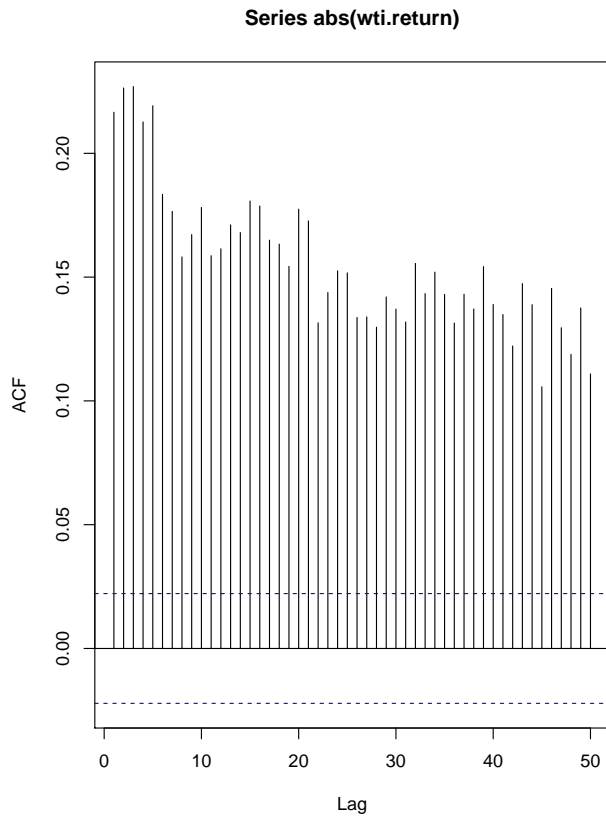
A challenge in analyzing financial time series in general, and spot oil market prices specifically, is that the variance structure may be independent, but not identically distributed. Oil prices exhibit periods of low volatility (i.e. relatively constant prices) and periods of high volatility (i.e. changing prices). This is referred to as volatility clustering. This violates the assumption in the most frequently used time series model, the autoregressive integrated moving average (ARIMA) model.
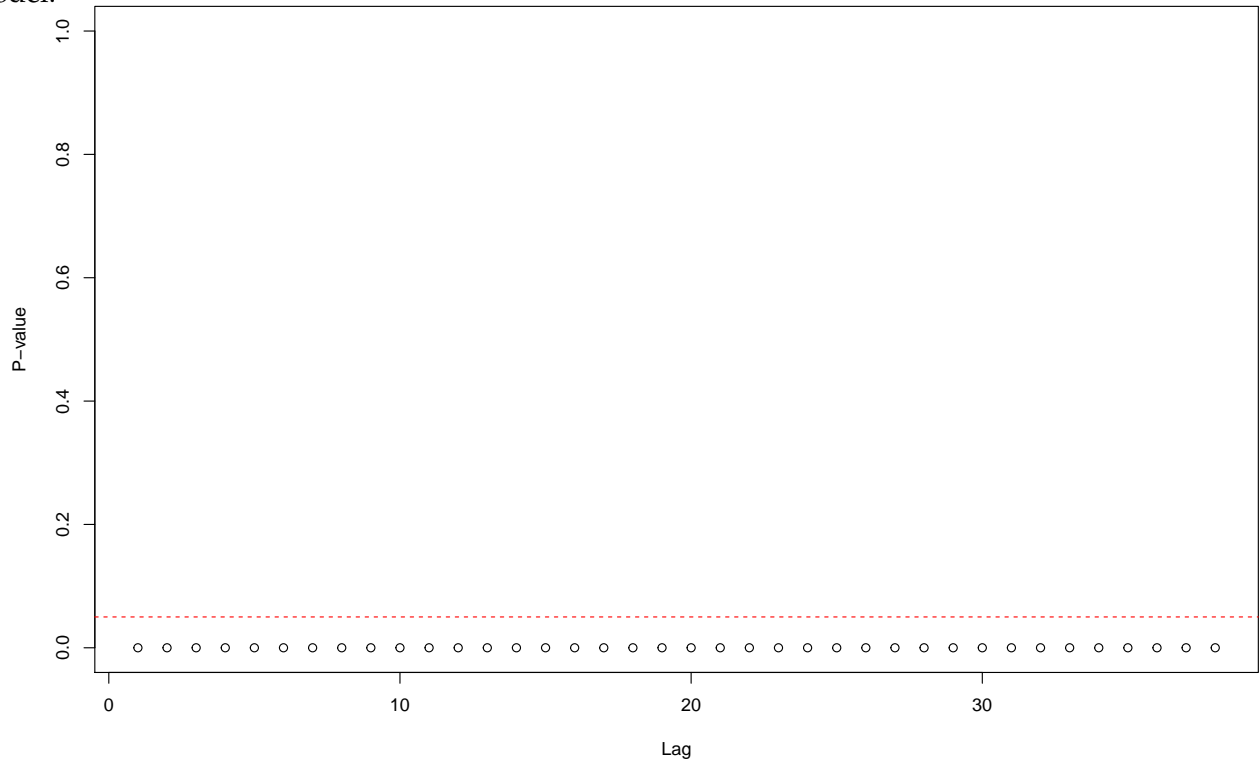


Price-Volatility Regression Analysis

Relating price level and the measures of volatility at each time in the series is a simple exploration of the research problem. The covariance and correlation measures of vectors representing price versus returns, 30-day, and 5-day historic volatility indicate a weak, negative relationship.

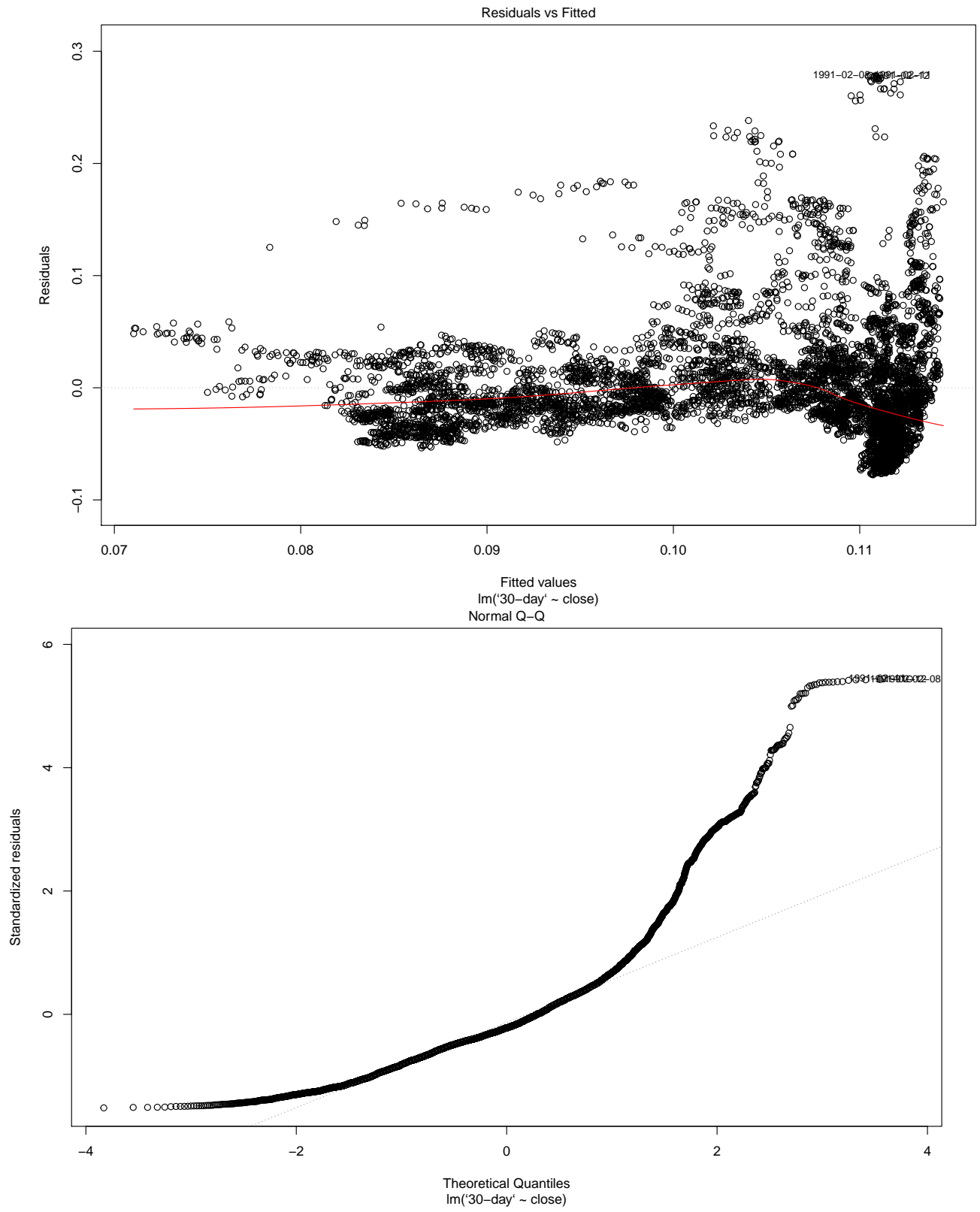|	Covariance	Correlation
return	-0.0396337	-0.0719290
30-day	-0.2933686	-0.1864200
5-day	-0.3757726	-0.1212286

```
## numeric(0)
```

```
## numeric(0)
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## numeric(0)
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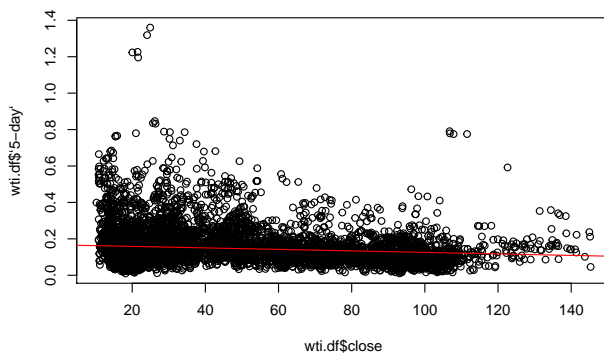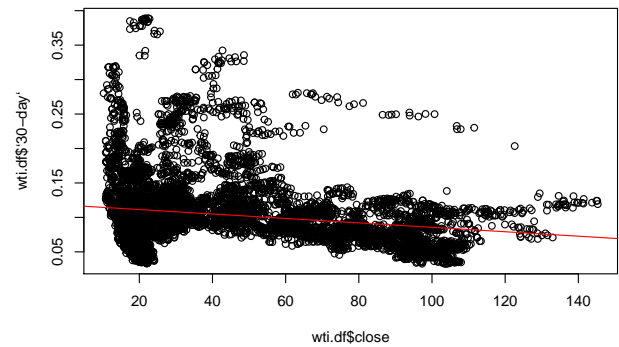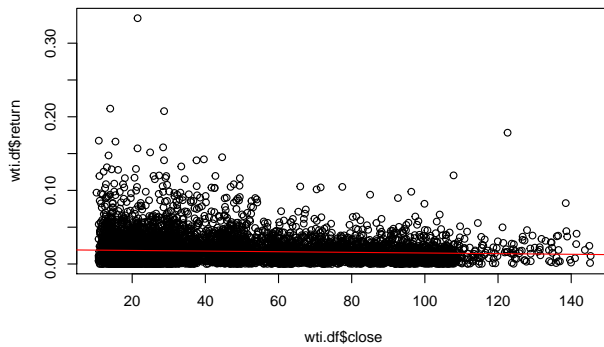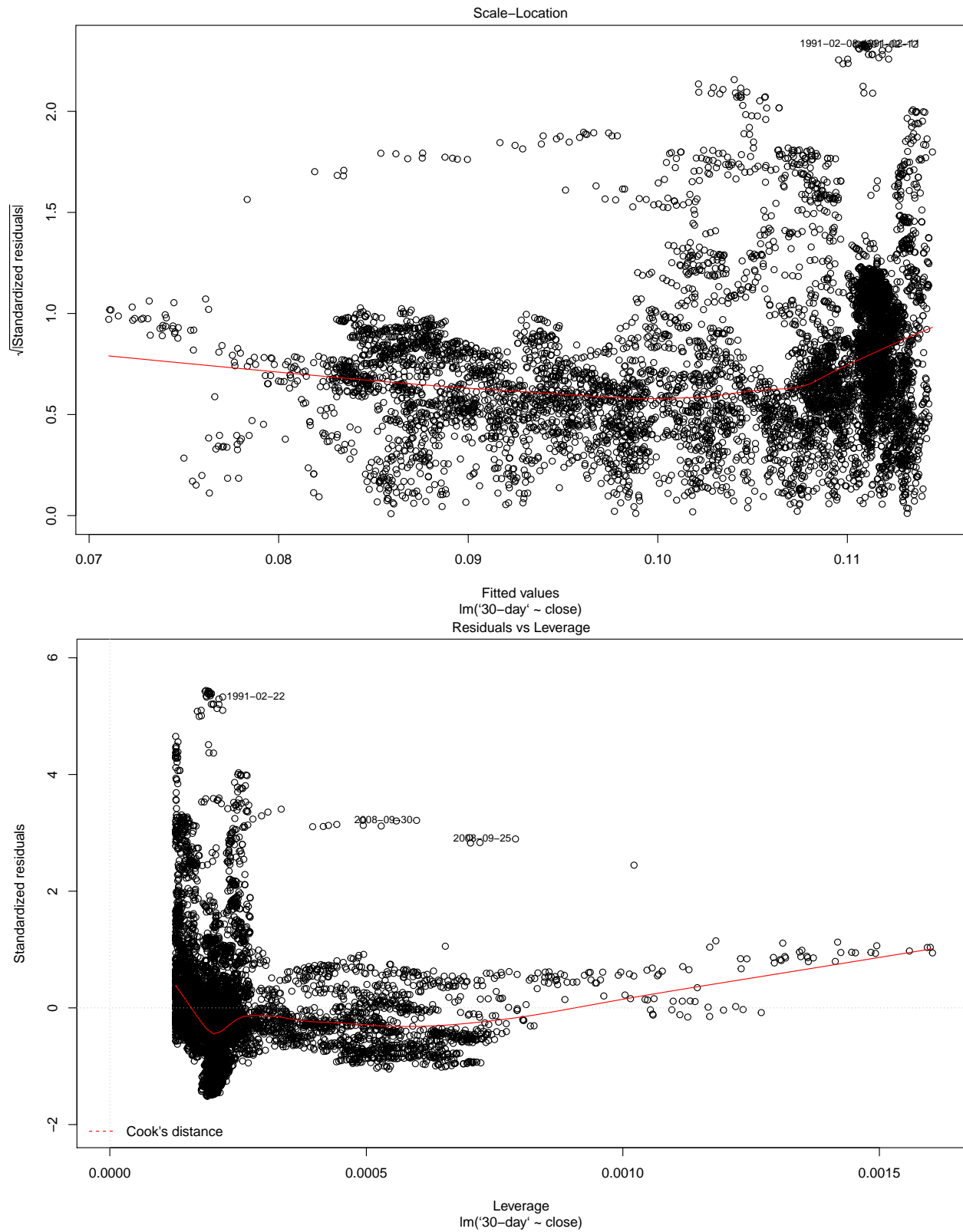

The case of 30-day historic volatility indicates a negative relationship between price level and volatility. However, this result appears to be due to a cluster high volatility around $20 per barrel, creating a leverage point. Residual analysis indicates that this is not a good relationship to model with linear regression. Residual analysis for the other volatility measures also display

Residuals vs Fitted

1991-02-08 1991-02-12

Residuals

Fitted values
lm('30-day' ~ close)

Normal Q-Q

1991-02-08

Standardized residuals

Theoretical Quantiles
lm('30-day' ~ close)

Scale–Location

√|Standardized residuals|

Fitted values
lm(`30-day` ~ close)

Residuals vs Leverage

Standardized residuals

Leverage
lm(`30-day` ~ close)

As seen in Figure 1, nominal oil prices have spent time as high as $145 per barrel. However, the majority of the time series is far lower, with a median price of $28 per barrel. This means that

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the dataset is unbalanced and higher price levels represent a smaller portion of the dataset. In addition, oil price (and financial time series in general) exhibits volatility clustering. Therefore, it is anticipated that this simple regression model based on price and volatility is not the best possible solution to the question of characterizing the dependency of volatility on price.

Comparing Volatility across Price Regimes

Changepoint detection aims to detect the point or points where the statistical properties of a sequence of observations change (Killick and Eckley, 2014). Changepoint detection was used to detect change in the oil price mean throughout the period of record using the Pruned Exact Linear Time (PELT) algorithm (Killick et al. 2012). The time series between these changepoints represent "price regimes" (i.e. time series between changepoints) which have generally similar mean oil price compared to the entire record.

Changepoint detection proceeds by minimizing a cost function over possible locations and number of changepoints. The cost function:
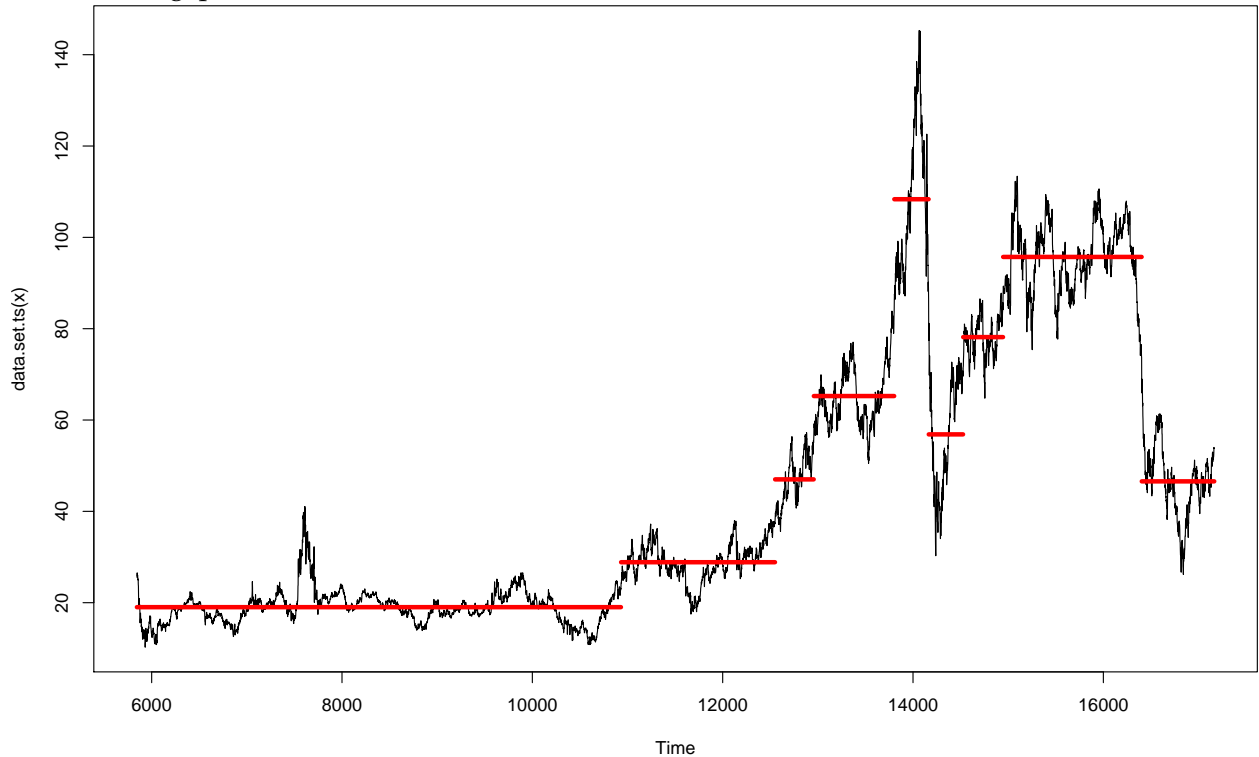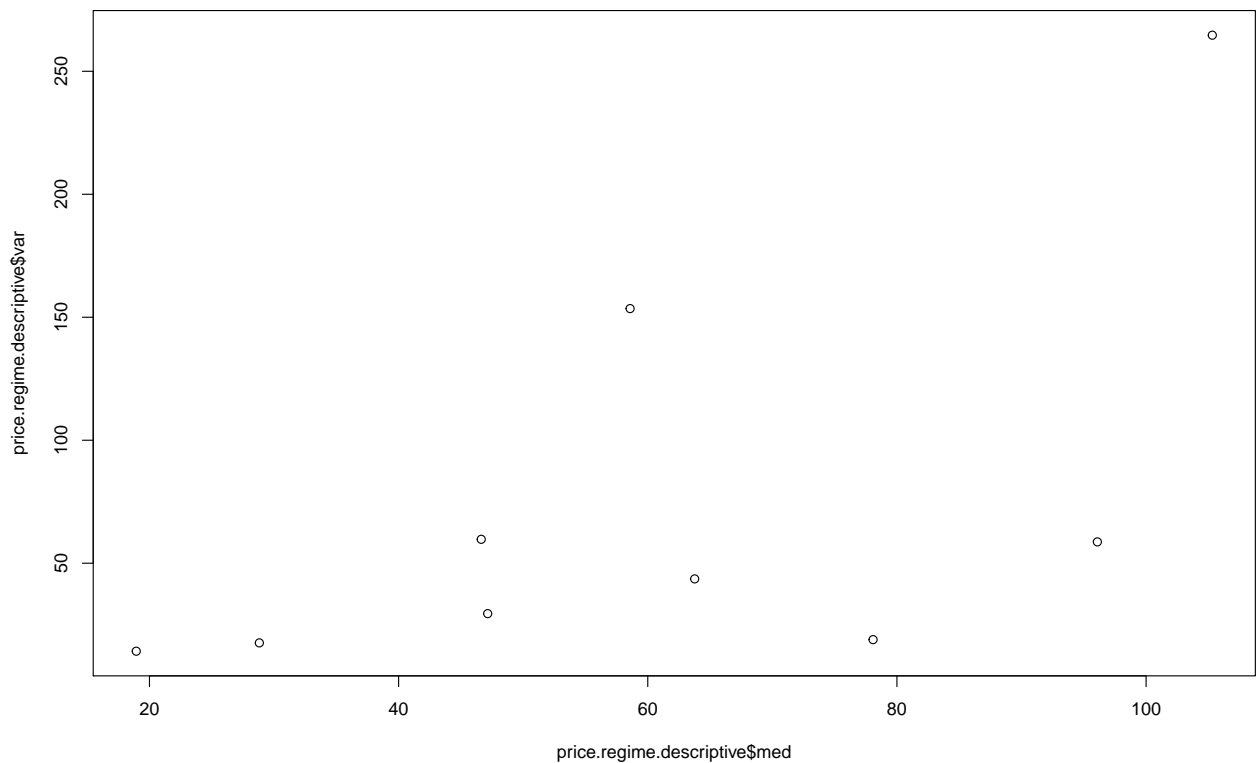
```
##
## Call:
## lm(formula = var ~ med, data = price.regime.descriptive)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -85.760 -35.751  -0.006  14.071 111.861
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -33.3214    57.1329  -0.583   0.5780
## med           1.7674     0.8623   2.050   0.0796 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 70.58 on 7 degrees of freedom
```

```
## Multiple R-squared:  0.375,  Adjusted R-squared:  0.2858
## F-statistic: 4.201 on 1 and 7 DF,  p-value: 0.07958
```

regime	med	var
1	18.940	14.22440
2	28.820	17.61040
3	47.150	29.50349
4	63.765	43.62747
5	105.315	264.67635
6	58.580	153.52032
7	78.085	18.92845
8	96.090	58.67639
9	46.630	59.71733

References