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Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search

Kissan Joseph[1], M. Babajide Wintoki*, Zelin Zhang

University of Kansas, School of Business, United States

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 searches serve as a valid proxy for investor sentiment — a set of beliefs about cash flows and investment 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 also expect 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 volumes, and that the sensitivity of returns to search intensity is positively related to the difficulty of a stock being arbitraged. More broadly, our study highlights the potential of employing online search data for other forecasting applications.

Keywords: Investor sentiment; Finance; Fama-French model; Portfolio tests; Marketing

1. Introduction

There is a growing recognition of the predictive value of data collected across various digital platforms. One such 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 considerable 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 & 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 the level of interest in competitive products.

* Corresponding author. Tel.: +1 785 864 7515.
E-mail addresses: kjoseph@ku.edu (K. Joseph), jwintoki@ku.edu (M. Babajide Wintoki), zelinzh@ku.edu (Z. Zhang).
[1] Tel.: +1 785 864 7535.

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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 of "what we collectively think" and "what might happen in the future" (Rangaswamy, Giles, & Seres, 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 search behavior measures to predict automobile sales and tourism. Ginsberg et al. (2009) find that a set of forty-five terms related to influenza successfully predicts the proportion of patients visiting health professionals with related symptoms. Moreover, employing such search behaviors yields predictions one to two weeks before the 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 behaviors. Indeed, such a cost-benefit perspective is the dominant paradigm that explains consumer search behavior (Klein & Ford, 2003; Stigler, 1961). Second, we advocate that 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 only worthwhile for someone who is 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—they are employed primarily to garner information about the company's stock performance. In contrast, a search for other terms, such as a company name, yields a range of information that can be widely removed from investing decisions (e.g. product information, store location, hours, etc.). We further suggest that a ticker search is more valuable for somebody who is considering a "buy" decision than for someone who is considering a "sell" decision. This is because someone who owns the stock will already be 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 searches have 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, there are fewer institutional investors. For these reasons, we believe that the majority of ticker searches will reflect the behavior of individual investors. In summary, our conceptualization of what ticker searches represent (buying interest among naïve, retail investors) is determined based 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 by Da, Engelberg, and Gao (2009). They analyze the intensity of search for stock tickers among Russell 3000 firms and obtain three findings which are useful for our purposes. First, they demonstrate that ticker searches are not explained by external events such as media coverage of the stock. Specifically, almost 95% of the cross-sectional variation in the level of search intensity occurs independently of the intensity of media coverage; thus, ticker searches are not a proxy for media coverage. Second, they find that ticker searches capture the search behavior of individual investors. In particular, across different market centers, changes in search intensity lead to a much higher level of trading on the market center that typically attracts less sophisticated individual investors (Madoff) than on market centers that attract the more sophisticated institutional investors (NYSE for NYSE stocks and Archipelago for NASDAQ stocks). This difference suggests that ticker search intensities may be more reflective of the search behavior of individual (or retail) investors than of 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, meaning that 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 the cost-benefit comparison associated with ticker searches 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 searches 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 searches serve as a valid proxy for a unique construct developed in the finance literature, namely, investor sentiment. In that body of literature, investor sentiment refers to a set of beliefs about cash flows and investment risks that are not necessarily justified by the facts at hand (Baker & Wurgler, 2007). These beliefs are generally associated with individual retail investors (Barber, Odean, & Zhu, 2009a; Lee, Shleifer, & Thaler, 1991). In effect, we posit that ticker searches reflect the 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 by Barber, Odean, and Zhu (2009b), we expect the behaviors of 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 and abnormal trading volumes 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 volumes. 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 searches in the preceding week. We then examine the subsequent stock returns and trading volumes 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 still occurs after controlling for the risk factors employed in the Carhart (1997) and Fama and French (1993) models of stock returns.[2]

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

[2] These risk factors are the overall performance of the market, firm size, book-to-market, and momentum. The expectations are that increased market performances, 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 portfolios 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 returns in the past year.

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

In addition, in order to gain a better understanding of the impact of the search intensity on financial returns, we further examine the four factors that are typically employed in the Carhart (1997) and Fama and French (1993) 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 the relevant literature in two disciplines that are fundamental to our inquiry, namely marketing and finance. We then describe our data and present our empirical findings in Sections 3 and 4. 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, the decisions as to what, when, where, and how much to search are made by comparing the marginal benefits to the marginal costs (Klein & Ford, 2003). In their empirical work, Klein and Ford (2003) find that these basic economic considerations continue to drive both the amount and breadth of search. 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 level of acceptance among these scholars that stock prices are driven by two types of investors: noise traders and arbitrageurs (Shleifer & Summers, 1990). Arbitrageurs trade on the basis of fundamentals, and strive to bring prices in line with the "true" value. Noise traders, on the other hand, trade on pseudo-signals, noise, and other popular trading models. Examples of the impacts of such pseudo-signals, noise, and other popular models in altering demand, and consequently prices, abound. Engelberg, Sasseville, and Williams (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, Kanatas, and Weston (2004) find that firms that advertise have shares that are more liquid, with 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 percentage of trading strategies are correlated, leading to aggregate demand shifts. As Shleifer and Summers (1990) elaborate, the reason for this is that the judgmental biases affecting investors in information processing tend to 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 are not always successful in bringing prices back in line with fundamentals. Thus, shifts in the demand for stocks that are independent of fundamentals may persist, and thus be 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 the results are updated every Sunday. Each keyword (e.g., the ticker symbol for Exxon, XOM) generates a time series with an entry for each week. We note that Google reports both raw search volume and normalized and scaled search volume. Normalization implies that each series has a mean of 1; thus, entries greater than 1 indicate an above average search intensity for that keyword, while entries less than 1 indicate a below average search intensity for that keyword. This normalization is consistent with what we are trying to explain, namely the percentage abnormal returns. Moreover, the data are also scaled to account for the natural temporal variation. That is, if the overall search intensity for all keywords is low in a given week due to holidays, the raw data are scaled appropriately, in order to make inter-temporal comparisons meaningful. This scaling is also appropriate for our investigation—a given search intensity should have a greater impact in a period of low overall search intensity than in a period with a high overall search intensity. Thus, our analysis is based on the normalized and scaled data.

Given our research objectives, we retrieve the 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 which report no search intensities in this period. We also exclude tickers that may have other meanings, such as ACE, COST, and ZION, to avoid the 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 the 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 of the search intensity to forecast abnormal returns and abnormal trading volumes 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 the ticker search in the preceding week. Q1 comprises the 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, then re-sorted at the beginning of the next trading week, based on the new levels of search intensity. For each portfolio, we then run regressions of the daily returns on the three factors of Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between portfolios of "small" and "big" stocks (SMB), and the return difference between portfolios of "high" and "low" book-to-market stocks (HML), augmented with the momentum factor of 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

Table 1
Returns from portfolios formed based on the search intensity in the previous week.

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

In this table, we present the 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 intensities and Q5 those with the highest search intensities. The firms are held in their respective portfolios for the entire trading week, before being re-sorted at the beginning of the next trading week based on the new search intensity levels. The raw returns reported are weekly returns. The abnormal returns are obtained by 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 portfolios of "small" and "big" stocks (SMB), and the return difference between portfolios 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 are in parentheses and 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.

* Significance at the 1% level.

** Significance at the 5% level.

factors have been found to explain cross-sectional differences in stock returns (Fama & French, 1993; Kothari & Warner, 2008, for example).[3] Thus, our abnormal returns are obtained by carrying out the following regression:

$$R_{pt} - R_{ft} = \alpha + \beta_m(R_{mt} - R_{ft}) + \beta_s \mathrm{SMB}_t + \beta_h \mathrm{HML}_t + \beta_u \mathrm{UMD} + \epsilon_t. \quad (1)$$

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 the raw returns. We find a nearly monotonic relationship between the search intensity and abnormal returns—as the level of the search intensity increases, the abnormal returns associated with the corresponding portfolio also increase. The results also show a significant difference between firms with high search intensities and those with a low search intensities. A portfolio that is "long" on high search intensities (Q5) and "short" on low search intensities (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 similar 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 the search intensity predicts the 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 intensities (Decile 10) and "short" on low search intensities (Decile 1) generates a risk-adjusted daily abnormal return of 0.0387% ($t = 1.92$)—which implies a weekly return of 0.19%.

[3] 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.

Table 2
Abnormal trading volume from portfolios formed based on the search intensity in the previous week.

	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

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 re-sorted at the beginning of the next trading week based on the new levels of search intensity. The daily abnormal volume is computed as $AV_{it} = (V_{it} - V_{i,\text{avg}})/(V_{i,\text{avg}})$, where V_{it} is the trading volume for firm i on day t, and $V_{i,\text{avg}}$ 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 of the values are significant at the 1% level or less.

Next, Table 2 displays our findings related to abnormal trading volumes. 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, $AV_{it} = (V_{it} - V_{i,\text{avg}})/(V_{i,\text{avg}})$, where V_{it} is the trading volume for firm i on day t, and $V_{i,\text{avg}}$ 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. In doing so, we find a clear association between the search intensity and abnormal trading volumes. Both the mean and 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 the firms in the highest search intensity portfolio and those in the lowest search intensity portfolio. That is, the firms with the highest search intensities have an average abnormal volume that is two and a half times (158%) higher than those with the lowest search intensities.

In an additional (untabulated) analysis, we examine the robustness of our trading volume analysis by defining the "expected" weekly trading volume as the trading volume in the week prior to portfolio formation. In this case, the 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: the abnormal weekly volume is 15.47% ($t = 6.67$) higher for the most searched firms (Q5) than for 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 volatilities. Baker and Wurgler (2006, 2007) argue and show that the volatility can be used as a proxy for the ease or difficulty of arbitrage—firms with low volatilities are easier to arbitrage than firms with high volatilities. We measure the volatility as the standard deviation of returns over the previous 12 months. Next, we construct a sentiment index based on the search intensity, which is the return difference between a portfolio of the most and 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 the firms in each volatility decile, we run regressions of the daily abnormal returns on the three factors from Fama and French (1993), the momentum factor of Carhart (1997), and our newly constructed sentiment index (SENT), which is based on the search intensity. If the search intensity does indeed capture the 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 of this analysis are presented in Table 4. Table 4 reveals systematic differences across the

Table 3
Correlation matrix of the sentiment factor with the Fama-French and momentum factors.

	$R_m - R_f$	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

This table shows the correlation between a sentiment factor (SENT) constructed from the 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 between the 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 portfolios 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).
$n = 1006$.
* Significant at the 1% level (two-tailed).

portfolios of firms with varying levels of volatility. First, as expected, the market beta increases as the 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 can be seen visually in Fig. 1, where the 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.[4] The sentiment betas show that the more difficult a stock is to arbitrage, the more positive the correlation between the stock's returns and the intensity with which the investors are searching online for the stock. Since an increased search activity precedes buying pressure, the biggest (abnormal) price increases are found in the firms which are the most difficult (at least in the short-term) for arbitrageurs to take opposite positions on in order to push prices back towards fundamentals.

To further investigate the interaction between the search intensity (investor sentiment) and volatility (arbitrage difficulty), we estimate the abnormal returns for 9 portfolios based on a three-by-three matrix of stocks, sorted first by the 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.

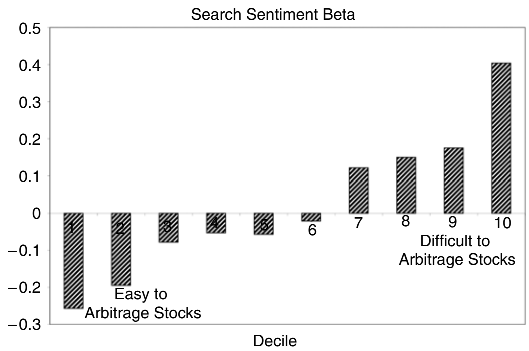

Fig. 1. Search index betas. The figure shows the search index betas for volatility sorted portfolios (where higher volatility stocks are riskier and harder to arbitrage). Daily returns are regressed on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between portfolios of "small" and "big" stocks (SMB); and the return difference between portfolios 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 least intensively searched stocks. The volatility is the standard deviation of the stock returns over the previous 12 months.

[4] In their work, however, the sentiment index is constructed on a markedly different set of six proxies, namely the 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.

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

In this table, we present the results from volatility sorted portfolio deciles (where higher volatility stocks are riskier and harder to arbitrage). The 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 portfolios of "small" and "big" stocks (SMB); and the return difference between portfolios 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 least intensively searched stocks. The volatility is the standard deviation of stock returns over the previous 12 months. t-statistics are in parentheses.

* Significant at the 1% level.
** Significant at the 5% level.
*** Significant at the 10% level.

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 is 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 relationship between search intensity and subsequent abnormal returns. In contrast, if we look down the third column of Table 5, we find no relationship between the 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 relationship between abnormal returns and the volatility. Indeed, we find that a long-short portfolio which 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 the search intensity as 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 (Barber et al., 2009a; Brown & Cliff, 2005; Schmeling, 2007, among others) is that while investor sentiment (or its proxy) tends to be positively correlated with stock returns in the short term, it tends

Table 5
Returns from search intensity and volatility dual-sorted portfolios.

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

In this table, we present abnormal returns (α) from portfolios which are 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 previous week. Each search intensity tercile is then further divided into three portfolios based on the volatility. This results in 9 (3×3) portfolios. α is obtained by regressing the daily returns on three factors from Fama and French (1993): the excess return on the market ($R_m - R_f$); the return difference between portfolios of "small" and "big" stocks (SMB); and the return difference between portfolios 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). The volatility is the standard deviation of the stock returns over the previous 12 months. t-statistics are in parentheses.

* Significant at the 1% level.
** Significant at the 5% level.
*** Significant at the 10% level.

to be negatively correlated with stock returns over a medium to long term horizon. In other words, the literature suggests that a positive (negative) investor sentiment is associated with negative (positive) long-run returns.

We extend our analysis by investigating the ability of the search intensity to forecast abnormal returns over medium to longer time horizons. As in our prior analysis, we sort firms into quintiles (Q) based on the 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 over the eight-week period following portfolio formation. The results of our analysis are presented in Table 6.

As we have already shown in Section 4.1, we see that the Week 1 returns are positive and significant. From Weeks 2 to 4, there is little change in portfolio returns. However, after Week 5, there is a reversal in portfolio returns—the daily abnormal returns for our search-intensity sorted portfolios from Weeks 5 to 8 are -0.0157 ($t = -2.87$). The horizon at which portfolio returns reverse is similar to that found by Barber et al. (2009a), who, using retail investor buying as a proxy for investor sentiment, find a strong negative relationship between stock returns and this proxy five to eight weeks after the magnitude of retail buying is observed. This medium-term reversal of search intensity sorted portfolios is illustrated strikingly in Fig. 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, which continues for at least 8 more weeks as prices drift downwards toward what they were prior to portfolio formation.

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 volumes.

Table 6
Longer horizon returns from portfolios formed based on search intensities.

	Holding period			
	Week 1	Weeks 2–4	Weeks 5–8	Weeks 1–8
α (Daily)	0.0280**	−0.0058	−0.0157*	−0.0064
	(2.45)	(−0.93)	(−2.87)	(−1.63)
Raw returns	0.1668**	0.0005	−0.0580***	0.0691
	(2.23)	(0.01)	(−1.70)	(0.32)

In this table, we present the 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 previous 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 the 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., the 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 portfolios of "small" and "big" stocks (SMB); and the return difference between portfolios 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 are in parentheses and are based on heteroscedasticity consistent standard errors.

* Significant at the 1% level.
** Significant at the 5% level.
*** Significant at the 10% level.

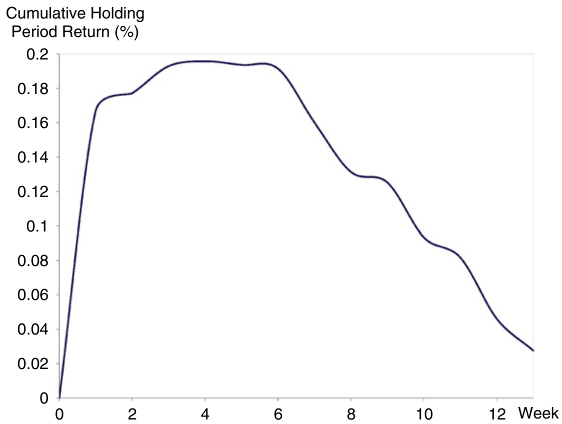

Fig. 2. Cumulative holding period returns for a long-short search intensity sorted portfolio. The figure shows cumulative holding period returns for a long-short search intensity sorted portfolio formed as follows: on the first trading day of each week, we sort the 470 firms in our sample into quintiles (Q) based on the search intensity in the previous week. Q1 contains the firms with the lowest search intensities and Q5 contains the firms with the highest search intensities. 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., the portfolio returns are Q5 *minus* Q1.

In our application, we find that the search intensity in the previous period forecasts abnormal returns and increased trading volumes in the current period. These results confirm and triangulate the findings of Da et al. (2009). Specifically, we find similar results (enhanced returns and increased trading volumes) for a different sample of firms (S&P 500 vs. Russell 3000). More importantly, we document a new finding pertaining to differences in return sensitivities across stocks that differ in return volatilities. In particular, the sensitivity of returns to the 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 Da et al. and Baker and Wurgler tell a consistent story: the intensity of searches for ticker symbols serves as a valid proxy for investor sentiment, which in turn is useful for forecasting stock returns and volumes. Moreover, an additional analysis reveals that our proxy of investor sentiment is strongly correlated with the market risk factor; consequently, search intensities merit further scrutiny in any model which 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 highlight the importance of including online consumer search activity when forecasting important outcomes in 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 that our work efforts will stimulate additional research on how online search behaviors may be gainfully used in other applications for forecasting purposes.

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Kissan Joseph is Associate Professor and Stockton Research Fellow at the School of Business, University of Kansas. He obtained his Ph.D. in marketing from Purdue University in 1992 (marketing and econometrics). His research interests include sales force compensation, pricing, pharmaceutical marketing and e-marketing. His research on these topics has appeared in the *Journal of Marketing*, *Marketing Science*, *Journal of Interactive Marketing*, *Industrial Marketing Management*, *Managerial and Decision Economics*, and the *Southern Economic Journal*. In addition, he has served on the editorial boards of the *Journal of Marketing* and the *Australasian Journal of Marketing*.

M. Babajide Wintoki is an Assistant Professor of Finance at the School of Business, University of Kansas. He obtained his Ph.D. in banking and finance from the University of Georgia. His research interests are in corporate finance and applied econometrics, and his research on these topics has appeared in the *Journal of Corporate Finance* and *Advances in Financial Economics*.

Zelin Zhang is a Ph.D. candidate in marketing at the School of Business, University of Kansas.