IIT Stuart School of Business
ILLINOIS INSTITUTE OF TECHNOLOGY

# Seasonally-Adjusted Value-at-Risk

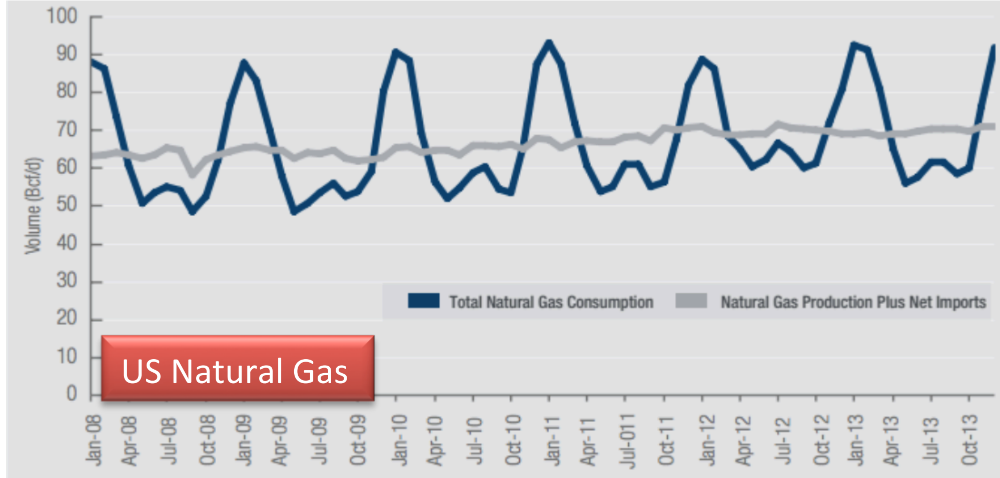
Matthew Dixon[1,2],
Leighton Dong[2]

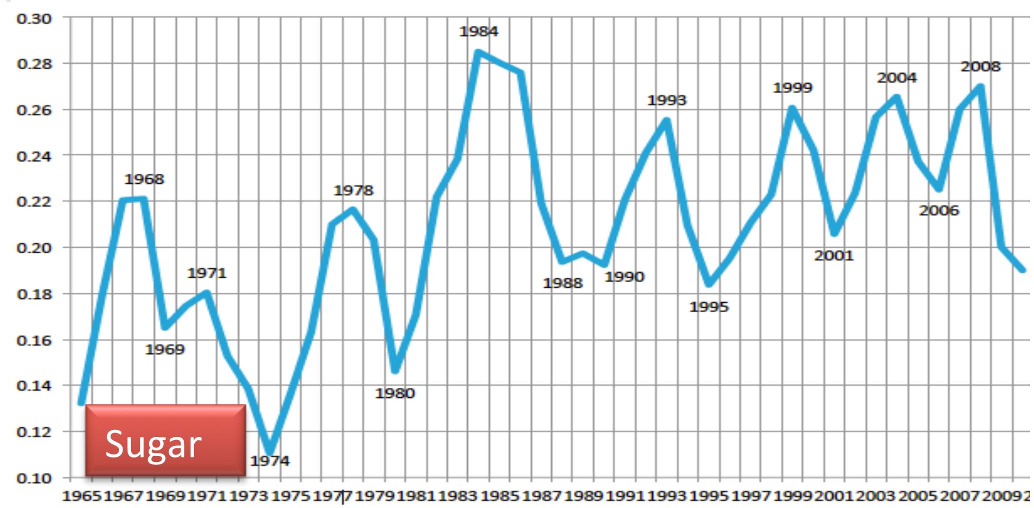
## R in Finance 2016, May 21st

1 Department of Finance, Illinois Institute of Technology
2 Quiota LLC

# Introduction

- The effect of seasonality in energy and agriculture futures is well understood [1]
- Several univariate forecasting techniques exist for capturing seasonality in historical prices. See e.g. [2,3]
- There are R packages for modeling seasonality in forecasting models. See e.g. [2]




1) Fama, E. F. & French, K. R., 1987. Commodity Futures Prices: Some Evidence on Forecast Power, Premiums, and the Theory of Storage. The Journal of Business, 60(1), pp. 55-73.
2) Alexios Ghalanos (2015). **rugarch**: Univariate GARCH models. R package version 1.3-6.
3) Sørensen, C., 2002. Modeling Seasonality in Agricultural Commodity Futures. The Journal of Futures Markets, 22(5), pp. 393, 426.

Define the (i,j)th element of the seasonal adjusted conditional variance matrix as

$$\Sigma_{i,j}(t) = \mathbb{E}[y_i(t)y_j(t) \mid \{y_i(t-1), y_i(t-2), \dots\}, \{y_j(t-1), y_j(t-2), \dots\}, S(t)]$$

Where $y_i(t)$ are the demeaned returns of the $i^{th}$ asset and S(t) is a variable representing the season at time t for some arbitrary time period, e.g. monthly, quarterly etc.

Without loss of generalization to a broad class of Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models, consider the following Exponentially Weighted Moving Average (EWMA) model for the evolution of the estimated conditional covariance matrix:

$$\hat{\Sigma}_{i,j}(t) = \lambda\hat{\Sigma}_{i,j}(t-1) + (1-\lambda)\mathbf{y}^T(t-1)\mathbf{y}(t-1), \forall i, j$$

# Filtering Historical Returns by Month



The historical returns are dissected into twelve discontiguous time series of historical daily returns representing each month.

| Date | Return |
|---|---|
| January 2010 | xxx |
| February 2010 | xxx |
| March 2010 | xxx |
| April 2010 | xxx |
| May 2010 | xxx |
| June 2010 | xxx |
| ... | ... |
| January 2011 | xxx |
| February 2011 | xxx |
| March 2011 | xxx |
| April 2011 | xxx |
| May 2011 | xxx |
| ... | ... |
| January 2012 | xxx |
| February 2012 | xxx |
| March 2012 | xxx |
| April 2012 | xxx |
| ... | ... |
| January 2013 | xxx |
| February 2013 | xxx |
| March 2013 | xxx |
| ... | ... |
| January 2014 | xxx |
| February 2014 | xxx |
| ... | ... |
| January 2015 | xxx |
| ... | ... |

| Date | Return |
|---|---|
| January 2010 | xxx |
| January 2011 | xxx |
| January 2012 | xxx |
| January 2013 | xxx |
| January 2014 | xxx |
| January 2015 | xxx |

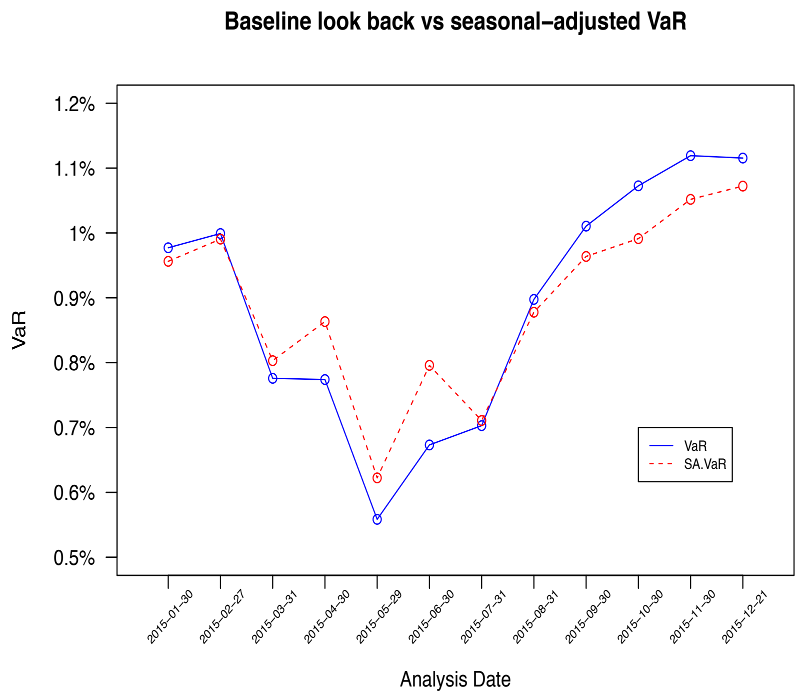
| Date | Return |
|---|---|
| February 2010 | xxx |
| February 2011 | xxx |
| February 2012 | xxx |
| February 2013 | xxx |
| February 2014 | xxx |
| ... | ... |

| Date | Return |
|---|---|
| March 2010 | xxx |
| ... | ... |

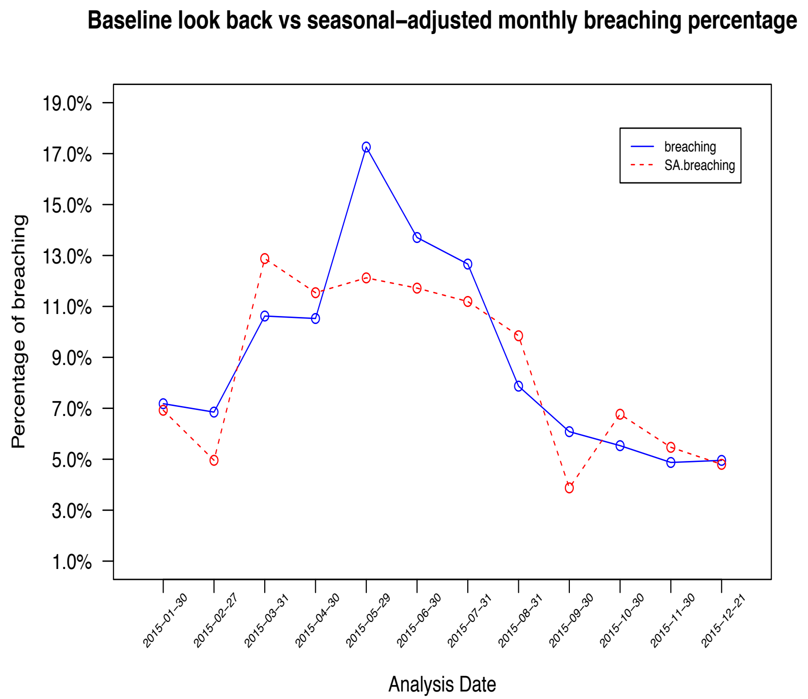
.
.
.

| Date | Return |
|---|---|
| ... | ... |
| December 2015 | xxx |

# Comparative Results




Comparison of the baseline parametric VaR estimates (blue line) and the seasonal adjusted parameter VaR estimates (red line).




Comparison of the percentage of daily losses in the historical look back period that breach the VaR estimate as estimated by the baseline model (blue line) and the seasonal adjusted model (red line).

# Frequency Test[1]



This table compares the test statistic (Z-score) for the frequency test applied to the baseline and seasonal adjusted (SA) parametric VaR estimates.

| Month | Baseline | SA |
|---|---|---|
| Jan | 3.639310333 | 1.006054546 |
| Feb | 3.1112978 | -0.020855976 |
| Mar | 9.53158782 | 4.153359932 |
| Apr | 9.443372561 | 3.420585455 |
| May | 21.10535488 | 3.7539984 |
| Jun | 15.10617557 | 3.487760554 |
| Jul | 13.40326516 | 3.289871146 |
| Aug | 5.05527541 | 2.555913804 |
| Sep | 1.92177444 | -0.585768943 |
| Oct | 0.953898857 | 0.934964749 |
| Nov | -0.228070175 | 0.243332132 |
| Dec | -0.081475255 | -0.102597835 |

1) Kupiec, Paul H. (1995). Techniques for verifying the accuracy of risk measurement models, Journal of Derivatives, 3 (2), 73–84.

# Conclusion



- Commodity portfolio risk managers seek to adjust the market risk of a portfolio for the effects of seasonality when the portfolio holds seasonal commodities
- We demonstrate a simple adjustment of the conditional covariance matrix estimator which yields a set of conditional covariance matrices for each season.
- By constructing separate multivariate volatility forecasting models for each season, we demonstrate Seasonal Adjusted Value-at-Risk (VaR) estimates that outperform standard VaR estimates during backtesting.