



**NTNU – Trondheim**  
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# Predictive Power of Google Search Volume on Stock Returns

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## Problem Description

In this paper we investigate whether Google search query data can be used to predict stock returns for individual firms, both short-term and over longer horizons. The key questions we investigate are: does Google search query data have predictive power for stock returns? Can inclusion of Google search query data improve existing prediction models? Do short-term changes in Google search query data impact returns differently than long-term changes?

Assignment was given on January 12<sup>th</sup>, 2015

Supervisor: Postdoc Peter Molnár



## Preface

This paper represents the final assignment of the Master of Science in Finance program through the Department of Industrial Economics and Technology Management at the Norwegian University of Science and Technology in Trondheim, Norway.

With increasing amounts of information being available online, we find it interesting to see if some of that information can be used to predict financial returns. We therefore investigate whether search query data from Google Trends can be used to predict stock returns.

We would like to direct massive thanks to Peter Mólnar who was our supervisor and a tremendous help for us! We are also grateful for valuable inputs from Einar Cathrinus Kjenstad, Svein Olav Krakstad and Štěpán Mikula. Finally, we would like to thank our girlfriends who have (to some degree) tolerated being neglected for the past months, and we are sorry, it is going to be worse when we start our careers...

Trondheim, June 9<sup>th</sup>, 2015

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# Predictive Power of Google Search Volume on Stock Returns

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## Abstract

We investigate whether search statistics from Google can be used to forecast stock returns over different time horizons. We use daily, weekly and quarterly Google searches, covering the period from 2010 to 2014. The results show a small, positive short-term relationship between daily searches and excess stock returns, a negative relationship between weekly searches and excess returns with subsequent reversal, while quarterly searches are positively related to excess returns without reversal. Next we examine a trading strategy based on our model. The trading strategy shows that there is economical value in including Google search statistics in forecasting models.

## Sammendrag

Vi undersøker om søkestatistikk fra Google kan brukes til å predikere aksjeavkastning over ulike tidshorisonter. Vi bruker daglige, ukentlige og kvartalvise Googlesøk, fra perioden 2010 til 2014. Resultatene viser en liten, positiv kortsiktig sammenheng mellom daglige søk og meravkastning, en negativ sammenheng mellom ukentlige søk og meravkastning med påfølgende reversering, mens kvartalvise søk har en positiv sammenheng med meravkastning uten reversering. Videre vurderer vi en handelsstrategi basert på vår modell. Handelsstrategien viser at det er økonomisk verdi i å inkludere søkestatistikk fra Google i prognosemodeller.

# 1 Introduction

The predictability of stock returns is a highly debated subject in finance. The proponents of the efficient market hypothesis (Malkiel, 2003, Porta et al., 1995, Welch and Goyal, 2008) argue that short-term stock returns are unpredictable and determined by random arrival of new information in accordance with Fama (1965). Other researchers argue that markets are not fully efficient and that returns are to some extent predictable (Ang and Bekaert, 2007, Campbell and Thompson, 2008, Campbell and Yogo, 2006, Cochrane, 2008, Lo and MacKinlay, 1988). There has also been increasing focus on the impact of investor sentiment and attention on stock returns (Baker and Wurgler, 2006, Barberis et al., 1998) and recent research utilizes data from news articles (Tetlock, 2007), Twitter (Bollen et al., 2011), Wikipedia (Moat et al., 2013) and Google (Da et al., 2011, Damien and Ahmed, 2013, Joseph et al., 2011, Preis et al., 2013, Preis et al., 2010).

Google is by far the most popular search engine in the US (comScore, 2015) and it records search statistics for all search terms and publishes them through Google Trends. Google search volume has previously been used as a proxy for investor attention (Da et al., 2011, Fink and Johann, 2014), investor sentiment (Joseph et al., 2011, Preis et al., 2013, Preis et al., 2010), and customer attention (Choi and Varian, 2012). In this paper, we will not make such a distinction. Instead we focus on the predictability, and associated expected profitability of trading strategies, made possible by Google search statistics. Although related, the different interpretations of what underlying characteristics Google search volume is capturing will lead to differences in inference; in particular which specific theory any result can illuminate beyond existing evidence.



A few attempts have been made to forecast financial markets based on Google Trends data, albeit with mixed results. Preis et al. (2010) investigates the correlation between returns and the Google Search Volume Index (henceforth SVI) for company names, but they do not find any significant correlation. Instead they find strong evidence that the SVI can be used to predict trading volume. Preis et al. (2013) investigate whether general search terms related to finance can be used to predict general market movements. They find that a strategy where the market portfolio is bought, or sold, based on certain keywords' SVI could outperform the market index by a yearly rate of 22%. Similar results were found by Moat et al. (2013) who create a trading strategy based on Wikipedia visitation statistics of the constituents of the Dow Jones Industrial Average. They also apply this strategy to Wikipedia articles for more general financial keywords with similar results. Kristoufek (2013) studies the effect of the SVI on portfolio diversification. He uses a diversification strategy based on penalizing stocks with high search volumes to create a portfolio that dominates the benchmark index as well as an equally weighted portfolio. The rationale behind his diversification strategy is the notion that search volume is correlated with stock riskiness. Damien and Ahmed (2013) seek to validate the previous claims that the SVI contains enough information to predict future financial index returns. They find that strategies based on financial keywords do not outperform strategies based on completely unrelated keywords. Da et al. (2011) studies the use of the SVI as a measure of investor attention and find that the SVI is correlated, but different from existing proxies of investor attention. They further find that an increase in the SVI predicts higher stock prices for the first two weeks with subsequent price reversal. Joseph et al. (2011) claims that the SVI on company tickers can be used as a measure of investor sentiment, and assess

whether it can be used to forecast stock returns and trading volume. They construct a portfolio based solely on the SVI which has abnormal returns.

It is not possible to download long-term time series of the daily SVI from Google directly, but we develop an algorithm to overcome this obstacle. As far as we know, only Fink and Johann (2014) uses the daily SVI to study stock returns, however they are using data for the German stock market. Our intuition is that daily data should improve our understanding of the dynamics of the SVI and returns because higher frequency data could capture effects that lower frequency data does not capture.

Where previous research has focused almost exclusively on the relationship between the weekly SVI and weekly excess returns, we want to examine the different impact on return from short-, medium- and long-term changes in the SVI. This allows us to build a more complete understanding of the relationship between the SVI and excess return. Therefore, we investigate whether the daily, weekly and quarterly SVI for company names predict stock returns for the firms in the S&P 1500, for forecasting horizons from one day up to six months.

We find a small, positive short-term relationship between daily searches and excess stock returns, a strong negative relationship between weekly searches and excess returns with subsequent reversal, while quarterly searches are positively related to excess returns without reversal. These relationships are robust in direction but vary in magnitude across several different time periods in the past 10 years as well as for different levels of market capitalizations. We construct a trading strategy based on the results and it outperforms both an equally weighted portfolio of the companies in our dataset, and a similar strategy that excludes the SVI.

This paper is structured as follows: In section 2 we describe the datasets, our preliminary calculations and our model. In section 3 we discuss the results, extensions and robustness. In section 4 we develop and evaluate a trading strategy based on our model. Section 5 concludes.

## 2 Data

The data we use in this paper is obtained from Wharton Research Data Services (WRDS), Kenneth R. French's online data library and Google Trends. The data from WRDS is from CRSP and Compustat and includes all relevant financial information for companies of the S&P 1500 index from January 1, 2004 through December 31, 2014. We also obtain daily values of Fama-French's three factors from French's online data library. We focus on the time period from 2010 to 2014 due to the data availability from Google (SVI).

Since the SVI is reported weekly, monthly, or not at all, for search words with low search volume, we are unable to include all 1500 companies from the S&P 1500. In addition we only include companies that were in the index at the end of 2014 and for which we have complete stock data. This yields 519 companies for the time period we focus on.

In order to study the impact of the SVI on stock returns we include several control variables in our analysis. These are previous returns, volatility, trading volume and bid-ask spreads. We standardize our independent variables due to the nature of the type of regression we use, especially because the companies in our sample vary a lot with respect to trading volumes and the SVI. These standardizations are explained in the next section.

## 2.1 Google Search Volume

Google searches are reported as an index over time for a particular search term, either globally or in chosen regions. Each index is defined from 0 to 100, where 100 represents the time where the search term had the largest share of the total queries in the chosen region. All the other values are relative to this maximum and only search volumes larger than an unknown lower limit are reported (Choi and Varian, 2012). In addition to geographical filtering, Google Trends also has a category filter for obtaining searches that are related to a certain topic. One of these is a finance filter, which means that the user has entered a finance-related website after searching for a term (Fink and Johann, 2014).

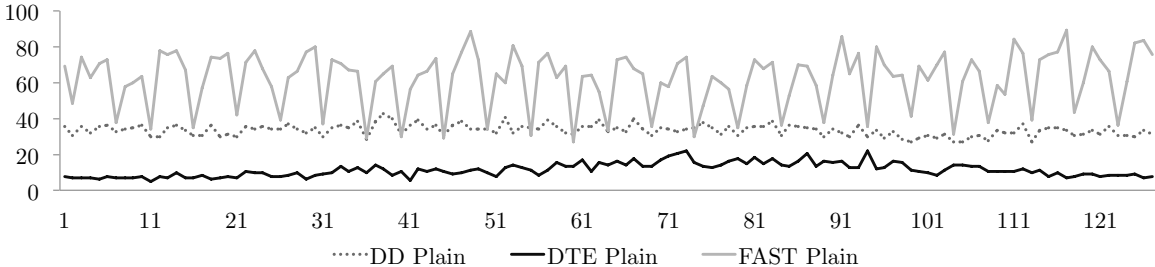
We use data for the US following Preis et al. (2013). They found that US data works better than global data when using the SVIs to predict movements in the US stock market. We focus on the official company names as search terms, but adjust some of the names to fit a more practical use (e.g. removing terms like .inc). When we study searches for company tickers, we apply a filter to remove some of the most common abbreviations. All company names we search for, and the corresponding tickers, are included in the appendix. In total we have obtained 3 datasets; the SVI for company names, with and without the finance filter, and the SVI for company tickers.

The plain SVI from Google is used to calculate a standardized SVI to represent abnormal search volumes (henceforth ASVI). Standardization makes these indices more comparable across companies (figure 1). In addition, it has the added benefit of reducing correlations between the daily values, weekly averages and quarterly averages which could cause difficulties in the linear regressions. We standardize by

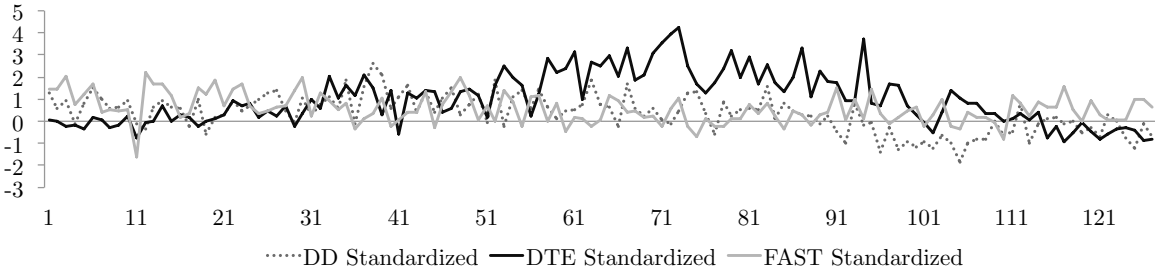
subtracting the mean and dividing by the standard deviation based on the previous year. In order to reduce weekly seasonality (e.g. people searching for restaurants on weekends) our mean search volume is calculated based on the search volume on only the given weekday during the previous year. We preserve information from searches on weekends and closed days by averaging searches on these days back to the previous open day. Our calculation of the ASVI is the following standardization:

$$ASVI_t = \frac{SVI_t - \frac{1}{52} \sum_{i=0}^{51} SVI_{t-7*i}}{\sigma_{SVI}} \tag{1}$$

Where  $\sigma_{SVI}$  is the standard deviation of SVI during the past year.



**Panel A:** Raw data from Google



**Panel B:** ASVI

**Fig. 1.** Comparison of search volumes for three companies before and after standardization with removal of weekly seasonality.

## 2.2 Stock Returns

We calculate daily returns at any given time as the total return adjusted for dividends and stock splits as:

$$R_t = \frac{(S_t + D_t)N_t}{S_{t-1}N_{t-1}} - 1 \quad (2)$$

Where  $R_t$ , is total return adjusted for dividends and stock splits,  $S$  is stock price,  $D$  is dividend,  $N$  is the number of shares outstanding,  $t$  is the time in days.

We use cumulative returns, over time periods from one day to six months, as our dependent variable in order to examine how the excess returns of a stock develop over time, given changes in ASVI and our control variables. This method offers a more complete picture than seen before and allows us to present our findings graphically. We calculate returns for holding periods over the next  $n$  days by:

$$R_{t,n} = \prod_0^n (R_{t+n} + 1) - 1 \quad (3)$$

We calculate firm specific Fama-French beta coefficients from a rolling 1 year regression:

$$R_t = R_{f,t} + \beta_{mkt,t} \cdot (R_{mkt,t} - R_{f,t}) + \beta_{smb,t} \cdot R_{smb,t} + \beta_{hml,t} \cdot R_{hml,t} + \varepsilon_t \quad (4)$$

Where  $R_f$  is the risk-free rate and  $\beta$  are stock sensitivities to the Fama-French factors.

Likewise, we calculate the cumulative beta-adjusted Fama-French contributions to returns over the next  $n$  trading days by equations 5-7. These represent the impact on stock returns from the sensitivity of the stock to the Fama-French factors.

$$F_{SMB,t,n} = \prod_0^n (R_{SMB,t+n} \cdot \beta_{SMB,t+n} + 1) - 1 \quad (5)$$

$$F_{HML,t,n} = \prod_0^n (R_{HML,t+n} \cdot \beta_{HML,t+n} + 1) - 1 \quad (6)$$

$$F_{MKT,t,n} = \prod_0^n (R_{MKT,t+n} \cdot \beta_{MKT,t+n} + 1) - \prod_0^n (R_{f,t+n} + 1) - 2 \quad (7)$$

Where  $F$  are the cumulative beta-adjusted Fama-French contributions to returns.

### 2.3 Volatility

Previous studies find a positive relationship between volatility and future returns (Banerjee et al., 2007, Bollerslev et al., 2009, French et al., 1987), and we therefore include volatility as a control variable in our model. We use a daily volatility measure that is not based on high-frequency data (due to data availability). This measure is the jump-adjusted Garman-Klass volatility estimator discussed by Molnár (2012). The calculation uses open, close, high and low prices during a trading day to calculate the realized volatility on that day. The formula is given in equation 8.

$$Vol_t = \frac{1}{2} \cdot (h_t - l_t)^2 - (2 \log(2) - 1) \cdot c_t^2 + j_t^2 \quad (8)$$

Where

$$c_t = \log(close_t) - \log(open_t)$$

$$l_t = \log(low_t) - \log(open_t)$$

$$h_t = \log(high_t) - \log(open_t)$$

$$j_t = \log(open_t) - \log(close_{t-1})$$

## 2.4 Trading Volume

Previous research finds evidence of a high-volume return premium (Barber and Odean, 2008, Gervais et al., 2001). We therefore include trading volume in our model and standardize it in the same way, and for the same reasons, as the SVI. Since weekly seasonality in trading volume is quite small (Lo and Wang, 2009), we do not model seasonality. This yields equation 9 for abnormal trading volume.

$$Abn\ Vlm_t = \frac{vlm_t - \frac{1}{252} \sum_{i=0}^{251} vlm_{t-i}}{\sigma_{vlm}} \quad (9)$$

Where  $\sigma_{vlm}$  is the standard deviation of volume during the past year.

## 2.5 Bid-Ask Spread

Amihud and Mendelson (1986) find that bid-ask spread has a positive effect on the expected returns of stocks, which can be explained as a liquidity risk premium. We include bid-ask spread as a control variable in our model, calculated as follows:

$$Bidask_t = \frac{ask_t - bid_t}{\frac{1}{2}(ask_t + bid_t)} \quad (10)$$

## 2.6 Model Specification

We conduct panel data regressions with fixed effects. We include the four control variables presented in subsections 2.2-2.5 in order to isolate the effect of the ASVI on returns. It also allows us to compare the impact of the ASVI to that of the control variables. Since we want to examine the impact on the otherwise unexplained (i.e. excess) returns we include the cumulative Fama-French factors defined in the previous section.



We use the abbreviation L3P for an operator that transforms a variable into a vector consisting of lagged short-, medium- and long-term components. For the short-term we use the previous day, for the medium-term we use the average of the previous week and for the long-term we use the average of the previous three months (i.e. quarterly). We run this model for cumulative holding periods from 1 until 126 trading days (i.e. half year). Our regression model is then as follows:

$$\begin{aligned}
R_{t,n} = & \alpha_n + \omega_{SMB,n} \cdot F_{SMB,t,n} + \omega_{HML,n} \cdot F_{HML,t,n} + \omega_{MKT_{RF},n} \cdot F_{MKT_{RF},t,n} + \boldsymbol{\beta}_n^T \cdot \\
& L3P(R_t) + \boldsymbol{\gamma}_n^T \cdot L3P(ASVI_t) + \boldsymbol{\delta}_n^T \cdot L3P(Abn Vlm_t) + \boldsymbol{\xi}_n^T \cdot L3P(Vol_t) + \boldsymbol{\delta}_n^T \cdot \\
& L3P(Bidask_t) + \epsilon_{t,n}
\end{aligned} \tag{11}$$

Where Greek letters are regression coefficients, bold letters are row vectors,  $T$  indicates that the vector is transposed, and  $n$  is the forecasting horizon.

We do not to present the results from our regression by its coefficients because not all of our variables are standardized, and thus the size of the coefficients depends on the scale of the underlying variables. Instead we use a measure of the impact on excess returns in basis points (0.01 percentage points) of a one standard deviation change in the independent variable. This measure makes comparison of the impact of different variables easier and allows us to interpret the magnitude of this impact directly.

## 2.7 VIF and Variable Selection

Before running our regression we evaluate whether multicollinearity is an issue in our data with the VIF (Variance Inflation Factor) test (Marquardt, 1970). The results show that only the bid-ask spread variables have significant

multicollinearity amongst themselves ( $VIF > 5$ ) and this should not be a problem when interpreting the SVI coefficients.

We also evaluate the choice of leaving in variables and all lags with the Akaike Information Criterion (AIC) as a part of the results section below (Akaike, 1974).

### 3 Results

In table 2 we present the regression results for the 5-day cumulative return forecast from all models in this paper. Please note that in these regressions the Fama-French regressors are not just Fama-French factors, but Fama-French factors multiplied by the betas for each company. Therefore the corresponding regression coefficients should not be interpreted at betas. Instead they should be close to 1. This is also why they are presented with their actual coefficients, and not with their impact in basis points as for our main variables of interest.

However, in addition to 5-day returns, we study returns on all horizons from one day to a half year. Presenting these results as tables would require hundreds of similar tables. For the rest of this section we will therefore present our results as graphs. In these graphs the y-axis denotes the impact of a one standard deviation change in the independent variable on cumulative excess return (basis points). The x-axis denotes the forecasting horizon (1 to 126 trading days). The thickness and darkness of the lines indicate the statistical significance level.

**Table 2.** Results for the 5-day (1 week) cumulative return forecast for all models presented in this paper. Table values are the impact in basis points of a one standard deviation change in the variable. \* denotes that the Fama-French factors are presented in actual coefficients and *not* I bympact in basis points. This is done because they are not predictors, and because now we can compare their value in the model to the assumed one by Fama and French (which would be 1). ' denotes the 10% significance level, " denotes the 5% significance level and "" denotes the 1% significance level

Variable	Main Model	Large-Cap	Medium-Cap	Small-Cap	Finance Filter	Finance-Avail	Ticker All	Ticker Abb.	Pre Crisis	Crisis	Recovery	Most Recent
<i>HML Factor *</i>	0.895	0.883	0.826	0.963	0.856	0.855	0.862	0.860	0.920	1.025	0.916	0.804
<i>SMB Factor *</i>	0.965	1.008	1.027	0.948	1.028	1.028	0.953	0.948	0.927	0.958	0.889	0.928
<i>MKT_RF Factor *</i>	0.999	0.983	1.019	0.992	0.997	0.997	1.003	0.998	0.985	1.056	0.993	0.997
Daily ASVI	0.812	-0.296	1.899	0.874	2.038	0.964	-0.375	-0.989	-0.204	-0.854	-0.043	-2.057
Weekly ASVI	-4.003	-2.985	-4.740	-4.341	-1.022	-4.738	-1.668	-0.673	-5.111	-6.615	-3.909	-2.594
Quarterly ASVI	-1.024	-3.366	-0.526	1.749	-6.227	-3.731	0.099	-0.260	1.298	2.055	1.867	-2.049
Daily Vol	0.203	-0.051	0.305	2.910	2.409	2.439	0.208	0.299	-1.404	11.565	0.030	-0.514
Weekly Vol	0.092	-0.837	0.740	4.290	3.624	3.674	0.208	-2.322	0.875	9.938	-1.178	-0.431
Quarterly Vol	0.203	0.320	0.317	-3.861	-6.320	-6.412	-0.874	-0.461	-5.684	37.868	4.090	-2.257
Daily Abn Vlm	1.599	-0.052	1.158	3.341	1.618	1.768	2.891	2.116	0.314	-5.214	3.191	2.181
Weekly Abn Vlm	-1.228	-1.207	-2.818	1.357	-2.485	-2.364	-0.625	-0.240	2.778	11.381	-5.791	0.802
Quarterly Abn Vlm	3.238	1.164	4.123	4.004	-0.847	-1.038	0.863	2.096	-4.872	-5.987	6.795	1.557
Daily Return	-2.563	-2.756	-0.982	-4.099	-4.040	-4.060	-2.142	-2.497	-5.549	-4.327	-0.654	-1.819
Weekly Return	-2.890	-2.335	-5.772	-1.436	-4.004	-3.982	-4.171	-2.712	-9.086	-17.739	-7.328	-0.688
Quarterly Return	-8.466	-4.047	-5.187	-14.697	1.070	0.963	-7.725	-7.092	-7.371	-18.117	-32.660	-11.695
Daily Bid-Ask	0.317	3.112	-2.351	0.501	-0.432	-0.426	-0.222	-0.540	-2.362	3.160	0.550	-3.260
Weekly Bid-Ask	-3.217	4.260	8.623	-8.295	-5.481	-5.558	-2.101	-3.329	-3.096	7.271	-0.162	3.776
Quarterly Bid-Ask	17.181	8.813	29.423	22.020	9.175	9.524	13.937	13.689	3.937	8.250	50.424	42.414
Constant	0.005	0.002	-0.001	0.007	-0.001	-0.001	0.005	0.005	0.007	0.006	0.013	0.006
# Companies	519	186	163	170	89	89	562	373	217	217	217	217
Average Market Cap	\$18.9bn	\$47.0bn	\$5.3bn	\$1.1bn	\$36.2bn	\$36.2bn	\$15.9bn	\$17.5bn	\$27.7bn	\$27.7bn	\$27.7bn	\$27.7bn

### 3.1 Main Model

In figure 2, panel A, we show that all averages of previous returns have a negative relationship with future returns for at least the next 6 months. The daily and weekly returns have a very volatile impact.

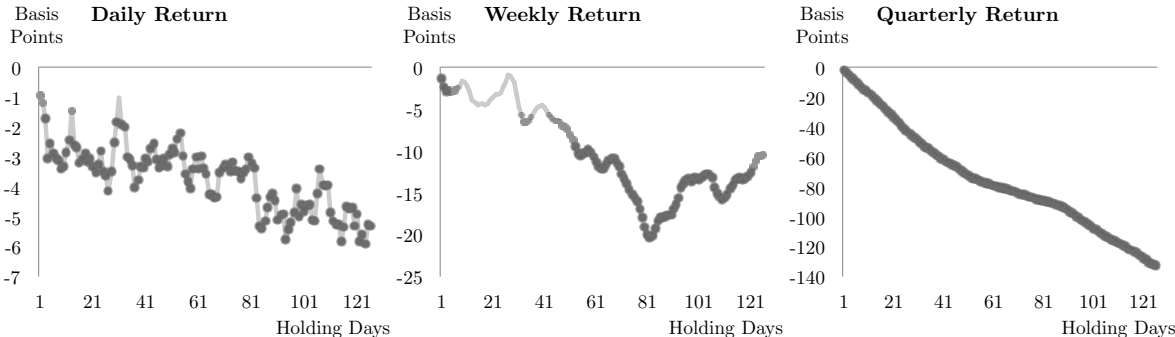
The daily ASVI starts with a small positive impact over the first weeks, followed by a slightly larger temporary negative impact and eventual reversal. However, most of the time the impact is not statistically significant. High weekly values of the ASVI have a significant, negative impact and subsequent partial reversal. The maximum excess returns occur after two months and is roughly 40 basis points per standard deviation of the ASVI, and a partial reversal occurs during the following three months. The quarterly variable has significant, positive impact in the long-run and stabilizes at roughly 55 basis points increase in cumulative excess returns after 3 months. The impacts of these ASVI variables are smaller than that of returns in the daily and quarterly variables but larger for the weekly one. The impacts of the different variables are further evaluated via the AIC test below.

The bid-ask spread contains the most predictive power of all independent variables in terms of basis points. However, the relationship between the daily and weekly bid-ask spread and future returns is pretty much non-existent. The quarterly bid-ask spread has a linear and positive relationship with future excess returns (at roughly 3 basis points per standard deviation per day), possibly indicating a systematic relationship in the market (liquidity risk premium) which is consistent with the findings of Amihud and Mendelson (1986).

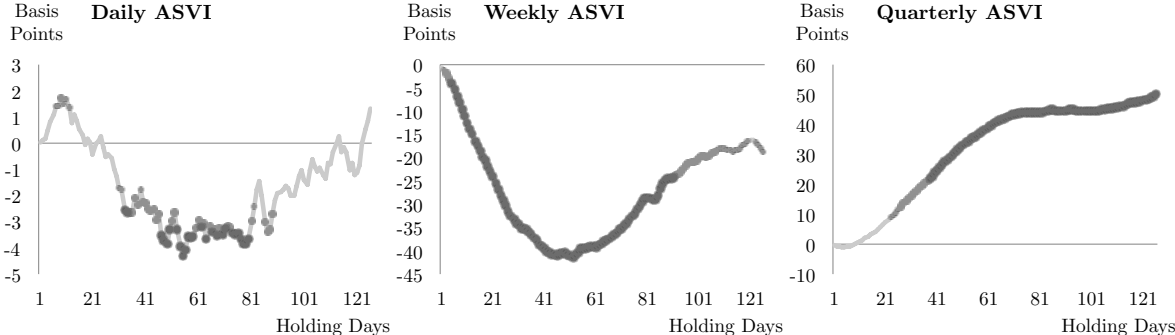
Daily and weekly volatility are shown to have very variable, insignificant and small impact on future excess returns. The quarterly volatility has a small, significant

and positive impact on returns with eventual long-term reversal. This positive impact is supportive of French et al. (1987) who find that returns are positively correlated to volatility.

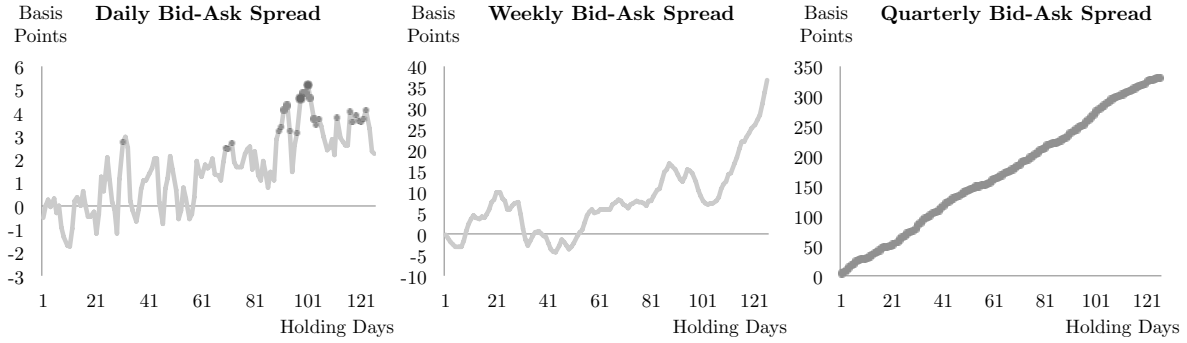
Daily abnormal trading volume has a small, positive relationship with future excess returns. The weekly component shows the opposite with a small, negative impact on returns in the following month. The quarterly average abnormal trading volume indicates that a relatively large quarterly trading volume (i.e. a long-term increase in trading volume) significantly precedes or leads to excess returns.



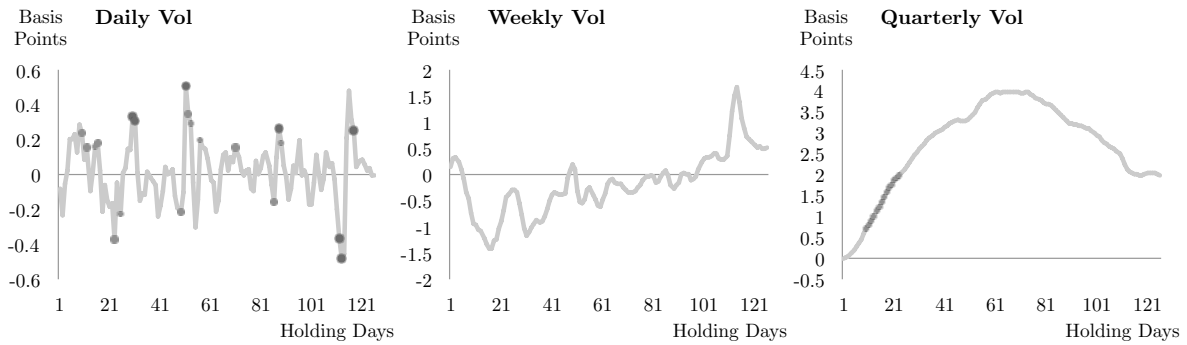
**Panel A:** Impact of average return on cumulative excess returns.



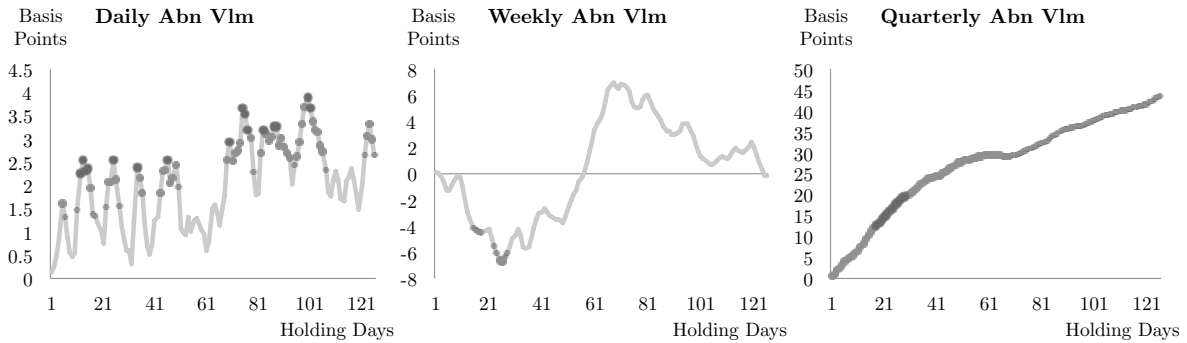
**Panel B:** Impact of average ASVI on cumulative excess returns.



**Panel C:** Impact of average bid-ask spread on cumulative excess returns.



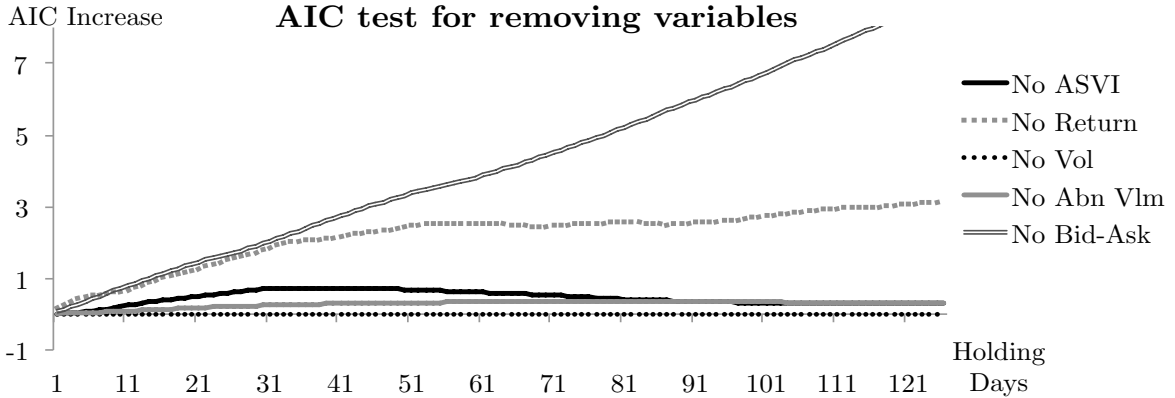
**Panel D:** Impact of average volatility on cumulative excess returns.



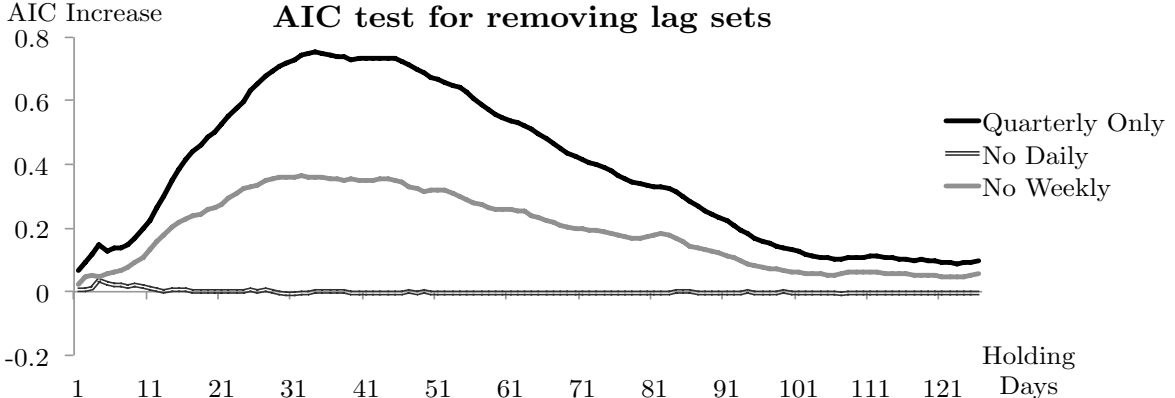
**Panel E:** Impact of average abnormal trading volume on cumulative excess returns.

**Fig. 2.** Results from our base model. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

Next we perform AIC tests to verify our choice of model. The values are defined as the difference in AIC of our model and a model without the variable or the set of lagged averages. The graphs show that all variables except volatility contribute to the model over all forecasting horizons. They also show that the ASVI is less important than returns and the bid-ask spread, but generally important than volume. The AIC test for removing lags shows that quarterly averages are the most important (not pictured due to scale). Removing the weekly averages also reduces the predictive power of the model. The daily averages are only relatively important in the short-run (the next 10 days). Removing both the weekly and daily variable is a worse than the sum of removing either.



(a): AIC increase (y-axis) when removing variables.



(b): AIC increase (y-axis) when removing lag sets.

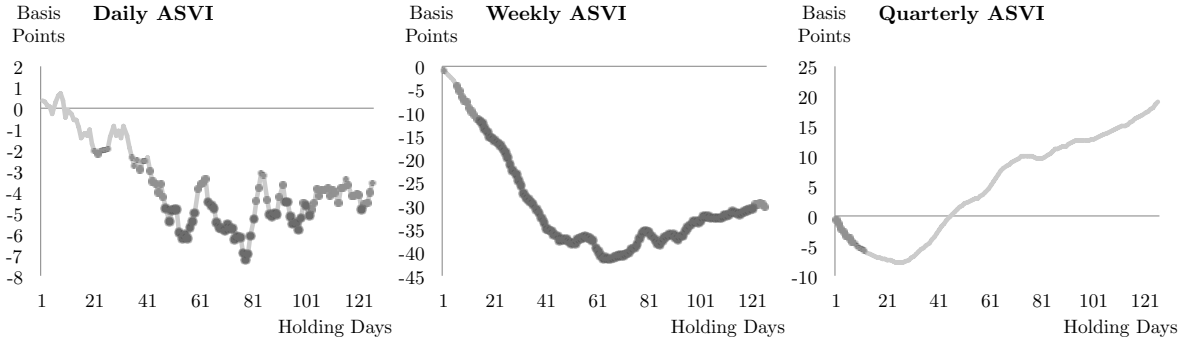
**Fig 3.** AIC increase (y-axis) as the loss of AIC value when removing variables

## 3.2 Large, Medium and Small Market Capitalization

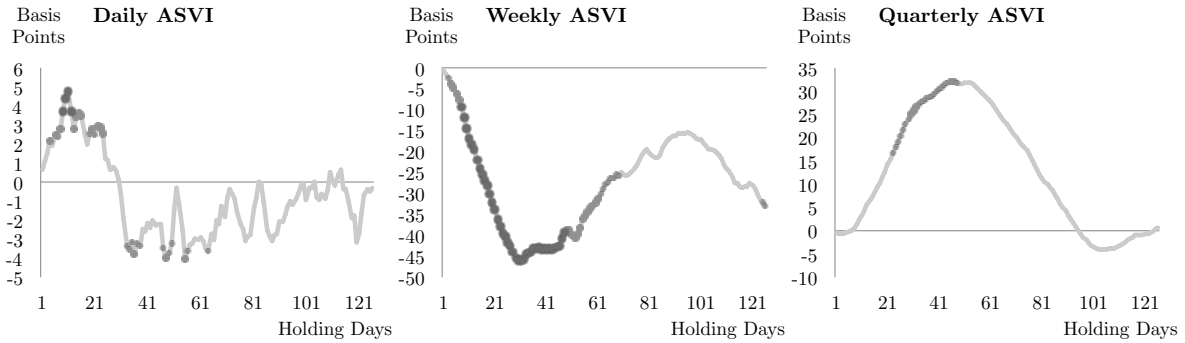
Da et al. (2011) and Joseph et al. (2011) find that the market capitalization of a firm is related to how sensitive its returns are to ASVI. To study this relationship, we divide the companies in our dataset into three similarly sized groups based on their market capitalization. The “small”, “medium” and “large” groups have average market capitalizations of \$1.1bn, \$5.3bn and \$47.0bn, respectively.

In figure 4, we show that the daily SVI has varying impact across the different company sizes and its effect seems uncertain. The weekly ASVI impacts are very similar in size across the subsets for the first two months, though long-term reversal decreases for larger companies. The impact of quarterly abnormal ASVI, however, is insignificant and small for the larger firms. The excess return of small firms has a significant and positive relationship to the level of quarterly ASVI. These results indicate that long-term growth in search volume (high quarterly average ASVI) does not precede excess returns for larger firms in the same way it does for smaller firms. Also the stock price of large firms recovers less from the negative impact of short-term increases in search volume than small firms.

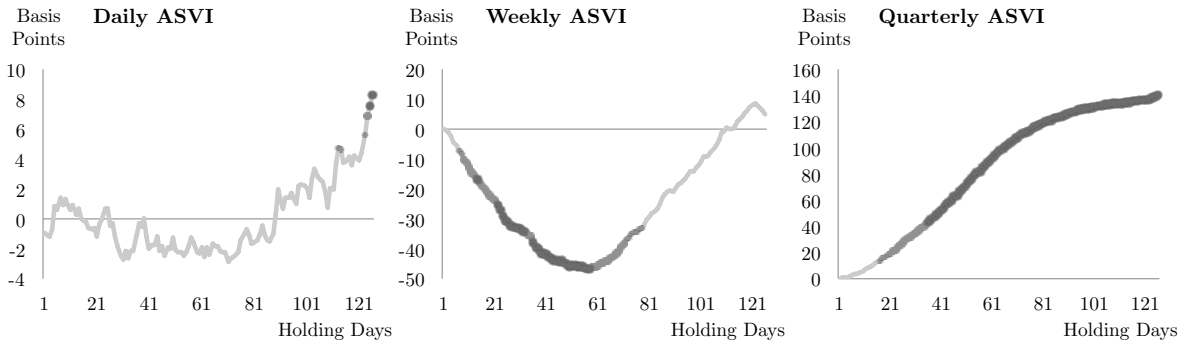




**Panel A:** Impact of ASVI on cumulative excess returns in the large-cap group



**Panel B:** Impact of ASVI on cumulative excess returns in the medium-cap group

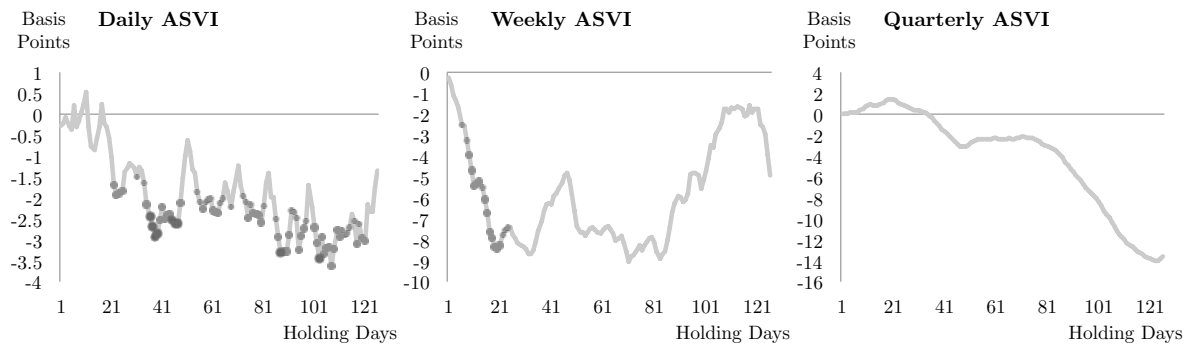


**Panel C:** Impact of ASVI on cumulative excess returns in the small-cap group

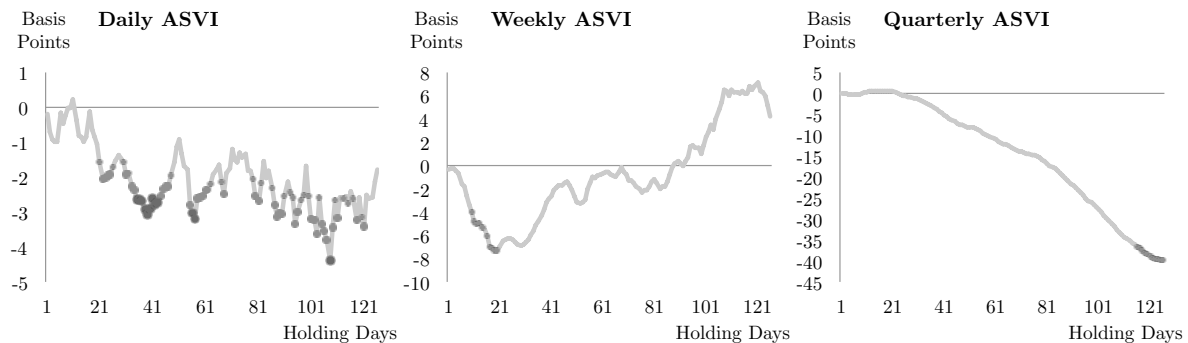
**Fig. 4.** Results of the ASVI variables in our model when running the regression on three separate groups based on market capitalization. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

### 3.3 Ticker ASVI

To verify our choice of search terms we also run our model for ASVI based on company tickers instead of company names. The results show a weaker relationship and are presented in panel A in figure 5. We also remove 189 of the companies with the most common abbreviations (like ALL and HOT) to attempt to capture a larger proportion of relevant searches. The results are presented in panel B. Neither model yields consistently significant results, and it seems likely that searches for tickers are less useful for predicting future returns than searches for names.



**Panel A:** Impact of average Ticker-ASVI on cumulative excess returns. (562 companies)



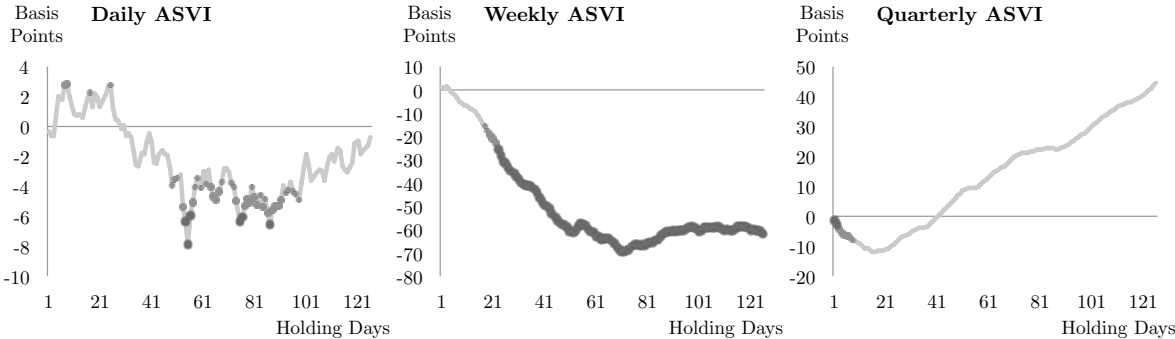
**Panel B:** Impact of average Ticker-ASVI on cumulative excess returns.  
(373 least common abbreviation ticker companies)

**Fig. 5.** Impact of ASVI with queries for tickers instead of company names. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

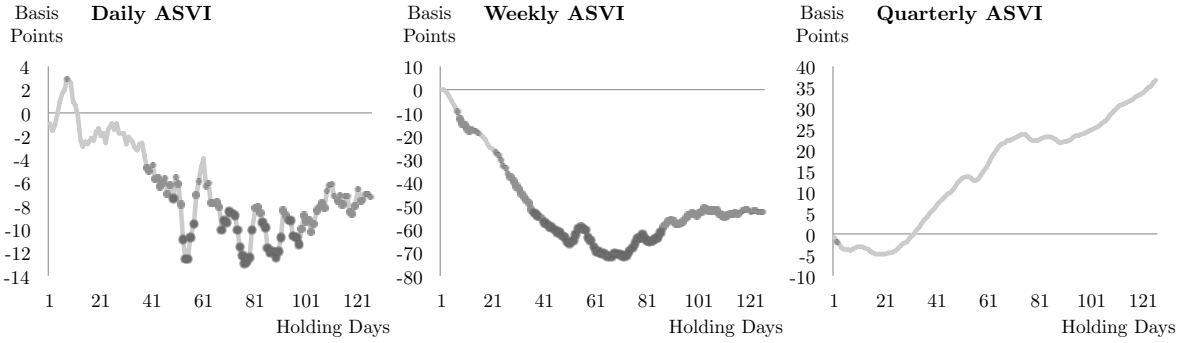
### 3.4 ASVI with Google Trends' Finance Filter

We also run a regression on our model using a financially filtered SVI dataset to see if this filter improves the predictive power of the SVI. Panel A in figure 6 shows the results when using financially filtered ASVI for the companies with available data (89 companies). Panel B shows the ASVI from our main model but only containing the companies available for panel A.

The searches Google interprets to be financially related (panel A) are very similar to the total amount of searches for the same company (panel B). We conclude that using regular searches is not a big loss over using the financial filter when it comes to capturing the relationship between online attention and subsequent stock market movements. The reason that these panels look different from the main one in figure 2, and much like the large cap firms in figure 4, is probably due to their large average market capitalization (\$36.2bn).



**Panel A:** Impact of average Financial ASVI on cumulative excess returns.  
(89 companies with financially filtered search volumes)



**Panel B:** Impact of average ASVI (all searches) on cumulative excess returns.

(89 companies with available financially filtered search volumes)

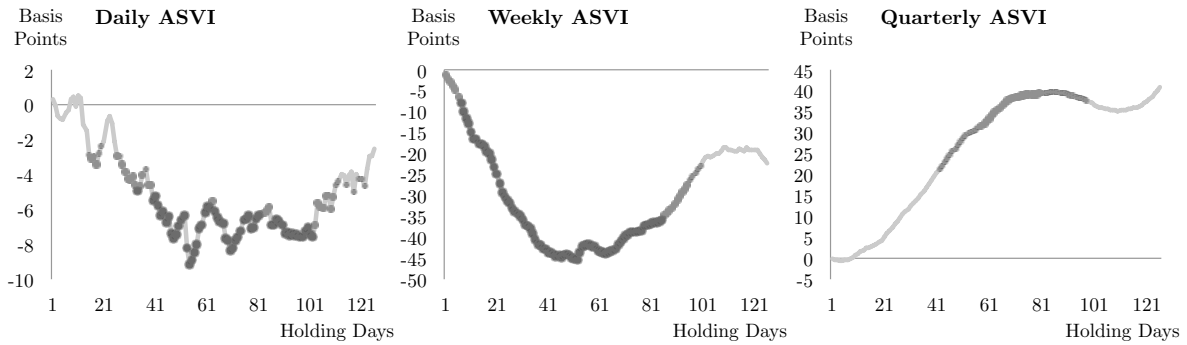
**Fig. 6.** Results from our model using Google Trends' finance filter. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

### 3.5 Different Time Periods

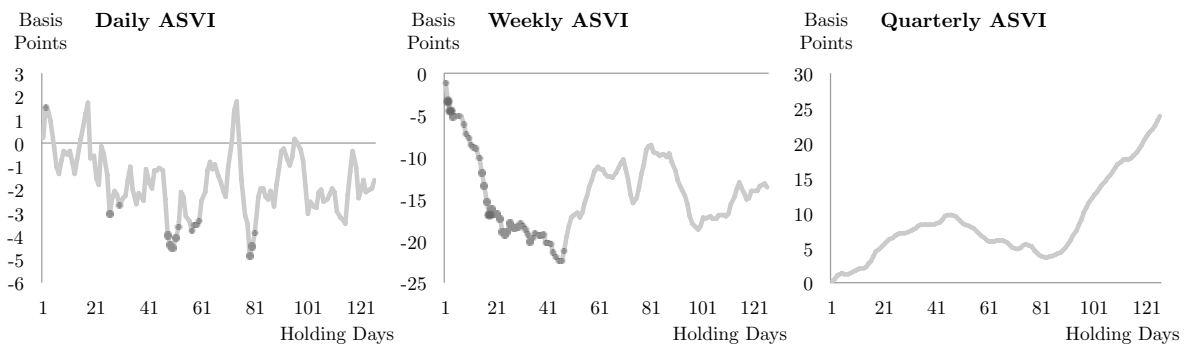
We further examine the subset of the 230 companies with daily search volumes available from 2004 to 2014. In figure 7 we present 5 panels of ASVI variables for different time periods. The first is the time period from our main analysis (2010-2014), the second is the period leading up to the 2007-2009 financial crisis, the third is the bulk of the financial crisis, the fourth is the first part of recovery and the fifth is the previous 3 years.

In panel A we see that the subset of companies available for all 10 years has similar characteristics to the full sample. There is less significance in the positive impact of quarterly ASVI and less reversal in the negative impact of the weekly ASVI, which is similar to the large-cap firms from figure 4. Indeed the average market cap of this subset is \$27.7bn, compared to \$18.9bn in the full sample. Furthermore, we

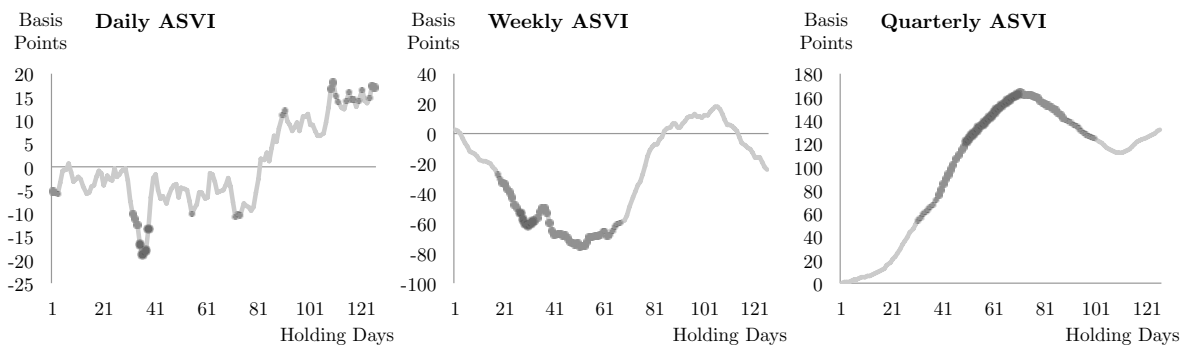
find that the shapes and directions of the daily, weekly and quarterly ASVI are consistent across the different time periods. Significance and magnitude of impact, however, are larger during the financial crisis and during the most recent years.



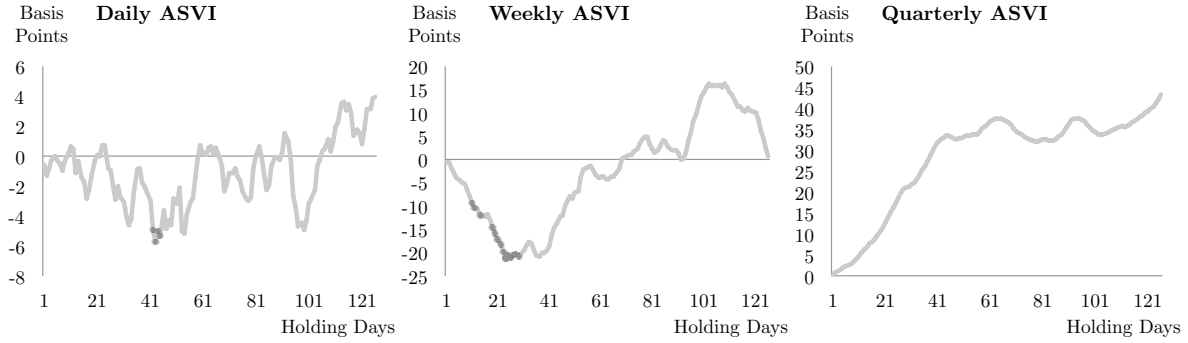
**Panel A:** Impact of average ASVI on cumulative excess returns. (April 2010 – December 2014)



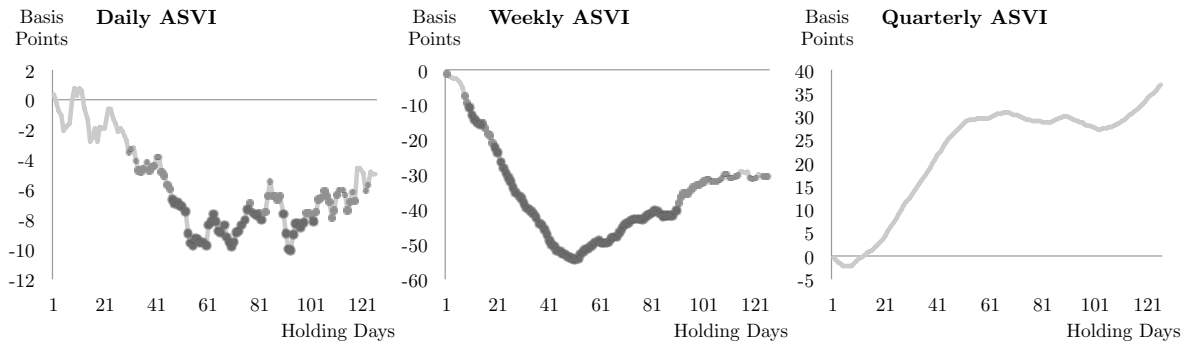
**Panel B:** Impact of average ASVI on cumulative excess returns. (April 2005 – September 2007)



**Panel C:** Impact of average ASVI on cumulative excess returns. (October 2007 – February 2009)



**Panel D:** Impact of average ASVI on cumulative excess returns. (March 2009 – December 2011)



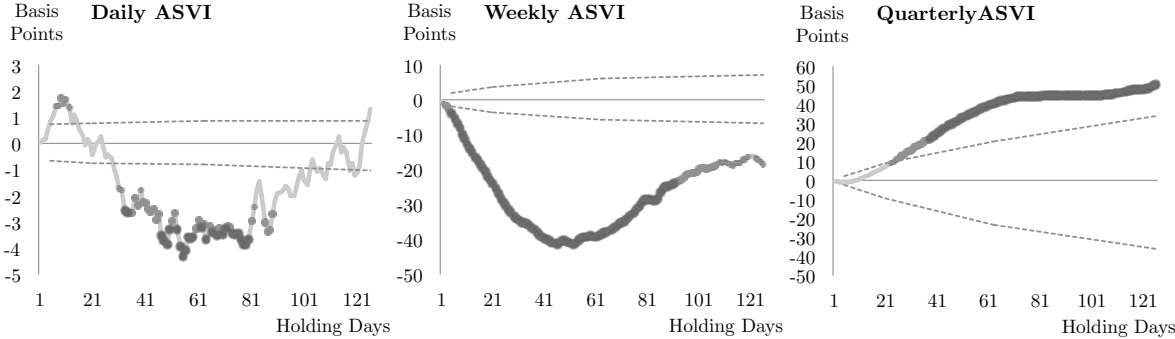
**Panel E:** Impact of average ASVI on cumulative excess returns. (January 2012 – December 2014)

**Fig. 7.** Results from our model in different time periods. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

### 3.6 Robustness

We also run our model for the plain SVI obtained straight from Google. This yields similar shapes with the exception of price reversal for the quarterly SVI and larger impacts in basis points. However the weekly ASVI has a VIF of 21.9 (daily 10.5 and monthly 12.3), which makes interpretation complicated.

Finally we run our model 200 times using random generated data with 0 mean and 1 standard deviation to model the ASVI. We construct confidence intervals for the basis point impacts at four different time horizons (one week, one month, three months and six months) and plot them against our results from our main model. The panel in figure 8 proves that the results from our base model are not due to the model structure itself.



**Fig. 8.** Results from our model compared to the 95% confidence level of a random variable. The y-axis denotes the impact on cumulative excess return in basis points of a one standard deviation change in the independent variable. The x-axis denotes the forecasting horizon (1 to 126 trading days). The thin, light grey line denotes insignificant impact. Small grey dots denote significance of the 10% level, medium grey dots indicate significance of the 5% level and large, dark dots indicate significance of the 1% level.

## 4 Trading Strategy

Next we create a trading strategy based on our base model to see if our findings are significant in an economic sense. We do this by running an adjusted version of our model (equation 12) as a rolling regression using only data from the previous year to avoid use of “future” data (i.e. we do not use the coefficients found for the whole data sample). In addition we do not include the Fama-French factors, yielding the following regression model:

$$R_{t,n} = \alpha_n + \boldsymbol{\beta}_n^T \cdot L3P(R_t) + \boldsymbol{\gamma}_n^T \cdot L3P(ASVI_t) + \boldsymbol{\delta}_n^T \cdot L3P(Abn Vlm_t) + \boldsymbol{\xi}_n^T \cdot L3P(Vol_t) + \boldsymbol{\delta}_n^T \cdot L3P(Bidask_t) + \epsilon_{t,n} \quad (12)$$

Where Greek letters are regression coefficients, bold letters are vectors,  $T$  indicates that the vector is transposed  $n$  is the forecasting horizon, and  $L3P$  is an operator that transforms a variable into a vector consisting of lagged short-, medium- and long-term components.

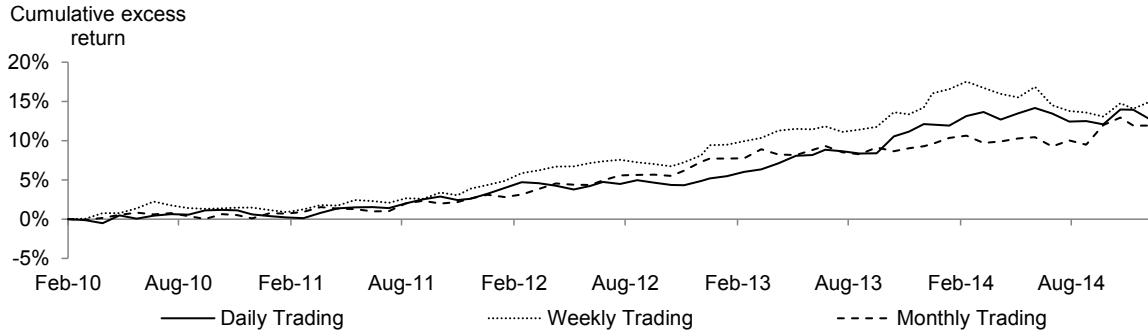
The expected return estimate for the next period is then based on the regression coefficients and the latest known values of the ASVI and the control variables (i.e. yesterday’s values). We then buy stocks with high expected returns and sell stocks with low expected returns. Initially, we arbitrarily choose to buy the top 25% and sell the bottom 25%.

In order to make our trading strategy realistic, it represents an actively managed mutual fund. We therefore combine the above mentioned strategy with an equally weighted portfolio of the companies in our dataset. This gives us a trading strategy (henceforth the ASVI strategy) which has a double long position in the companies with the highest returns predicted by our model, no position in those with the lowest predicted returns and a long position in those in between.

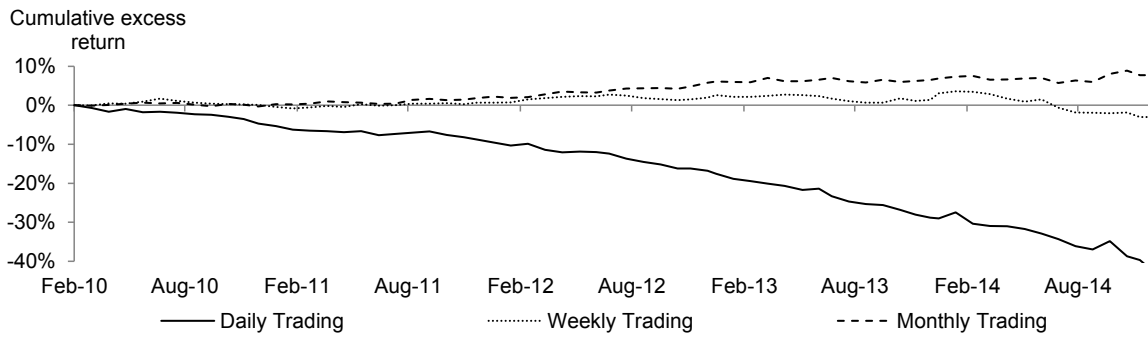


The ASVI strategy is evaluated at three trading frequencies; daily, weekly and monthly. Each position is re-weighted based on new information at the time of trading. Transaction cost is assumed to be 0.06% which is the sum of a 0.02% brokerage fee and half a bid/ask spread of 0.08% (the average bid-ask spread of the companies in our dataset). We compare the ASVI strategy with an equally weighted portfolio of the stocks in our dataset as a proxy for the market (a comparison which eliminates any effect of survivorship bias). We also compare the ASVI strategy with a similar trading strategy excluding the ASVI variables (henceforth benchmark strategy). We do the latter comparison in order to find the added economic benefit of the ASVI variables.

Comparison of the ASVI strategy and the equally weighted portfolio is shown in figure 9. The figure shows that the trading strategy excluding transaction costs with daily, weekly and monthly trading frequencies would outperform the equally weighted portfolio by an annual rate of 2.4%, 2.8% and 2.3%, respectively. In the presence of transaction costs only the monthly trading frequency would outperform the equally weighted portfolio (by 1.5% annually). This is expected because the estimated excess returns change for each period leading to large shifts of positions in the portfolio. With frequent trading regimes transaction costs quickly outweigh any benefits from the strategy.



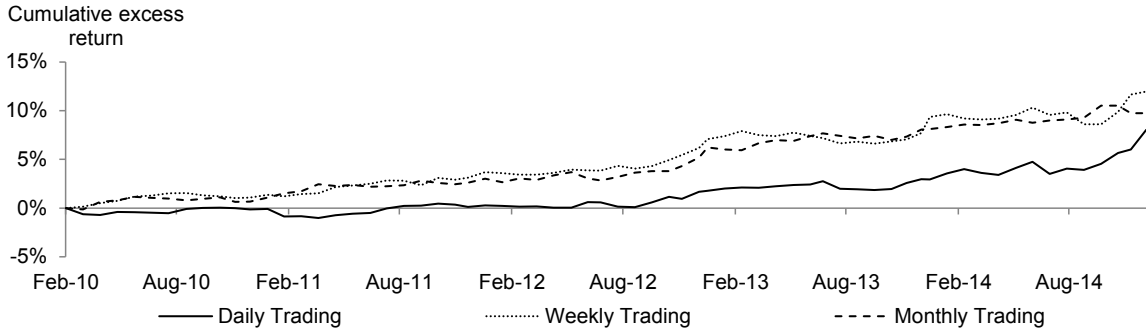
(a) Cumulative excess return over the equally weighted portfolio, excluding transaction costs



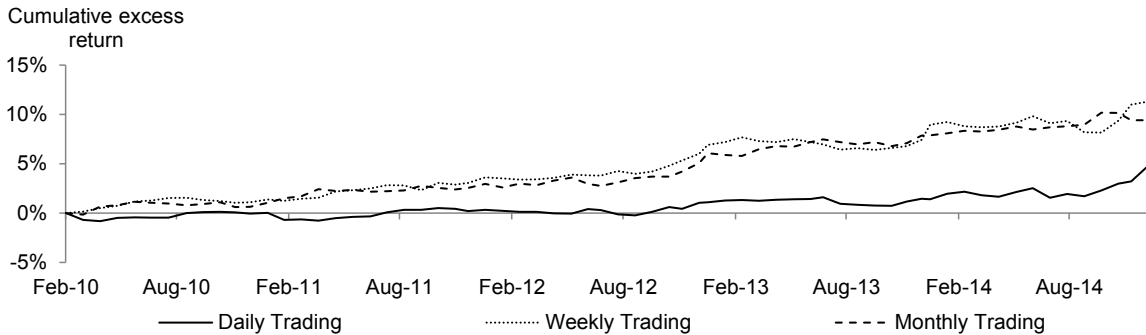
(b) Cumulative excess return over the equally weighted portfolio, including transaction costs

**Fig. 9.** Cumulative excess return over the equally weighted portfolio since 2010 for the ASVI strategy (y-axis), for different trading frequencies. Positive values indicate that the ASVI strategy outperforms the equally weighted portfolio.

Next we compare the ASVI strategy with the benchmark strategy to analyze the impact of the ASVI. Figure 10 shows that all trading frequencies perform better when the ASVI variables are included, both with and without transaction costs.



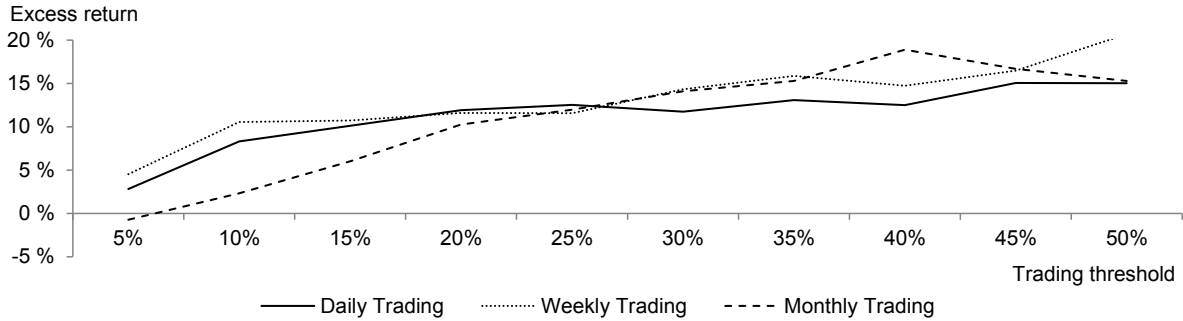
(a) Cumulative excess return over the benchmark strategy, excluding transaction costs



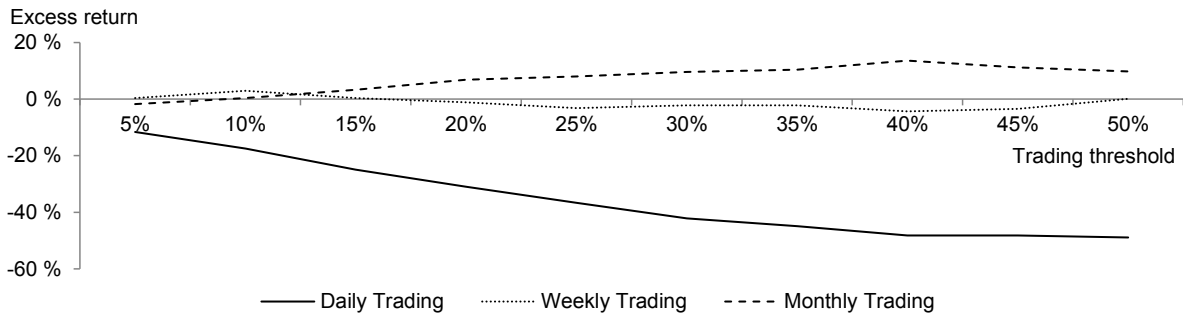
(b) Cumulative excess return over the benchmark strategy, including transaction costs

**Fig. 10.** Cumulative excess return over the benchmark strategy since 2010 for the ASVI strategy (y-axis), for different trading frequencies. Positive values indicate that the ASVI strategy outperforms the benchmark strategy.

It is also of interest to look at results given other thresholds for when the different positions (double long, long, or no position) are taken, which will also provide insight into the robustness of the ASVI strategy. We compare the performance versus the equally weighted portfolio for the different trading frequencies and different position thresholds (e.g. at 5%, the companies with the 5% highest/lowest expected returns are bought/sold). As can be seen in figure 11, the ASVI strategy is more profitable than the equally weighted portfolio for all trading frequencies and almost all position thresholds when transaction costs are excluded. When transaction costs are included, the monthly trading regime is the only trading frequency which consistently outperforms the equally weighted portfolio.



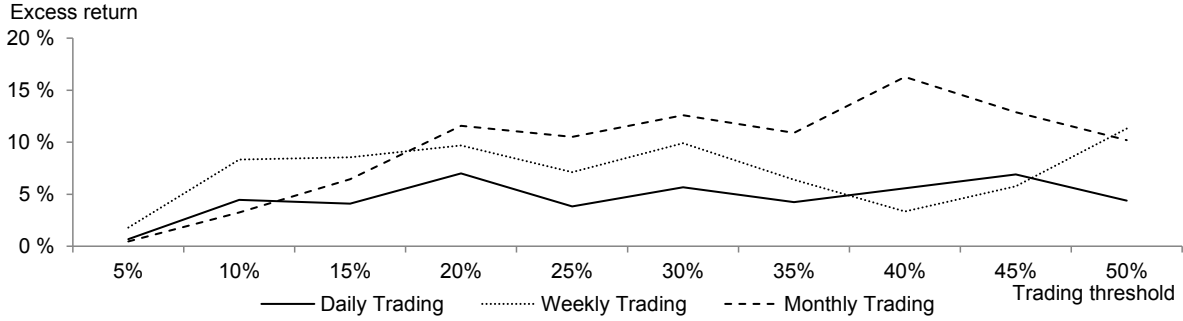
(a) Excess return over the equally weighted portfolio, excluding transaction costs



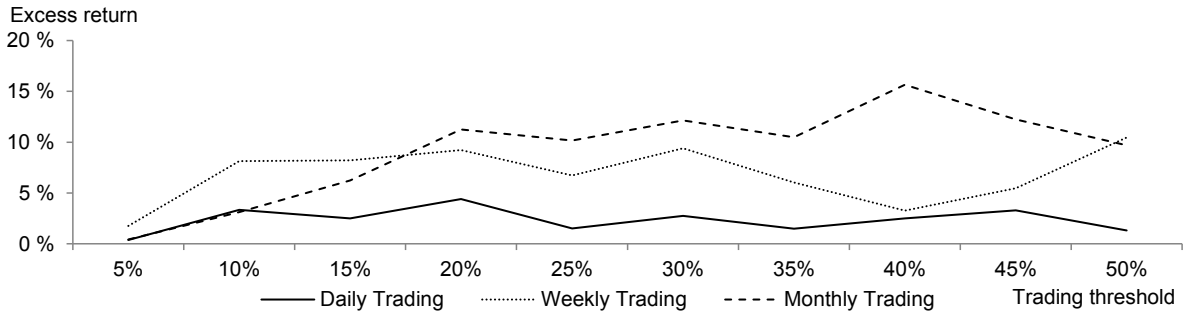
(b) Excess return over the equally weighted portfolio, including transaction costs

**Fig. 11.** Excess return over the equally weighted portfolio from 2010 to 2014 for the ASVI strategy for different trading frequencies. The x-axis denotes different versions of the trading strategies with different position thresholds. The y-axis denotes the excess return of the ASVI strategy relative to the equally weighted portfolio. Positive values indicate that the ASVI strategy outperforms the equally weighted portfolio.

Figure 12 shows the difference in excess return since 2010 for the ASVI strategy and the benchmark strategy. The figure shows that the ASVI strategy is consistently above the benchmark for all trading frequencies, both including and excluding transaction costs. This confirms that ASVI is a valuable variable when including it in a trading strategy.



(a) Excess return over the benchmark strategy, excluding transaction costs



(b) Excess return over the benchmark strategy, including transaction costs

**Fig. 12.** Excess return over the benchmark strategy (excluding ASVI) from 2010 to 2014 for the ASVI strategy for different trading frequencies. The x-axis denotes different versions of the trading strategies with different position thresholds. The y-axis denotes the excess return of the ASVI strategy relative to the benchmark strategy. Positive values indicate that the ASVI strategy outperforms the benchmark strategy.

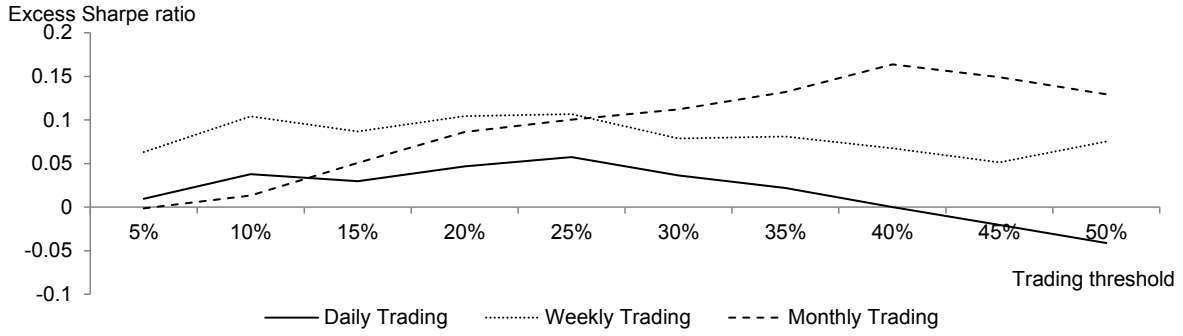
We also use the Sharpe ratio (1966) for comparison of the ASVI strategy with the equally weighted portfolio and the benchmark strategy. Table 2 shows the respective Sharpe ratios for the discussed strategies and trading frequencies. Table 2 confirms that the ASVI strategy is better than both comparables for all trading frequencies when transaction costs are not taken into account. The ASVI strategy has the same Sharpe ratio as the equally weighted portfolio for the weekly trading regime when transaction costs are included, and it is better than both comparables for the monthly trading regime. The equally weighted portfolio has the highest Sharpe ratio for the daily trading regime when transaction costs are included. This

is due to the frequent, and therefore high, transaction costs. Please note that our model aims to predict returns, not Sharpe ratios.

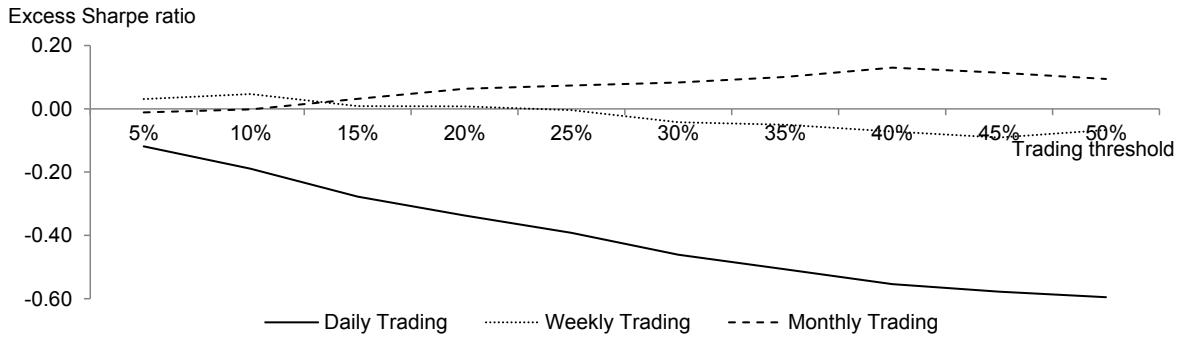
**Table 3.** Sharpe ratios for the ASVI and benchmark strategies using the 25<sup>th</sup> percentile for when different positions are taken. The risk-free rate is 1%.

Trading Frequency	Strategy	<i>Excluding Transaction Costs</i>			<i>Including Transaction Costs</i>		
		Average Return	Volatility	Sharpe Ratio	Average Return	Volatility	Sharpe Ratio
Daily	ASVIS strategy	20.5 %	12.5 %	1.56	14.2 %	12.0 %	1.10
	Benchmark Strategy	20.0 %	12.7 %	1.49	13.9 %	12.3 %	1.05
	Equally Weighted PF	19.2 %	12.1 %	1.51	19.0 %	12.1 %	1.49
Weekly	ASVIS strategy	24.9 %	11.4 %	2.10	23.2 %	11.2 %	1.98
	Benchmark Strategy	24.0 %	12.3 %	1.88	22.4 %	12.1 %	1.77
	Equally Weighted PF	23.6 %	11.4 %	1.99	23.5 %	11.4 %	1.98
Monthly	ASVIS strategy	19.4 %	15.6 %	1.18	18.9 %	15.5 %	1.15
	Benchmark Strategy	18.4 %	15.8 %	1.11	18.0 %	15.7 %	1.08
	Equally Weighted PF	18.2 %	15.9 %	1.08	18.2 %	15.9 %	1.08

Figure 13 shows that the ASVI strategy has higher Sharpe ratios than the equally weighted portfolio for all position thresholds for the weekly and monthly trading frequencies when transaction costs are excluded. The daily trading frequency has higher Sharpe ratios than the equally weighted portfolio for all position thresholds below the 40<sup>th</sup> percentile. When transaction costs are included, the monthly trading regime is the only frequency which outperforms the equally weighted portfolio for most position thresholds.



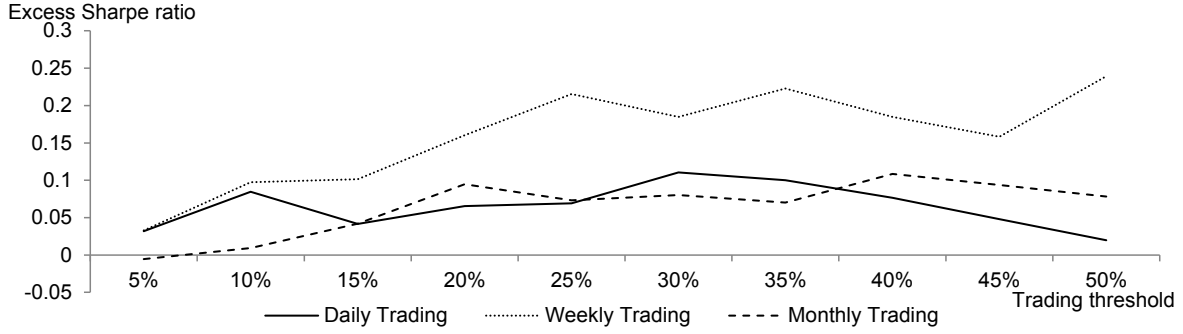
(a) Excess Sharpe ratio over the equally weighted portfolio, excluding transaction costs



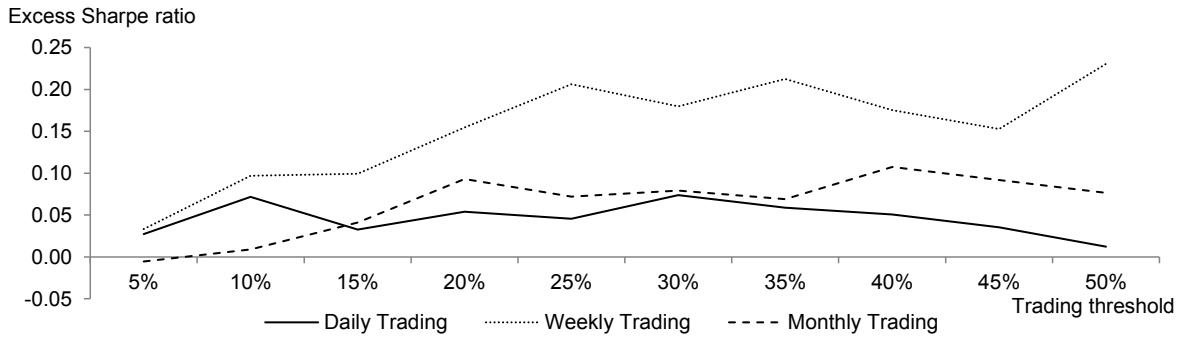
(b) Excess Sharpe ratio over the equally weighted portfolio, including transaction costs

**Fig. 13.** Sharpe ratios of the ASVI strategy minus the Sharpe ratio of the equally weighted portfolio (y-axis) for different percentiles for when the different positions are taken (x-axis). The figure includes daily, weekly and monthly trading frequencies. Positive values indicate that the ASVI strategy outperforms the equally weighted portfolio.

When comparing our strategy with the benchmark strategy, we see that our strategy has a Sharpe ratio, which is consistently above the benchmark (figure 14). This is consistent with the results shown in figure 12 and is further evidence of the predictive power of the ASVI.



(a) Excess Sharpe ratio over the benchmark strategy, excluding transaction costs



(b) Excess Sharpe ratio over the benchmark strategy, including transaction costs

**Fig. 14.** Sharpe ratios of the trading strategy minus the Sharpe ratio of the benchmark strategy (y-axis) for different percentiles for when the different positions are taken (x-axis). The figure includes daily, weekly and monthly trading frequencies. Positive values indicate that the ASVI strategy outperforms the benchmark strategy.

## 5 Conclusion

Google Trends supplies massive amounts of aggregate data on information search activity. In this paper we study the effect of abnormal search volumes on subsequent stock returns. Since we use daily search data, we are able to study the impact of increased or decreased search activity over various horizons – daily, weekly and quarterly. We find a small, positive short-term relationship between daily searches and stock returns. There is a significant and negative relationship between medium-term (weekly) abnormal search volumes with partial price reversal over the following six months. Long-term averages of abnormal search volumes lead to lasting, increased returns for the following six months. In the



absence of transaction costs these effects are large enough to create trading strategies which outperforms the market by roughly 2.5% annually, depending on trading frequency. Due to high turnover, only the strategy with a monthly trading frequency is able to outperform the market in the presence of transaction costs.

We also present evidence that company name search activity has a stronger relationship to stock market returns than ticker searches. The Google Trends finance filter does not capture different search interest than the unfiltered searches in terms of predicting stock returns. When it comes to company size we find that stock returns of small companies are more sensitive to long-term increases in search volumes than larger companies. On the other hand, returns of larger companies are more sensitive to short-term increases in searches. Finally, we present evidence that searches have more predictive power during times of crisis. and that in recent years search volumes have become more related to excess returns than before.

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## 6 Appendix

### 6.1 Data Downloading

Google adjusts data in such a way that the relative maximum for a query is always 100. In addition, Google only gives daily data for queries with shorter time periods than three months. It is possible to compare up to five searches in the same data set. We can therefore download five different time periods for the same search term in one data set with the same maximum. Our query indices are created by downloading daily data for one year and three months at a time (01 Jan year 1 – 31 Mar year 2) which are internally adjusted. We then let the three last months of download 1 overlap with the first three months of download 2 and multiply the entire latter year by the ratio to which these three months in year 1 are higher or lower than the former year (the sum of the last three months in download 1 divided by the first three months in download 2). After performing the previous exercise, we adjust the complete dataset such that the maximum value is 100 by dividing all values by the maximum value and multiplying them with 100. This isn't necessary, but we have done it to make the dataset on the same form as originally from Google. To make sure that our index for the whole time period didn't become materially different than the index directly from Google, we used average daily data for each week as the respective week's search volume and compared it with weekly SVI for the same time period. The average absolute difference between our weekly index and the index from Google for a test sample of 10 companies was 3.8% and the correlation was 99.4%, which we assume, is attributable to round off errors.

This download algorithm is more efficient than the one developed by Fink and Johann (2014). It reduces the number of downloads required by 58% for our dataset. It also allows all data to be downloaded in one batch, without any human interference. The correlation between GSV acquired using our algorithm and the algorithm of Fink and Johann (2014) is 0.9971.

## 6.2 Companies Used (and attempted used) in This Paper Including the Search Terms Used on Google Trends

IPI,Intrepid Potash; CAB,Cabela's; CBRL,Cracker Barrel; CHS,Chico's Fas; CST,CST Brands; DORM,Dorman Products; DRI,Darden; DW,Drew Industries; ESI,ITT Educational; FDO,Family Dollar; FTD,FTD Companies; GT,Goodyear; HAR,Harman International; HOT,Starwood Hotels; ICON,Iconix Brand; IGT,IGT; IPG,Interpublic Group; ISCA,International Speedway; LYV,Live Nation; MCRI,Monarch Casino; MHO,MI Schottenstein Homes; NWSA,News Corporation; ORLY,O'Reilly; RYL,Ryland Group; SAIC,SAIC; SCI,SCI; SNI,Scripps Networks Interactive; UTI,Universal Technical Institute; WEN,Wendy's; WGO,Winnebago Industries; AAN,Aaron's; AAP,Advance Auto Parts; ACAT,Arctic Cat; AEO,American Eagle Outfitters; AMCX,AMC; AMZN,Amazon; AN,AutoNation; ANF,Abercrombie & Fitch; ANN,AnnTaylor; APEI,American Public Education; APOL,Apollo; ARO,Aeropostale; ASNA,Dress Barn; AZO,AutoZone; BBBY,Bed Bath & Beyond; BBY,Best Buy; BC,Brunswick; BGFV,Big 5 Sporting Goods; BID,Sotheby's; BIG,Big Lots; BJRI,BJ's; BKE,Buckle; BKS,Barnes & Noble; BOBE,Bob Evans Farms; BWA,Borgwarner; BWLD,Buffalo Wild Wings; BWS,Brown Shoe; BYD,Boyd Gaming; CAKE,Cheesecake Factory; CATO,Cato; CBK,Christopher & Banks; CBS,CBS; CCL,Carnival; CECO,Career Education; CMCSA,Comcast; CMG,Chipotle; CNK,Cinemark; COH,Coach; CPLA,Capella Education; CRI,Carters; CROX,CROCS; CVC,Cablevision Systems; DECK,Deckers Outdoor; DG,Dollar General; DHI,DR Horton; DIN,DineEquity; DIS,Walt Disney; DKS,Dick's Sporting Goods; DLPH,Delphi Automotive; DLTR,Dollar Tree; DPZ,Domino's Pizza; DTV,DIRECTV; DV,DeVry; DWA,DreamWorks Animation; EAT,Brinker; ELY,Callaway Golf; ETH,Ethan Allen Interiors; EXPE,Expedia; F,Ford Motor; FINL,Finish Line; FL,Foot Locker; FOSS,Fossil; FOXA,Twenty-First Century Fox; FRAN,Francesca's; FRED,Fred's; GCI,Gannett;

GCO,Genesco; GES,Guess; GHC,Graham Company; GIII,G-III Apparel; GM,General Motors;  
GME,GameStop; GNTX,Gentex; GPC,Genuine Parts; GPI,Group 1 Automotive; GPS,Gap;  
GRMN,Garmin; HAS,Hasbro; HBI,Hanesbrands; HD,Home Depot; HELE,Helen of Troy;  
HHS,Harte-Hanks; HI,Hillenbrand; HIBB,Hibbett Sports; HOG,Harley-Davidson; HRB,Block H &  
R; HSNI,HSN; HVT,Haverty Furniture; HZO,MarineMax; IILG,Interval Leisure; IRBT,iRobot;  
JACK,Jack in the Box; JAH,Jarden; JAKK,JAKKS Pacific; JCI,Johnson Controls; JCP,JC Penney;  
JW-A,John Wiley & Sons; JWN,Nordstrom; KATE,Kate Spade; KBH,KB Home; KMX,Carmax;  
KORS,Michael Kors; KSS,Kohl's; LAD,Lithia Motors; LAMR,Lamar Advertising; LB,L Brands;  
LEG,Leggett & Platt; LEN,Lennar; LKQ,LKQ; LOW,Lowe's; LTM,Life Time Fitness; LZB,La-Z  
Boy; M,Macy's; MAR,Marriott; MAT,Mattel; MATW,Matthews; MCD,McDonald's; MCS,Marcus;  
MDC,MDC; MDP,Meredith; MGAM,Multimedia Games; MHFI,McGraw-Hill; MHK,Mohawk  
Industries; MNRO,Monro Muffler Brake; MOV,Movado; MTH,Meritage; MUSA,Murphy USA;  
MW,Men's Wearhouse; NFLX,NetFlix; NILE,Blue Nile; NKE,NIKE; NPK,National Presto;  
NTRI,NutriSystem; NVR,NVR; NWL,Newell Rubbermaid; NYT,New York Times; ODP,Office  
Depot; OMC,Omnicom; OTR,Outerwall; OXM,Oxford Industries; PBY,Pep Boys Manny;  
PCLN,Priceline; PERY,Perry Ellis; PETM,PETsMART; PETS,PetMed Express; PHM,Pulte;  
PII,Polaris; E,Children's Place; PNK,Pinnacle; PNRA,Panera Bread; POOL,Pool; PVH,Phillips-  
Van Heusen; PZZA,Papa John's; RCII,Rent-A-Center; RGR,Sturm Ruger; RGS,Regis; RL,Polo  
Ralph Lauren; ROST,Ross Stores; RRGB,Red Robin Gourmet Burgers; RT,Ruby Tuesday;  
RUTH,Ruth's Hospitality; SAH,Sonic Automotive; SBUX,Starbucks; SCHL,Scholastic; SCSS>Select  
Comfort; SGMS,Scientific Games; SHW,Sherwin-Williams; SIG,Signet Jewelers; SKX,Skechers;  
SMP,Standard Motor Products; SMRT,Stein Mart; SONC,Sonic; SPAR,Spartan Motors;  
SPF,Standard Pacific; SPLS,Staples; SSI,Stage Stores; SSP,EW Scripps; STMP,Stamps;  
STRA,Strayer Education; SUP,Superior Industries; TGT,Target; THO,Thor Industries;  
TIF,Tiffany; TIME,Time; TJX,TJX; TOL,Toll Brothers; TPX,Tempur-Pedic; TRIP,TripAdvisor;  
TSCO,Tractor Supply; TUES,Tuesday Morning; TUP,Tupperware; TWC,Time Warner Cable;  
TWX,Time Warner; TXRH,Texas Roadhouse; UA,Under Armour; UEIC,Universal Electronics;  
UNF,Unifirst; URBN,Urban Outfitters; VAC,Marriott Vacations; VFC,VF; VIAB,Viacom;  
VOXX,Audiovox; VSI,Vitamin Shoppe; WHR,Whirlpool; WSM,Williams-Sonoma;  
WWW,Wolverine World Wide; WYN,Wyndham; WYNN,Wynn; YUM,Yum; ZQK,Quiksilver;  
ZUMZ,Zumiez; CVGW,Calavo Growers; LXU,LSB; MJN,Mead Johnson Nutrition; SLGN,Silgan;

BF/B,Brown-Forman; CAG,ConAgra Foods; CALM,Cal Maine Foods; CASY,Casey's General Stores; COST,Costco; CVS,CVS; UVV,Universal Corp; ADM,Archer-Daniels-Midland; ANDE,Andersons; AOI,Alliance One; AVP,Avon; BGS,B&G Foods; BNNY,Annie's; CCE,Coca-Cola; CENTA,Central Garden & Pet; CHD,Church & Dwight; CL,Colgate-Palmolive; CLX,Clorox; CPB,Campbell Soup; DAR,Darling; DF,Dean Foods; DMND,Diamond Foods; DPS,Dr Pepper Snapple; EL,Estee Lauder; ENR,Energizer; FLO,Flowers Foods; GIS,General Mills; GMCR,Green Mountain Coffee Roasters; HAIN,Hain Celestial; HRL,Hormel Foods; HSH,The Hillshire Brands; HSY,Hershey Foods; INGR,Ingredion; IPAR,Inter Parfums; JJSF,J&J Snack Foods; K,Kellogg; KMB,Kimberly-Clark; KO,Coca-Cola; KR,Kroger; KRFT,Kraft Foods; LANC,Lancaster Colony; LNCE,Lance; LO,Lorillard; MDLZ,Mondelez; MKC,McCormick; MNST,Monster Beverage; MO,Altria; PBH,Prestige Brands; PEP,Pepsi; PG,Procter & Gamble; PM,Philip Morris; POST,Post; RAI,Reynolds American; SAFM,Sanderson Farms; SAM,Boston Beer; SENE,Seneca Foods; SJM,JM Smucker; SPTN,Spartan Stores; STZ,Constellation Brands; SVU,Supervalu; SWY,Safeway; SYY,Sysco; TAP,Molson Coors; THS,TreeHouse Foods; TR,Tootsie Roll; TSN,Tyson Foods; UNFI,United Natural Foods; WAG,Walgreen; WDFC,WD-40; WFM,Whole Foods; WMT,Wal-Mart; WWAV,WhiteWave Foods; APC,Anadarko; AREX,Approach Resources; BAS,Basic Energy Services; CAM,Cameron International; CHK,Chesapeake Energy; CJES,C&J Energy; CLD,Cloud Peak Energy; CNX,CONSOL Energy; COG,Cabot; CRK,Comstock Resources; CRZO,Carrizo; DNR,Denbury; DVN,Devon Energy; EOG,EOG Resources; ERA,Era Group; FTI,FMC Technologies; GEOS,Geospace Technologies; GPOR,Gulfport Energy; GPRE,Green Plains; HES,Hess Corporation; HLX,Helix Energy; HOS,Hornbeck Offshore; NBR,Nabors Industries; NR,Newpark Resources; PQ,Petroquest Energy; PTEN,Patterson UTI; RDC,Rowan Companies; SE,Spectra Energy; SFY,Swift Energy; SGY,Stone Energy; SM,SM Energy; SPN,Superior Energy; TTI,Tetra Technologies ; VLO,Valero Energy; WPX,WPX Energy; XEC,Cimarex Energy; ACI,Arch Coal; APA,Apache; ATW,Atwood Oceanics; BBG,Bill Barrett; BHI,Baker Hughes; BRS,Bristow; BTU,Peabody Energy; CKH,SEACOR; COP,ConocoPhillips; CRR,Carbo Ceramics; CVX,Chevron; DO,Diamond Offshore Drilling; DRC,Dresser-Rand; DRQ,Dril-Quip; ESV,Ensco; EXH,Exterran; FST,Forest Oil; GIF, Gulf Island Fabrication; HAL,Halliburton; HFC,HollyFrontier; HP,Helmerich & Payne; INT,World Fuel Services; IO,ION Geophysical; KMI,Kinder Morgan; MCF,Contango Oil & Gas; MPC,Marathon Petroleum; MRO,Marathon Oil; MTRX,Matrix Service; MUR,Murphy Oil; NBL,Noble Energy; NE,Noble; NFX,Newfield Exploration; NOG,Northern Oil

and Gas; NOV,National Oilwell Varco; OIL,Oceaneering; OIS,Oil States; OXY,Occidental Petroleum; PDCE,PDC Energy; PES,Pioneer Energy Services; PSX,Phillips 66; PVA,Penn Virginia; PXD,Pioneer Natural Resources; RIG,Transocean; ROSE,Rosetta Resources; RRC,Range Resources; SLB,Schlumberger; SWN,Southwestern Energy; TDW,Tidewater; TESO,Tesco; TSO,Tesoro; UNT,Unit Corp; WMB,Williams Cos; XOM,Exxon Mobil; CMO,Capstead Mortgage; NAVI,Navient; RNR,RenaissanceRe; WPG,Washington Prime; CHCO,City Holding; CLGX,CoreLogic; AIV,AIMCO; EWBC,East West Bank; NBTB,NBT Bank; STBA,ST Bank; STI,SunTrust Bank; SUSQ,Susquehanna; TCB,TCF Bank; TCBI,Texas Capital Bank; TMP,Tompkins Financial; TRMK,Trustmark; TRST,Trustco Bank; UBSI,United Bank; UCBI,United Community Bank; USB,US Bank; VLY,Valley National Bank; WABC,Westamerica Bank; WBS,Webster Bank; WIBC,Wilshire Bank; WTFC,Wintrust Bank; ZION,Zions Bank; AKR,Acadia Realty; AMG,Affiliated Managers Group; AMP,Ameriprise; ARE,Alexandria Real Estate; ASBC,Associated Bank; AVB,AvalonBay; BEN,Franklin Resources; BK,BNY Mellon; BMR,BioMed Realty; CATY,Cathay Bank; CBSH,Commerce Bank; CBU,Community Bank; CFNL,Cardinal Financial; CFR,Frost Bank; CHSP,Chesapeake Lodging; CINF,Cincinnati Financial; CLI,Mack-Cali; CLMS,Calamos; COLB,Columbia Bank; COR,Coresite; CPT,Camden Property; CSH,Cash America; CTRE,CareTrust REIT; CVBF,CVB Financial; CYN,CNB; DCOM,Dime Bank; DFS,Discover; DRE,Duke Realty; ECPG,Encore Capital; EGP,EastGroup Properties; EPR,EPR Properties; ESS,Essex Property; ETFC,Etrade Financial; EVR,Evercore; EZPW,EZPW; FAF,First American Bank; FCF,First Commonwealth Bank; FFBC,First Financial Bank; FFIN,First Financial Bank; FHN,First Horizon; FITB,Fifth Third Bank; FMBI,First Midwest Bank; FNB,FNB; FNF,Fidelity National Bank; FNFG,First Niagara; FRT,Federal Realty; FULT,Fulton Bank; GBCI,Glacier Bank; GGP,General Growth Properties; GNW,Genworth; GOV,Government Properties Income Trust; HAFC,Hanmi Bank; HBAN,Huntington Bank; HCBK,Hudson City Bank; HCI,HCI Group; HCN,Health Care REIT ; HIG,Hartford Financial; HIW,Highwoods Properties; HME,Home Properties of New York; HOMB,Home Bank; HPT,Hospitality Properties Trust; HR,Healthcare Realty Trust; HST,Host Hotels; IBOC,IBC Bank; INDB,Independent Bank; ITG,ITG; KIM,Kimco Realty; KRC,Kilroy Realty; KRG,Kite Realty; LHO,LaSalle Hotels; LNC,Loln National; LUK,Leucadia National; MAA,Mid-America Apartments; MBFI,MB Financial; MTB,MT Bank; NNN,National Retail Properties; NPBC,National Penn Bank; NTRS,Northern Trust; NWBI,Northwest Bank; NYCB,New York Community Bank; O,Realty

Income; ONB,Old National Bank; ORIT,Oritani Financial; PACW,PacWest Bank; PB,Prosperity Bank; PBCT,People's United Bank; PNC,PNC Bank; PRU,Prudential Financial; PVTB,Private Bancorp; RE,Everest Re Group; RF,Regions Financial; RGA,Reinsurance Group of America; RJF,Raymond James; ROIC,Retail Opportunity Investments; SAFT,Safety Insurance; SBNY,Signature Bank; SBRA,Sabra Health; SEIC,SEI Investments; SF,Stifel Financial; SFG,Stancorp Financial; SFNC,Simmons First; SIVB,SVB Financial; SLG,SL Green Realty; SNV,Synovus; STC,Stewart Information Services; STL,Sterling Bank; TROW,T Rowe Price; UBA,Urstadt Biddle; UMBF,UMB Financial; UVE,Universal Insurance; VNO,Vornado Realty; VPF,ViewPoint Financial; VRTS,Virtus Investment Partners; WRI,Weingarten Realty Investors; XL,XL Group; BBCN,BBCN ; AAT,American Assets Trust; ACC,American Campus Communities; ADC,Agree Realty; AEC,Associated Estates Realty; AF,Astoria Financial; AFG,American Financial Group; AFL,AFLAC; AHL,Aspen Insurance; AIG,AIG; AIZ,Assurant; AJG,Arthur J Gallagher; ALL,Allstate; AMSF,Amerisafe; AON,Aon; AXP,American Express; BAC,Bank of America; BANR,Banner; BBT,BB&T; BFS,Saul Centers; BKMU,Bank Mutual; BLK,BlackRock; BOFI,BoFi; BOH,Bank of Hawaii; BPFH,Boston Private; BRKL,Brookline Bank; BRO,Brown & Brown; BXP,Boston Properties; BXS,BancorpSouth ; C,Citigroup; CB,Chubb; CBG,CB Richard Ellis; CBOE,CBOE; CDR,Cedar Shopping Centres; CMA,Comerica; CME,Chicago Mercantile Exchange; COF,Capital One; CUZ,Cousins Properties; DRH,Diamondrock Hospitality; EHTH,eHealth; EIG,Employers; EQR,Equity Residential; EQY,Equity One; EV,Eaton Vance; EXR,Extra Space Storage; FBP,First Bank; FCFS,First Cash; FII,Federated Investors; FMER,FirstMerit; FNGN,Financial Engines; FOR,Forestar; FSP,Franklin Street Properties; FXCM,FXCM; GDOT,Green Dot; GHL,Greenhill; GS,Goldman Sachs; GTY,Getty Realty; HBHC,Hancock; HCC,HCC Insurance; HCP,HCP; HF,HFF; HMN,Horace Mann Educators; ICE,IntercontinentalExchange; IPCC,Infinity Property & Casualty; IRC,Inland Real Estate; IVZ,Invesco; JLL,Jones Lang Lasalle; JNS,Janus Capital; JPM,JP Morgan Chase; KEY,KeyCorp; KMPR,Kemper; L,Loews; LM,Legg Mason; LPT,Liberty Property; LTC,LTC; LXP,Lexington Realty; MAC,Macerich; MATX,Matson; MCO,Moody's; MCY,Mercury General; MET,Metlife; MIG,Meadowbrook Insurance; MKTX,MarketAxess; MMC,Marsh & McLennan; MPW,Medical Properties; MS,Morgan Stanley; NAVG,Navigators Group; NDAQ,Nasdaq OMX Group; OFC,Corporate Office Properties; OHI,Omega Healthcare; ORI,Old Republic; OZRK,Bank of the Ozarks; PCH,Potlatch; PCL,Plum Creek Timber; PEI,Pennsylvania Real Estate; PFG,Prival



Financial; PFS,Provident Financial; PGR,Progressive; PJC,Piper Jaffray; PKY,Parkway Properties;  
PL,Protective Life; PLD,Prologis; PNF,Pinnacle Financial; PPS,Post Properties;  
PRA,ProAssurance; PRAA,Portfolio Recovery; PRI,Primerica; PSA,Public Storage; PSB,PS  
Business Parks; REG,Regency Centers; RLI,RLI; RYN,Rayonier; SCHW,Charles Schwab;  
SIGI,Selective Insurance; SKT,Tanger Factory Outlet Centers; SLM,SLM; SNH,Senior Housing  
Properties; SPG,Simon Property; SSS,Sovran Self Storage; STT,State Street; SWS,SWS;  
TAYC,Taylor Capital; TCO,Taubman Centers; THG,Hanover Insurance; TMK,Torchmark;  
TRV,Travelers; UDR,UDR; UFCS,United Fire & Casualty; UMPQ,Umpqua; UNM,Unum;  
VTR,Ventas; WAFD,Washington Fed; WDR,Waddell & Reed; WFC,Wells Fargo; WRB,WR  
Berkley; WRLD,World Acceptance; Y,Alleghany; AHS,AMN Healthcare; ALGN,Align Technology;  
ALXN,Alexion; BIIB,Biogen Idec; BIO,Bio-Rad; BRLI,Bio Reference; CAH,Cardinal Health;  
CBST,Cubist Pharmaceuticals; CRL,Charles River; CYH,Community Health Systems; ICUI,ICU  
Medical; IDXX,IDEXX; IPCM,IPC The Hospitalist; IPXL,Impax Labs; KND,Kindred Healthcare;  
LGND,Ligand Pharmaceuticals; MDCO,The Medicines Company; MDSO,Medidata Solutions;  
MGLN,Magellan Health Services; MOH,Molina Healthcare; SIRO,Sirona Dental; SLXP,Salix  
Pharmaceuticals; THC,Tenet Healthcare; UHS,Universal Health Services; VIVO,Meridian  
Bioscience; VRTX,Vertex Pharmaceuticals; WCG,Wellcare Health Plans; ABAX,Abaxis;  
ABBV,AbbVie; ABC,AmerisourceBergen; ABMD,Abiomed; ABT,Abbott Laboratories;  
ACOR,Acorda Therapeutics; ACT,Actavis; AET,Aetna; AFAM,Almost Family; AFFX,Affymetrix;  
AGN,Allergan; AIRM,Air Methods; AKRX,Akorn ; ALOG,Analogic; AMED,Amedisys;  
AMGN,Amgen; AMRI,Albany Molecular Research; AMSG,Amsurg; ANIK,Anika Therapeutics;  
BABY,Natus Medical; BAX,Baxter; BCR,CR Bard; BDX,Becton Dickinson; BMY,Bristol-Myers  
Squibb; BSX,Boston Scientific; CBM,Cambrex; CCRN,Cross Country Healthcare; CELG,Celgene;  
CERN,Cerner; CFN,CareFusion; CHE,Chemed; CI,CIGNA; CNC,Centene; CNMD,Conmed;  
COO,Cooper Companies; COV,Covidien; CPSI,Computer Programs & Systems; CRVL,Corvel;  
CRY,Cryolife; CVD,Covance; CYBX,Cyberonics; CYNO,Cynosure; DGX,Quest Diagnostics;  
DVA,Davita; ENDP,Endo Pharmaceuticals; ESRX,Express Scripts; EW,Edwards Lifesciences;  
FRX,Forest Laboratories; GB,Greatbatch; GILD,Gilead Sciences; GTIV,Gentiva Health;  
HAE,Haemonetics; HGR,Hanger Orthopedic; HMSY,HMS; HNT,Health Net; HOLX,Hologic;  
HRC,Hill-Rom; HSIC,Henry Schein; HSP,Hospira; HSTM,HealthStream; HUM,Humana;  
HWAY,Healthways; IART,Integra Lifesciences; ISRG,Intuitive Surgical; IVC,Invacare;

JNJ,Johnson & Johnson; LCI,Lannett; LDR,Landauer; LH,Lab of America; LHCG,LHC; LLY,Eli Lilly; LMNX,Luminex; LPNT,Lifepoint Hospitals; MASI,Masimo; MCK,McKesson; MD,Mednax; MDT,Medtronic; MMSI,Merit Medical; MNK,Mallkrodt; MNTA,Momenta Pharmaceuticals; MRK,Merck; MTD,Mettler-Toledo; MWIV,MWI Veterinary Supply; MYL,Mylan; NEOG,Neogen; NUVA,NuVasive; OCR,Omnicare; OMCL,OmniceLL; OMI,Owens & Minor; PDCO,Patterson; PFE,Pfizer; PKI,PerkinElmer; PMC,PharMerica; PRGO,Perrigo; PRXL,PAREXEL; QCOR,Questcor Pharmaceuticals; QSII,Quality Systems; REGN,Regeneron Pharmaceuticals; RGEN,Repligen; RMD,ResMed; SMA,Symmetry Medical; SPPI,Spectrum Pharmaceuticals; SRDX,SurModics; STE,STERIS; STJ,St Jude Medical; SYK,Stryker; TECH,Techne; TFX,Teleflex; THOR,Thoratec; TMO,Thermo Fisher; UNH,Unitedhealth; UTHR,United Therapeutics; VAR,Varian Medical; WAT,Waters; WLP,WellPoint; WOOF,VCA Antech; WST,West Pharmaceutical; XRAY,Dentsply; ZMH,Zimmer; ZTS,Zoetis; EBS,Emergent Biosolutions; CMN,Cantel Medical; POWL,Powell; AEGN,Insituform; AIN,Albany International; ASTE,Astec Industries; ATK,ATK; AYI,Acuity Brands; B,Barnes Group; BCO,Brink's; CEB,CEB; DE,Deere; DXPE,DXP Enterprises; DY,Dycom; EMR,Emerson Electric; ESE,ESCO Technologies; ESL,Esterline; EXPD,Expeditors; FBHS,Fortune Brands; GEO,Geo Group; GY,Gencorp; HUBG,Hub Group; JBT,John Bean; KSU,Kansas City Southern; LECO,Loln Electric; LII,Lennox International; LLL,L3 Communications; MSM,MSC Direct; NPO,EnPro Industries; RECN,Resources Connection; ROK,Rockwell Automation; ROP,Roper Industries; SWK,Stanley Black & Decker; TDY,Teledyne Technologies; TTEK,Tetra Tech; UTIW,UTi Worldwide; VMI,Valmont Industries; AAON,Aaon; AAWW,Atlas Air Worldwide; ABM,ABM Industries; ACET,Aceto; ACM,Aecom Technology; ADT,ADT; AGCO,AGCO; AIR,AAR; AIT,Applied Industrial Technologies; ALEX,Alexander & Baldwin; ALK,Alaska Air; ALLE,Allegion; AME,AMETEK; AMWD,American Woodmark; AOS,AO Smith; APOG,Apogee Enterprises; ARCB,ArcBest; ASEI,American Science & Engineering; ASGN,On Assignment; ATU,Actuant; AVAV,Aerovironment; AVY,Avery Dennison; AZZ,AZZ; BA,Boeing; BDC,Belden; BEAV,BE Aerospace; BGC,General Cable; BGG,Briggs & Stratton; BMI,Badger Meter; BRC,Brady; CAT,Caterpillar; CDI,CDI; CHRW,CH Robinson; CIR,Circor; CLC,CLARCOR; CLH,Clean Harbors; CMI,Cummins; CNW,Con-way; COL,Rockwell Collins; CPRT,Copart; CR,Crane; CSL,Carlisle; CSX,CSX; CTAS,Cintas; CUB,Cubic; CVEO,Civeo; CW,Curtiss-Wright; CXW,Corrections of America; DAL,Delta Air Lines; DCI,Donaldson; DHR,Danaher; DLX,Deluxe;

DNB,Dun & Bradstreet; DNOW,NOW; DOV,Dover; EFX,Equifax; EGL,Engility; EME,Emcor;  
ENS,EnerSys; ETN,Eaton; EXPO,Exponent; FAST,Fastenal; FCN,FTI Consulting; FDX,FedEx;  
FELE,Franklin Electric; FIX,Comfort Systems USA; FLR,Fluor; FLS,Flowserve; FSLR,First Solar;  
FSS,Federal Signal; FWRD,Forward Air; GD,General Dynamics; GE,General Electric; GFF,Griffon;  
GGG,Graco; GK,G & K Services; GMT,GATX; GVA,Granite Construction; GWR,Genesee &  
Wyoming; GWW,WW Grainger; HCSG,Healthcare Services; HII,Huntington Ingalls; HNI,HNI;  
HON,Honeywell; HSC,Harsco; HSII,Heidrick & Struggles; HTLD,Heartland Express;  
HUB/B,Hubbell; IEX>IDEX; IIVI,II-VI; IR,Ingersoll-Rand; IRM,Iron Mountain; ITT,ITT;  
ITW,Illinois Tool Works; JBHT,JB Hunt; JBLU,JetBlue; JEC,Jacobs Engineering; JOY,Joy  
Global; KAMN,Kaman; KBR,KBR; KELYA,Kelly Services; KEX,Kirby; KFY,Korn Ferry;  
KMT,Kennametal; KNX,Knight Transportation; LDL,Lydall; LMT,Lockheed Martin; LNN,Lindsay;  
LSTR,Landstar System; LUV,Southwest Airlines; MAN,Manpower; MAS,Masco; MINI,Mobile Mini;  
MLHR,Herman Miller; MLI,Mueller Industries; MMM,3M; MOG/A,Moog; MSA,Mine Safety  
Appliances; MWW,Monster Worldwide; NCI,Navigant Consulting; NDSN,Nordson; NLSN,Nielsen;  
NOC,Northrop Grumman; NSC,Norfolk Southern; NSP,Insperity; NX,Quanex Building Products;  
ODFL,Old Dominion Freight Line; ORB,Orbital Sciences; OSK,Oshkosh; PBI,Pitney Bowes;  
PCAR,PACCAR; PCP,Precision Castparts; PGTI,PGT; PH,Parker-Hannifin; PLL,Pall;  
PNR,Pentair; PWR,Quanta Services; R,Ryder System; RBC,Regal Beloit; RHI,Robert Half;  
ROCK,Gibraltar Industries; ROL,Rollins; RRD,RR Donnelley; RRTS,Roadrunner Transportation;  
RSG,Republic Services; RTN,Raytheon; SAIA,Saia; SKYW,SkyWest; SNA,Snap On; SPW,SPX;  
SRCL,Stericycle; SSD,Simpson Manufacturing; SXI,Standex; SYKE,Sykes Enterprises; TASR,Taser  
International; TBI,TrueBlue; TEX,Terex; TG,Tredegar; TGI,Triumph; TILE,Interface;  
TKR,Timken; TNC,Tennant; TRN,Trinity Industries; TTC,Toro; TWI,Titan International;  
TXT,Textron; UFPI,Universal Forest Products; UNP,Union Pacific; UPS,UPS; URI,United  
Rentals; URS,URS; USTR,United Stationers; UTX,United Technologies; VICR,Vicor; VVI,Viad;  
WAB,Wabtec; WAGE,WageWorks; WCN,Waste Connections; WERN,Werner Enterprises;  
WIRE,Encore Wire; WM,Waste Management; WSO,Watsco; WTS,Watts Industries;  
WWD,Woodward Governor; XLS,Exelis; XYL,Xylem; ACIW,ACI Worldwide; ADBE,Adobe  
Systems; ADVS,Advent Software; AEIS,Advanced Energy; AKAM,Akamai; ARW,Arrow  
Electronics; AVGO,Avago Technologies; BR,Broadridge; BRKS,Brooks Automation; CACI,CACI;  
CKP,Checkpoint Systems; CNQR,Concur Technologies; CSCO,Cisco Systems; CSGS,CSGI;

CTSH,Cognizant; CTXS,Citrix; CVLT,Commvault; DST,DST Systems; ENTR,Entropic;  
EPAY,Bottomline Technologies; EPIQ,Epiq Systems; FARO,FARO Technologies; FFIV,F5;  
FIS,Fidelity National; FLIR,Flir; FORR,Forrester Research; GTAT,GT Advanced Technologies;  
HPY,Heartland Payment Systems; IDTI,Integrated Device Technology; IM,Ingram Micro;  
IRF,International Rectifier Corp; JCOM,J2 Global; JNPR,Juniper Networks; KLAC,KLA-Tencor;  
LOGM,LogMeIn; MKSI,MKS Instruments; MRCY,Mercury Systems; MTSC,MTS Systems;  
MU,Micron Technology; NTCT,Netscout; PKT,Procera Networks; RBCN,Rubicon Technology;  
SLAB,Silicon Laboratories; SNCR,Synchronoss Technologies; STX,Seagate Technology; TSS,Total  
System Services; TTMI,TTM Technologies; VDSI,VASCO Data Security; VECO,Veeco  
Instruments; VSH,Vishay Intertechnology; XOXO,XO Group; A,Agilent Technologies;  
AAPL,Apple; ACN,Accenture; ACXM,Axiom; ADI,Analog Devices; ADP,Automatic Data  
Processing; ADS,Alliance Data Systems; ADSK,Autodesk; ADTN,ADTRAN; AGYS,Agilysys;  
ALTR,Altera; AMAT,Applied Materials; AMD,Advanced Micro Devices; ANSS,ANSYS;  
APH,Amphenol; ARRS,Arris; ATML,Atmel; AVT,Avnet; AXE,Anixter; BBOX,Black Box;  
BCOR,Blucora; BELFB,Bel Fuse; BHE,Benchmark Electronics; BLKB,Blackbaud;  
BRCM,Broadcom; CA,CA; CAMP,CalAmp; CATM,Cardtronics; CBR,CIBER; CCMP,Cabot  
Microelectronics; CDNS,Cadence Design; CEVA,CEVA; CGNX,Cognex; CIEN,CIENA;  
CMTL,Comtech; CNVR,Conversant; COHR,Coherent; COHU,Cohu; CPWR,Compuware;  
CREE,Cree; CRM,Salesforce; CRUS,Cirrus Logic; CSC,Computer Sciences; CTS,CTS;  
CVG,Convergys; CY,Cypress Semiconductor; DAKT,Daktronics; DBD,Diebold; DDD,3D Systems;  
DGII,Digi; DHX,Dice; DIOD,Diodes; DRIV,Digital River; DSPG,DSP; DTSI,DTS; EA,Electronic  
Arts; EBAY,eBay; EBIX,Ebix; EFII,Electronics For Imaging; EGOV,NIC; EMC,EMC;  
EQIX,Equinix; ESIO,Electro Scientific; EXAR,Exar; EXLS,Exlservice; FB,Facebook; FCS,Fairchild  
Semiconductor; FDS,FactSet Research; FEIC,FEI; FICO,Fair Isaac; FISV,Fiserv; FN,Fabrinet;  
FTNT,Fortinet; GLW,Corning; GOOG,Google; GPN,Global Payments; HITT,Hittite Microwave;  
HLIT,Harmonic; HPQ,Hewlett-Packard; HRS,Harris; IBM,IBM; IDCC,InterDigital; IGTE,iGATE;  
INFA,Informatica; INTC,Intel; INTU,Intuit; ISIL,Intersil; IT,Gartner; ITRI,Itron; IVAC,Intevac;  
JBL,Jabil Circuit; JDSU,JDS Uniphase; JKHY,Jack Henry; KLIC,Kulicke & Soffa; KN,Knowles;  
KOPN,Kopin; LDOS,Leidos; LFUS,Littelfuse; LLTC,Linear Technology; LPSN,LivePerson;  
LRCX,Lam Research; LXX,Lexmark; MA,Mastercard; MANH,Manhattan Associates;  
MANT,Mantech; MCHP,Microchip Technology; MCRL,Micrel; MCRS,MICROS Systems;

MEAS,Measurement Specialties; MEI,Method Electronics; MENT,Mentor Graphics;  
MMS,MAXIMUS; MSCC,Microsemi; MSFT,Microsoft; MSI,Motorola; NANO,Nanometrics;  
NATI,National Instruments; NCR,NCR; NEWP,Newport; NSIT,Insight Enterprises; NSR,NeuStar;  
NTAP,NetApp; NTGR,Netgear; NVDA,Nvidia; ONE,Higher One; OPEN,OpenTable; OPLK,Oplink  
Communications; ORCL,Oracle; PAY,VeriFone; PAYX,Paychex; PKE,Park Electrochemical;  
M,Polycom; PLT,Plantronics; PLXS,Plexus; POWI,Power Integrations; PRFT,Perficient;  
PRGS,Progress Software; PSEM,Pericom Semiconductor; PTC,PTC; QCOM,QUALCOMM;  
QLGC,Qlogic; QNST,QuinStreet; RFMD,RF Micro Devices; RHT,Red Hat; ROG,Rogers Corp;  
ROVI,Rovi; RSTI,Rofin-Sinar; RTEC,Rudolph Technologies; RVBD,Riverbed Technology;  
SANM,Sanmina; SCOR,Comscore; SCSC,ScanSource; SLH,Solera; SMCI,Super Micro Computer;  
SMTC,Semtech; SNDK,SanDisk; SNPS,Synopsys; SNX,Synnex; SUNE,SunEdison; SWI,SolarWinds;  
SWKS,Skyworks; SYMC,Symantec; SYNA,Synaptics; TDC,Teradata; TECD,Tech Data; TEL,TE  
Connectivity; TER,Teradyne; TIBX,TIBCO; TNGO,Tangoe; TQNT,Triquent Semiconductor;  
TRAK,DealerTrack; TRMB,Trimble Navigation; TTEC,TELETECH; TTWO,Take-Two  
Interactive; TXN,Texas Instruments; TYL,Tyler Technologies; TYPE,Monotype Imaging;  
UTEK,Ultratech Stepper; VRSN,VeriSign; VRTU,Virtusa; VSAT,ViaSat; WDC,Western Digital;  
WEX,WEX; WU,Western Union; XLNX,Xilinx; XRX,Xerox; XXIA,Ixia; YHOO,Yahoo;  
ZBRA,Zebra Technologies; DD,Dupont; APD,Air Products; ATI,Allegheny Technologies;  
ATR,AptarGroup; CF,CF Industries; CLF,Cliffs Natural Resources; CYT,Cytec; EMN,Eastman  
Chemical; FTK,Flotek Industries; GSM,Globe Specialty Metals; HAYN,Haynes International;  
IFF,IFF; IP,International Paper; MLM,Martin Marietta; MOS,Mosaic Company; MTX,Minerals  
Technologies; MYE,Myers Industries; RTI,RTI International; SCL,Stepan Company; SXC,SunCoke  
Energy; AA,Alcoa; AKS,AK Steel; ALB,Albemarle; ARG,Airgas; ASH,Ashland; AVD,American  
Vanguard; BCC,Boise Cascade; BCPC,Balchem; BLL,Ball; BMS,Bemis; CAS,A M Castle;  
CBT,Cabot; CCC,Calgon Carbon; CENX,Century Aluminum; CLW,Clearwater Paper;  
CMC,Commercial Metals; CMP,Compass Minerals; CRS,Carpenter Technology; DEL,Deltic  
Timber; DOW,Dow Chemical; ECL,Ecolab; EXP,Eagle Materials; FCX,Freeport McMoRan Copper  
& Gold; FF,FutureFuel; FMC,FMC; FUL,HB Fuller; GEF,Greif Bros; GLT,PH Glatfelter;  
HW,Headwaters; HWKN,Hawkins; IPHS,Innophos; KOP,Koppers; KRA,Kraton Performance  
Polymers; KS,KapStone Paper and Packaging; KWR,Quaker Chemical; LPX,Louisiana Pacific;  
LYB,LyondellBasell; MON,Monsanto; MTRN,Materion; MWV,MeadWestvaco; NEM,Newmont

Mining; NEU,NewMarket; NP,Neenah Paper; NUE,Nucor; OI,Owens-Illinois; OLN,Olin; OMG,OM; PKG,Packaging of America; POL,PolyOne; PPG,PPG; PX,Praxair; RGLD,Royal Gold; RKT,Rock-Tenn; RPM,RPM; RS,Reliance Steel & Aluminum; SEE,Sealed Air; SHLM,A Schulman; SIAL,Sigma-Aldrich; SLCA,US Silica; SMG,Scotts Company; SON,Sonoco Products; STLD,Steel Dynamics; SWC,Stillwater Mining; SWM,Schweitzer-Mauduit; SXT,Sensient Technologies; TXI,Texas Industries; UFS,Domtar; VAL,Valspar; VMC,Vulcan Materials; WOR,Worthington Industries; WPP,Wausau Paper; WY,Weyerhaeuser; X,United States Steel; ZEP,Zep; ZEUS,Olympic Steel; ALGT,Allegiant; BYI,Bally Technologies; DISCA,Discovery; BH,Biglari; LL,Lumber Liquidators; MED,Medifast; SZMK,Digital Generation; TW,Towers Watson; V,Visa; TSRA,Tessera Technologies; AOL,AOL; ININ,Interactive Intelligence; MSTR,MicroStrategy; NTLS,NTELOS; OSIS,OSI Systems; TWTC,Time Warner Telecom; ATNI,ATN; CCI,Crown Castle; LMOS,Lumos Networks; TDS,Telephone & Data Systems; AMT,American Tower; CBB,Cinnati Bell; CBEY,Cbeyond; CTL,CenturyLink; EGHT,8x8; FTR,Frontier Communications; GNCMA,General Communication; T,AT&T; USMO,USA Mobility; VZ,Verizon; WIN,Windstream; ATO,Atmos Energy; CMS,CMS Energy; CNP,Centerpoint Energy; DTE,DTE Energy; DUK,Duke Energy; GAS,AGL Resources; GXP,Great Plains Energy; HE,Hawaiian Electric; MDU,MDU Resources; NEE,NextEra Energy; NFG,National Fuel Gas; NRG,NRG Energy; PNW,Pinnacle West Capital; PNY,Piedmont Natural Gas; SRE,Sempra Energy; TE,TECO Energy; TEG,Integrys Energy; UNS,Unisource Energy; WR,Westar Energy; XEL,Xcel Energy; AEE,Ameren; AEP,American Electric Power; AES,AES; ALE,Allete; AVA,Avista; AWR,American States Water; BKH,Black Hills; CNL,Cleco; D,Dominion Resources; ED,Consolidated Edison; EE,El Paso Electric; EGN,Energen; EIX,Edison; EQT,EQT; ETR,Entergy; EXC,Exelon; FE,FirstEnergy; IDA,IDA; LG,Laclede; LNT,Alliant Energy; NI,Nisource; NJR,New Jersey Resources; NU,Northeast Utilities; NWE,Northwestern; NWN,Northwest Natural Gas; OGE,OGE Energy; OGS,ONE Gas; OKE,ONEOK; PCG,PG&E; PEG,Public Service Enterprise; PNM,PNM Resources; POM,Pepco; PPL,PPL; SCG,SCANA; SJI,South Jersey Industries; SO,Southern Company; STR,Questar; SWX,Southwest Gas; UGI,UGI; UIL,Uil; VVC,Vectren; WEC,Wisconsin Energy; WGL,WGL; WTR,Aqua America; ENSG,Ensign Group; MPWR,Monolithic Power; QEP,QEP Resources; UHT,Universal Health Realty; ACE,ACE; BRK/B,Berkshire Hathaway; IBKR,Interactive Brokers; KALU,Kaiser Aluminum; KIRK,Kirkland's; LQDT,Liquidity Services; MDRX,Allscript Healthcare;

MSCI,MSCI; ORN,ORION MARINE; RAX,Rackspace Hosting; SHOO,Steven Madden; TYC,Tyco  
International