Forecasting Abnormal Stock Returns and Trading Volume Using Investor Sentiment: Evidence from Online Search ⋆

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Abstract

We examine the ability of online ticker searches (e.g. XOM for Exxon Mobil) to forecast abnormal stock returns and trading volumes. Specifically, we argue that online ticker search serves as a valid proxy for investor sentiment – a set of beliefs about cash flows and investments risks that are not necessarily justified by the facts at hand – which is generally associated with less sophisticated, retail investors. Based on prior research on investor sentiment, we expect online search intensity to forecast stock returns and trading volume, and that highly volatile stocks, which are more difficult to arbitrage, will be more sensitive to search intensity than less volatile stocks. In a sample of S&P 500 firms over the period 2005–2008, we find that, over a weekly horizon, online search intensity reliably predicts abnormal stock returns and trading volume, and that the sensitivity of returns to search intensity is positively related to the difficulty with which a stock can be arbitraged. We conclude by offering guidelines for the utilization of online search data in other forecasting applications.

Key words: Investor Sentiment, Finance, Fama-French Model, Portfolio Tests, Marketing

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1 Introduction

There is growing recognition about the predictive value of data collected across various digital platforms. One rich repository of predictive data is online searches. According to Hal Varian, chief economist at Google, changes in search queries such as “unemployment office” and “jobs” help predict increases in initial jobless claims (Tuna (2010)). Clearly, this suggested link between online search behavior and important market outcomes is of much interest to business practitioners. For example, the theory of buyer behavior posits that a consumer’s search for information precedes his or her purchase decision (Beatty and Smith (1987)). As such, measures of consumer search behavior can help managers better predict sales of products in various product categories, suggest the most appropriate time to launch a promotional campaign, or even track interest in competitive products.

Interestingly, today’s digital environment provides previously unavailable measures of consumer search behavior. In particular, Google, the search engine with the highest market share, publicly provides information on the intensity of search for any keyword. Similarly, emerging social platforms such as Twitter and Facebook can also potentially provide real-time information on search behavior. Clearly, the availability of measures of consumer search behavior is only going to increase as we move further into the digital age. Consonant with this marketplace trend, scholars are coming to recognize that what individuals are searching for leaves a trail about “what we collectively think” and “what might happen in the future” (Rangaswamy et al., 2009, p.58). In effect, data on search behavior results in a database of intentions (Batelle, 2005). Not surprisingly, the information contained in online search behavior is being vigorously analyzed by researchers in many applications. Choi and Varian (2009), for example, employ measures of search behavior to predict automobile sales and tourism. Ginsberg et al. (2009) find that a basket of forty-five terms related to influenza successfully predicts the proportion of patients visiting health professionals with related symptoms. Moreover, employing search behavior yields predictions one to two weeks before Centers for Disease Control (CDC) reports. The essential premise embodied in these works is that a measure of search behavior contains information that can forecast future outcomes.

We add to these ongoing efforts by conceptualizing what the intensity of online search might represent and subsequently examine its ability to forecast abnormal stock returns and trading volume. More broadly, our work offers the following two contributions. First, we advance the notion that employing a cost-benefit perspective is particularly fruitful in understanding the predictive content of online search behavior. Indeed, such a cost-benefit perspective is the dominant paradigm that explains consumer search behavior (Stigler, 1961; Klein and Ford, 2003). Second, we advocate that employing such a cost-benefit analysis must be developed and interpreted in the context of the specific application being considered.

We choose to focus on the search for financial tickers (e.g., XOM for Exxon Mobil) as our measure of investor search behavior. We posit that the effort required to process the results of a ticker query is worthwhile only for someone seriously considering an investment decision. This is because there are few other reasons for an individual to conduct an online search for a company's ticker – these are employed primarily to garner information about the company's stock performance. In contrast, a search for other terms, such as company name, yields a variety of information that is fairly removed from investing decisions (e.g. product information, store location, hours, etc). We further suggest that ticker search is relatively more valuable for somebody considering a "buy" decision rather than a "sell" decision. This is because someone who owns the stock is already knowledgeable about the company's history and recent stock performance. In this regard, we note that most trading platforms display extant returns and news feeds pertaining to stocks owned by the investor. As such, ticker search has a better cost-benefit ratio for potential buyers than for current owners. Finally, we also suggest that a search query for a ticker symbol is likely to characterize the behavior of naïve, retail investors as opposed to sophisticated, institutional investors. This is because sophisticated, institutional investors can easily access and analyze precise sources of information from in-house proprietary information databases. Moreover, institutional investors are fewer in number. For these reasons, we believe that the bulk of ticker search will reflect the behavior of individual investors. In sum, our conceptualization of what ticker search represents (buying interest among naïve, retail investors) is determined primarily on the basis of the cost-benefit arguments suggested in previous research.

Our conceptualization is closely related to that found in the working paper of Da et al. (2009). These researchers analyze the intensity of search for stock tickers among Russell 3000 firms and obtain three findings useful for our purposes. First, they demonstrate that ticker search is not explained by external events such as media coverage of the stock. Specifically, almost 95 percent of the cross-sectional variation in the level of search intensity occurs independently of the intensity of media coverage; thus, ticker search is not a proxy for media coverage. Second, they find that that ticker search captures the search behavior of individual investors. In particular, across different market centers, changes in search intensity lead to much higher trading on the market center that typically attracts less-sophisticated individual investors (Madoff) than on the market center that attracts the more-sophisticated institutional investors (NYSE for NYSE stocks and Archipelago for NASDAQ stocks). This difference suggests that ticker search intensity may be more reflective of the search behavior of individual (or retail) investors rather than the search behavior of sophisticated (or institutional) investors.

Finally, Da et al. (2009) also find support for the price pressure hypothesis stemming from the work of Barber and Odean (2008). Barber and Odean note that when buying a stock, investors are faced with a formidable decision problem. There are thousands of stocks to choose from with varying levels of potential performance;

consequently, the benefits of acquiring information are relatively high. In contrast, when selling a stock, individuals primarily focus on past returns, which are typically available on trading platforms. Thus, it follows that that the cost-benefit comparison associated with ticker search will favor buying over selling. As such, increases in the intensity of ticker search should be accompanied by increased buying pressure with an attendant increase in stock price. In their empirical work, Da et al. (2009) do find this effect: within their sample of Russell 3000 firms, stocks experiencing large increases in search outperform those experiencing large decreases by about 11 basis points per week or about 5.7% per year.

Building on the work of Da et al. (2009), we posit that ticker search serves as a valid proxy for a unique construct developed in the finance literature, namely, investor sentiment. In that literature, investor sentiment refers to set of beliefs about cash flows and investment risks that are not necessarily justified by the facts at hand (Baker and Wurgler, 2007). These beliefs are generally associated with individual retail investors (Lee et al., 1991; Barber et al., 2009a). In effect, we posit that ticker search reflects buying pressure among less-sophisticated, individual investors who may be prone to invest for a wide variety of reasons unrelated to fundamentals. Moreover, following the empirical evidence reported in Barber et al. (2009b), we expect the behavior of the less-sophisticated individual investors to be correlated since they are driven by the same underlying reasons. Consequently, we hypothesize that increases in search intensity for a ticker symbol will forecast both abnormal returns as well as abnormal trading volume for the associated stock.

In our empirical work, we analyze all stocks in the S&P 500 and find that increases in search intensity do indeed foreshadow abnormal returns and excessive trading volume. Our empirical strategy is as follows: on the first trading day of every week, we sort our sample of S&P 500 firms into five quintiles based on the intensity of ticker search in the preceding week. We then examine the subsequent stock return and trading volume across these quintiles. With respect to returns, we find that a portfolio that is long on firms in the highest search intensity quintile and short on firms in the lowest search intensity quintile generates abnormal returns of 14 basis points per week, or approximately 7% annually. We note that this abnormal return occurs after controlling for the risk-factors employed in the Fama and French (1993) and Carhart (1997) models of stock returns. [1]

[1] These risk-factors are the overall performance of the market, firm size, book-to-market, and momentum. The expectations are that increased market performance, small firms, high book-to-market firms, and firms with recent high returns (momentum) will provide additional returns. The risk-factor for market performance is constructed by computing the return of the overall market relative to the risk-free rate, $R_m - R_f$. The risk-factor for size, *SMB*, is constructed by employing the return difference between a portfolio of "small" and "big" stocks. The risk-factor for book-to-market, *HML*, is constructed by employing the return difference between a portfolio of "high" and "low" book-to-market stocks. Finally, the risk-factor for momentum, *UMD*, is constructed by employing the difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low

With respect to trading volume, we find that both the mean and median values of trading volume increase uniformly as we move from the portfolio with the lowest search intensity to the portfolio with highest search intensity. Specifically, there is a difference of 1.58 between firms in highest search intensity portfolio and firms in the lowest search intensity portfolio. That is, firms with the highest search intensity have an average abnormal volume that is two and a half times (158%) higher than those with the lowest search intensity. Overall, these findings confirm and triangulate the empirical findings documented in the emerging work of Da et al. (2009) in their sample of Russell 3000 firms.

More strikingly, we hypothesize that the sensitivity of returns to search intensity will be lowest for easy-to-arbitrage stocks and highest for difficult-to-arbitrage stocks. This is because arbitrageurs can more readily correct the excess returns generated by investor sentiment in the former scenario. Such a premise is consistent with the arguments and findings presented in the literature that addresses investor sentiment (Baker and Wurgler, 2007; Shleifer and Summers, 1990). As suggested by Baker and Wurgler (2007), we use the volatility of stock returns in the previous year as a measure of the difficulty of arbitrage – stocks with higher volatility are riskier and consequently more difficult to arbitrage than stocks with lower volatility. Here, we sort our sample of firms into deciles based on volatility. We then construct a search sentiment index by utilizing the return difference between a portfolio of high search intensity stocks and a portfolio of low search intensity stocks and find that the "sentiment betas" are indeed lowest for the deciles with low volatility stocks and highest for the deciles high volatility stocks. In other words, the more difficult a stock to arbitrage, the more sensitive are the stocks returns to changes in online search intensity. *These findings are unique to our research endeavor and further confirm the premise that search intensity serves as a valid proxy for investor sentiment. As such, search intensity should have the same forecasting properties as other measures of investor sentiment*.

In addition, to better understand the impact of search intensity on financial returns, we further examine the four factors that are typically employed in the Fama and French (1993) and Carhart (1997) models of stock returns, namely, $R_m - R_f$, SMB, HML, and UMD, along with the factor that we create from our measure of investor sentiment. We label this new factor as $SENT$. We find that $SENT$ is positively correlated with $R_m - R_f$. Moreover, its correlations with HML and UMD are similar to the correlations of $R_m - R_f$ with HML and UMD. These findings suggest that $SENT$ most closely mimics the market risk-factor. Moreover, since it generates incremental returns after controlling for the extant risk-factors, it clearly possesses incremental information content. *Thus, $SENT$ is a risk-factor that merits further scrutiny in any model that attempts to forecast stock returns*.

The rest of the paper is organized as follows. In the next section, we briefly review

returns in the past year.

the relevant literature in two disciplines that are fundamental to our inquiry, namely, marketing and finance. Then, we describe our data and present our empirical findings. Finally, we conclude by discussing the implications of our key findings.

2 Literature Review

The marketing literature has clearly demonstrated that search is an important antecedent to purchase. Moreover, consumer search behavior is explained by an implicit cost-benefit analysis (Stigler, 1961). Specifically, what, when, where, and how much to search is made by comparing marginal benefits to marginal costs (Klein and Ford, 2003). In their empirical work, Klein and Ford (2003) find that these basic economic considerations continue to drive the amount and breadth of searchers. For example, they find that higher income individuals do less searching and that internet-experienced individuals conduct a greater proportion of their searches online.

Turning to the finance literature, there is a growing acceptance among these scholars that stock prices are driven by two types of investors: noise traders and arbitrageurs (Shleifer and Summers, 1990). Arbitrageurs trade on the basis of the fundamentals and strive to bring prices in line with "true" value. Noise traders, on the other hand, trade on pseudo-signals, noise, and other popular trading models. Examples of the impact of such pseudo-signals, noise, and other popular models in altering demand, and consequently, prices abound. Engelberg et al. (2009), for example, find that the attention generated by Jim Cramer, the host of the popular TV show Mad Money, yields an average abnormal overnight return of over 3%. Barber and Odean (2008) demonstrate that individual investors are net buyers of stocks in the news. Finally, Grullon et al. (2004) find that firms that advertise have shares that are more liquid and smaller bid-ask spreads, which they attribute to the fact that advertising draws more local small-scale investors to the firm.

Now, while some trading in the market brings noise traders with different models who cancel each other out, a substantial fraction of trading strategies are correlated, leading to aggregate demand shifts. As Shleifer and Summers (1990) elaborate, the reasons for this is that the judgmental biases afflicting investors in information processing tend to the be the same. For example, subjects in psychological experiments tend to make the same mistake; they do not make random mistakes. Indeed, Barber et al. (2009a) utilize brokerage data and find that individual investors predominantly buy the same stocks as each other contemporaneously and that this buying pressure drives prices upwards. Similarly, Schmeling (2007) employs survey data and finds that individual investor sentiment forecasts stock market returns. In effect, these studies reveal that arbitrageurs not always successful in bringing prices prices back in line with fundamentals. Thus, shifts in demand for stocks that are independent of fundamentals may persist, and are thus observable. This observability is particularly useful in our analysis. Since the supply curve for stocks is inelastic (at least in the short run), any buying pressure on stocks that follows a period of increased search activity should lead to a sharp and immediate increase in stock prices. This makes financial markets a particularly compelling context in which to examine the effect of search behavior since any buying shocks that arise from investor interest should be observed as abnormal or unexpected returns before arbitrageurs can correct any mispricing.

3 Data

We obtain our data from: http://www.google.com/insights/search/. This public website provides a measure of search intensity for any keyword from January 2004 onwards. The reporting interval is weekly, and results are updated every Sunday. Each keyword (e.g., ticker symbol for Exxon, XOM) generates a time series with an entry for each week. We note that Google reports both the raw search volume as well as search volume that are normalized and scaled. Normalization implies that each series has a mean of 1; thus, entries greater than 1 indicate above average search intensity for that keyword while entries less than 1 indicate below average search intensity for that keyword. This normalization is consistent what we are trying to explain, namely, percentage abnormal returns. Moreover, the data are scaled to account for natural temporal variation. That is, if overall search intensity for all keywords is low in a given week due to holidays, the raw data are scaled appropriately to make inter-temporal comparisons meaningful. This scaling is also appropriate for our investigation – a given level of search intensity should be more impactful in a period of low overall search intensity than in a period of high overall search intensity. Thus, our analysis is based on the normalized and scaled data.

Given our research objectives, we retrieve intensity of search for all tickers in the S&P 500 and focus on the period 2005–2008. We exclude the year 2004 because there are many tickers that report no search intensity in this period. We also exclude tickers that may have other meanings such as ACE, COST, and ZION to avoid contamination of our measure of search intensity. This leaves us with a sample of 470 firms.

Finally, we obtain stock returns, volume data, and measures of return volatility from the Center for Research in Security Prices (CRSP) database.

4 Findings

4.1 Search Intensity and Short-Horizon Returns

We start our empirical analysis by investigating the ability to of search intensity to forecast abnormal returns and abnormal trading volume in the following week. Specifically, on the first trading day of every week, we sort our sample of 470 firms into five quintiles based on the intensity of ticker search in the preceding week. Q1 is comprised of firms with the lowest search intensity while Q5 contains the firms with the highest search intensity. The firms are held in the portfolio for the entire trading week and then resorted at the beginning of the next trading week based on the new levels of search intensity. For each portfolio, we then run regressions of daily returns on the three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (*SMB*) and the return difference between a portfolio of "high" and "low" book-to-market stocks (*HML*), augmented with a momentum factor from Carhart (1997) (*UMD*), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year. These factors have been found to explain cross-sectional differences in stock returns (see for example, Fama and French (1993) and Kothari and Warner (2008)).[2] Thus, our abnormal returns are obtained by carrying out the following regression:

$$R_{pt} - R_{ft} = \alpha + \beta_m(R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \beta_u UMD + \varepsilon_t \qquad (4.1)$$

The implied 5-day return is calculated as $(1+\alpha)^5 - 1$, which is the total return from holding the portfolio for one trading week.

The results of this analysis are shown in Table 1. Alongside the risk-adjusted analysis we also present raw returns. We find a near monotonic relationship between search intensity and abnormal return – as the level of search intensity increases, the abnormal return associated with the corresponding portfolio increases. The results also show a significant difference between firms with high search intensity and those with a low search intensity. A portfolio that is "long" on high search intensity (Q5) and "short" on low search intensity (Q1) generates daily abnormal returns of 0.0280%. The implied 5-day return of such a portfolio is 0.14% which translates to about 7.2% annually. Even without the risk adjustment, we find a sim-

[2] The factor data are constructed by Ken French and are made available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The construction of these factors is described on the website.

ilar result using raw returns – firms in Q5 earn 17 basis points more than those in Q1 in the week following the sort based on search intensity. This finding also clearly demonstrates that search intensity predicts buying pressure, as reflected in the above average returns. We find similar results if we sort our firms into deciles rather than quintiles. In that case, a portfolio that is "long" on high search intensity (Decile 10) and "short" on low search intensity (Decile 1) generates a risk-adjusted daily abnormal returns of 0.0387% ($t = 1.92$) – which implies a weekly return of 0.19%.

Next, Table 2 displays findings related to abnormal trading volume. For each firm, we compute the abnormal trading volume as the difference between the trading volume on a given day and its average over the entire sample period, i.e., the daily abnormal volume, $AV_{it} = (V_{it} - V_{i,avg})/V_{i,avg})$, where V_{it} is the trading volume for firm i on day t and $V_{i,avg}$ is the average daily volume over the entire sample period. As in Table 1, we compose portfolios based on search intensity. For each portfolio, we then compute the average abnormal trading volume for all firms in that portfolio. Doing so, we find a clear association between search intensity and abnormal trading volume. Both the mean and the median values increase uniformly as we move from the portfolio with the lowest search intensity to the portfolio with the highest search intensity. Moreover, there is a difference of 1.58 between firms in the highest search intensity portfolio and firms in the lowest search intensity portfolio. That is, firms with the highest search intensity have an average abnormal volume that is two and a half times (158%) higher than those with the lowest search intensity.

In additional (untabulated) analysis, we examine the robustness of our trading volume analysis by defining "expected" weekly trading volume as trading volume in the week prior to portfolio formation. In this case, abnormal trading volume (AV_{it}) is simply the change in trading volume from the week prior to portfolio formation, to the week following portfolio formation, scaled by the prior week's trading volume. In other words, $AV_{it} = (V_{it} - V_{i,t-1})/V_{i,t-1})$, where V_{it} is the trading volume for firm i in week t and $V_{i,t-1}$ is the lagged weekly volume. Using this definition we find results similar to those reported in Table 2: abnormal weekly volume is 15.47% (t=6.67) higher for the most searched firms (Q5) than in the least searched firms (Q1).

4.2 Search Intensity and Cross-sectional Variation in Arbitrage

Next, we examine the behavior of abnormal returns when we sort our sample of firms into deciles based on past volatility. Baker and Wurgler (2006, 2007) argue and show that volatility can be used as a proxy for the ease or difficulty of arbitrage – firms with low volatility are easier to arbitrage than firms with high volatility. We measure volatility as the standard deviation of returns over the previous 12 months. Next, we construct a sentiment index based on search intensity, which is the re-

Table 1
Returns from Portfolios Formed Based on Search Intensity in Prior Week
In this table, we present raw and abnormal (risk-adjusted) returns from portfolios formed as follows: on the first trading day of each week we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the prior week. Q1 contains the firms with the lowest search intensity and Q5 contains the firms with the highest search intensity. The firms are held in their respective portfolios for the entire trading week and are then resorted at the beginning of the next trading week based on the new levels of search intensity. The raw returns reported are weekly returns. The abnormal returns are obtained from the regression of the daily time series of returns on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (SMB) and the return difference between a portfolio of "high" and "low" book-to-market stocks (HML), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD). α is the daily abnormal return (in percentage terms). t-statistics (in parentheses) are based on heteroscedasticity consistent standard errors. The implied 5-day (weekly) abnormal return of the difference between the highest and lowest quintile (Q5 minus Q1) is calculated as $(1+\alpha)^5 - 1$, and expressed in percentage terms. a, b, c represent significance at the one percent, five percent and ten percent level respectively.

Portfolio	Raw Returns	α	$R_m - R_f$	SMB	HML	UMD	R^2
Q1	0.05%	0.0127	1.0100^a	0.1521^a	−0.0065	−0.1363^a	97.56%
		(1.63)	(106.12)	(7.86)	(0.23)	(−10.58)	
Q2	0.12%	0.0246^a	1.0631^a	0.0993^a	0.0046	−0.1291^a	96.86%
		(2.64)	(73.81)	(2.86)	(0.11)	(−8.82)	
Q3	0.11%	0.0203^a	1.0258^a	0.0740^a	−0.0063	−0.0652^a	97.81%
		(2.77)	(133.33)	(4.46)	(0.25)	(−4.74)	
Q4	0.11%	0.0295^a	1.0523^a	0.0632^a	0.0242	−0.0677^a	97.56%
		(3.72)	(109.57)	(2.63)	(0.78)	(−6.31)	
Q5	0.22%	0.0408^a	1.1300^a	0.1312^a	0.1418^a	−0.0848^a	96.98%
		(4.17)	(104.33)	(4.46)	(4.58)	(−5.01)	
Q5 *minus* Q1	0.17%	0.0280^b	0.1200	−0.0209	0.1482^a	0.0515^b	23.66%
		(2.45)	(9.87)	(−0.78)	(3.96)	(2.39)	
Implied 5-day return of Q5 *minus* Q1	0.17%	0.14%					

turn difference between a portfolio of the most and the least intensively searched stocks ($SENT$). Table 3 shows the correlation of $SENT$ with the Fama-French and momentum factors ($R_m - R_f$, HML, SMB and UMD). We find that $SENT$ is positively correlated with $R_m - R_f$. Moreover, its correlations with HML and UMD are similar to the correlations of $R_m - R_f$ with HML and UMD. These findings suggest that $SENT$ most closely mimics the market risk-factor. Then, for firms in each volatility decile, we run regressions of the daily abnormal returns on the three

Table 2
Abnormal Trading Volume from Portfolios Formed Based on Search Intensity in Prior Week
In this table, we present the average cumulative abnormal trading volume of portfolios formed as follows: on the first trading day of each week we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the prior week. Q1 contains the firms with the lowest search intensity and Q5 contains the firms with the highest search intensity. The firms are held in their respective portfolios for the entire trading week and are then resorted at the beginning of the next trading week based on the new levels of search intensity. The daily abnormal volume is computed as $AV_{it} = (V_{it} - V_{i,avg})/V_{i,avg})$, where V_{it} is the trading volume for firm i on day t and $V_{i,avg}$ is the average daily volume over the entire sample period. We then calculate the cumulative abnormal trading volume for the trading week and find the portfolio average. All the values are significant at the 1% level or smaller.

	Cumulative Abnormal Trading Volume	
	Mean	Median
Q1	−0.7392	−0.4210
Q2	−0.4296	−0.1712
Q3	−0.1783	0.0495
Q4	0.0224	0.2331
Q5	0.8445	0.7181
Q5 *minus* Q1	1.584	1.217

factors from Fama and French (1993), the momentum factor in Carhart (1997) and our newly constructed sentiment index (*SENT*) that is based on search intensity. If search intensity does indeed capture investor sentiment, we should expect the betas associated with *SENT* to increase as we move from the easy-to-arbitrage, low volatility stocks to the difficult-to-arbitrage, high volatility stocks.

The results from this analysis are presented in Table 4. Table 4 reveals systematic differences across the portfolios of firms with varying levels of volatility. First, as expected, the market beta increases as volatility increases. However, for our analysis, the key results center round the betas associated with *SENT*. As expected, the betas associated with *SENT* generally increase as we go from the low-volatility decile to the high-volatility decile. This is visually seen in Figure 1, where the

Table 3

Correlation Matrix of Sentiment factor with Fama-French and Momentum factors

This table shows the correlation between a Sentiment factor ($SENT$) constructed from Search Intensity and the Fama-French and Momentum factors. The Sentiment factor is constructed as follows: on the first trading day of each week we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the prior week. Q1 contains the firms with the lowest search intensity and Q5 contains the firms with the highest search intensity. $SENT$ is the time-series of the difference in daily returns of Q5 and Q1, i.e. Q5 *minus* Q1. The Fama-French factors are: the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (*SMB*) and the return difference between a portfolio of "high" and "low" book-to-market stocks (*HML*), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD).

	$R_m - R_f$	SMB	HML	UMD	$SENT$
$R_m - R_f$	1.00				
SMB	−0.05	1.00			
HML	0.33*	−0.10	1.00		
UMD	−0.44*	0.04	−0.55*	1.00	
$SENT$	0.45*	−0.04	0.31*	−0.21	1.00

n = 1006; * significant at the 1% level (two-tailed)

various betas are depicted as bar charts. This figure is strikingly similar to the sentiment betas displayed in the work of Baker and Wurgler (2007), which are also constructed for ten deciles based on the return volatility over the previous 12 months.[3] The sentiment betas show that the more difficult a stock is to arbitrage, the more positive the correlation between the stock's return and the intensity with which the investors are searching online for the stock. Since increased search activity precedes buying pressure, the biggest (abnormal) price increases are found in

[3] In their work, however, the Sentiment Index is constructed on a markedly different set of six proxies, namely: trading volume, dividend premium, closed-end fund discount, the number and first-day returns on IPOs, equity in new issues, and mutual fund series.

Table 4

Returns from Volatility Sorted Portfolios

In this table, we present results from volatility sorted portfolio deciles (where higher volatility stocks are riskier and harder to arbitrage). Daily returns are regressed on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (SMB) and the return difference between a portfolio of "high" and "low" book-to-market stocks (HML), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD), as well as a Search Index ($SENT$) which is the return difference between a portfolio of the most and the least intensively searched stocks. Volatility is standard deviation of stock returns in the previous 12 months. t-statistics are in parentheses. a, b, c represent significance at the one percent, five percent and ten percent level respectively.

Portfolio	α	$R_m - R_f$	SMB	HML	UMD	$SENT$
Q1	0.0180	0.8234[a]	-0.0781[a]	0.015	0.0483[a]	−0.2567[a]
	(1.54)	(83.63)	(−4.03)	(0.61)	(3.47)	(−7.84)
Q2	0.0178	0.8732[a]	−0.0812	0.1579[a]	−0.0584[a]	−0.1946[a]
	(1.49)	(86.87)	(−4.10)	(6.28)	(−4.12)	(−5.82)
Q3	0.0032	0.9232[a]	−0.0323[c]	0.1517[a]	−0.0896[a]	−0.0779[a]
	(0.30)	(101.69)	(−1.81)	(6.68)	(−7.00)	(−2.58)
Q4	0.0169	0.9737[a]	−0.0550[a]	0.0376	−0.1365[a]	−0.0528[c]
	(1.55)	(105.91)	(−3.04)	(1.63)	(−10.52)	(−1.73)
Q5	0.0236[b]	1.0608[a]	0.0697[a]	0.0051	−0.0983[a]	−0.0568[b]
	(2.49)	(133.14)	(4.45)	(0.25)	(−8.74)	(−2.14)
Q6	0.0203[b]	1.0438[a]	0.0780[a]	0.0437[b]	−0.0646[a]	−0.0211
	(2.03)	(124.45)	(4.73)	(2.08)	(−5.46)	(−0.76)
Q7	0.0129	1.1133[a]	0.1766[a]	0.0149	−0.1413[a]	0.1214[a]
	(1.07)	(109.48)	−8.83	(0.58)	(−9.85)	(3.59)
Q8	0.0359[a]	1.1990[a]	0.1254[a]	−0.0541[b]	−0.0994[a]	0.1501[a]
	(2.81)	(111.72)	(5.94)	(−2.02)	(−6.57)	(4.21)
Q9	0.0397[b]	1.2031[a]	0.3974[a]	0.0628[c]	−0.1281[a]	0.1751[a]
	(2.56)	(92.04)	(15.45)	(1.92)	(−6.95)	(4.03)
Q10	0.0656[a]	1.3440[a]	0.4130[a]	−0.1568[a]	−0.2036[a]	0.4041[a]
	(2.93)	(71.43)	(11.15)	(−3.33)	(−7.67)	(6.46)

the firms that are most difficult (at least in the short-term) for arbitrageurs to take opposite positions and push prices back towards fundamentals.

To further investigate the interaction between search intensity (investor sentiment) and volatility (difficulty of arbitrage), we estimate abnormal returns for 9 portfolios based on a three-by-three matrix of stocks sorted first by search intensity and then by volatility. The results of this double-sort analysis are presented in Table 5.

The rows represent the terciles of search intensity while the columns represent the terciles of volatility.

The results in Table 5 are quite striking and support those reported in Table 4: the more difficult a stock is to arbitrage, the more positive the correlation between the stock's return and the intensity with which the investors are searching online for the stock. For example, if we look down the first column of Table 5, we find that, at high levels of volatility, there is a strong relation between search intensity and subsequent abnormal returns. In contrast, if we look down the third column of Table 5, we find no relation between search intensity and abnormal returns. Similarly, if we look across the rows (especially at high and medium levels of search intensity), we find a strong relation between abnormal returns and volatility. Indeed we find that a long-short portfolio that buys the firms with the *highest* levels of search intensity *and* volatility and shorts the firms with the *lowest* levels of search intensity *and* volatility, earns a daily abnormal return of 0.0698% (t=2.86) in the week following portfolio formation, which translates to a weekly return of 0.35% and an annualized return of 19%.

4.3 Search Intensity, Longer Horizon Returns, and Reversals

Thus far, our analysis has focused on search intensity as being a proxy for investor sentiment and the ability of this proxy to forecast abnormal returns over a relatively short horizon (one week). However, a common theme that runs through the finance literature (e.g. Brown and Cliff (2005), Schmeling (2007), Barber et al. (2009a), among others) is that while investor sentiment (or their proxies) tend to be positively correlated with stock returns in the short term, over a medium to long term horizon, they tend to be negatively correlated with stock returns. In other words, prior literature suggests that positive (negative) investor sentiment is associated with negative (positive) long-run returns.

We extend our analysis by investigating the ability of search intensity to forecast abnormal returns over a medium to longer time horizon. As in our prior analysis, we sort firms into quintiles (Q) based on search intensity in the previous week and form a portfolio that is comprised of a long position in the top quintile of firms (Q5) and a short position in the lowest quintile of firms (Q1). We then track the returns of the portfolio for the eight-week period following portfolio formation. The results of our analysis are presented in Table 6.

As we have already documented in section 4.1, we see that Week 1 returns are positive and significant. From Week 2 to 4, there is little change in portfolio returns. However after Week 5, there is a reversal of portfolio returns – daily abnormal returns for our search-intensity sorted portfolios from Week 5 to 8 is -0.0157 (t=-2.87). The horizon at which portfolio returns reverse are similar to that found

Table 5

Returns from Search Intensity and Volatility Dual-Sorted Portfolios

In this table, we present abnormal returns (α) from portfolios jointly sorted on search intensity and volatility (where higher volatility stocks are riskier and harder to arbitrage). On the first trading day of each week we sort the 470 firms in our sample into terciles based on the search intensity in the prior week. Each search intensity tercile is then further divided into three portfolios based on volatility. This results in 9 (3 x 3) portfolios. α is obtained by regressing daily returns on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (SMB) and the return difference between a portfolio of "high" and "low" book-to-market stocks (HML), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD). Volatility is standard deviation of stock returns in the previous 12 months. t-statistics are in parentheses. a, b, c represent significance at the one percent, five percent and ten percent level respectively.

		Volatility			
Search Intensity		High	Med	Low	High *minus* Low
	High	0.0728[a]	0.0207[c]	0.0101	0.0627[b]
		(3.99)	(1.92)	(0.92)	(2.50)
	Med	0.0497[a]	0.0172[c]	0.0111	0.0386[c]
		(3.33)	(1.83)	(0.97)	(1.79)
	Low	0.0340[b]	0.0140	0.0030	0.0310
		(2.26)	(1.36)	(0.28)	(1.45)
	High *minus* Low	0.0389[b]	0.0067	0.0071	
		(2.32)	(0.51)	(0.67)	
	High/High *minus* Low/Low				0.0698[a]
					(2.86)

by Barber et al. (2009a) who, using retail investor buying as a proxy for investor sentiment, find a strong negative relation between stock returns and this proxy five to eight weeks after the magnitude of retail buying is observed. The medium-term reversal of search intensity sorted portfolios is strikingly illustrated in Figure 2. In Week 1, we see a strong abnormal positive return which plateaus between Week 2 and 4. From Week 5, there is a gradual reversal of this positive return that continues for at least 8 more weeks as prices drift downwards toward what they were prior to portfolio formation.

Table 6

Longer Horizon Returns from Portfolios Formed Based on Search Intensity

In this table, we present raw and abnormal (risk-adjusted) returns from a portfolio that is formed as follows: on the first trading day of each week we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the prior week. Q1 contains the firms with the lowest search intensity and Q5 contains the firms with the highest search intensity. The firms are held in their respective portfolios for the entire trading week and are tracked for eight weeks following portfolio formation. We then form a portfolio that is comprised of a long position in the top quintile of firms (Q5) and a short position in the lowest quintile of firms (Q1), i.e., portfolio returns are Q5 *minus* Q1. The raw returns reported are weekly returns. The abnormal returns are obtained from the regression of the daily time series of returns on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (SMB) and the return difference between a portfolio of "high" and "low" book-to-market stocks (HML), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD). α is the daily abnormal return (in percentage terms). t-statistics (in parentheses) are based on heteroscedasticity consistent standard errors. a, b, c represent significance at the one percent, five percent and ten percent level respectively.

	Holding Period			
	Week 1	Week 2–4	Week 5–8	Week 1–8
α	0.0280^b	-0.0058	-0.0157^a	-0.0064
(Daily)	(2.45)	(-0.93)	(-2.87)	(-1.63)
Raw returns	0.1668^b	0.0005	-0.0580^c	0.0691
	(2.23)	(0.01)	(-1.70)	(0.32)

5 Conclusion

Today's digital environment provides previously unavailable measures of consumer search behavior. Not surprisingly, there is growing interest in employing these data for predictive purposes in a wide variety of applications. We add to these ongoing efforts by conceptualizing what the intensity of online search might represent and subsequently examine its ability to forecast abnormal stock returns and trading volume.

In our application, we find that search intensity in the previous period forecasts abnormal returns and increased trading volume in the current period. These results confirm and triangulate the findings in Da et al. (2009). Specifically, we find similar results (enhanced return and increased trading volume) for a different sample of firms (S&P 500 vs. Russell 3000). More importantly, we document a new finding pertaining to differences in return sensitivity across stocks that differ in return volatility. In particular, the sensitivity of returns to search intensity is lowest for easy-to-arbitrage, low volatility stocks and highest for difficult-to-arbitrage, high volatility stocks. In this way, our work builds on that of Baker and Wurgler (2007) who employ markedly different measures of investor sentiment. Taken together, our work and the efforts of of Da et al. and Baker and Wurgler (2007) tell a consistent story: the intensity of search for ticker symbols serves as a valid proxy for investor sentiment which, in turn, is useful for forecasting stock returns and volume. Moreover, additional analysis reveals that our proxy for investor sentiment is strongly correlated to the market risk factor; consequently, search intensity merits further scrutiny in any model that attempts to forecast abnormal returns and trading volumes.

Admittedly, while the trading rule behind our findings – long on high search intensity stocks and short on low search intensity stocks – may not be profitable because of the trading costs associated with re-balancing the portfolio every week, it is very possible that employing a screen of search intensity in tandem with other screens may indeed prove to be return-enhancing. In addition, it is also possible that more timely measures of search intensity, such as those emerging on Facebook, Twitter, and other social network sites, may be profitable even after accounting for trading costs. Overall, these findings speak to the importance of including online consumer search activity in forecasting important outcomes in the financial markets.

In closing, we believe that our efforts constitute an important first-step in better understanding and characterizing the predictive content of real-time measures of online search activity. We hope our work efforts will stimulate additional research on how online search behavior may be gainfully used for forecasting purposes in other applications.

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Figure 1
Search Index Betas

The Figure shows the Search index betas for volatility sorted portfolios (where higher volatility stocks are riskier and harder to arbitrage). Daily returns are regressed on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between a portfolio of "small" and "big" stocks (SMB) and the return difference between a portfolio of "high" and "low" book-to-market stocks (HML), augmented with a momentum factor from Carhart (1997), which is the return difference between a portfolio of stocks with high returns in the past year and a portfolio of stocks with low returns in the past year (UMD), as well as a Search Index ($SENT$) which is the return difference between a portfolio of the most and the least intensively searched stocks. Volatility is standard deviation of stock returns in the previous 12 months.

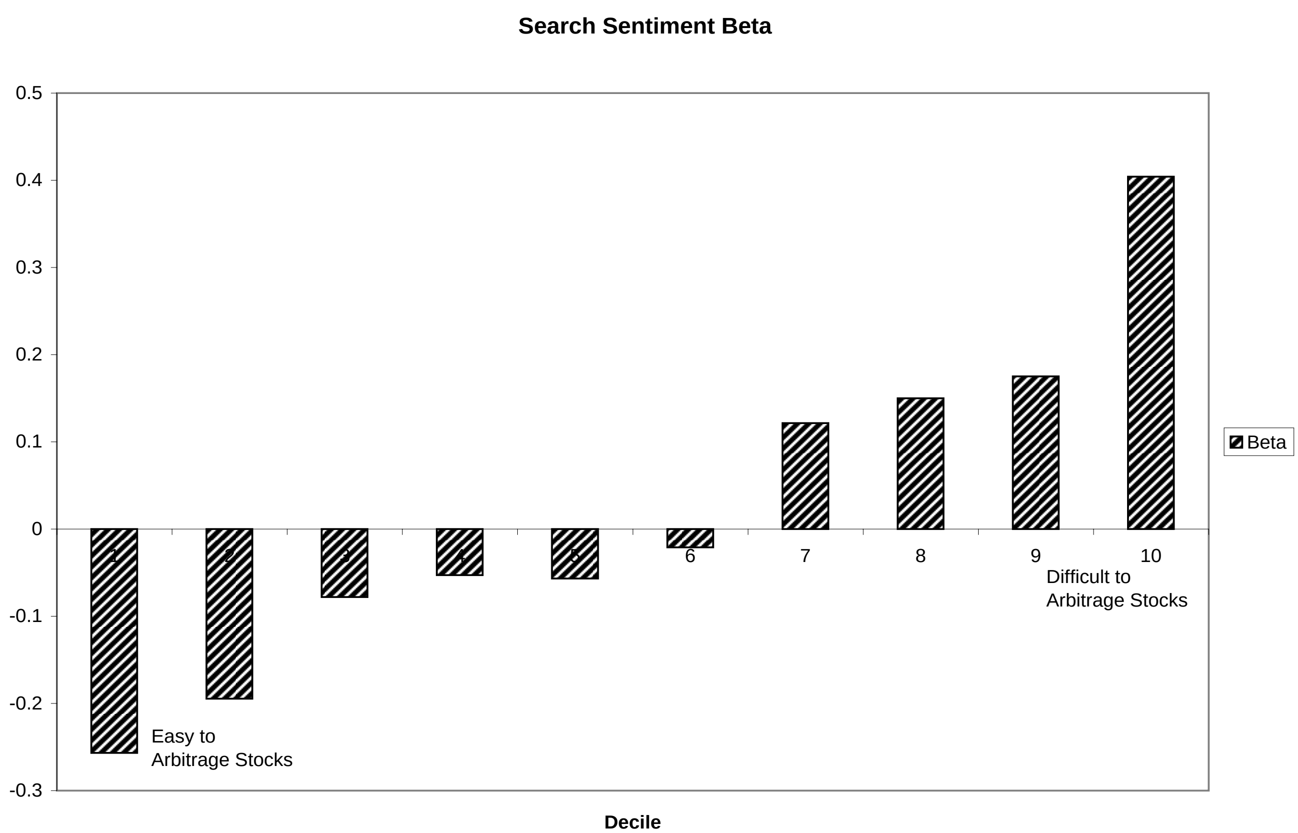

Figure 2
Cumulative Holding Period Returns for Long-Short Search Intensity Sorted Portfolio.

The figure shows cumulative holding period returns for long-short search intensity sorted portfolio formed as follows: on the first trading day of each week we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the prior week. Q1 contains the firms with the least search intensity and Q5 contains the firms with the highest search intensity. The firms are held in their respective portfolios for the entire trading week and are then tracked for thirteen weeks following portfolio formation. We then form a portfolio that is comprised of a long position in the top quintile of firms (Q5) and a short position in the lowest quintile of firms (Q1), i.e., portfolio returns are Q5 *minus* Q1.