Optimal Conditioning Information with Google's Search Queries for Portfolio Management

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Topics

Motivation

- The question to construct actively managed portfolios optimally using conditioning information has been around since Hansen e Richard (1987).
- The goal has been to try to derive better portfolios strategies that respond conditionally or unconditionally efficiently to predictive information.

Goal of Conditioning Information in Mean-Variance Optimization

To provide signals about the state of the economy or anything that could help forecast the future price of financial assets.

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- In the past few years another literature has been growing: nowcasting
- Choi e Varian (2012) claim that predicting the present (nowcasting), can be useful to forecast near-term values of economic indicators.
- It has grounds in the availability of new sources of data: internet search pages (Google, Yahoo, Bing!) and social media (Twitter especially), are some examples.
- These new information should be seen as a valuable instrument to, rather of predicting the **future**, actually predicting the **present**.

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Paper's Question

Would it be the case that we could extract good economic/financial signals from this literature to use as conditioning information for mean-variance optimal portfolios framework?

(Un)Conditionally Efficient Portfolios

Main findings:

- For in-sample and recursive experiments out-of-sample, we see that Google Trends outperforms standard variables used as predictors in this type of analysis (cumulative returns and higher sharpe ratios).
- Google Trends shows a higher volatility when compared to other approaches.

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Topics

- Consider that there are N risky assets, indexed by $i = 1, \ldots, N$

- Let $\mathbf{R}_t$ be a vector N-dimensional vector with the gross returns of N risky assets at time t

- Denote the vector of excess of returns by $\mathbf{r}_t = \mathbf{R}_t - \mathbf{1}R_f$, where $\mathbf{1}$ is a an N-dimensional vector of ones, and R_f the return of the risk-free asset

$$\mathbf{R}_{p,t+1} = \mathbf{x}(\mathbf{Z}_t)'\mathbf{r}_t + R_f$$

where $\mathbf{x}(\mathbf{Z}_t)$ is an N-dimensional vector of portfolio weights, which is a function of the conditioning information $\mathbf{Z}$

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Fixed-weight Problem: *no-information tracking error (NITE)*

For problems that ignores any conditioning information when forming the strategies, the solution of the following problem provides the portfolio weights:

$$\begin{aligned} min_{\mathbf{x}} \quad & \mathbf{x}'\Omega\mathbf{x} \\ \text{s.t.} \quad & \mathbf{x}'\mu + (1 - \mathbf{x}'\mathbf{1}R_f) = \mu_p \end{aligned}$$

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Proposition 1: The minimum-variance portfolio, which is the solution of problem above, in the presence of a risk-free asset R_f and with a expected return μ_p is given by:

$$x_p = \frac{\mu_p - R_f}{(\mu - R_f \mathbf{1})\,\Omega^{-1}\,(\mu - R_f \mathbf{1})}\Omega^{-1}\,(\mu - R_f \mathbf{1})$$

where R_p represents the return of the portfolio and R_b denotes the benchmark return.

Proof: Standard optimization solution (Lagrangian).

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Unconditional Mean Variance Efficiency Problem

Under *unconditional mean variance efficiency*, the active manager's problem is to minimize the unconditional error variance, $Var(R_p - R_b)$, for a given level of alpha $\bar{\alpha}_p = \mathbb{E}(R_p - R_b)$

$$\begin{aligned} min_{x(Z)} \quad & Var(R_p - R_b) \\ \text{s.t.} \quad & \mathbb{E}(R_p - R_b) = \alpha_p \end{aligned}$$

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Proposition 2: Following Chiang (2015), the unique solution to the problem given on equation above without constraint on portfolio risk, is determined by the following function for the portfolios weights:

$$\begin{aligned} x(Z) &= \lambda_1 x_{mv}(Z) + \lambda_2 x_h(Z) \\ &= \lambda_1 \Omega(Z)^{-1}\mu(Z) + \lambda_2 \Omega(Z)^{-1}\gamma(Z) \end{aligned}$$

Details

Topics

- Even though news are taken as unpredictable, may exist exist some early indicators from online social social media, suchs as blogs, Twitter feeds, and many others that could assist in the task to predict various economic and commercial indicators (BOLLEN; MAO; ZENG, 2011).

- Important question in text analytics: which words/expressions to choose?

- Perlin et al. (2017) investigate the impact of Internet search frequency on financial variables by investigating a larger set of words and a more extensive dataset.

- To select the expressions they used:
  - a finance dictionary,
  - 4 different finance-related books.

- Findings: a significant portion of the chosen set of words is able to robustly affect **traded volume**, **returns** and the **volatility** of returns. [VAR models along with Granger causality tests]

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Google Trends

- Free tool developed by Google.
- It analyzes the popularity of top search queries in Google Search across various regions and language.
- Allow users to compare the relative search volume of searches between two or more terms.
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Instruments - Standard

- In asset pricing literature, there are many instruments that are used as predictor for asset returns, such as dividend yield (Fama e French (1988)) and the earnings-price ratio (Lamont (1998)).
- The drawback of most of these instruments is that they are not available weekly or daily.
- The goal is to construct unconditionally efficient portfolios that respond quickly to the available information.

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Instruments - Standard

Standard Set Instruments

- We employ a set of 5 variables that meet the criteria above:
  1. Moody's Seasoned Aaa Corporate Bond Yield (WAAA)
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  3. 1-Month Treasury Constant Maturity Rate (WGS1MO)
  4. 10-Year Treasury Constant Maturity Rate (WGS10YR)
  5. 30-Year Treasury Constant Maturity Rate (WGS30YR)

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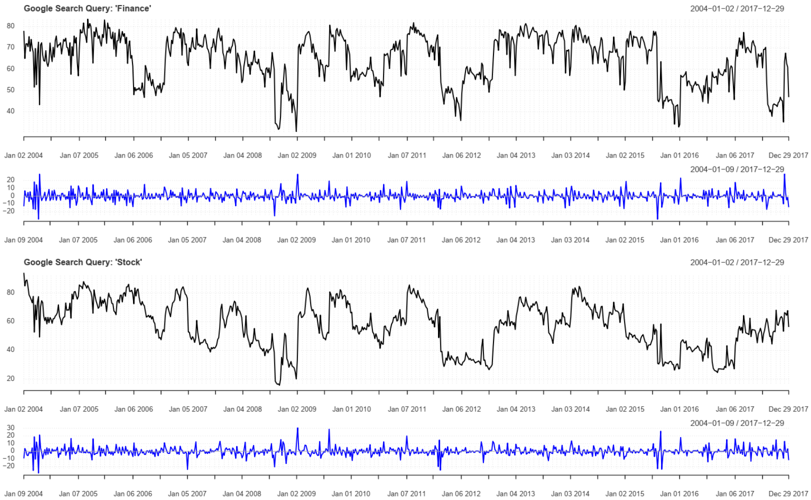
Instruments - Google Trends

Time Series of the Google Trends Instruments (jan-2004 to dec-2017)



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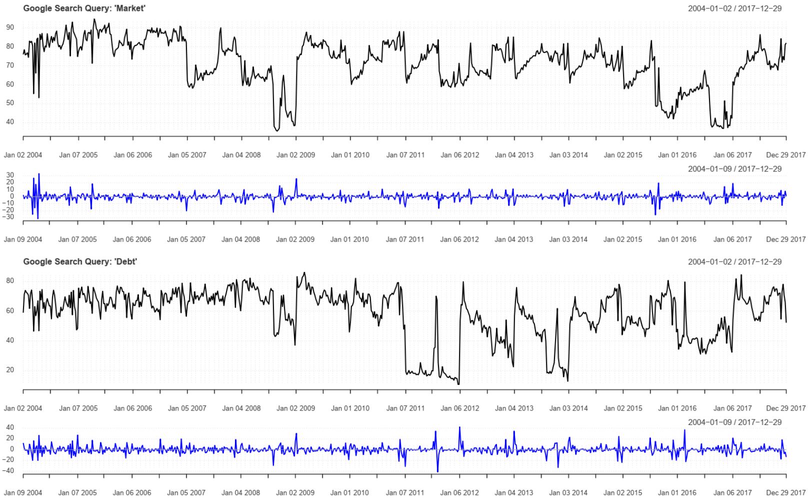

Table: Correlations among all set of instruments for the entire sample (from jan-2004 to dec-2017)

	Finance	Stock	Market	Debt	WAAA	WBAA	WGS1MO	WGS10YR	WGS30YR
Finance	1								
Stock	0.743	1							
Market	0.231	0.485	1						
Debt	0.456	0.31	0.04	1					
WAAA	0.039	0.095	0.045	0.051	1				
WBAA	0.02	0.058	0.01	0.027	0.863	1			
WGS1MO	-0.072	-0.102	-0.078	0.001	-0.096	-0.107	1		
WGS10YR	0	0.047	0	0.061	0.843	0.715	0.021	1	
WGS30YR	0.025	-0.002	0.013	0.04	0.354	0.296	0.002	0.389	1

Portfolios

- We used three portfolios portfolios for our analysis:
  - 5 industry portfolios
  - 6 portfolios formed on size and book-to-market (2 x 3)
  - 25 portfolios formed on size and book-to-market (5 x 5)
- We work with log (continuously compounded) returns

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In-Sample

Table: In-Sample Results - 5 Industry Portfolios

	Standard Instruments				Google Trends				No conditional Information			
	α				α				α			
	0.1%	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**
5 Industry Portfolios												
Annualized Return	0.03	0.11	0.20	0.34	0.07	0.22	0.40	0.68	0.05	0.27	0.56	1.09
Annualized Std Dev	0.04	0.13	0.25	0.49	0.06	0.20	0.37	0.72	0.11	0.17	0.34	0.71
Annualized Sharpe	0.85	0.83	0.80	0.70	1.10	1.10	1.08	0.95	0.46	1.58	1.64	1.53
VaR	-0.01	-0.03	-0.06	-0.11	-0.01	-0.04	-0.08	-0.16	-0.02	-0.04	-0.08	-0.16
Alpha	0.01	0.05	0.09	0.18	0.04	0.13	0.25	0.54	0.00	0.22	0.56	1.52
Beta	0.35	1.16	2.19	4.23	0.50	1.68	3.16	6.10	0.84	0.98	1.16	1.52
Tracking Error	0.08	0.02	0.14	0.37	0.06	0.09	0.26	0.61	0.05	0.13	0.31	0.69
Information Ratio	-0.28	2.54	1.07	0.78	0.19	1.81	1.34	1.05	-0.09	1.72	1.64	1.54
Omega	1.35	1.35	1.35	1.35	1.46	1.47	1.47	1.47	1.20	1.69	1.67	1.62
Pain Ratio	4.59	4.50	4.33	3.82	6.90	6.93	6.78	5.96	1.76	10.63	9.68	8.07

Recursive Window

Out-of-Sample (Fixed)

- Firstly, we estimate our models for conditioning information (2004-2007).
- Then, as new information is available weekly, we update the conditional moments of our strategies.
- At the end of week t , we re-estimate:

$$\mu_t(Z_t) = \mathbb{E}(r_t | Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0})$$

$$\Omega_t(Z_t) = \mathbb{E}(r_t r_t' | Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0})$$

$$\gamma_t(Z_t) = \mathbb{E}\left[r_t(r_{t,b} - \mu_{t,b}) | Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0}\right]$$

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- Then, $\longrightarrow$ form the weight for the next period $x_{t+1}(Z_t) \longrightarrow$ re-balance the portfolio accordingly to the estimated $x_{t+1}(Z_t)$.
- As a matter of comparison, for *5 industry portfolios* for each from $t = 1$ to $t = 523 = T$ (out-of-sample), we ran (individually) 5 linear regressions to obtain: $\mu_t(Z_t)$, $\Omega_t(Z_t)$, and $\gamma_t(Z_t)$.
- Totalizing $523 \times 5 = 2,615$ regressions.

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- As a matter of comparison, for *5 industry portfolios* for each from $t = 1$ to $t = 523 = T$ (out-of-sample), we ran (individually) 5 linear regressions to obtain: $\mu_t(Z_t)$, $\Omega_t(Z_t)$, and $\gamma_t(Z_t)$.

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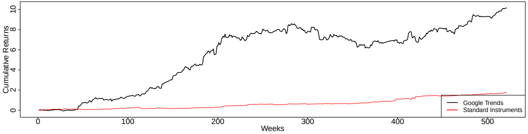
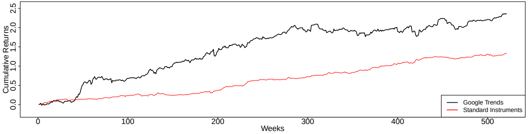
Recursive Window

Cumulative Returns - Recursive Window (from jan-2008 to dec-2017)

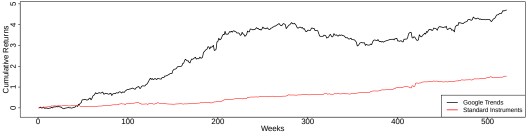
Cumulative Returns – Rolling Windows – 6 Portfolios Formed on Size and Book–to–Market (2x3)



Cumulative Returns – Rolling Windows – 5 Industry Portfolios



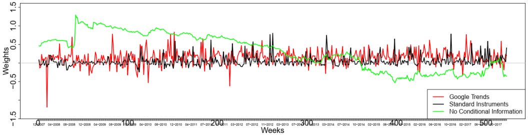
Cumulative Returns – Rolling Windows – 25 Portfolios Formed on Size and Book–to–Market (5x5)



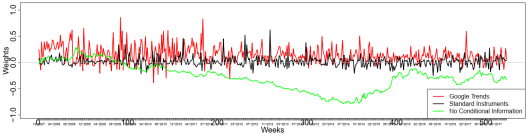
Recursive Window

Weekly Weights - 5 Industry Portfolios - Recursive Window (from jan-2008 to dec-2017

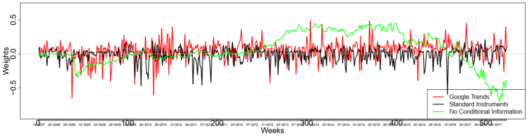
Portfolio Weights – 5 Industry Portfolios – Asset – 1



Portfolio Weights – 5 Industry Portfolios – Asset – 2



Portfolio Weights – 5 Industry Portfolios – Asset – 3



Recursive Window

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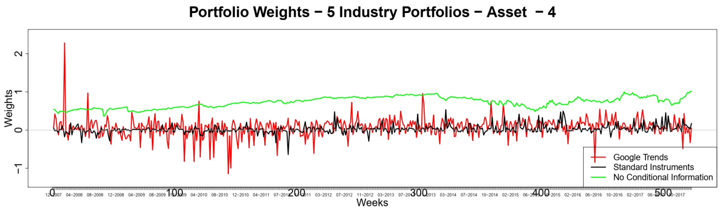

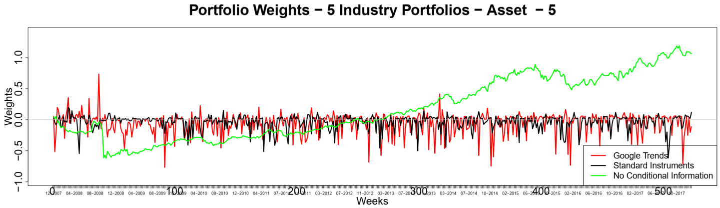

Conclusion

- This paper seeks to address the question whether "nowcasting" can be incorporated in the mean-variance optimization framework.
- We use Google Trends search expressions with statistical power to predict market as instruments in the unconditional mean-variance portfolio efficiency framework.

Main findings:

- For in-sample and recursive experiments out-of-sample, we see that Google Trends outperforms standard variables used as predictors in this type of analysis.
- Google Trends as instruments produces higher cumulative returns and higher sharpe ratios.
- Google Trends shows a higher volatility when compared to the other approaches.
- Suggesting that the information provided from web searches may have some level of noise.

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Extensions

- In order to seek better and robust results, possible extensions are:
  - use simulation experiments (block bootstrap) to analyse robustness (behavior found could be sample specific?),
  - incorporate some noise reduction in the data,
  - model a different return generating process (DGP): $R_{i,t} = g(\mathbf{Z}_t)$
  - estimate the models with daily data, which should result in even faster response to the instrument's information

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- use other variables that makes use of nowcasting that seeks to measure the economic state and investor's sentiment (such as **FEARS**, see Da, Engelberg e Gao (2014))
- evaluate the performance of the models in the conditional mean-variance framework
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30, 31, 32, 33, 34, 35

Methodology

Return

where,

$$\mu(Z) = \mathbb{E}(r|Z),$$
$$\Omega(Z) = \mathbb{E}(rr'|Z),$$
$$\gamma(Z) = \mathbb{E}\left[r(r_b - \mu_b)|Z\right]$$
$$\lambda_1 = \frac{(\bar{\alpha}_p + \mu_b) - \eta_2}{\eta_1}$$
$$\lambda_2 = 1$$
$$\eta_1 = \mathbb{E}(\eta_1(Z)) \qquad \eta_1(Z) = \mu(Z)'\Omega(Z)^{-1}\mu(Z) = x_{mv}(Z)'\mu(Z)$$
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Proof: As Chiang (2015) shows, the solution is found using calculus of variations.

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Return 1

Return 2

- From Hansen e Richard (1987) we know that **unconditionally efficient portfolios must be conditionally efficient, but not the converse.**

- When there is conditioning information, mean variance efficiency may be defined in terms of:
  - the conditional means and variances (conditionally efficient)
  - terms of unconditional moments

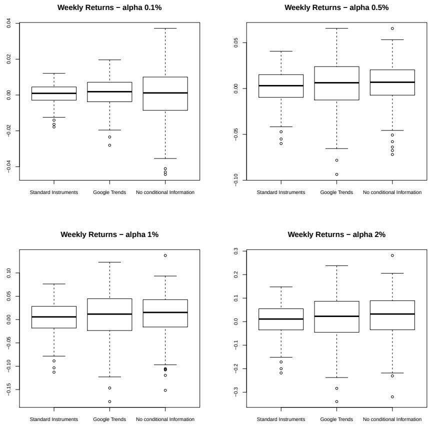
Unconditional Mean Variance Efficiency with Respect to the Information

Objective is to maximize the unconditional mean relative to the unconditional variance, where **portfolio strategies may be functions of the information**.

In-sample Performance

Weekly returns boxplots - 5 industry portfolios (In-Sample)

Return



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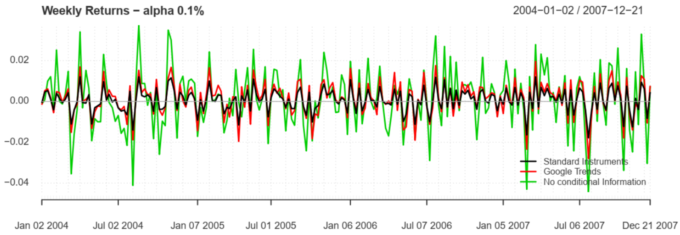

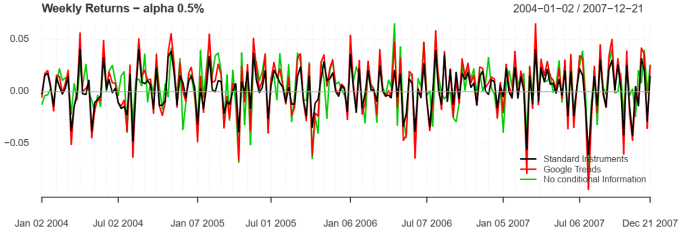

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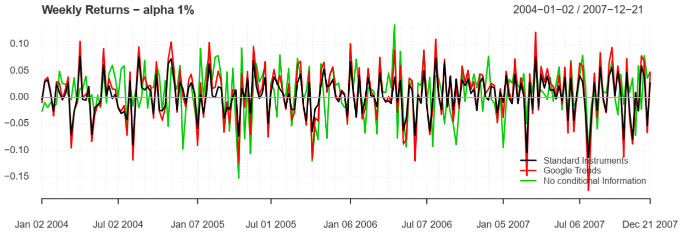
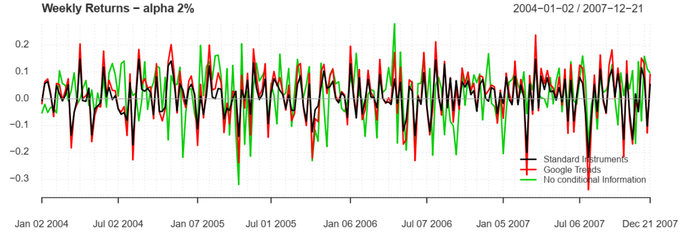
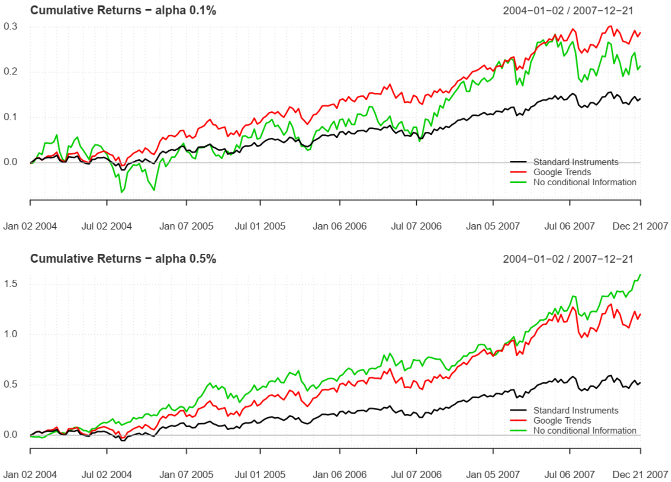




In-sample Performance

Cumulative Returns - 5 industry portfolios (In-Sample)



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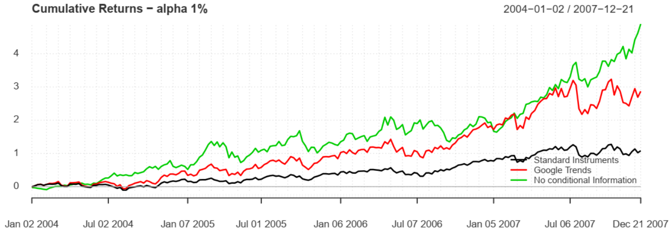

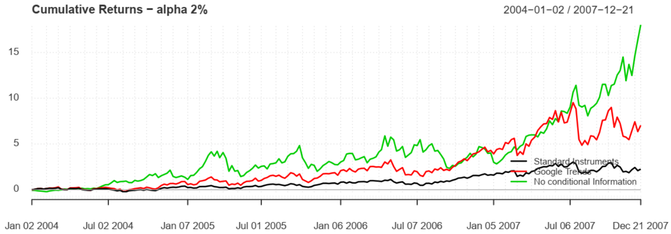

Out-of-sample Performance

5 Industry Portfolios

Recursive Window

Table: Out-of-Sample Results - 5 Industry Portfolios

	Standard Instruments			Google Trends			No conditional Information		
		α			α			α	
	0.1%	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**
5 Industry Portfolios									
Annualized Return	0.03	0.09	0.12	0.04	0.08	0.05	0.10	0.04	-0.07
Annualized Std Dev	0.06	0.21	0.40	0.09	0.31	0.59	0.16	0.21	0.36
Annualized Sharpe	0.48	0.41	0.31	0.38	0.26	0.08	0.64	0.17	-0.20
VaR	-0.01	-0.05	-0.09	-0.02	-0.07	-0.14	-0.04	-0.05	-0.09
Alpha	0.00	0.02	0.03	0.00	0.00	-0.01	0.05	-0.01	-0.09
Beta	0.33	1.12	2.10	0.50	1.66	3.11	0.77	0.86	0.97
Tracking Error	0.13	0.03	0.21	0.10	0.13	0.40	0.07	0.13	0.32
Information Ratio	-0.28	0.79	0.28	-0.31	0.14	-0.04	0.49	-0.24	-0.45
Omega	1.23	1.23	1.23	1.19	1.19	1.19	1.31	1.12	0.99
Pain Ratio	1.06	0.90	0.68	0.78	0.54	0.17	1.82	0.23	-0.16

Out-of-sample Performance

Cumulative Returns - 5 industry portfolios (Out-of-Sample)

Recursive Window