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

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2018

Abstract

This paper studies new sources of signals to be incorporated in a mean-variance framework for portfolio optimization. We assess the performance of unconditionally efficient strategies from Chiang [2015] using Google Trends as conditioning information, both in sample and out of sample. Comparing with standard instruments used in this type of analysis, we show that Google Trends data improves the risk-return trade-off. However, Google Trends signals are more volatile when used in weekly data. The motivation for this approach comes from the growing nowcasting literature, which has shown to be useful in forecast near-term values of economic indicators.

Keywords: Portfolio Efficiency. Conditional Information. Google Trends.
JEL Classification: C12, C13, C58, G11, G12

1 Introduction

The literature of mean-variance optimization in the presence of conditioning information has grown substantially in the past years. The motivation of this concept has grounds on information asymmetry. In summary, while it is well know that the portfolio management goal is to obtain a higher expected return than a pre-specified benchmark, while seeking to minimize the volatility of the assets; this can be done either with or without conditioning information. The theoretical implications derived for Hansen and Richard [1987] started a chain of studies seeking how to construct optimal portfolios from a manager point of view, who uses conditioning information to build his portfolios, but that is evaluated by economic agents who do not have access to predictive information.

The question to construct actively managed portfolios optimally using conditioning information has been debated since then. The main goal has been to try to derive better portfolios strategies that respond conditionally or unconditionally efficiently to predictive information. However, not much attention has been put on the information used when building these portfolios.

Since the goal of using conditioning information is to provide signals about the state of the economy or anything that could help forecast the future price of financial assets, to focus on finding better signals should be seen as an important topic to this literature. Should come as no surprise that, nowadays, with the advance of information technology, we have access new type of datasets that can be used to extract better signals. Internet search pages such as Google, Yahoo! and Bing can provide a rich and large datasets of social information; thus, being able to generate economic activity indicators.

Ettredge et al. [2005] is considered the first paper that used web search data to forecast economic activities. Since then, Choi and Varian [2012] claim that predicting the present, or "nowcasting", can be useful to forecast near-term values of economic indicators. The authors used Google Trends, a real-time daily and weekly index of the volume of queries users search on Google search engine. They say that Google Trends should be seen as a valuable instrument to, rather of predicting the future, actually predict the present.

In this paper we study mean-variance efficient strategies using Google Trends as conditioning information, both in-sample and out-of-sample. Comparing with standard instruments used in this type of analysis, we show that Google Trends data provides a better signal and can provide more value to portfolio management in the continuously updating portfolio weights approach for out-of-sample experiments. This experiment is motivated by the "nowcasting" literature, in which predictive instruments are available in real time, allowing the mean-variance optimization to respond faster to changes in the economic environment.

The structure of this paper is as follows. Next section introduces the methodology, presenting the unconditionally mean-variance efficient portfolios and the weights solution when information is used to construct the unconditional moments. In the same section, we also present the standard solution of the mean-variance efficient portfolios. In section 3 we present the "nowcasting" approach using web searches from Google. Section 4 presents our empirical analysis comparing the predictability and performance of the unconditionally mean-variance efficient portfolios. The analysis is done in-sample and out-of-sample. Finally, section

6 concludes. Additional results, tables and figures are presented in Appendix A.

2 Methodology

In asset pricing literature we consider that there are N risky assets, indexed by $i = 1, \ldots, N$. The investors have access to a risk-free asset (or a safe asset). Denoting $\mathbf{R}_t$ as a vector N-dimensional vector with the gross returns of N risky assets at time t. If we denote by R_f the return of the risk-free asset, we obtain the vector of excess of returns $\mathbf{r}_t = \mathbf{R}_t - \mathbf{1}R_f$, where $\mathbf{1}$ is a an N-dimensional vector of ones.

At the beginning of the each time t, the active manager has available conditioning information $\mathbf{Z}_t$, which is unavailable to his clients. The manager's goal is to form a portfolio choosing the weights $\mathbf{x}(\mathbf{Z}_t)$ out of the N risky assets, investing the remaining funds in the risk-free asset. Therefore, the return at time $t+1$ on such strategy is hence:

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

For problems that ignore any conditioning information when forming the strategies (that is what some authors consider 'fixed-weight' strategies, or *no-information tracking error (NITE)* as Chiang [2015] refers), the solution of the following problem provides the portfolio weights:

$$\begin{array}{rc} min_{\mathbf{x}} & \mathbf{x}'\mathbf{\Omega}\mathbf{x} \\ \text{s.t.} & \mathbf{x}'\mu + (1 - \mathbf{x}'\mathbf{1}R_f) = \mu_p \end{array} \tag{2}$$

where the μ is the unconditional mean and Ω is the unconditional covariance matrix of the N risky assets.

Proposition 1: The minimum-variance portfolio, which is the solution of problem given on equation 2, in the presence of a risk-free asset R_f and with a expected return μ_p is given by:

$$x_p = \frac{\mu_p - R_f}{(\mu - R_f\mathbf{1})\,\Omega^{-1}\,(\mu - R_f\mathbf{1})}\Omega^{-1}\,(\mu - R_f\mathbf{1}) \tag{3}$$

Proof: This result is standard. The solution is obtained forming a Lagrangian and solving for x; see Campbell et al. [1997].

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 $\bar{\alpha}_p = \mathbb{E}(R_p - R_b)$

$$\begin{array}{rc} min_{x(Z)} & Var(R_p - R_b) \\ \text{s.t.} & \mathbb{E}(R_p - R_b) = \alpha_p \end{array} \tag{4}$$

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

Proposition 2: Following Chiang [2015], the unique solution to the problem given on equation 4 without constraint on portfolio risk, is determined by the following function for the portfolios weights:

$$\begin{aligned} x(Z) &= \lambda_1 x_{mv}(Z) + \lambda_2 x_h(Z) \\ &= \lambda_1 \Omega(Z)^{-1}\mu(Z) + \lambda_2 \Omega(Z)^{-1}\gamma(Z) \end{aligned} \tag{5}$$

where,
$\mu(Z) = \mathbb{E}(r|Z)$,

$\Omega(Z) = \mathbb{E}(rr'|Z)$,
$\gamma(Z) = \mathbb{E}\left[r(r_b - \mu_b)|Z\right]$
$\lambda_1 = \dfrac{(\bar{\alpha}_p + \mu_b) - \eta_2}{\eta_1}$
$\lambda_2 = 1$
$\eta_1 = \mathbb{E}(\eta_1(Z)) \qquad \eta_1(Z) = \mu(Z)'\Omega(Z)^{-1}\mu(Z) = x_{mv}(Z)'\mu(Z)$
$\eta_2 = \mathbb{E}(\eta_2(Z)) \qquad \eta_2(Z) = \mu(Z)'\Omega(Z)^{-1}\gamma(Z) = x_h(Z)'\mu(Z)$

Proof: As Chiang [2015] shows, the solution is found using calculus of variations.

Ferson and Siegel [2001], Ferson et al. [2006] and Chiang [2015] refer to $x_{mv}(Z)$ as the "mean-variance portfolio" and to $x_h(Z)$ as"hedging demand". Notice that $\lambda_1 x_{mv}(Z)$ captures mean-variance investing behavior, being proportional to the tangency portfolio on the minimum unconditional variance boundary. The term $\lambda_2 x_h(Z)$ captures what is understood as the "hedging demand" induced by the benchmark. Intuitively, to minimize tracking error, the manager tends to hedge fluctuations in the benchmark.

Chiang [2015] discuss how varying the allocations λ_1 and λ_2 in equation 5 can deal with so many different portfolio constraints; which has importance to improve the out-of-sample performance of classical mean-variance portfolio solutions.

3 Nowcasting & Google Searches

A persistent question in the broad field of finance literature is how economic agents react to different type of information. Importantly as well is the question of how quickly information moves to reach investors, and consequently, how price of risky assets in the financial markets react to these new available information. This brings the efficient market hypothesis to scene, with the seminal works of Fama [1965]. More recently, with the advance of information technology, we have access to new type of datasets that can be used to extract better signals. Nowcasting methods, can be useful to forecast near-term values of economic indicators.

That is what has been motivating a growing literature. The idea is that, 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 et al. [2011]). Da et al. [2014] use internet search queries volume from Google to create a financial and economic index (Financial and Economic Attitudes Revealed by Search - FEARS), and show that it can predict short-term return reversals, temporary increases in volatility, and also predict mutual fund flows out of equity funds and into bond funds.

Bollen et al. [2011] analyze the text content of daily Twitter feeds by two mood tracking tools (OpinionFinder and Google-Profile of Mood States). They show that the accuracy of DJIA predictions can be significantly improved by the inclusion of specific public mood dimensions but not others. Joseph et al. [2011] using online ticker (e.g. "MSFT" for Microsoft) searches as a proxy for investor sentiment, the authors show that for a sample of S&P 500 firms over the period 2005-2008, for weekly horizon, online search intensity reliably predicts abnormal stock returns and trading volumes, and that the sensitivity of returns to search intensity is positively related to the difficulty of a stock being arbitraged.

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. The authors, instead of using ticker symbols (or market names) to collect web searches volume data, use a different methodology for selecting the expressions. They use a finance dictionary[1] and four different finance-related books[2] to select the words. Out of the 14,479 unique finance expressions out of the finance dictionary, they selected the top 15 ones in the number of occurrences in the four finance-related books[3].

Using VAR models along with Granger causality tests, the authors find that a significant portion of the chosen set of words is able to robustly affect different aspects of the financial market, such as the traded volume, returns and the volatility of returns. On top of that, they show statistically robust results of predictability, even when comparing the selected expressions to random words.

Google Trends is a free[4] tool developed by Google that analyzes the popularity of top search queries in Google Search across various regions and language, allowing users to compare the relative search volume of searches between two or more terms.

For a expression, Google Trends assign values from 0 to 100 representing relative search volume for that specific expression. In order to calculate the relative frequency, Google's algorithm considers all uses of the word. This feature, what we consider it a positive characteristic, by looking at the search volume for a particular word, one can find the search frequency for many variations that use the same word[5]. It is important to point out that the Google Trends data may change when accessed in different dates owing to the use of the maximum value of search queries in the normalization process. When a new maximum is found in the dataset, it changes all the previous values of normalized search frequency.

[1] Investopedia - *http://www.investopedia.com/dictionary/*

[2] Jaffe et al. [2004], Lynch et al. [2000], Graham and McGowan [2005], Brealey et al. [2011]

[3] The 15 words selected: *Finance, Cap, Capital, Corporate Finance, Value, Par, Stock, Market, Risk, Cash, Dividend, Journal, Option, Year, Debt*

[4] Even though the tool being free, Google incorporated quota limits for Trends searches limiting the number of search queries done per IP-device in a given day.

[5] Notice that if the same user search multiple times the same expression, Google's algorithm will disregard these searches towards the computation of the final frequency index of Google Trends.

4 Empirical Analysis

In this section we assess gains of predictability of Google Trends as the set of instruments against the standard set of instruments commonly used in unconditional efficiency for standard portfolios. The idea is to evaluate if Google searches can be considered a good set of instrument as conditional information to construct efficient portfolios.

With the availability of internet searches queries in real-time daily and weekly, we might expect Google Trends can provide contemporaneous forecasting information to asset prices. Therefore, we focus to use weekly, instead of monthly data, in this empirical analysis seeking to evaluate how fast and predictable the instruments derived from Google Trends can be used to form unconditional efficient portfolios.

Since Google Trends data is available beginning on January 1st 2004, we decided to use weekly data for all risky assets and instruments from the first week of January 2004 to the last week of December 2017.

4.1 Instruments

4.1.1 Standard Instruments

In asset pricing literature there is considerable evidence demonstrating that stock returns are predictable. For instance, the nominal short interest rate (Fama and Schwert [1977]), dividend yield (Fama and French [1988]), and the earnings-price ratio (Lamont [1998]) are notorious used instruments in the literature. Many others has been proposed, such as the 3-month Treasury-bill yield (see Ferson and Qian [2004]) and the spread between corporate bond yields with different ratings. This spread is derived from the difference between the Moody's Baa and Aaa corporate bond yields (see Keim and Stambaugh [1986]; Ferson and Siegel [2009]). Another commonly used instrument is the spread between the 10-year and 1-year Treasury-bill yield with constant maturity (see Fama and French [1989]; Ferson and Siegel [2009]). Ferson and Qian [2004] argues that the percentage change in the U.S. inflation, measured by the Consumer Price Index (CPI) is an important instrument for the economic state.

The drawback of most of these instruments is that they are not available weekly or daily. Since the goal is to construct unconditionally efficient portfolios that respond quickly to the available information, which should resemble nowcasting approaches, we only can choose a small group of these predictors to be part of our standard instruments.

In this paper, we employ a set of 5 variables that meet the criteria above: (i) Moody's Seasoned Aaa Corporate Bond Yield (WAAA), (ii) Moody's Seasoned Baa Corporate Bond Yield (WBAA), (iii) 1-Month Treasury Constant Maturity Rate (WGS1MO) (iv) 10-Year Treasury Constant Maturity Rate (WGS10YR), and (v) 30-Year Treasury Constant Maturity Rate (WGS30YR). These five predictive instruments form what we call the set of *standard instruments*. All the data were extract from the FRED. Figure 8 in Appendix A shows the time series of the standard instruments. In order to impose stationarity, we use the first difference of the data.

4.1.2 Google Trends

To compare with the standard instruments set, we use search queries from Google. Following the approach from Perlin et al. [2017] we restricted the Google Trends search queries to the time series data of the following expressions: *Finance*, *Stock*, *Market*, and *Debt*, which are the expressions that have robust results in the VAR estimation result and the Granger-causality tests done by the authors.

Figure 1 shows the search volume for each one of our four expressions for the entire sample period. Below the graph of each time series of each Google instrument, we plot the first difference of the volume of queries. We can note that the series are not necessarily stationary, and some of them present some seasonal pattern. We decided to use the first difference of the series, since it removed any unit root from them.

Table 1 – 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

Table 1 presents the correlations among the two set of instruments, Google Trends and the standard instruments for predictability for the entire sample (jan-2004 to dec-2017). Google Trends instruments include the following search queries: *Finance*, *Stock*, *Market*, and *Debt*. What we denominate as standard instruments include the following predictive variables: (i) Moody's Seasoned Aaa Corporate Bond Yield (WAAA), (ii) Moody's Seasoned Baa Corporate Bond Yield (WBAA), (iii) 1-Month Treasury Constant Maturity Rate (WGS1MO) (iv) 10-Year Treasury Constant Maturity Rate (WGS10YR), and (v) 30-Year Treasury Constant Maturity Rate (WGS30YR)

Table 1 presents correlations among the two set of instruments, Google Trends and the standard instruments for the entire sample, ranging from the first week of January 2004 to the last week of December 2017. We can see that *Finance* and *Stock* variables from Google Trends have a collinearity. *Market* and *Stock* also show a reasonably correlation. Among the standard set of instruments we see some collinearity between WAAA and WGS10YR; between WAAA and WBAA; and WBAA and WGS10YR. More importantly, analyzing the correlations between the variables from both sets, we do not see much multicollinearity, being the correlation between the expression *Stock* from Google Trends set and the WAAA from the standard set the highest one (9.5%).

Figure 1 – Time Series of the Google Trends Instruments (jan-2004 to dec-2017)

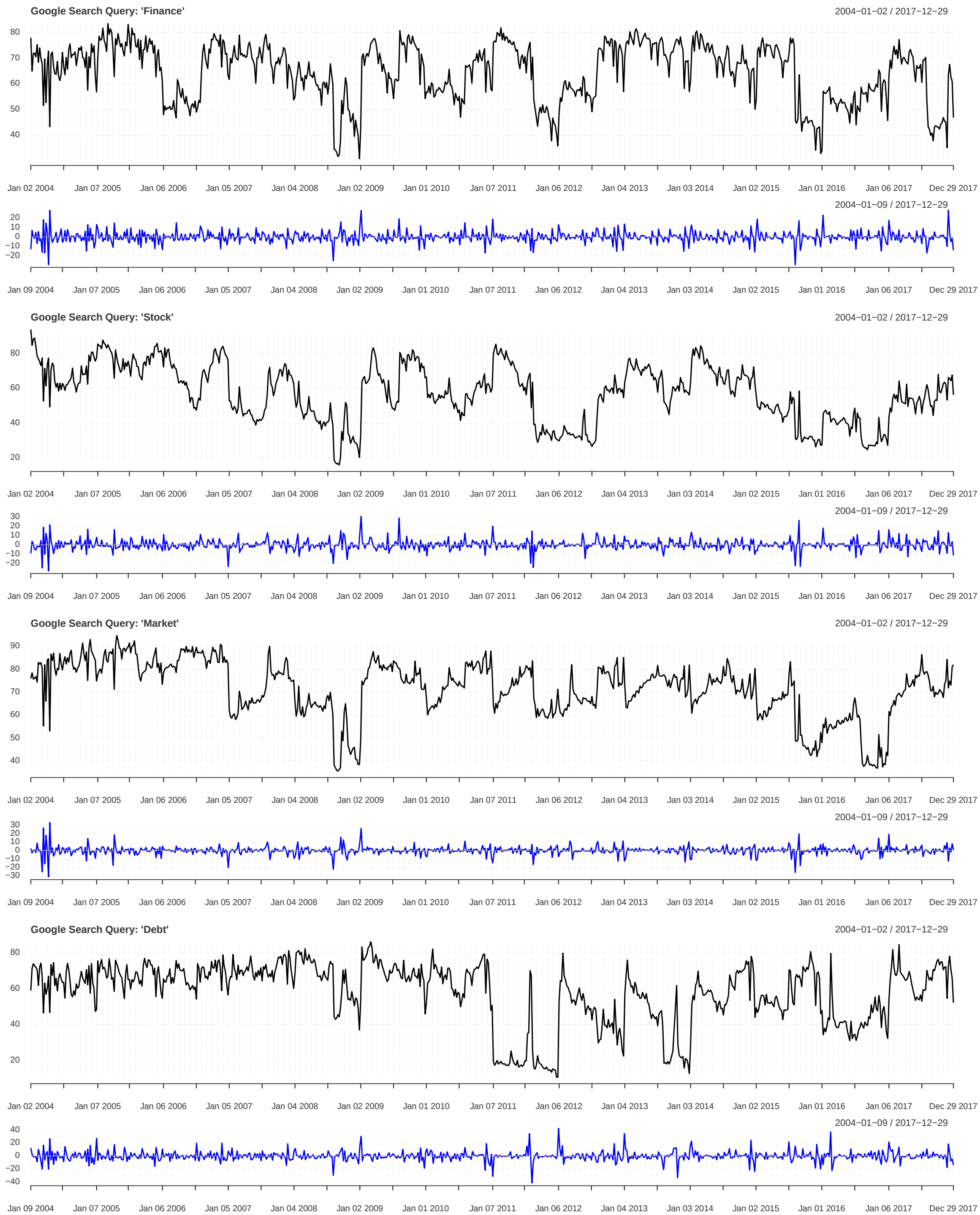

Figure 1 plots the time series of the 4 instruments derived from the Google Trends search queries: (i) "Finance, (ii) "Stock", (iii) "Market", and (iv) "Debt". The vertical axes of all plots are in percentage. Below the plot of each expression, the first difference of the series is shown.

4.2 Portfolios

We used three portfolios portfolios for our analysis. Following the literature, we used (i) the 5 industry portfolios, (ii) 6 portfolios formed on size and book-to-market (2 x 3), and the (iii) 25 portfolios formed on size and book-to-market (5 x 5). All data were extracted from Kenneth French's website French[6].

Notice that, given the time window used in this paper, which has the time length of 14 years, we do not see reasons to turn the data into real returns. Thus, we use only nominal returns in our analysis. Once it is preferable to work with log (continuously compounded) returns, we transform our variables to: $r_{i,t} = ln(R_{i,t})$, where $r_{i,t}$ represents the net return of asset i at time t. [7]

We split the empirical analysis in three sections. First, we evaluate our different sets of instruments (Google Trends and standard instruments) in an in-sample analysis. We consider our three portfolios for different value of alphas for data spanning from the first week of January 2004 until the last week of December 2007. For the out-of-sample section we considered two experiments: (i) using the predictive model from the in-sample results we assess our different sets of instruments for all three portfolio for the remaining of the data, i.e., from the first week of January 2008 to the last week of December of 2017. After that, we also run (ii) "recursive window" experiments, in which the model is updated weekly as new information from the set of instruments is available.

5 Results

5.1 In-sample Performance

Since we have three portfolios, in order to avoid excess of tables, and also because the results are consistent across portfolios, for the in-sample analysis (period spanning from January 2004 to December 2007) we provide only the results for the *5 industry portfolios*. The in-sample results for the two remaining portfolios[8] are presented in the Appendix A. This table reports the results for four previously chosen target alphas ($0.1\%, 0.5\%, 1\%$ and 0.1%), i.e., they represent the target weekly return for each strategy.

We can see a clear pattern. Firstly, for small alphas when using Google Trends as conditioning information provides a higher annualized return when compared to using the standard set of instruments as predictive source. However, this comes with a higher volatility. For instance, for $\alpha = 0.1\%$ the standard deviation for weekly return is 50% for Google Trends strategy when compared to the standard instruments (i.e., 6% and 4% respectively); and for $\alpha = 0.5\%$ the volatility is almost 50%, they are 20% and 13% respectively).

[6] $http : //mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$

[7] Recall that, $R_{i,t} = \dfrac{p_{t+1} + d_{t+1}}{p_t} \quad \Rightarrow \quad r_{i,t} = ln(p_{t+1} + d_{t+1}) - ln(p_t)$, where p_t is the price of the asset and d_t its dividend at time t.

[8] *6 portfolios formed on size and book-to-market (2 x 3)* and *25 portfolios formed on size and book-to-market (5 x 5)*

Table 2 – 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

Table 2 presents in-sample estimation for the 5 industry portfolios using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the in-sample period that ranges from the first week of jan-2004 to the last week of dec-2007.

Figure 2 – Weekly returns boxplots - 5 industry portfolios (In-Sample)

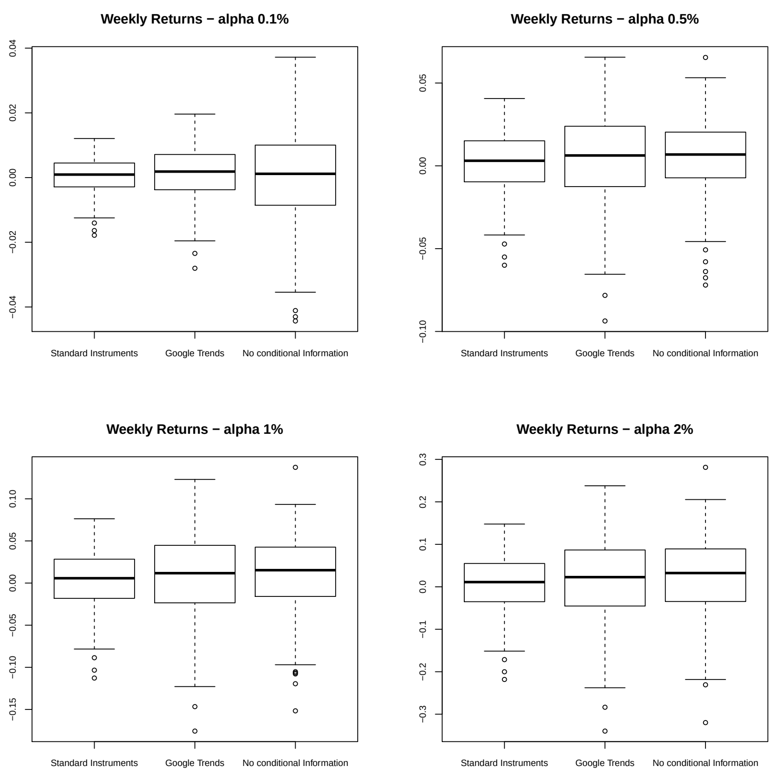

Figure 2 shows 4 panels for the in-sample (first week of jan-2004 to the last week of dec-2007) weekly returns boxplots for the 5 industry portfolios. Each panel represent a different target alphas (ranging from 0.1%, 0.5%, 1% and 0.1%).

Figure 3 – Weekly Returns - 5 industry portfolios (In-Sample)

Figure 3 shows 4 panels for the in-sample (first week of jan-2004 to the last week of dec-2007) weekly returns for the 5 industry portfolios. Each panel represent a different target alphas (ranging from 0.1%, 0.5%, 1% and 0.1%).

Figure 4 – Cumulative Returns - 5 industry portfolios (In-Sample)

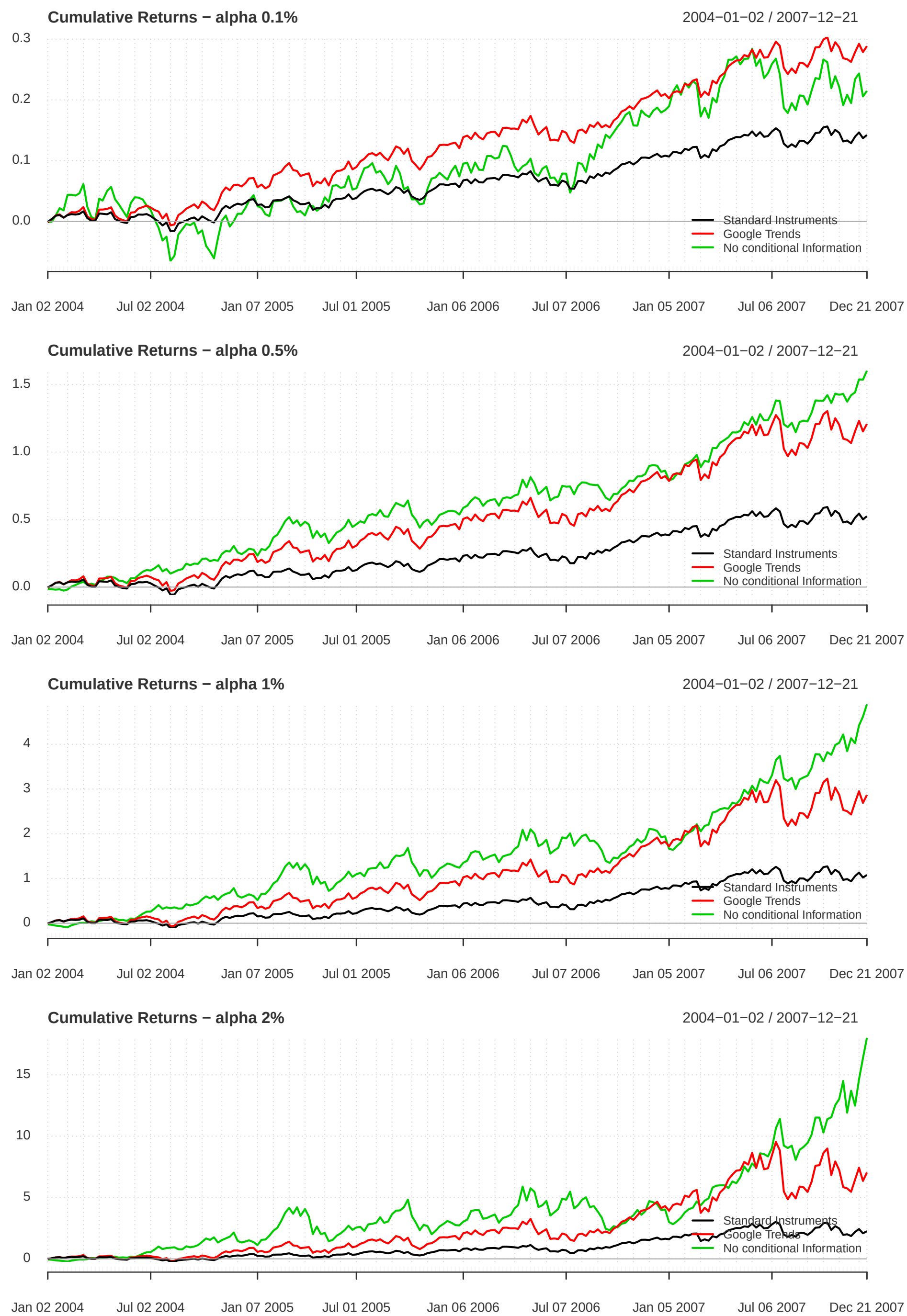

Figure 4 shows 4 panels for the in-sample (first week of jan-2004 to the last week of dec-2007) weekly returns for the 5 industry portfolios. Each panel represent a different target alphas (ranging from $0.1\%, 0.5\%, 1\%$ and 0.1%).

Figure 2 shows this fact using boxplots (in Appendix A, figure 9 and figure 10 are present the boxplots for the other portfolios.). Comparing only both conditioning information sets, for any alpha Google Trends results always in higher interquartile distances, higher median and standard deviation. In Figure 3 we have plotted the time series of the weekly returns for all three strategies. With it we can see a high correlation between the weekly returns of both strategies that makes use of conditioning information. As the plots also make it clear, the variation of the returns using Google Trends is higher, what shows an initial evidence of this strategy respond more aggressively to its instruments.

Analyzing the annualized Sharpe Ratios from table 2, we see that Google Trends instruments results in a consistently higher Sharpe Ratio for target alphas considered. Again, we see the clear pattern for this statistic too: for higher targets, Google Trends improvement shrinks compared to standard conditioning information. We also estimate the CAPM-alpha and CAPM-beta. For both of them, Google Trends also results in higher in-sample estimates.

Table 2 also presents commonly used finance measures, such as the 95% confidence level VaR[9], the tracking error[10], the information ratio[11], the Omega[12] measure and the pain ratio[13]. All these measures are consistent with the facts above for both sets of instruments.

Finally, figure 4 shows the cumulative returns for all 4 target alphas considered. We see that the use of Google Trends as conditioning information results in higher final return when compared to the standard instruments (for any target return).

5.2 Out-of-sample Performance

We split the out-of-sample analysis in two different experiments. First, we use the estimates from the the in-sample analysis, i.e., from the subsample from jan-2004 to dec-2007, and then we assess the behavior of the unconditionally efficient portfolios using either Google Trends or the standard set of instruments as conditioning information. As done in the in-sample analysis, we also evaluate the performance of the fixed weight strategy with no use of conditioning information as a comparison.

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9 $VaR_{.95}(r) = inf\,\{r \in \mathbb{R} : F_R(r) > .95\}$, i.e., the .05-quartile

10 Tracking error is a measure of the unexplained portion of performance relative to a benchmark i.e.,

$$TrackingError = \sqrt{\frac{(R_p - R_b)^2}{len(R_p)\sqrt{scale}}}$$

11 Information ratio is the active premium divided by the tracking error.

12

$$Omega = \frac{\int_L^b (1 - F(R_p))}{\int_a^L F(R_p)}$$

13 Pain ratio is the difference of the portfolio return and the risk free rate divided by the *pain index* (drawdown since previous peak), i.e.,

$$Painratio = \frac{R_p - R_f}{\sum_{i=1}^{T} \frac{|D_i|}{t}}$$

where D_i is the drawdown since previous peak in period i

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

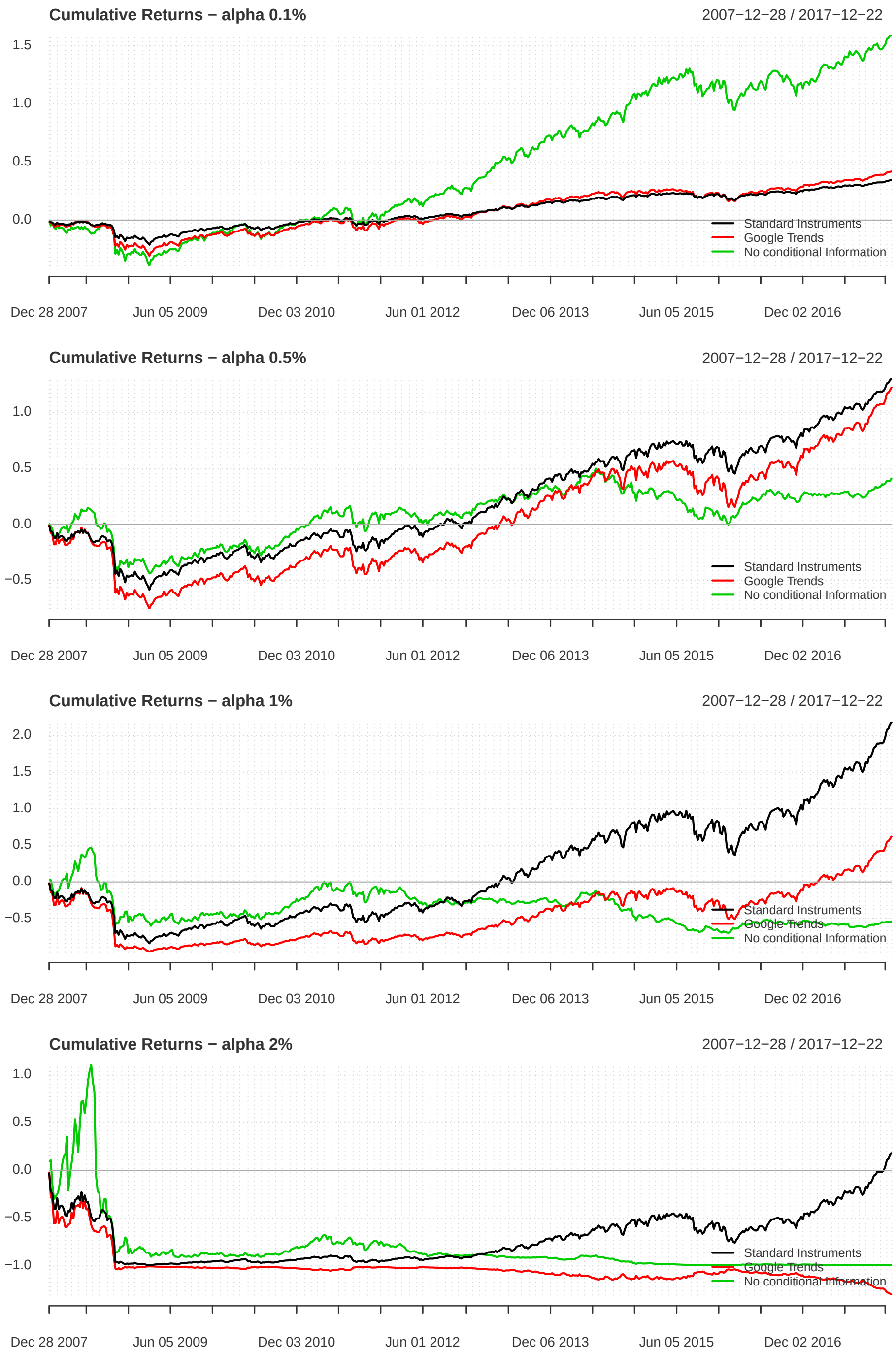


Figure 5 shows 4 panels for the out-of-sample (first week of jan-2008 to the last week of dec-2017) weekly returns for the 5 industry portfolios. Each panel represent a different target alphas (ranging from 0.1%, 0.5%, 1% and 0.1%).

Table 3 – 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

Table 3 presents out-of-sample estimation using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the out-of-sample period that ranges from the first week of jan-2008 to the last week of dec-2017.

The second experiment is done with "recursive window" approach. The idea in this framework of analysis is to re-estimate the conditional moments of our strategies weekly as new information becomes available. Thus, allowing to re-balance the portfolios weekly in such a way to respond to changes in market.

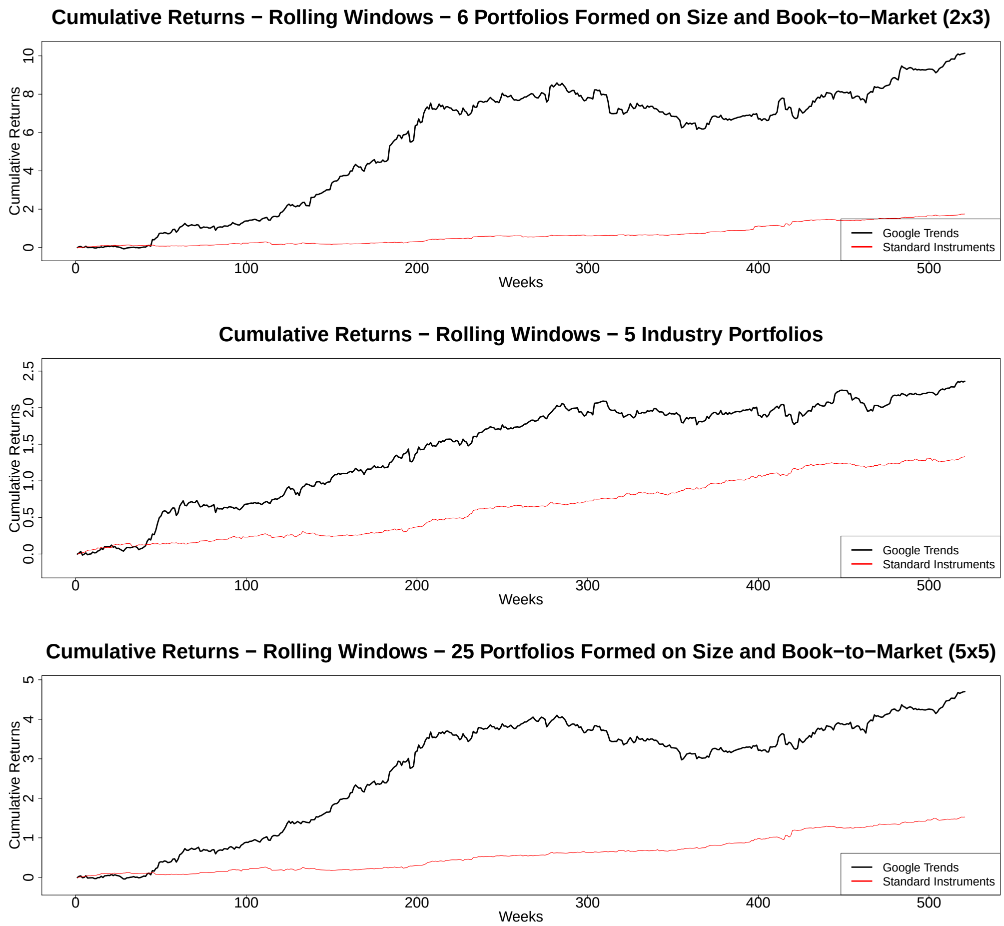
The first analysis for the out-of-sample is done using the estimates from the sub-sample jan-2004 to dec-2007, and evaluating them in the entire remaining sample (jan-2008 to dec-2017). Table 3 presents the out-of-sample performance for the *5 industry portfolios*. Again, in Appendix A, table 6 and table 7 we present the results for the remaining portfolios.

As it should be expected such experiment out-of-sample does not perform well. Especially if we consider the change in the market expectations, as it changes from bull to bear between the end of the first sub-sample (when the estimation is performed) and the beginning of the out-of-sample. Clearly, for low target alphas ($< 0.5\%$) fixed-weight strategy, in which the optimization is done without use of any conditioning information outperforms the unconditional mean-variance portfolio efficient portfolios formed using any of the sets of conditioning information. In Appendix A we present the weekly returns boxplots for all three portfolios.

5.3 Recursive Window

For the recursive window experiments, we estimate our models for conditioning information, using the data from 2004-2007. Then, as new information is available weekly, we update the conditional moments of our strategies and re-balance our portfolio in the beginning of the next week. The goal is to resemble the nowcasting approach with instruments that are available in real time (or close to it). Thus, at the end of week t , from equation 5 we

Figure 6 – Cumulative Returns - Recursive Window (from jan-2008 to dec-2017)



Cumulative returns plots of the recursive window experiment for target of $\alpha = 0.01$ for all three portfolios: (i) the 5 industry portfolios, (ii) 6 portfolios formed on size and book-to-market, and the (iii) 25 portfolios formed on size and book-to-market

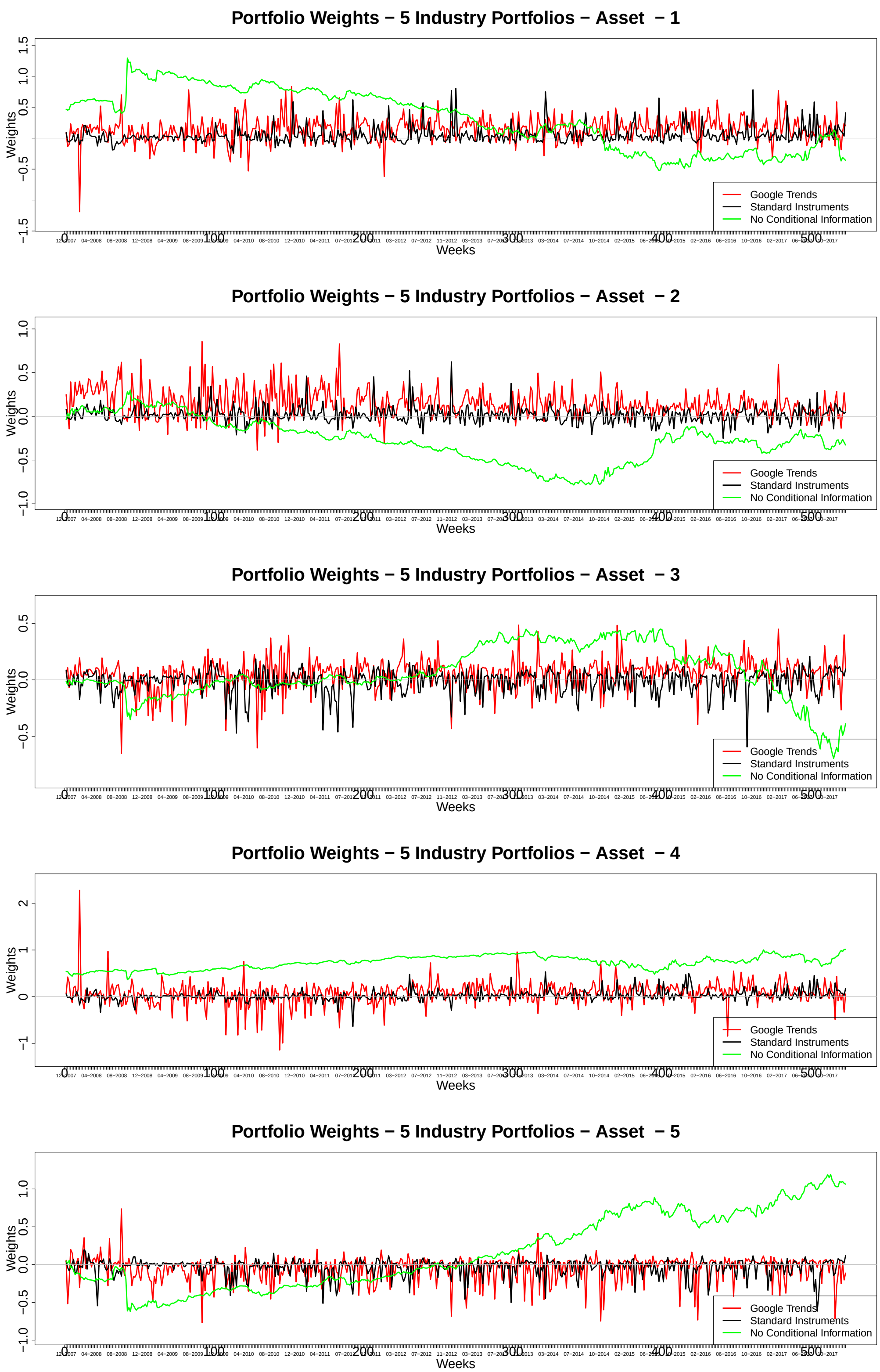
re-estimate $\mu_t(Z_t) = \mathbb{E}(r_t|Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0})$, as well as:

$$\begin{aligned} \Omega_t(Z_t) &= \mathbb{E}(r_t r_t' | Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0}) \\ \gamma_t(Z_t) &= \mathbb{E}\left[r_t(r_{t,b} - \mu_{t,b}) | Z_t, Z_{t-1}, Z_{t-2}, \ldots, Z_{t_0}\right] \end{aligned} \tag{6}$$

after obtaining these estimates for each week, we could form the weight for the next period $x_{t+1}(Z_t)$ and re-balance the each portfolio at $t+1$ accordingly to the estimated $x_{t+1}(Z_t)$.

As a matter of comparison, using *5 industry portfolios* as an example, for each from $t = 1, 2, \ldots, T$, where $T = 523$ (which represents the number of weeks out-of-sample), we ran (individually) 5 (number of assets) linear regressions totalizing $523 \times 5 = 2,615$ regressions. So we were able to obtain: $\mu_t(Z_t), \Omega_t(Z_t)$, and $\gamma_t(Z_t)$, for each t. Therefore, we update our

Figure 7 – Weekly Weights - 5 Industry Portfolios - Recursive Window (from jan-2008 to dec-2017)



Plots of the estimated weekly weights with recursive window experiment for the 5 Industry Portfolios and target $\alpha = 0.01$.

conditional moments.

For the fixed-weight strategy, we decided to allow for the re-estimation of the unconditional moments. Thus, in equation 3, as new information arrives, we can reestimate the unconditional parameters μ_p and Ω. We believe that for the fixed-weights strategy this approach has the merit of updating information and thus, being more suitable to compare this experiment of expanding time window with the efficient portfolio strategies using both sets of conditioning information. Another approach to deal with fixed-weight minimum variance portfolios strategies would be to fix the estimated moments throughout the analysis. However, clearly this approach would not fit in the type of analysis we seek here.

The best way to present the results it is using plots. Figure 6 plots the cumulative returns for all three portfolio in analysis from the first week of 2008 to the last week of 2017 (end of our sample). In order to save space, we show the recursive window experiments only for alpha equal to 0.01%. We can state that results are similar to figure 6 for the remaining targets. However, as seen in the previous sections (5.1 and 5.2) we see that as the target alpha increases Google Trends performs drops. We justify this behavior to the fact that the weekly re-balance using Google Trends results in a more volatile weights for the assets. Thus, the strategy with these instruments overreacts seeking to reach the target alpha to changes of the instruments.

Most importantly, figure 6 shows how the Google Trends sets of instruments delivers a high performance when compared to the standard set of instruments. Importantly to recall that the first year of this analysis covers the 2008 bear market (consequence of the financial crisis). Clearly the first the 50 weeks do not show any significant difference among both strategies, which is much clear after the first year of this subsample. However the difference between both strategies becomes more evident after the first year. We believe that figure 6 is an important result and sheds light on the use of nowcasting techniques and instruments on providing good and timely signs about the market.

Figure 7 plots the estimated weights for each of different strategies for the 5 industry portfolios. Each panel represent the weight for the following assets: Cnsmr, Manuf, HiTec, Hlth and Other. Notice that, in line with mentioned earlier, Google Trends results in more volatile weights compared to the ones estimated from the standard set of instruments. As expected, we can see that while the fixed-weight portfolios varies throughout the sample, but not much, since its standard deviation is the lowest compared to using conditioning information. In Appendix A we present the weights for the 6 portfolios formed on size and book-to-market as well for target $\alpha = 0.1\%$ (figure 14). We also present the time series of the weekly returns for all three portfolios (figures 15, 16 and 17) .

6 Conclusions

This paper seeks to address the question whether "nowcasting" can be incorporated in the mean-variance optimization framework. The literature of contemporaneous forecasting has been growing and providing evidence of some predictability power of financial assets for variables derived from this approach.

We use Google Trends search queries with expressions previously shown with statistical power to predict market returns as instruments in the unconditional mean-variance portfolio efficiency framework. We assess the in-sample and out-of-sample performance of the strategies. Especially for recursive experiments, where the conditioning information is used close to the nowcasting frequency, we see that Google Trends outperforms standard variables used as predictors in this type of analysis. This is seen with higher cumulative returns and higher sharpe ratios.

One fact that is consistent throughout the analysis is that Google Trends shows a higher volatility when compared to the other approaches. A possible explanation is that using Google Trends as instruments may lead to over-reaction changes in portfolios position's due to changes in the instruments. Perhaps, this can suggest that the information provided from web searches may have some level of noise. Further research to try to investigate and control it may lead to better results.

In order to seek better and robust results, possible extensions are: (i) incorporate some noise reduction in the data, (ii) try to estimate the models with daily data, which should result in even faster response to the instrument's information, (iii) use other variables that makes use of nowcasting that seeks to measure the economic state and investor's sentiment (such as FEARS, see Da et al. [2014]), and (iv) evaluate the performance of the models in the conditional mean-variance framework,as well as (v) assess other models of unconditional efficiency (such as Brandt and Santa-Clara [2006], and Peñaranda [2016]).

Bibliography

Johan Bollen, Huina Mao, and Xiaojun Zeng. Twitter mood predicts the stock market. *Journal of computational science*, 2(1):1–8, 2011.

Michael W Brandt and Pedro Santa-Clara. Dynamic portfolio selection by augmenting the asset space. *The Journal of Finance*, 61(5):2187–2217, 2006.

Richard A Brealey, Franklin Allen Allen, and Stewart Myers. *Principles of Corporate Finance*, volume 10. Tata McGraw-Hill, 2011.

John Y Campbell, Andrew Wen-Chuan Lo, Archie Craig MacKinlay, et al. *The Econometrics of Financial Markets*, volume 2. Princeton University Press, 1997.

I-Hsuan Ethan Chiang. Modern portfolio management with conditioning information. *Journal of Empirical Finance*, 33:114–134, 2015.

Hyunyoung Choi and Hal Varian. Predicting the present with google trends. *Economic Record*, 88:2–9, 2012.

Zhi Da, Joseph Engelberg, and Pengjie Gao. The sum of all fears investor sentiment and asset prices. *The Review of Financial Studies*, 28(1):1–32, 2014.

Michael Ettredge, John Gerdes, and Gilbert Karuga. Using web-based search data to predict macroeconomic statistics. *Communications of the ACM*, 48(11):87–92, 2005.

Eugene F Fama. The behavior of stock-market prices. *The journal of Business*, 38(1):34–105, 1965.

Eugene F Fama and Kenneth R French. Dividend yields and expected stock returns. *Journal of financial economics*, 22(1):3–25, 1988.

Eugene F Fama and Kenneth R French. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics*, 25(1):23–49, 1989.

Eugene F Fama and G William Schwert. Asset returns and inflation. *Journal of financial economics*, 5(2):115–146, 1977.

W. E. Ferson and A. F. Siegel. Testing portfolio efficiency with conditioning information. *Review of Financial Studies*, 22(7):2735–2758, Jul 2009. ISSN 1465-7368. doi: 10.1093/rfs/hhn112.

Wayne Ferson, Andrew F Siegel, and Pisun Tracy Xu. Mimicking portfolios with conditioning information. *Journal of Financial and Quantitative Analysis*, 41(3):607–635, 2006.

Wayne E Ferson and Meijun Qian. Conditional performance evaluation, revisited. *Research Foundation Monograph of the CFA Institute*, 2004.

Wayne E Ferson and Andrew F Siegel. The efficient use of conditioning information in portfolios. *The Journal of Finance*, 56(3):967–982, 2001.

B Graham and B McGowan. *The Intelligent Investor*. HarperCollins, 2005.

Lars Peter Hansen and Scott F Richard. The role of conditioning information in deducing testable restrictions implied by dynamic asset pricing models. *Econometrica*, pages 587–613, 1987.

Jeffrey Jaffe, Ross Randolph Westerfield, et al. *Corporate finance*. Tata McGraw-Hill Education, 2004.

Kissan Joseph, M Babajide Wintoki, and Zelin Zhang. Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, 27(4):1116–1127, 2011.

Donald B Keim and Robert F Stambaugh. Predicting returns in the stock and bond markets. *Journal of Financial Economics*, 17(2):357–390, 1986.

Owen Lamont. Earnings and expected returns. *The journal of Finance*, 53(5):1563–1587, 1998.

Peter S Lynch, Peter Lynch, and John Rothchild. *One up on Wall Street: how to use what you already know to make money in the market*. Simon and Schuster, 2000.

Francisco Peñaranda. Understanding portfolio efficiency with conditioning information. *Journal of Financial and Quantitative Analysis*, 51(3):985–1011, 2016.

Marcelo S Perlin, Joao F Caldeira, André AP Santos, and Martin Pontuschka. Can we predict the financial markets based on google's search queries? *Journal of Forecasting*, 36(4):454–467, 2017.

APPENDIX A – Additional Tables and Figures

1 Data

Figure 8 – Time Series of the Standard Set of Instruments (jan-2004 to dec-2017)

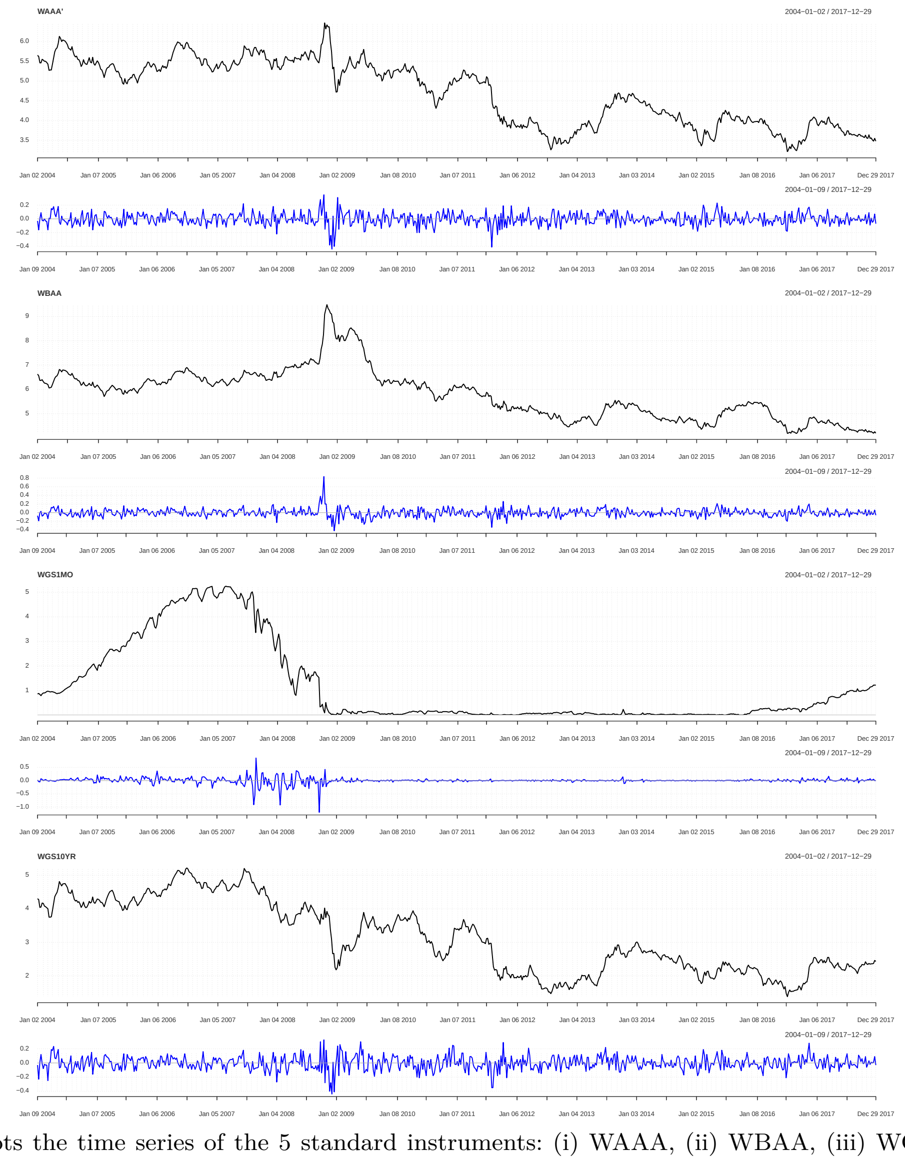


Figure 8 plots the time series of the 5 standard instruments: (i) WAAA, (ii) WBAA, (iii) WGS1MO, (iv) WGS10YR, and (v) WGS30YR. The vertical axes of all plots are in percentage. Below the plot of each expression, the first difference of the series is shown.

2 In-Sample

Table 4 – In-Sample Results - 6 Portfolios Formed on Size and Book-to-Market)

	Standard Instruments				**Google Trends**				**No conditional Information**			
	$\boldsymbol{\alpha}$				$\boldsymbol{\alpha}$				$\boldsymbol{\alpha}$			
	0.1%	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**
6 Portfolios Formed on Size and Book-to-Market (2x3)												
Annualized Return	0.04	0.12	0.21	0.34	0.08	0.24	0.38	0.28	0.05	0.28	0.59	1.19
Annualized Std Dev	0.05	0.16	0.29	0.57	0.10	0.32	0.60	1.16	0.10	0.14	0.30	0.67
Annualized Sharpe	0.80	0.77	0.73	0.60	0.82	0.76	0.62	0.24	0.52	2.05	1.94	1.79
VaR	-0.01	-0.04	-0.07	-0.13	-0.02	-0.07	-0.14	-0.27	-0.02	-0.02	-0.06	-0.13
Alpha	0.01	0.04	0.08	0.16	0.03	0.10	0.20	0.42	0.01	0.26	0.64	1.80
Beta	0.40	1.34	2.52	4.87	0.82	2.76	5.18	10.03	0.69	0.51	0.29	-0.14
Tracking Error	0.07	0.05	0.18	0.45	0.02	0.21	0.49	1.05	0.08	0.14	0.31	0.68
Information Ratio	-0.27	1.36	0.83	0.59	0.86	0.86	0.62	0.18	-0.08	1.67	1.74	1.73
Omega	1.33	1.33	1.33	1.33	1.34	1.34	1.34	1.34	1.22	1.94	1.79	1.68
Pain Ratio	3.84	3.72	3.51	2.90	4.02	3.69	3.05	1.19	1.47	17.97	13.66	10.53

Table 4 presents in-sample estimation for the 6 portfolios formed on size and book-to-market using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the in-sample period that ranges from the first week of jan-2004 to the last week of dec-2007.

Table 5 – In-Sample Results - 25 Portfolios Formed on Size and Book-to-Market

	Standard Instruments				**Google Trends**				**No conditional Information**			
	$\boldsymbol{\alpha}$				$\boldsymbol{\alpha}$				$\boldsymbol{\alpha}$			
	0.1%	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**	**0.1%**	**0.5%**	**1%**	**2%**
25 Portfolios Formed on Size and Book-to-Market (5x5)												
Annualized Return	0.04	0.11	0.20	0.31	0.08	0.23	0.35	0.22	0.05	0.29	0.65	1.63
Annualized Std Dev	0.05	0.16	0.30	0.57	0.10	0.33	0.61	1.18	0.07	0.09	0.17	0.34
Annualized Sharpe	0.75	0.72	0.68	0.54	0.79	0.71	0.58	0.19	0.77	3.21	3.89	4.75
VaR	-0.01	-0.04	-0.07	-0.13	-0.02	-0.07	-0.14	-0.27	-0.01	-0.02	-0.03	-0.06
Alpha	0.01	0.04	0.08	0.16	0.03	0.10	0.20	0.42	0.04	0.27	0.64	1.73
Beta	0.40	1.35	2.53	4.89	0.83	2.78	5.22	10.09	0.31	0.34	0.38	0.44
Tracking Error	0.07	0.05	0.19	0.46	0.03	0.22	0.50	1.07	0.10	0.11	0.18	0.34
Information Ratio	-0.28	1.14	0.78	0.55	0.77	0.82	0.59	0.15	-0.02	2.15	3.42	4.63
Omega	1.31	1.31	1.31	1.31	1.33	1.33	1.33	1.33	1.32	2.63	2.88	2.83
Pain Ratio	3.33	3.23	3.02	2.42	3.60	3.28	2.64	0.86	1.37	40.41	60.33	67.17

Table 5 presents in-sample estimation for the 25 portfolios formed on size and book-to-market using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the in-sample period that ranges from the first week of jan-2004 to the last week of dec-2007.

Figure 9 – Weekly Returns Boxplots - 6 Portfolios Formed on Size and Book-to-Market (In-Sample)

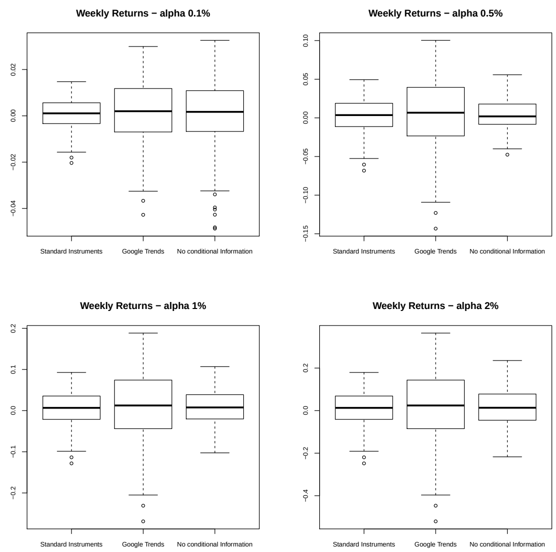


Figure 9 shows 4 panels for the in-sample (first week of jan-2004 to the last week of dec-2007) weekly returns boxplots for the 6 portfolios formed on size and book-to-market. Each panel represent a different target alpha (ranging from 0.1%, 0.5%, 1% and 0.1%).

Figure 10 – Weekly Returns Boxplots - 25 Portfolios Formed on Size and Book-to-Market (In-Sample)

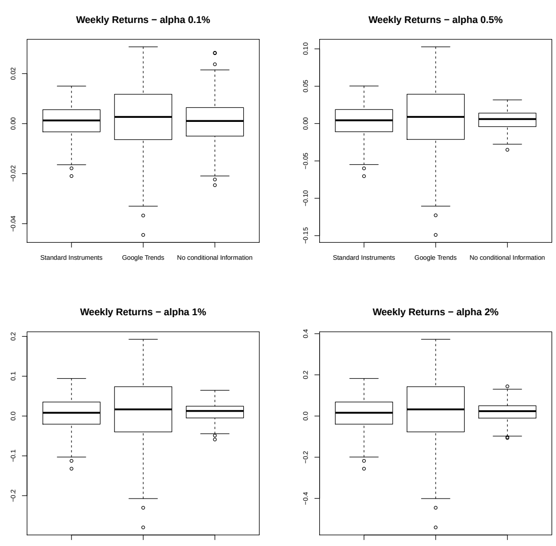


Figure 10 shows 4 panels for the in-sample (first week of jan-2004 to the last week of dec-2007) weekly returns boxplots for the 25 portfolios formed on size and book-to-market. Each panel represent a different target alpha (ranging from 0.1%, 0.5%, 1% and 0.1%).

3 Out-of-Sample

Table 6 – Out-of-Sample Results (6 portfolios formed on size and book-to-market)

	Standard Instruments			**Google Trends**			**No conditional Information**		
		$\boldsymbol{\alpha}$			$\boldsymbol{\alpha}$			$\boldsymbol{\alpha}$	
	0.1%	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**
6 Portfolios Formed on Size and Book-to-Market (2x3)									
Annualized Return	0.03	0.07	0.07	0.05	0.05	-0.32	0.09	0.08	-0.07
Annualized Std Dev	0.08	0.26	0.48	0.16	0.54	1.02	0.16	0.30	0.65
Annualized Sharpe	0.36	0.28	0.15	0.31	0.10	-0.31	0.55	0.27	-0.11
VaR	-0.02	-0.06	-0.11	-0.04	-0.12	-0.23	-0.04	-0.06	-0.13
Alpha	0.00	-0.01	-0.01	-0.01	-0.02	-0.04	0.05	0.03	0.01
Beta	0.40	1.35	2.53	0.85	2.85	5.35	0.64	1.12	1.73
Tracking Error	0.11	0.08	0.30	0.04	0.36	0.83	0.13	0.22	0.58
Information Ratio	-0.33	0.08	0.03	-0.40	-0.03	-0.46	0.19	0.06	-0.24
Omega	1.18	1.18	1.18	1.17	1.17	1.17	1.27	1.18	1.10
Pain Ratio	0.76	0.57	0.31	0.64	0.20	-0.64	1.15	0.42	-0.11

Table 6 presents in-sample estimation for the 6 portfolios formed on size and book-to-market using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the out-of-sample period that ranges from the first week of jan-2008 to the last week of dec-2017.

Table 7 – Out-of-Sample Results (25 portfolios formed on size and book-to-market)

	Standard Instruments			**Google Trends**			**No conditional Information**		
		$\boldsymbol{\alpha}$			$\boldsymbol{\alpha}$			$\boldsymbol{\alpha}$	
	0.1%	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**	**0.1%**	**0.5%**	**1%**
25 Portfolios Formed on Size and Book-to-Market (5x5)									
Annualized Return	0.03	0.07	0.07	0.05	0.06	-0.21	0.09	0.18	0.29
Annualized Std Dev	0.08	0.25	0.47	0.16	0.53	1.00	0.16	0.18	0.30
Annualized Sharpe	0.37	0.28	0.16	0.32	0.12	-0.21	0.54	1.00	0.97
VaR	-0.02	-0.06	-0.11	-0.04	-0.12	-0.23	-0.04	-0.04	-0.06
Alpha	0.00	-0.01	-0.01	0.00	-0.01	-0.03	0.05	0.14	0.27
Beta	0.39	1.32	2.48	0.83	2.78	5.22	0.65	0.69	0.74
Tracking Error	0.12	0.08	0.29	0.04	0.35	0.81	0.13	0.14	0.27
Information Ratio	-0.32	0.09	0.04	-0.31	0.00	-0.33	0.18	0.83	0.83
Omega	1.17	1.17	1.17	1.17	1.17	1.17	1.26	1.45	1.44
Pain Ratio	0.82	0.62	0.35	0.72	0.26	-0.47	0.71	2.47	3.35

Table 7 presents out-of-sample estimation for the 25 portfolios formed on size and book-to-market using (i) Google Trends, (ii) standard set of predictive instruments, and (iii) no conditioning information for the in-sample period that ranges from the first week of jan-2008 to the last week of dec-2017.

Figure 11 – Weekly Returns Boxplots for the 5 Industry Portfolios (Out-of-Sample)

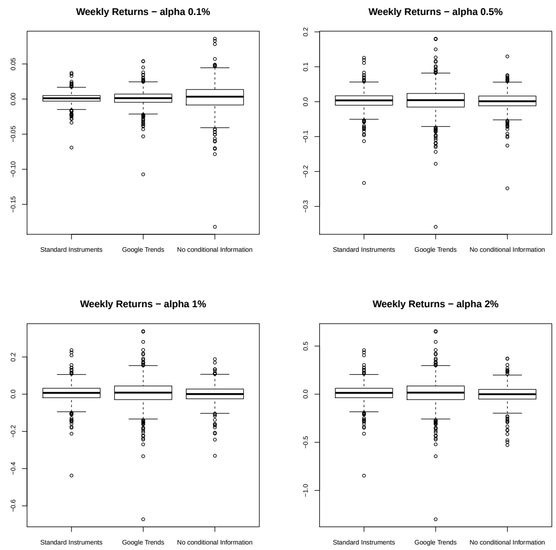


Figure ?? shows 4 panels for the weekly returns boxplots for the 5 industry portfolios for the out-of-sample analysis (first week of jan-2008 to the last week of dec-2017). Each panel represent a different of target alpha (ranging from $0.1\%, 0.5\%, 1\%$ and 0.1%).

Figure 12 – Weekly Returns Boxplots for the 6 Portfolios Formed on Size and Book-to-Market (Out-of-Sample)

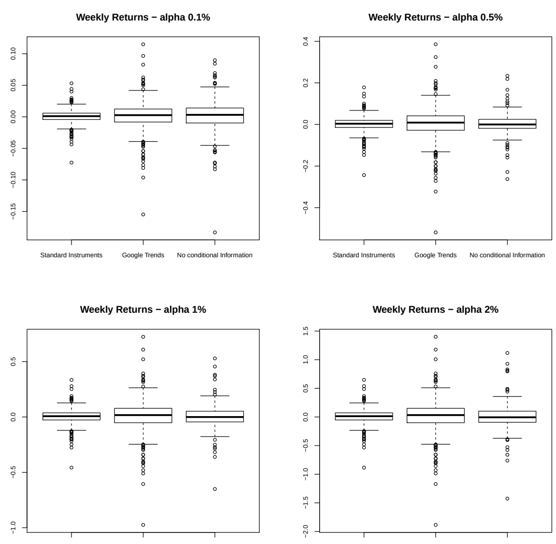


Figure ?? shows 4 panels for the weekly returns boxplots for the 6 portfolios formed on size and book-to-market for the out-of-sample analysis (first week of jan-2008 to the last week of dec-2017). Each panel represent a different of target alpha (ranging from $0.1\%, 0.5\%, 1\%$ and 0.1%).

Figure 13 – Weekly Returns Boxplots for the 25 Portfolios Formed on Size and Book-to-Market (Out-of-Sample)

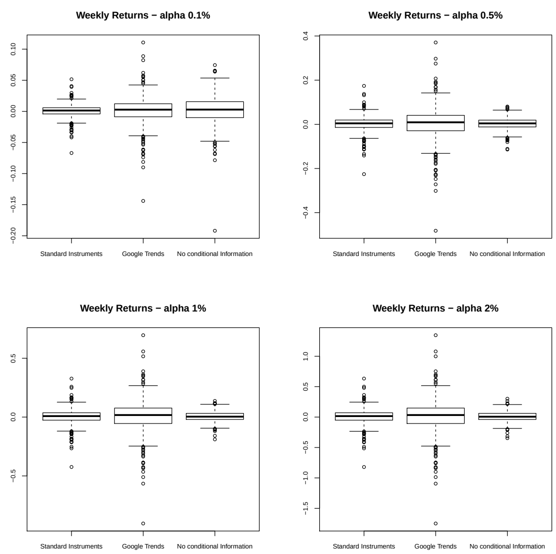


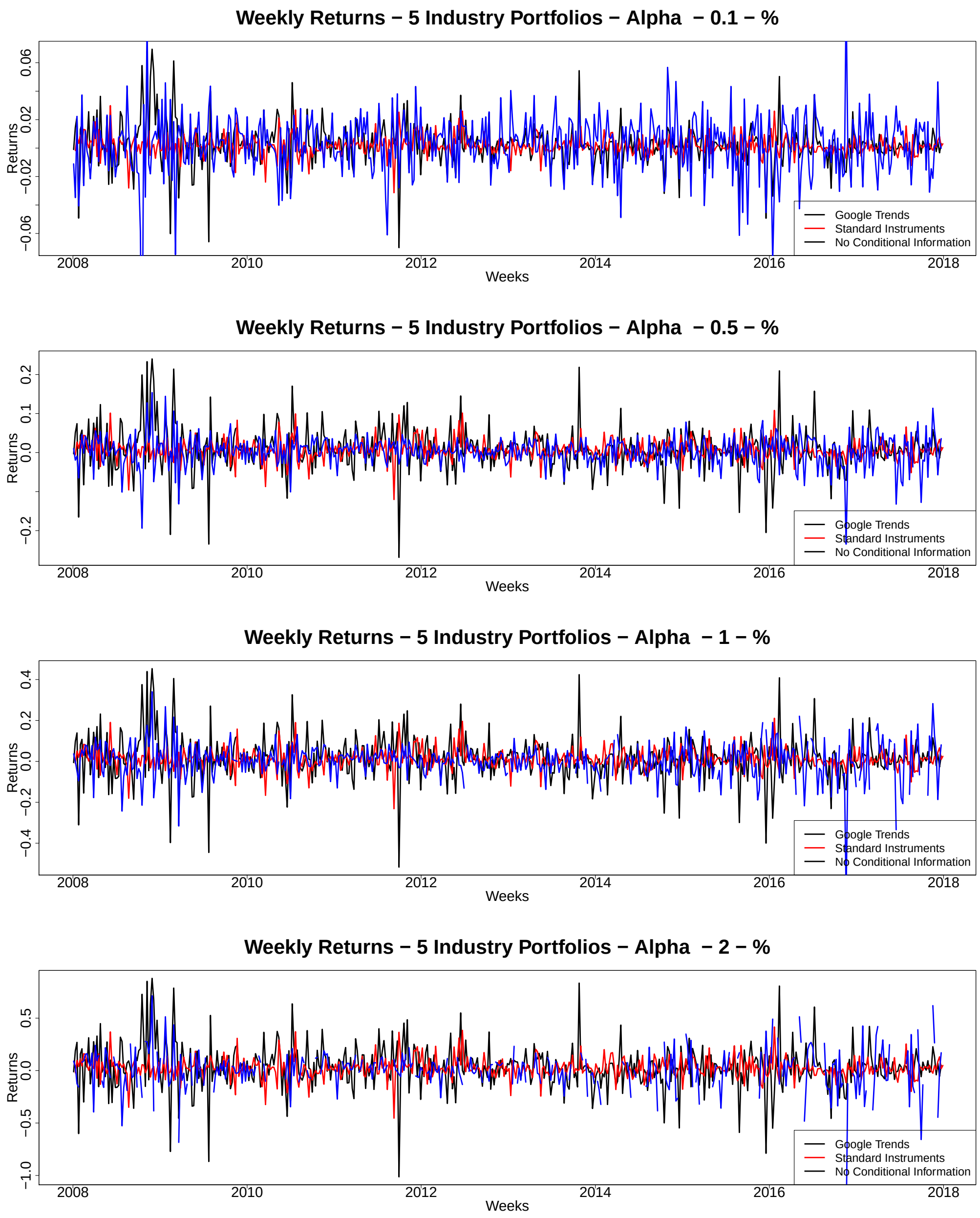
Figure 13 shows 4 panels for the weekly returns boxplots for the 25 portfolios formed on size and book-to-market for the out-sample analysis (first week of jan-2008 to the last week of dec-2017). Each panel represent a different of target alphas (ranging from $0.1\%, 0.5\%, 1\%$ and 0.1%).

4 Recursive Window

Figure 14 – Weekly Weights - 6 Portfolios Formed on Size and Book-to-Market - Recursive Window (jan-2008 to dec-2017)

Figure 14 plots the estimated weekly weights using the recursive window experiment for the 6 portfolios formed on size and book-to-market and target $\alpha = 0.01$.

Figure 15 – Weekly Returns - 5 Industry Portfolios (Recursive Window)



Plots of

Figure 15 shows 4 panels with the the weekly returns for the 5 industry portfolios (recursive experiment). Each panel represent a different target alphas (ranging from $0.1\%, 0.5\%, 1\%$ and 0.1%).

Figure 16 – Weekly Returns - 6 Portfolios Formed on Size and Book-to-Market (Recursive Window)

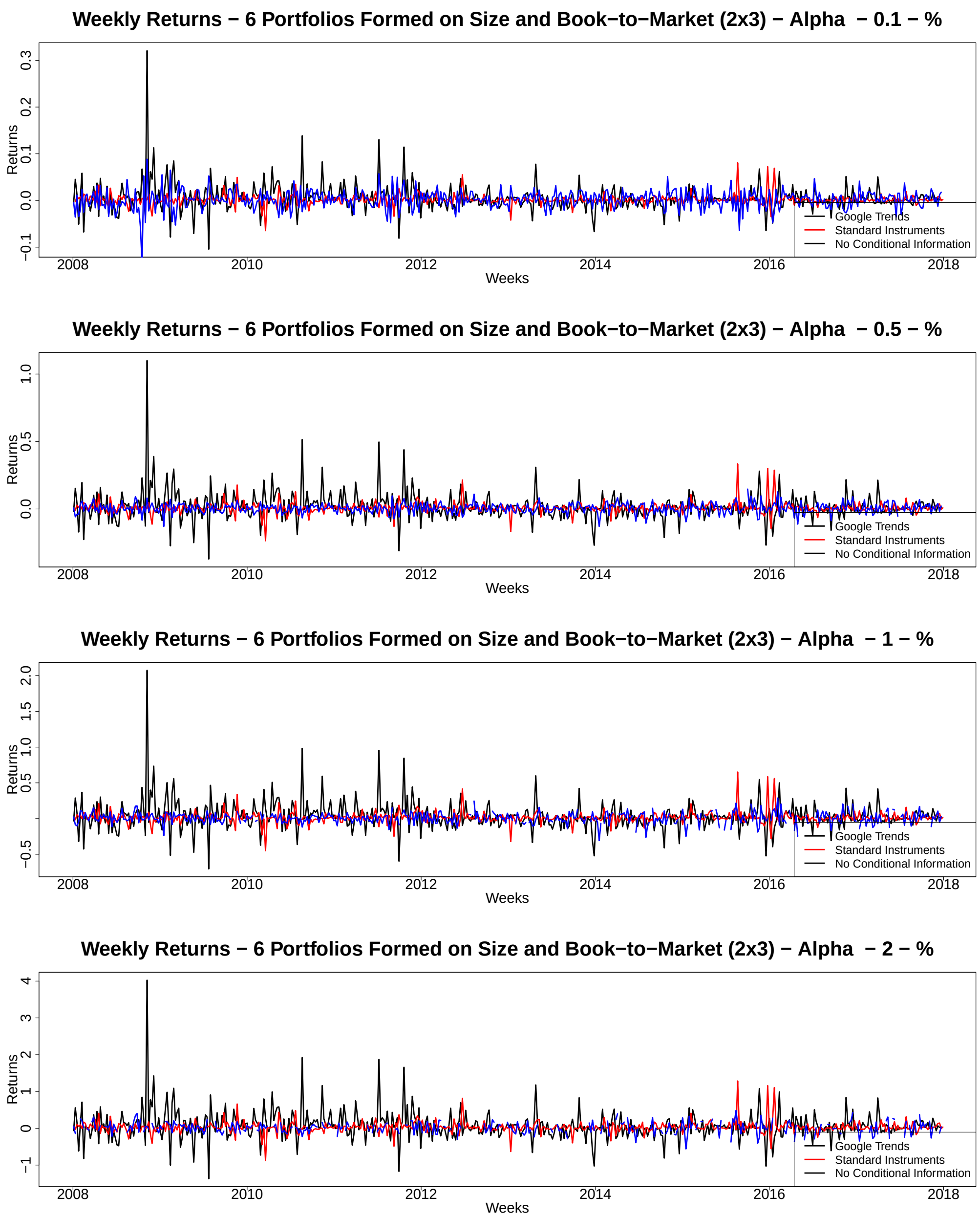


Figure 16 shows 4 panels with the the weekly returns for the 6 portfolios formed on size and book-to-market (recursive experiment). Each panel represent a different target alphas (ranging from 0.1%, 0.5%, 1% and 0.1%).

Figure 17 – Weekly Returns - 25 Portfolios Formed on Size and Book-to-Market (Recursive Window)

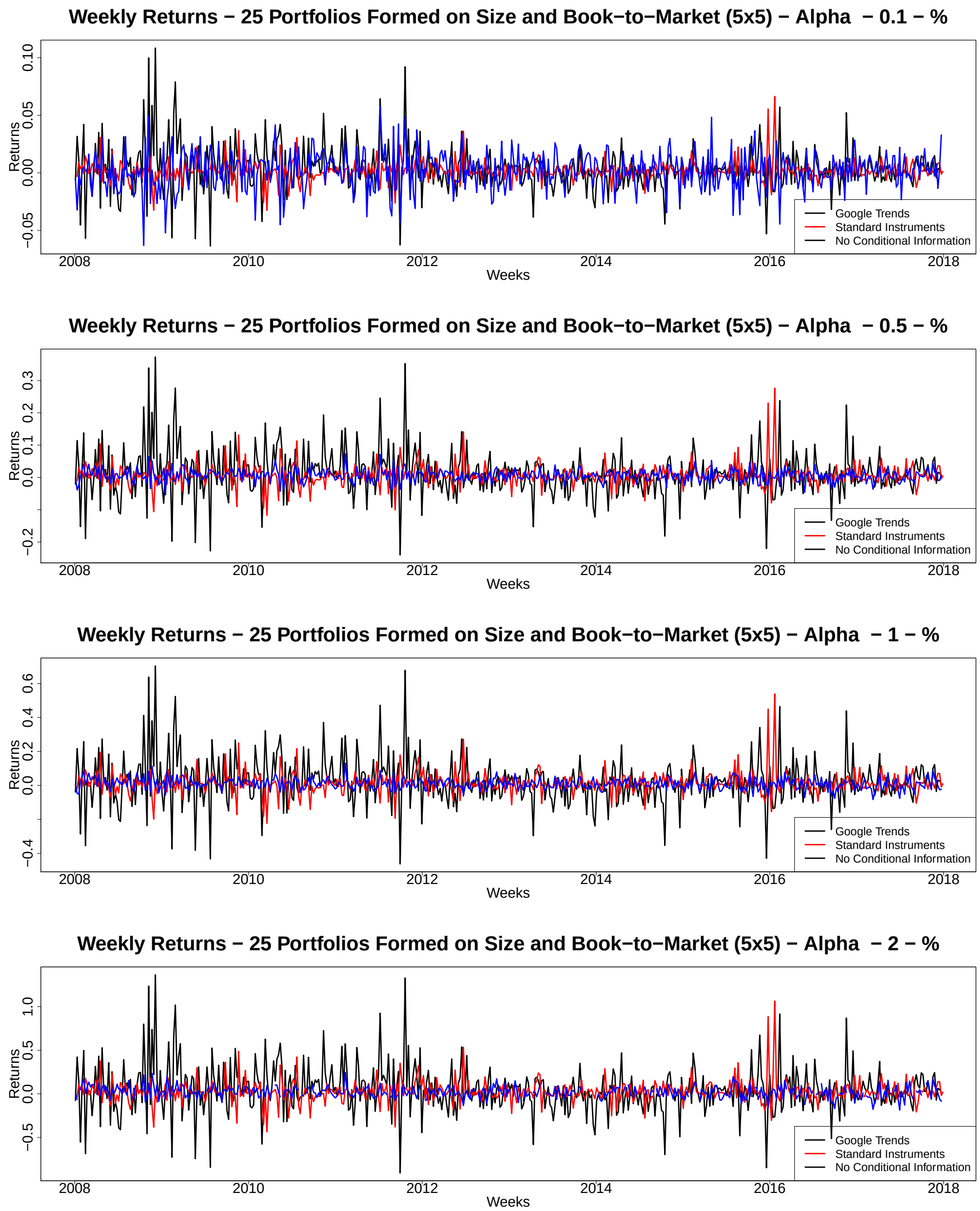


Figure 17 shows 4 panels with the the weekly returns for the 25 portfolios formed on size and book-to-market (recursive experiment). Each panel represent a different target alphas (ranging from 0.1%, 0.5%, 1% and 0.1%).