

Mixing Data of Different Sampling Frequencies in the Frequency Domain: a Daily System of Macro-Indicators

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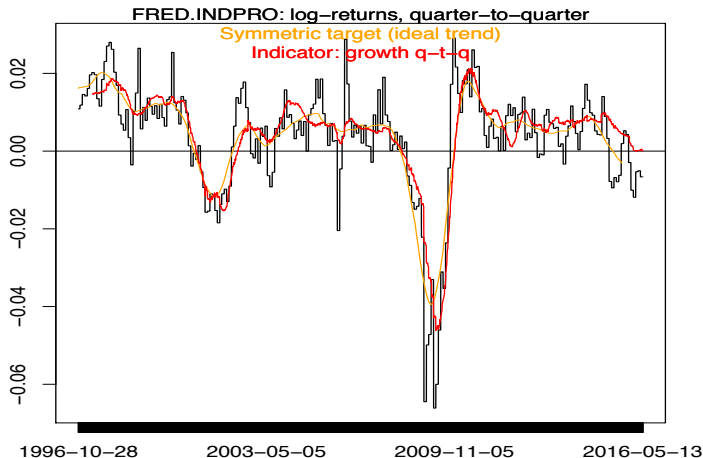
May 17, 2016
R/Finance 2016, Chicago

Empirical Example: Daily Indicator Design IPI

- Target: IPI (cutoff= $\pi/12$ or 24 months)
- Explaining series: **monthly** (IPI,NFP,UNEM), **weekly** (ICSA) and **daily** (SP500, VIX)

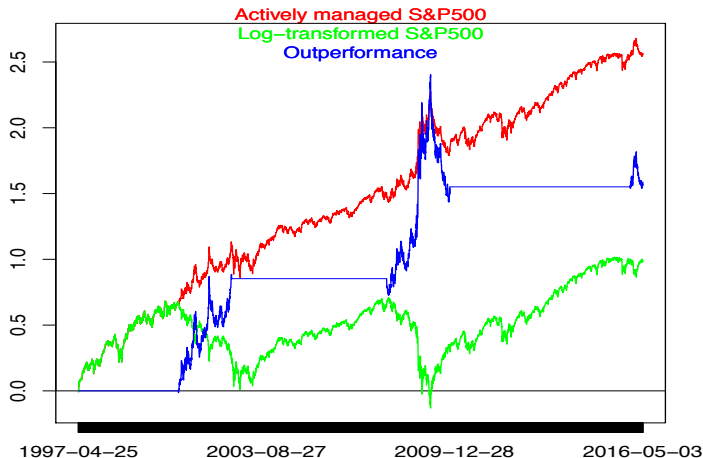
IPI: Daily Indicator (Design 1)

Design: neutral (q-t-q log-diffs: 1990-01-01 to 2016-05-16)



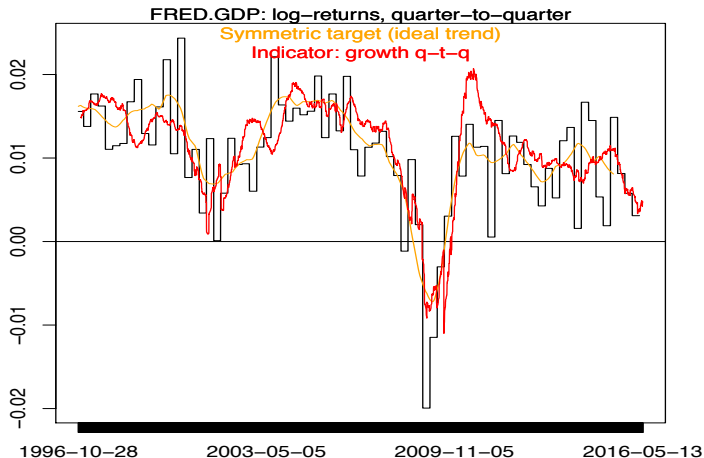
Trading Opportunities (S&P500)

Log-transformed S&P500 (green) vs. actively managed design (i



Estimation Lag 3×75 Days (3 Quarters)

Design: neutral (q-t-q log-diffs: 1990-01-01 to 2016-05-16)



A Practitioner's Defense of Return Predictability

Xiao Qiao

University of Chicago Booth School of Business

- Bulk of data from Bloomberg, Federal Reserve Bank of St. Louis, U.S. Census Bureau
- Short interest of Rapach, Ringgenberg, and Zhou (2015) from Matt Ringgenberg

Construct 20 variables from the predictability literature

- Price ratios: dividend yield, price to earnings, CAPE, etc
- Rates: bond yield, default spread, term spread, etc
- Real economy: Baltic Dry Index, new orders/sales, cay
- Technical: moving average, PCA-tech
- Sell in May, variance risk premium, CPI, short interest

Information in Return Predictors

	DP	PE	BM	CAPE	PCA-price	BY	DEF	TERM	CAY	SIM	VRP	IC	BDI	NOS	CPI	PCR	MA	PCA-tech	OIL
DP																			
PE	-0.38																		
BM	0.48	-0.76																	
CAPE	-0.59	0.75	-0.96																
PCA-price	-0.63	0.92	-0.93	0.97															
BY	-0.03	0.08	-0.12	0.13	0.10														
DEF	0.15	-0.39	0.53	-0.48	-0.41	-0.16													
TERM	0.22	-0.12	0.49	-0.52	-0.44	0.17	0.25												
CAY	0.42	0.15	-0.02	-0.07	0.03	0.07	-0.08	0.12											
SIM	-0.15	0.04	-0.07	0.05	0.07	0.21	-0.03	0.06	0.07										
VRP	0.05	-0.08	0.22	-0.17	-0.07	-0.19	0.54	0.04	0.16	-0.13									
IC	0.12	-0.16	0.07	-0.14	-0.15	-0.23	0.36	-0.06	0.12	0.01	0.38								
BDI	-0.09	0.06	-0.07	0.06	0.08	0.11	-0.12	-0.03	0.05	-0.03	0.11	-0.09							
NOS	-0.14	-0.19	-0.15	0.15	0.00	-0.01	-0.32	-0.32	-0.05	-0.39	-0.04	-0.12							
CPI	0.08	0.06	-0.20	0.16	0.04	-0.09	-0.21	-0.18	-0.13	-0.02	-0.39	-0.04	-0.15	0.35					
PCR	-0.65	0.60	-0.84	0.86	0.87	0.05	-0.21	-0.36	-0.16	0.03	0.02	0.03	0.02	0.02	-0.05				
MA	0.00	0.11	-0.21	0.25	0.12	0.17	-0.54	-0.16	-0.09	0.00	-0.41	-0.41	0.03	0.23	0.11	0.05			
PCA-tech	0.02	-0.05	-0.07	0.13	0.02	0.25	-0.48	-0.15	-0.06	0.05	-0.38	-0.38	0.00	0.22	-0.05	-0.06	0.80		
OIL	-0.19	0.08	-0.09	0.11	0.14	0.35	-0.21	0.00	-0.01	0.14	-0.09	-0.11	0.29	0.00	-0.06	-0.09	0.04	0.06	
SI	0.14	-0.15	0.18	-0.22	-0.17	-0.10	0.34	-0.05	0.03	-0.03	0.13	0.21	-0.01	0.05	0.23	-0.34	-0.31	-0.25	0.05

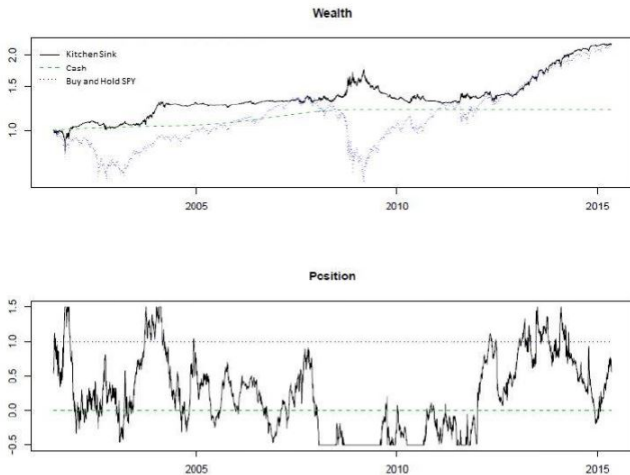
Correlation matrix of predictor variables. Positive correlations are in green and negative correlations are in red.

Relationship with Market Returns

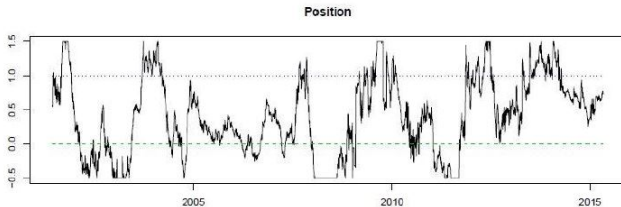
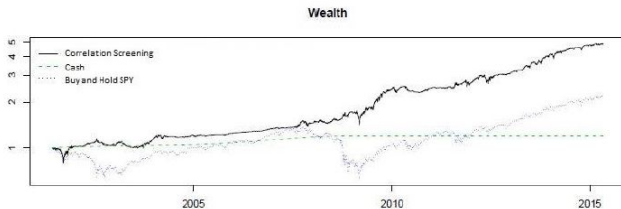
	R_1M	R_3M	R_6M	R_12M
DP	0.07	0.14	0.21	0.32
PE	-0.08	-0.15	-0.21	-0.25
BM	0.07	0.11	0.19	0.26
CAPE	-0.06	-0.09	-0.16	-0.24
PCA-price	-0.08	-0.13	-0.19	-0.28
BY	-0.05	-0.05	-0.04	0.06
DEF	-0.06	-0.09	-0.04	0.02
TERM	-0.03	-0.06	-0.04	0.08
CAY	0.11	0.19	0.30	0.45
SIM	-0.04	-0.13	-0.15	-0.02
VRP	0.17	0.32	0.29	0.24
IC	0.09	0.12	0.08	-0.03
BDI	0.10	0.22	0.14	0.03
NOS	-0.08	-0.17	-0.20	-0.25
CPI	-0.15	-0.27	-0.32	-0.29
PCR	-0.02	-0.03	-0.08	-0.16
MA	0.11	0.20	0.21	0.21
PCA-tech	0.11	0.18	0.24	0.27
OIL	0.03	0.04	-0.04	-0.13
SI	-0.14	-0.24	-0.28	-0.30

Correlation between predictors and one-, three-, six-, and 12-month future market returns. Positive correlations are in green; negatives are in red.

Kitchen Sink Performance



Correlation Screening Performance





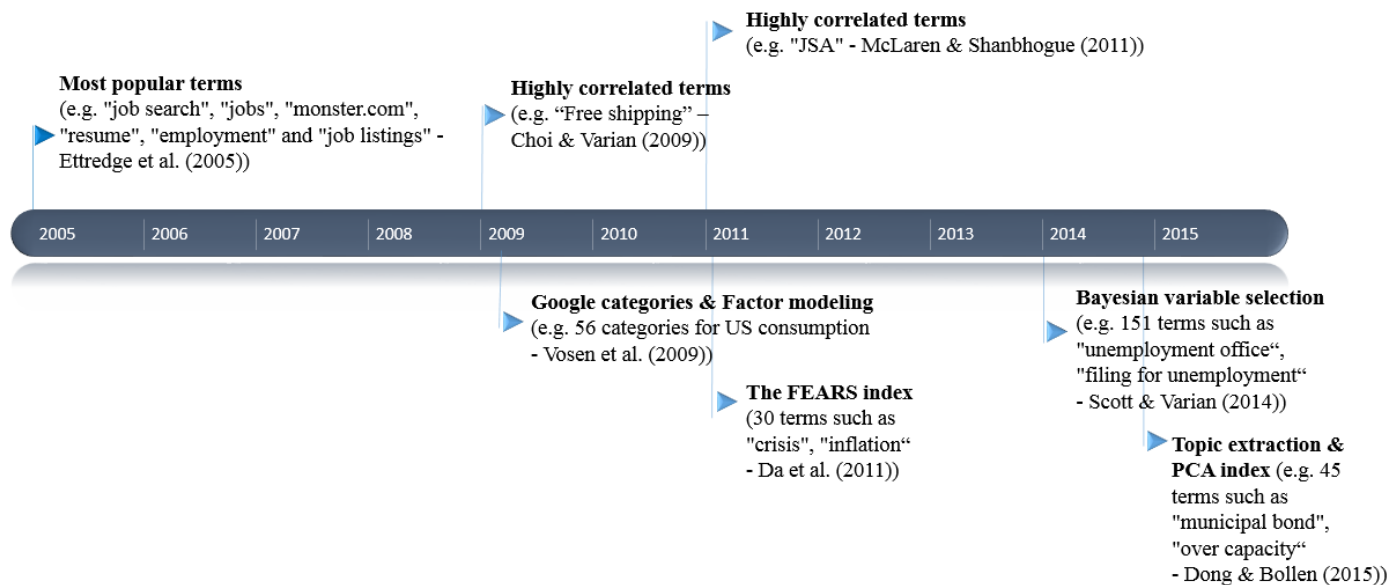
Construction of Google Search Indices by Applying Principal Component Analysis

Sile Li & Shannon Callan, CFA

Contacts:
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(646) 843-6048

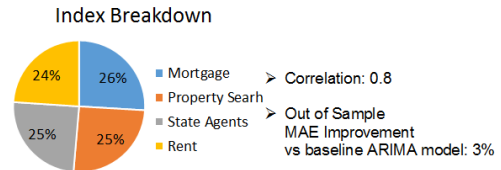
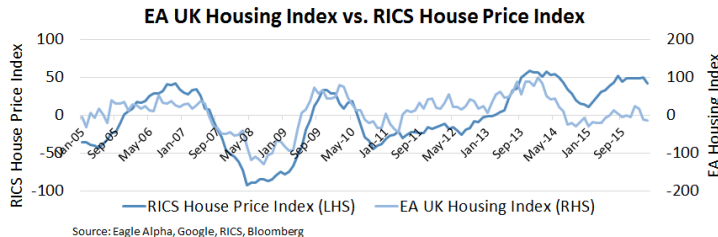
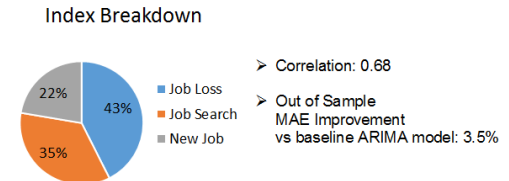
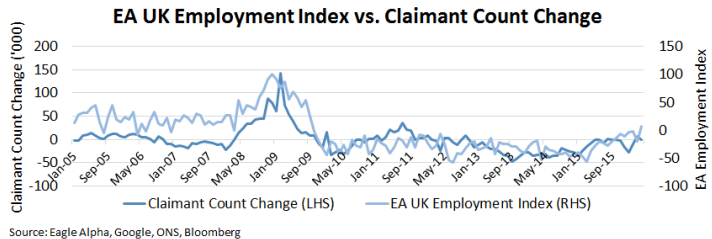
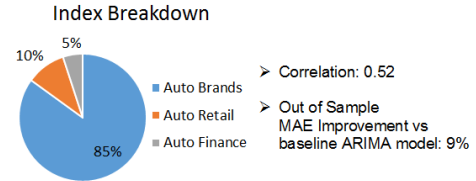
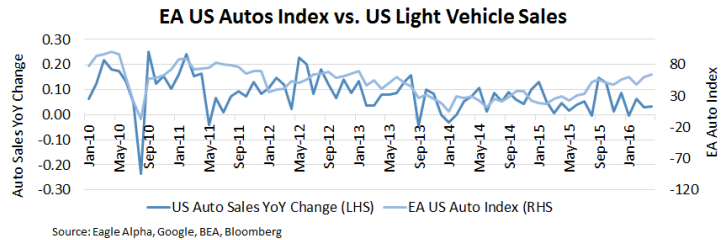
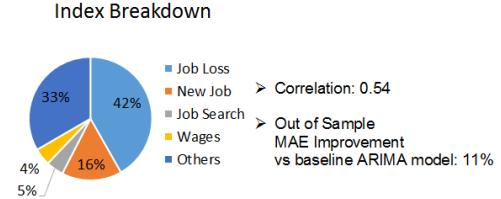
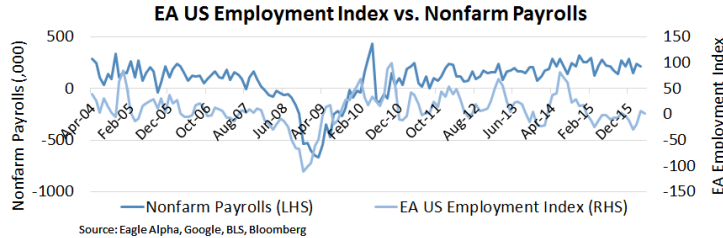
20th May 2016

- Internet Search Data (Google, Baidu)
 - ▶ Advantages: new information, continuous information, broadness, easy access
 - ▶ Disadvantages: relatively short history, sampling bias, diverse and dynamic search behaviors
- Studies Have Shown Predictive Value for Economic and Financial Metrics
 - ▶ Unemployment rate, house price, consumption, tourism, inflation, commodity price volatility, stock market return and volatility etc. in various countries.
- Evolution of Methodology



- Term Selection (packages *BMA*, *BSTS*)
 - ▶ Primitive list
 - ▶ Harvard dictionary economic keywords
 - ▶ Find related searches in Google Trends and Google Correlate
 - ▶ Filtering via correlation, Bayesian variable selection, term loading in PCA analysis
- Obtain Data and Process (packages *gtrendsR*, *zoo*, *robustHD*, *seas*)
 - ▶ Convert time frequency, remove outliers, winsorize, and seasonal adjustment
- Apply Principal Component Analysis (function *prcomp*)
- Index Creation
 - ▶ Create index from top principal component(s)
 - ▶ Use of rolling window
 - ▶ Track category loadings within the index

Eagle Alpha's Online Search Index gauges search behaviours related to specific economic activities. It is a composite indicator which measures the co-movement of multidimensional and dynamic search terms.

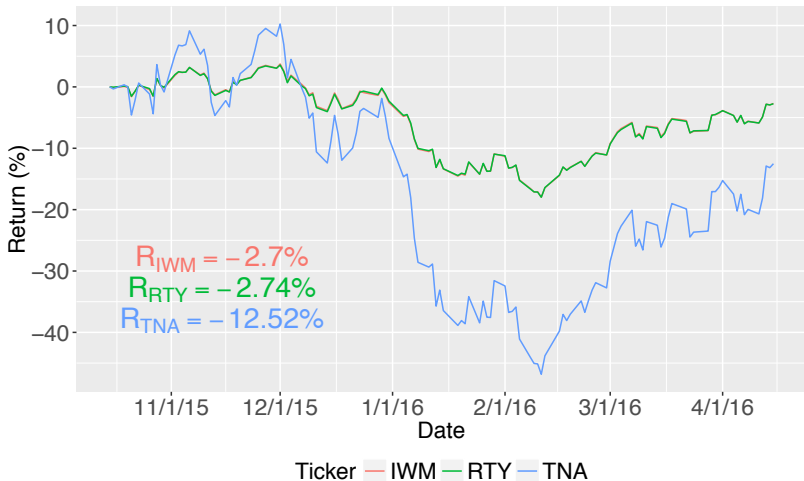


Simulation of Leveraged ETF Volatility Using Nonparametric Density Estimation

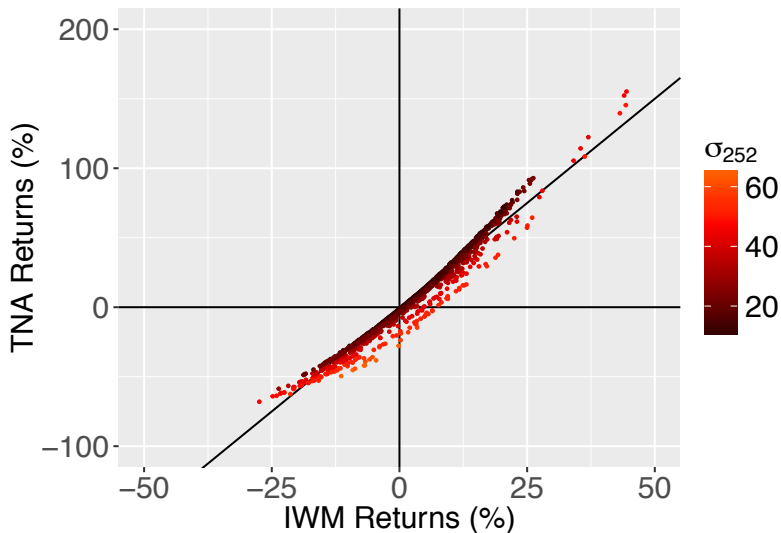
Matthew Ginley

May 20th, 2016

Russell 2000 (RTY), +1x ETF (IWM), +3x ETF (TNA), 10/15/15 - 4/15/16



Rolling 62 Day Returns, +1x ETF vs. +3x ETF, 11/05/08 - 4/15/16



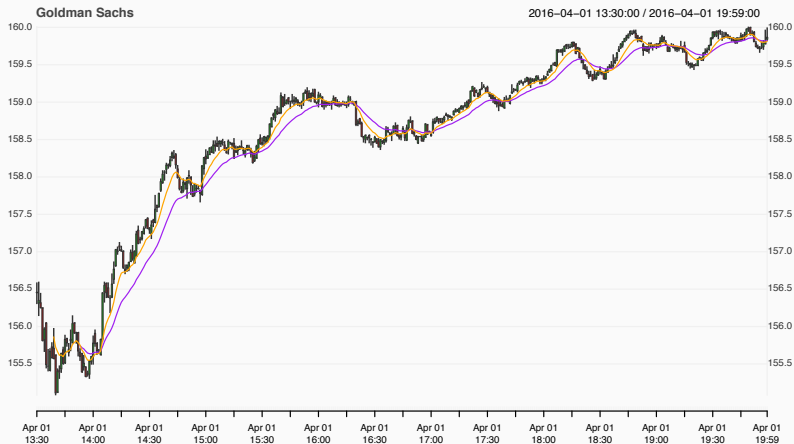
QUANTITATIVE ANALYSIS OF DUAL MOVING AVERAGE INDICATORS IN AUTOMATED TRADING SYSTEMS

Doug Service

May 21, 2016

CFRM Program
Applied Mathematics
University of Washington

Dual Moving Average Technical Trading Strategy [Jaekle and Tomasini(2009)]

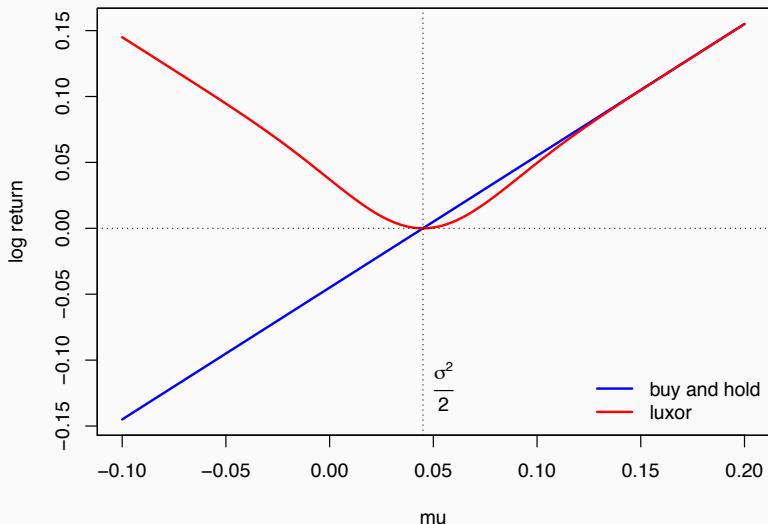


Long position - fast MA above slow MA

Short position - fast MA below slow MA

STRATEGY ANALYSIS: LOG RETURN

$$\frac{d\mathbb{E}[r_t]}{dt} = \left(\mu - \frac{\sigma^2}{2}\right) \left(1 - 2\Phi\left[-\frac{2}{\sigma^2}\left(\mu - \frac{\sigma^2}{2}\right)\frac{\tau_1 + \tau_2}{\tau_2 - \tau_1}\right]\right) \quad \sigma = 0.3, \tau_1 = 3, \tau_2 = 20, t = 1$$



Portfolio optimization modeling

Laura Vana, Florian Schwendinger, Ronald Hochreiter

Saturday 21st May, 2016

```
install.packages("ROML.portfolio", repos="http://R-Forge.R-project.org")
install.packages("ROML", repos="http://R-Forge.R-project.org")
library(ROML); library(ROML.portfolio)
data(djia2013)

m <- model()
m$variable(portfolio, lb = -1) # portfolio choice vector
m$maximize(reward(portfolio))
m$subject_to(cvar(portfolio, 0.95) <= 0.02)
m$subject_to(cvar(portfolio, 0.99) <= 0.03)
m$subject_to(portfolio[2] + portfolio[10] + portfolio[20] <= 0.5)
m$subject_to(turnover(portfolio) <= 0.5)
solution <- optimize(m, solver = "glpk", data = list(returns = djia2013))
```

Some Linguistics of Quantitative Finance

Pat Burns
2016 May
R in Finance, Chicago

I started with a logic proposition:

- I'd rather not get through all my slides
- It's almost Saturday night (the talk was Saturday after lunch)

therefore

Heckling is encouraged

(However in the event the audience failed to heckle.)

Agenda

- **Increase your ignorance**
- **Start a quant community to-do list**

(Suggested heckle: What if I don't want to be ignorant? And I don't.)

Response: This is **my** agenda, yours may vary.)

Risk parity

Equalize the **variance**
contribution from the various **groups**

In risk parity we have some grouping of assets, and we arrange our portfolio so that an equal amount of variance comes from each group.

(The audience found great humor in “risk parity” immediately following *bête noire*. That was unintended, but welcome nonetheless.)

The next slide is a picture you’ve seen before, which is it?

(The audience nominated *inferno*, gas can, and *bête noire*.)

There was a vote — certainly an unamerican election since there were more than two parties.

Bête noire was not very popular. The gas can probably had a slight edge.)

Risk parity (part 2)

Big weight in **low** volatility assets
suggests low expected return

But we were talking about risk parity's return problem.

There is an obvious solution ...



just lever up.

Photo from istock.



So here's the plan:

Put yourself at the designated location, and wait for global warming.

S
B
S

I think this is SBS.

**Smartpeople
Being
Stupid**

(Others might have a harsher opinion of this levering proposition. Far be it from me to be so cynical.)