IT DEPENDS ON WHEN YOU SEARCH

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Jun Li

Naveen Jindal School of Management, University of Texas at Dallas,
Richardson, TX U.S.A. {jun.li3@utdallas.edu}

Xianwei Liu, Qiang Ye

School of Management, Harbin Institute of Technology,
Harbin, CHINA {xianwei.liu@hit.edu.cn} {yeqiang@hit.edu.cn}

Feng Zhao

Naveen Jindal School of Management, University of Texas at Dallas,
Richardson, TX U.S.A. {feng.zhao@utdallas.edu}

Xiaofei Zhao

McDonough School of Business, Georgetown University,
Washington, DC U.S.A. {xiaofei.zhao@georgetown.edu}

Abstract

Existing studies have found that online search is a revealed measure for investor attention and a useful predictor of stock returns. We study the heterogeneity in retail investor attention by comparing search conducted on weekdays vs. weekends and investigate the price pressure channel and information processing channel for stock return predictability. According to the information processing channel, weekends afford retail investors more time for the intensive cognitive analysis necessary to make better predictions. Alternatively, weekend search might better capture the price pressure from retail investors' trading activities. We provide empirical results that support the information processing channel. We first show that weekend search, rather than weekday search, predicts large-cap stock returns in both the cross-section and time series. Additionally, our findings on retail trading activity contradict the price pressure channel in that weekday search, rather than weekend search, leads to a subsequent retail order imbalance. Overall, our study contributes to the literature on the predictive power of online search on stock returns, which has mainly focused on the price pressure channel, yielding significant results for small-cap stocks only.

Keywords: Internet search, time heterogeneity, retail investor attention, stock returns, trading activities

1. Introduction

The recent surge in retail investors' trading activities, fueled by the increasing availability of information technology, has attracted much attention among regulators and the media.[1] For example, retail trading in "meme" stocks such as GameStop is facilitated by the Reddit discussion board and the Robinhood trading platform. Beyond memes and mania, the fast-paced frenzy in retail trading illustrates the deep structural changes in financial markets concerning the diminishing information frictions that retail investors are facing. Retail investors commonly use search engines to acquire information during their investment decision-making process. Online search is thus a revealed attention measure: when you search for something with a search engine, you are undoubtedly paying attention to it. Existing studies have explored online search to study the impact of retail investor attention on stock returns. This study takes this exploration one step further: we examine the market implications of the heterogeneity in retail investors' attention by exploring variations in online search over weekdays and weekends.

Exploring predictability in financial markets with novel data sources has been an active search area in the information systems and finance literatures.[2] In particular, online search activity provides researchers with a direct and timely measure of investor attention or interest and has shown predictive power in financial markets. Da et al. (2011) found that Google search activities can predict stock returns. An additional refinement of search trend data in terms of keywords or entities can further improve predictions (Brynjolfsson et al., 2016). Ben-Rephael et al. (2017) found that search activities from Bloomberg Terminal lead those from Google search and facilitate permanent price adjustments. Leung et al. (2017) showed that searches across multiple stocks lead to co-movement in returns. Agarwal et al. (2017) further demonstrated that cross-predictability for stocks linked in supply chains varies with co-search intensity. Shangguan et al. (2022) proposed a composite metric based on attention and co-attention with better predictive performance for stock returns.

In this paper, we explore the variations in search conducted on weekdays and weekends separately in predicting stock returns. New to the literature, we found that compared with weekday search, weekend search has stronger predictive power for stock returns. Theoretically,

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[1] An SEC report on the recent GameStop trading stated, "The underlying motivation of such buy volume cannot be determined. . . . It was the positive sentiment, not the buying-to-cover, that sustained the weeks-long price appreciation of GameStop stock" ("Staff Report on Equity and Options Market Structure Conditions in Early 2021," October 14, 2021, https://www.sec.gov/page/sec-staff-release-gamestop-report). An article in *The Economist* stated, "Retail investors made up a tenth of trading volumes in America in 2019. By January this year their share had risen to a quarter" ("A New Epoch for Retail Investors Is Just Beginning," February 4, 2021, https://www.economist.com/finance-and-economics/ 2021/02/06/a-new-epoch-for-retail-investors-is-just-beginning).

[2] Online search activity is used for predicting stock returns (Da et al., 2011; Drake et al., 2012; Agarwal et al., 2017; Kang et al., 2021), cryptocurrency (Mai et al., 2018), and corporate sales (Geva et al., 2017).

our findings could result from two channels: differences in information processing capacity (i.e., the information processing channel) and differences in the price pressure generated by retail investor trading activities (the price pressure channel). The arguments for the information processing channel are as follows. Weekends relax attention constraints for retail investors since they are often limited by the amount of time they can divert from their main job on weekdays. According to psychological studies on human cognitive limitations, the difference between weekends and weekdays is important (Kahneman, 1973; Miller, 1956; Pashler & Johnston, 1998).[3] These studies have shown that the severity of limitations depends crucially on the type of tasks—from simple perceptual analysis to more central cognitive analysis requiring memory retrieval and action planning. This attention limitation is more severe for intensive cognitive analysis, such as analyzing stock price movements, and hence negatively affects investors' information processing ability on weekdays. Alternatively, according to the price pressure channel, weekend search can lead to more retail trading activities that drive up prices.[4] This is the commonly proposed channel in the literature (e.g., Da et al., 2011). Determining which channel is more likely to generate our findings is therefore an important question. We present several sets of findings to distinguish these two channels.

First, the price pressure channel works better for small-cap stocks than for large-cap stocks, which typically face few trading frictions and receive the most coverage from financial analysts and the news media. In contrast, the information processing channel can explain why search data can predict returns even for large-cap stocks: the wealth of information can exacerbate the attention constraint in information processing (Simon, 1973). Indeed, Da et al. (2011) found that the stock return predictability by online search is stronger for small-cap stocks. Cziraki et al. (2021) further challenged the predictive power of the search-based predictors in Da et al. (2011), showing little predictive power for the S&P 500 stocks. Since the S&P 500 stocks make up the majority of the stock market value, these findings cast doubt on whether retail investor attention can commonly predict stock returns. Filling an important void in the existing studies, we found that weekend search can predict large-cap stock returns and even aggregate market returns and determined that it generates significant alphas from the cross-section of S&P 500 stocks. These findings also lend support to the information processing channel.

Second, we conducted further analysis using trading volume and the retail trading order imbalance. We found that weekend search has a limited impact on the aggregate retail order imbalance but

[3] These psychological findings have been incorporated in the theoretical modeling of limited investor attention, such as Peng and Xiong (2006).

[4] Zheng (1999) and Keswani and Stolin (2008) found that retail money flows to mutual funds that outperform in the following quarter and argue that retail investors are informed about the fund managers' ability. In contrast, Lou (2012) suggested that the outperformance of these funds is driven by mechanical price pressure from the retail money flow rather than by fund managers' ability to pick undervalued stocks.

predicts overall trading volume from both retail and institutional investors.[5] In contrast, weekday search leads to a significant retail order imbalance but has no predictive power for the future overall trading volume. These findings indicate that the retail investors who search on weekdays account for the larger portion of retail trades but they cannot predict future returns or overall trading volume. On the other hand, the trades from retail investors who search on weekends are relatively small, consistent with the fact that weekend search volume is much smaller than weekday search volume. These findings do not support the channel of buying pressure that leads to higher stock returns but rather indicate that retail investors searching on weekends are able to predict future stock returns.

Additionally, we explored the dynamic relation between weekday and weekend search and found that weekend search is more persistent than weekday search. We determined that, compared to the news-based sentiment measures, weekday search correlates with the components in the sentiment measures that do not have return predictive power, whereas weekend search is not correlated with the sentiment measures. These findings are consistent with the notion that persistent cognitive resources are devoted to weekend search, lending support to the information processing channel.

Our study contributes to the literature on stock return predictability at both the aggregate and cross-sectional levels. The literature is very large; thus, we refer to Koijen and van Nieuwerburgh (2011) for an excellent review on the aggregate stock market return prediction and Nagel (2013) for a review on the cross-sectional stock market return prediction. We found that weekend search has strong predictive power, with magnitudes comparable to news-based predictors (Tetlock, 2007; Tetlock et al., 2008). The return predictability of weekend search comes from both the cross-section and time series and is stronger among the smaller stocks within the S&P 500 index. In the cross-section, we constructed long-short portfolios based on weekend search that generate abnormal returns of more than 3% per annum. In the time series, we determined that the aggregate weekend search has strong predictive power for equally weighted market returns.

Our study also makes important contributions to the emerging fintech research area.[6] The development of internet and information technologies has profoundly changed financial markets in information acquisition and investment decisions (Jia et al., 2020; Li & Wang, 2017). Our paper adds to the literature showing that online search has become an integral part of individual decision-making and a valuable source of information in predictive analytics (Da et al., 2011; Sparrow et al., 2011; Du et al., 2015; Ghose et al., 2014). Our paper also relates to the growing

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[5] Retail investors are typically considered to be less active than institutional investors among the S&P 500 stocks.

[6] The fintech research area is a combination of the internet, information technologies, and finance, including P2P lending, big data funds, cryptocurrency, and blockchain, as well as AI applications (Agarwal & Dhar, 2014; Buchak et al., 2018; Hendershott et al., 2021; Zhang & Zhang, 2015).

body of literature in both information systems and finance that examines retail-investor-oriented internet platforms (Luo et al., 2013; Xu & Zhang, 2013; Chen et al., 2014; Deng et al., 2018). In particular, we overcome the challenge of predicting large-cap stock returns using search data from retail investors.

Our study directly relates to the literature that explores heterogeneity in search data in order to make better predictions. We advocate for the collection and exploration of more granular data relying on information technology and demonstrate the power of such an approach to advance the understanding of retail investor attention. This is an important topic in fintech because the recent surge in retail investor trading is particularly linked to the increasing availability of information technology. Our paper relates to the research area that answers the question of whether information technology can level the playing field for retail investors. By exploring heterogeneity in retail investor attention, we distinguish the information processing channel from the price pressure channel, both of which are affected by the advancement in information technology. We found that retail investors possess information processing capacity when the attention constraint is relaxed (e.g., on weekends); thus, the development of information acquisition channels (e.g., search engines and information-sharing platforms) can potentially be beneficial to their investment performance.

2. Related Work and Hypothesis Development

2.1 Online Search Activity and Retail Investor Attention

Online search activity helps researchers overcome a substantial challenge in measuring investor attention or interest.[7] Da et al. (2011) found that the Google abnormal search volume index (ASVI) captures retail investor attention and can predict stock returns. Drake et al. (2012) found that more searches prior to the firms' earnings announcements make it more likely that the stock prices will quickly reflect that information. Da et al. (2015) constructed a sentiment index by aggregating the search volume of queries related to household concerns and found that it can predict short-term return reversals and temporary increases in market volatility. Leung et al. (2017) showed that when investors search multiple stocks consistently over time, comovement in returns occurs. Agarwal et al. (2017) further showed that cross-predictability for stocks linked in supply chains is stronger when co-search intensity is low.

With better data availability, researchers can explore the heterogeneity in online search and strengthen their ability to make predictions. One research direction is refining the selection of

[7] Traditional attention measures such as extreme returns, headlines, and advertising expenses (Barber & Odean, 2008; Chemmanur & Yan, 2019; Grullon et al., 2004; Lou, 2014; Yuan, 2015) are indirect and assume that events such as extreme returns or coverage in the news media should guarantee investor attention. In contrast, online search is a direct and unambiguous measure of attention: when you search for a stock (or other keywords) in Google, you are undoubtedly paying attention to it.

keywords in search (Brynjolfsson et al., 2016). Another direction is exploring the heterogeneity in search activities. Ben-Rephael et al. (2017) used the search activities from Bloomberg Terminal to measure the attention of institutional investors, as opposed to retail investor attention from Google search. They found that institutional investors respond more quickly to major news events, lead retail attention, and facilitate permanent price adjustments. This suggests that the well-documented price drifts following both earnings announcements and analyst recommendation changes are driven by announcements to which institutional investors fail to pay sufficient attention.

In this paper, we examine the heterogeneity in the timing of searches to provide a deeper understanding of the impact of retail investor attention on stock returns. The impact of retail investor trading activities on stock returns has been extensively studied in the finance literature. Frazzini and Lamont (2008) showed that retail investors tend to invest in mutual funds that hold overvalued stocks. Akbas et al. (2015) found that such fund flow exacerbates stock market anomalies. Lou (2012) showed that institutional investors take advantage of retail investors. However, retail investor attention may relate to subsequent stock returns beyond the impact of trading activities, which we discuss in the following section.

2.2 Weekend Search and Stock Return Predictability

Traditional asset pricing models assume that new information is instantaneously incorporated into prices, which requires that investors allocate sufficient attention to new information relevant to the asset prices. Theoretical studies on behavioral finance (e.g., Hirshleifer & Teoh, 2003; Merton, 1987; Peng & Xiong, 2006) have relaxed this assumption and provided a framework wherein limited attention affects asset prices. Empirical studies have documented that investor attention can predict trading behaviors and stock returns in both the time series (e.g., Yuan, 2015; Li & Yu, 2012) and the cross-section (Barber & Odean, 2008; Da et al., 2011).[8]

While the amount of information increases with the technology development, the processing capacity of human beings remains constrained (Simon, 1973), which can lead to information overload (Mendelson & Pillai, 1998). There is a large body of psychological research on human attention and the ability to simultaneously perform different tasks. Pashler and Johnston (1998) summarized the results on human cognitive limitations when faced with multiple tasks. The severity of limitations depends crucially on the type of tasks processed by the human cognitive machinery. The limitation is less severe for simple perceptual analysis, such as reading a newspaper while listening to music. However, the human brain has major limitations in terms of more central cognitive analysis that requires memory retrieval and action planning, in which case the human brain is compared to a single-processor computer. Psychological studies have also

[8] Investor disagreement and sentiment may also interact with each other to generate different return predictabilities (for example, Cen et al., 2013 and Cen et al., 2016).

revealed that the "bottleneck" is retrieving information from long-term memory, again using the analogy to a digital computer with switching and buffering capabilities. Retail investors' information processing capacities can vary, as can the predictability of their online search behavior. We exploit a simple and intuitive distinction in the time dimension of search: weekdays versus weekends. Weekends afford retail investors more time for intensive cognitive analysis, a pattern well understood by the financial news media.[9]

Based on the above discussion, we present two potential channels through which search on weekends, as opposed to weekdays, may better predict stock returns. First, retail investors may have more cognitive resources at their disposal for information processing on weekends, assuming that they hold regular jobs on weekdays. The cognitive analysis required in their regular jobs often goes beyond simple perceptual machinery and directly competes with the cognitive capacity associated with the task of predicting stock price movements (Hirshleifer & Teoh, 2003; Hirshleifer et al., 2009). Furthermore, weekdays typically feature an overabundance of news, announcements, and stock market events (Ahern & Sosyura, 2015; Fang & Peress, 2009), which further strains the information processing capacity of retail investors. However, if weekend search can serve as a proxy for attention from retail investors devoted to persistent and rigorous investment analysis, we expect that weekend search may predict stock returns better than weekday search. We call this channel the *information processing channel*.

A second channel through which retail investor attention can predict future stock returns is *price pressure*. Barber and Odean (2008) showed that retail investors are net buyers of attention-grabbing stocks, and an increase in the level of their attention results in temporary positive pressure on prices. The timing of search matters since not all search leads to trading actions. Psychology studies have suggested that the effect of limited attention is more severe for intensive cognitive analysis, such as planning trading actions. Because the attention constraint is tighter on weekdays, we conjecture that weekend search is more likely to lead to trading. Furthermore, search prompted by news often does not lead to trading activities because the information is already publicly known (Drake et al., 2012; Stewart et al., 1992; Zhao, 2017). Since higher-order imbalance can induce higher price pressures and therefore higher returns, weekend search might work better for predicting future stock returns.

Even though retail investors may pay attention to both good and bad news on a stock, they tend to react more strongly to good news because of the higher cost of selling. Barber and Odean (2008) showed that retail investor attention leads to net buying from retail investors. The reasoning behind this argument is as follows: retail investors may pay attention to many different

[9] For example, the weekend editions of *The Wall Street Journal* are filled with columns offering investment advice to sophisticated individual investors.

stocks that they own or do not own. When retail investors buy, they can choose from a large set of available alternatives. However, when they sell, they mostly sell what they own; as a result, attention to bad news may not lead to selling. Even when short-selling is possible, the trading costs are significantly different between buying and short-selling a stock, and retail investors face more acute restrictions and higher costs associated with short-selling stocks. This asymmetry between buying and selling stocks means that increased attention to a stock should lead, on average, to a net buying of the stock by retail investors.

Based on the aforementioned two channels, we propose the following hypothesis:

H1: *Weekend search predicts future stock returns better than weekday search.*

As discussed above, weekend search may have better predictive power for stock returns than weekday search via two main channels: information processing and price pressure. We differentiate these two channels by investigating the relation between weekend search and the retail order imbalance. According to the price pressure channel, retail investor attention on weekends should lead to higher buying pressure and thus more positive retail order imbalance, relative to weekday search. Specifically, we investigate the relation between ASVI and the retail order imbalance, and between ASVI and the aggregate trading volume from both retail and institutional investors to examine the price pressure channel.

The price pressure channel faces several important challenges. First, investors who search on weekends may make up a small fraction of retail investors since weekend search volume is smaller than weekday search volume. As a result, even if weekend search is more likely to be followed by trading, the aggregate retail trading volume associated with weekend search can still be dominated by those associated with weekday search. Second, institutional trading volume is typically larger than retail trading volume, so the retail order imbalance may not lead to an aggregate order imbalance that induces price pressure. As a result, buying pressure from retail investors may not drive up stock prices if retail trading volume is dwarfed by institutional trading volume—a more common scenario for large-cap stocks. Third, the price pressure channel typically finds stronger empirical support in small-cap stocks, as shown in Da et al. (2011), where the price impact caused by an order imbalance is more pronounced.

In our empirical analysis, we examine large-cap stocks in the S&P 500 index, which capture approximately 80% of the total market capitalization. Hou et al. (2020) found that many existing empirical results on stock return predictability exist mostly for small-cap stocks and cannot be extended to the entire market. Since large-cap stocks are generally more efficiently priced and less affected by various market frictions, it is more difficult to find return predictability among large-cap stocks. The finding that weekend search improves predictability for large-cap stocks contributes to the large literature on stock return predictability.

3. Data and Variable Construction

3.1 Data and Samples

Google Trends provides a search volume index (SVI) on a daily basis for the time window of less than three months. For time windows of over three months, Google Trends provides only weekly data. Google Trends also provides a function called "Compare Time Ranges" with which one can select different time windows (the maximum number of time ranges is five) of the same search term. The SVIs are scaled by the SVI's time series maximum for all time windows, ranging from 0 to 100.

We extracted the daily SVI time series from Google Trends one year at a time by downloading the four quarters (e.g., January 2010-March 2010, April 2010-June 2010, July 2010-September 2010, and October 2010-December 2010) in a year one at a time using the "Compare Time Ranges" function. For each ticker, the resulting SVIs are comparable across days within a year but not comparable across different years, as the scaling factors could be different over the years. To overcome this problem, we introduced the same "control time window" in the fifth time range for each ticker. If this control time window comprises the maximum SVI during the sample period from January 2004 to December 2019, then the scaling factor for the same ticker would be the same across different years. Thus, the yearly downloaded daily SVIs of the same ticker are comparable using this approach. In order to fix the control time window for each ticker, we first downloaded the weekly SVIs for each ticker from January 2004 to December 2019 and then determined the quarter in which the maximum (100) SVI of each ticker appeared. As Figure 1 shows, if the maximum SVI of MSFT appeared in the last quarter of 2007, the control time window for MSFT should be October 2007-December 2007.

Note that if the search volume is too low for a stock in Google Trends, it would return missing daily search data. In order to obtain nonmissing daily search volume data from Google Trends, we focused on stocks in the S&P 500 index. The S&P 500 index contains the largest U.S. firms, which represent more than 80% of the total U.S. equity market's capitalization; thus, our results were less likely to be affected by the bid-ask bounce.

3.2 Variables

Table 1 defines the main variables used in the empirical analysis. The dependent variable in this study is the weekly abnormal stock returns (Monday open to Friday close in week_{t+1}). The SVI-based variables are the explanatory variables of interest in this study. Following Da et al. (2011), we computed the abnormal SVI (ASVI) by subtracting the eight-week average lagged log (SVI) from the current log (SVI), which takes into account the week-to-week variation in SVI. We computed the weekday ASVI ($ASVI_{15}$) and the weekend ASVI ($ASVI_{67}$) separately. Intuitively, $ASVI_{15}$ ($ASVI_{67}$) reflects the percentage change in weekday (weekend) SVI over previous weeks.

Other variables such as market capitalization (Cap), institutional holdings (IH), advertising expenses to sales (AD), and the turnover (Turnover) were included as control variables. We also controlled for news variables from the RavenPack news database. The number of news items for each stock is defined following an approach similar to that in Da et al. (2011). We also added the news impact projection measure (NIP) provided by RavenPack news database. This measure captures the projected news impact and is trained based on a test set of large companies by RavenPack. Therefore, it fit well in our setting as a control variable. We also controlled for the multiclassifier sentiment score (MCQ) provided by RavenPack. This sentiment measure combines information from multiple sources such as news commentary and editorials, earnings evaluations, reports associated with corporate actions, and analyst recommendation information. These measures were created based on RavenPack's proprietary machine learning algorithms and are readily available to subscribed researchers. In addition, from the I/B/E/S database, we included the number of analysts, forecast dispersion, and forecast revision. In the prediction of stock returns, we further controlled for several return-based measures of momentum and reversal (abnormal stock returns in the previous week, the previous four weeks, and the previous 25 weeks), as in Veenman and Verwijmeren (2021) and Mayew and Venkatachalam (2012).

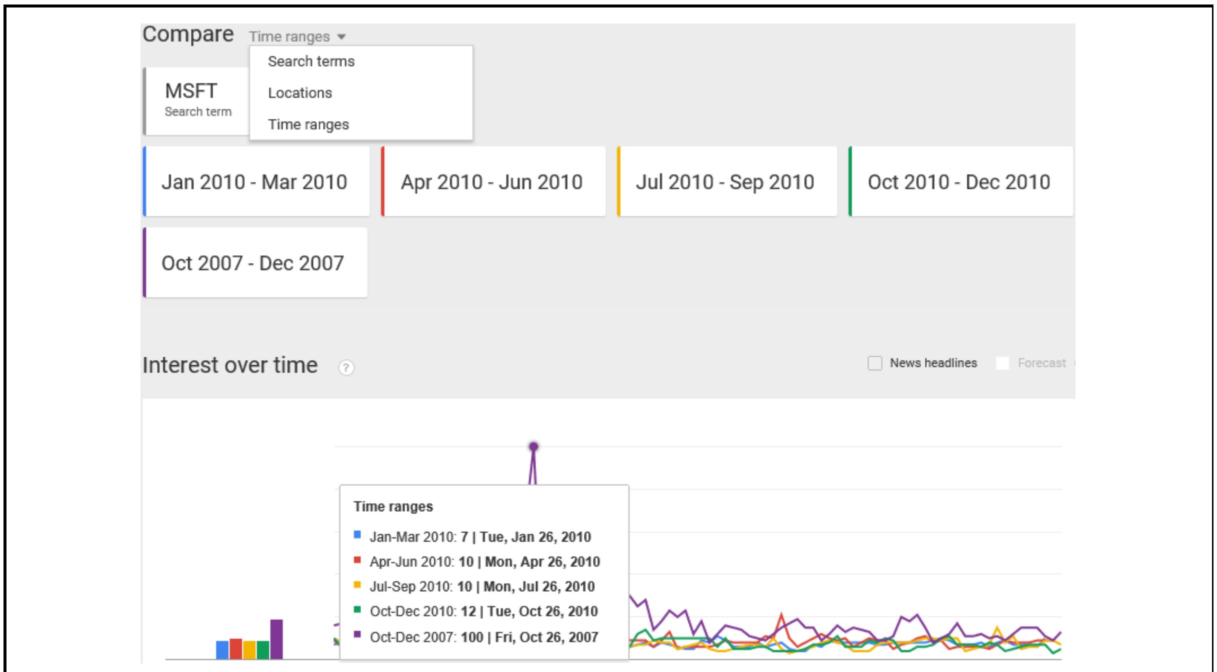

Figure 1. The Function of "Compare Time Ranges" in Google Trends

Table 1. Description of Variables	
Variable	**Description**
SVI	The weekly average of daily search volume in a whole week based on stock tickers
SVI_{15}	The weekly average of daily search volume on weekdays (Monday to Friday) based on stock tickers
SVI_{67}	The weekly average of daily search volume on weekends (Saturday to Sunday) based on stock tickers
ASVI	Abnormal SVI of a whole week, calculated by the log of SVI minus the log of the average SVI over the previous eight weeks
$ASVI_{15}$	Abnormal SVI of weekdays in a week, calculated by the log of SVI_{15} minus the log of the average SVI_{15} over the previous eight weeks
$ASVI_{67}$	Abnormal SVI of weekends in a week, calculated by the log of SVI_{67} minus the log of the average SVI_{67} over the previous eight weeks
DASVI	Daily abnormal SVI, calculated by the log of SVI on day *t* minus the log of the average SVI over the previous 30 days following Ben-Rephael et al. (2017)
Ret	Stock return
AbsRet	Absolute value of return
AbnRet	CRSP's daily abnormal stock return
OI	Retail order imbalance, as in Boehmer et al. (2021)
Turnover	Daily stock turnover
Cap	Market capitalization
IH	The percentage of institutional holdings of a stock, as in Ben-Rephael et al. (2017)
AD	The firm's advertising expenses to sales, as in Da et al. (2011)
Number of news	The number of news items for each stock provided by RavenPack news database
NIP	The news impact projection measure provided by RavenPack news database
MCQ	The multi classifier sentiment score provided by RavenPack
Number of analysts	Number of analysts covering the stock using the most recent information
Forecast dispersion	Standard deviation of analyst earnings per share forecasts
Forecast revision	Analyst one-quarter-ahead forecast revision, measured as the difference between the median forecast for quarter *t*+1 earnings issued after and before the quarter *t* earnings announcement date, scaled by price two days before the earnings announcement. The median forecast before (after) the quarter *t* earnings announcement is measured as the last (first) forecast of all individual I/B/E/S analysts issuing forecasts over the 90-day period prior to (after) the quarter *t* announcement date.

Table 2. Summary Statistics			
	ASVI	**$ASVI_{15}$**	**$ASVI_{67}$**
Mean	-0.0971	-0.1181	-0.2811
S.D.	0.5522	0.6164	0.9494
Bivariate correlations (all correlations are significant at the 1% level)			
ASVI	1		
$ASVI_{15}$	0.9028	1	
$ASVI_{67}$	0.3981	0.0816	1

Note: The variables are measured at a weekly frequency from 2004 to 2019. All variables are defined in Table 1.

3.3 Summary Statistics

Table 2 reports the descriptive statistics and pairwise correlations between the attention measures used in this study. ASVI, $ASVI_{15}$, and $ASVI_{67}$ are calculated as the weekly average of daily search volume in a whole week, weekdays, and the weekend, respectively, subtracting their eight-week average lagged values, respectively. Although the correlation between ASVI and $ASVI_{15}$ is over 0.90, the correlation between ASVI and $ASVI_{67}$ is only 0.40, suggesting that while the variation in ASVI mainly comes from weekday search, weekend search picks up different variations from the weekday search. Consistent with our discussion in earlier sections that weekend search can be generated by a distinct subset of retail investors.

4. Empirical Results

4.1 Google Search and Stock Return Predictability

Da et al. (2011) found that higher ASVI leads to higher returns in the following weeks, and that the effect exists mostly for the smaller stocks. We hypothesize that weekend search, as opposed to weekday search, can be more powerful in predicting future returns, even for large stocks.

Specifically, we analyzed the return predictability of weekend search versus weekday search and present these results in Table 3. We conducted a weekly analysis in Table 3a and a daily analysis in Table 3b. First, we confirmed that previous studies found no effect of ASVI (Specification 1) or

$ASVI_{15}$ (Specification 2) on future abnormal stock returns.[10] More importantly, our results show a sharp difference in the return predictability between the weekend search (Specification 3) and the weekday search (Specification 2). Unlike $ASVI_{15}$, a higher $ASVI_{67}$ can lead to significantly higher returns in the subsequent week. We included both $ASVI_{67}$ and $ASVI_{15}$ in Specification 4, and the coefficient for $ASVI_{67}$ is statistically significant at the 1% level. Strikingly, the magnitude of the coefficient estimate of $ASVI_{67}$ is on par with the news-based stock return predictors recently proposed in the literature (Tetlock, 2007; Tetlock et al., 2008), a strong indication of economic significance for $ASVI_{67}$.

Besides the control variables used in Da et al. (2011), we also included several predictors proposed in recent studies, such as the news impact projection measure (NIP) and the multiclassifier sentiment score (MCQ) provided by the RavenPack news database. To account for stock price momentum or reversal, we included the past 1-, 4-, and 25-week abnormal returns. However, the predictive power of weekend ASVI is qualitatively unchanged regardless of whether these controls are included—an indication of the robustness of our main findings. Furthermore, we included analyst forecast dispersion and forecast revision as control variables, finding that they are insignificant in our sample. Overall, our variable of interest, weekend ASVI, still has strong predictive power for future stock returns above and beyond the common stock return predictors. In terms of magnitude, the effects of NIP and MCQ are comparable to weekend ASVI. Thus, the results support H1 that weekend search can better predict stock returns.

We chose a weekly frequency in our benchmark analysis following Da et al. (2011). A potential concern for our finding is that subsequent weekly returns are closer to weekends than weekdays, so the stronger return predictive power for weekend search may be somewhat mechanical. To address this concern, we further conducted daily analysis to account for any intraweek patterns. Specifically, we computed the ASVI for each day of the week and regressed abnormal returns of the next trading day on the daily ASVI series (DASVI). The results are presented in Table 3b. While the abnormal returns on Mondays can be significantly predicted by the daily ASVI on weekends, the return predictive power of the daily ASVI of all other days is much weaker. To summarize, our finding that weekend search predicts the subsequent abnormal returns for large-cap stocks is novel to the literature and indicates the importance of exploring the time-dimensional heterogeneity in internet search-based attention measures.

[10] Our result is consistent with Cziraki et al. (2021), who found no evidence of an empirical relation between ASVI and future abnormal stock returns in S&P 500 stocks.

Table 3a. ASVI and S&P 500 Stock Returns—Panel A: Weekly Analysis				
	(1)	**(2)**	**(3)**	**(4)**
ASVI	0.0016			
	(0.0022)			
$ASVI_{15}$		0.0004		0.0001
		(0.0022)		(0.0022)
$ASVI_{67}$			0.0068***	0.0068***
			(0.0021)	(0.0021)
Cap	-0.0242***	-0.0242***	-0.0244***	-0.0244***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
IH	0.0019	0.0019	0.0020	0.0020
	(0.0035)	(0.0035)	(0.0035)	(0.0035)
AD	-0.0205*	-0.0204*	-0.0204*	-0.0204*
	(0.0113)	(0.0113)	(0.0113)	(0.0113)
Number of news	0.0006	0.0007	0.0006	0.0006
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
NIP	0.0077***	0.0077***	0.0077***	0.0077***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
MCQ	0.0046**	0.0046**	0.0045**	0.0045**
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Number of analysts	0.0038	0.0039	0.0034	0.0033
	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Forecast dispersion	0.0065	0.0065	0.0065	0.0065
	(0.0048)	(0.0048)	(0.0048)	(0.0048)
Forecast revision	0.0021	0.0021	0.0021	0.0021
	(0.0104)	(0.0104)	(0.0104)	(0.0104)
$AbnRet_{[t-1]}$	-0.0214***	-0.0214***	-0.0214***	-0.0214***
	(0.0055)	(0.0055)	(0.0055)	(0.0055)
$AbnRet_{[t-4, t-1]}$	0.0199***	0.0199***	0.0199***	0.0199***

	(0.0047)	(0.0047)	(0.0047)	(0.0047)
AbnRet$_{[t-25, t-1]}$	-0.0317***	-0.0317***	-0.0317***	-0.0317***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Turnover	0.0036	0.0036	0.0036	0.0036
	(0.0062)	(0.0062)	(0.0062)	(0.0062)
Fixed effect	Yes	Yes	Yes	Yes
Obs.	255,059	255,059	255,059	255,059
R^2	0.0018	0.0018	0.0019	0.0019

Note: The dependent variable is the abnormal returns (Monday open to Friday close) during the next week. All variables are standardized and defined in Table 1. The sample includes S&P 500 stocks from 2004 to 2019. Robust standard errors, reported in parentheses, are clustered at the stock level. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 3b. ASVI and S&P 500 Stock Returns—Panel B: Daily Analysis

	(1)	(2)	(3)	(4)	(5)
	Sat./Sun.	**Mon.**	**Tue.**	**Wed.**	**Thu.**
DASVI	0.0037***	0.0000	-0.0011	0.0043*	-0.0000
	(0.0014)	(0.0020)	(0.0023)	(0.0024)	(0.0023)
Other controls	Yes	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes	Yes
Obs.	262,761	287,098	287,809	282,485	280,937
R^2	0.0029	0.0012	0.0016	0.0012	0.0020

Note: The dependent variable is the abnormal returns on the next day (AbnRet$_{t+1}$). DASVI is calculated at the daily level for the prediction of Tuesday to Friday AbnRet and combined Saturday and Sunday for the prediction of Monday AbnRet. All variables are standardized and defined in Table 1. The firm fixed effects are included in the regression. The sample includes S&P 500 stocks from 2004 to 2019. Robust standard errors, reported in parentheses, are clustered at the stock level. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Besides the panel regression results shown in Tables 3a-b, we further investigated whether the return predictive power of weekend ASVI came from the time series or the cross-section. To explore the time series dimension, we aggregated the weekly, weekday, and weekend ASVI in a value-weighted manner and investigated whether these aggregate measures can predict aggregate market returns. The literature on stock market predictability (e.g., Welch & Goyal, 2008) has found it challenging to predict aggregate stock market returns, especially for S&P 500 stocks.

In Table 4, we report the regression results from predicting both value-weighted and equally weighted S&P 500 stock returns with the aggregate ASVI measures. Interestingly, the weekend ASVI had statistically significant and positive predictive power for the equally weighted market return in the subsequent week. The R^2 was 0.8% at a weekly frequency. On the other hand, all three ASVIs could not significantly predict the value-weighted market returns at the 5% significance level. These results suggest that the aggregate weekend search has strong predictive power for the smaller stocks within the S&P 500, although all S&P 500 stocks are considered to be the largest and most liquid stocks in the U.S. stock market.

Table 4. Predicting Aggregate Market Returns with ASVIs

	Predicting aggregate equally-weighted returns			**Predicting aggregate value-weighted returns**		
	ASVI	**$ASVI_{15}$**	**$ASVI_{67}$**	**ASVI**	**$ASVI_{15}$**	**$ASVI_{67}$**
Cons	0.001	-0.002	0.035*	-0.041***	-0.041***	-0.037***
	(0.013)	(0.014)	(0.019)	(0.010)	(0.010)	(0.011)
ASVI	0.257*	0.168	0.226***	0.158*	0.130*	0.060
	(0.137)	(0.125)	(0.075)	(0.092)	(0.077)	(0.052)
R^2	0.004	0.001	0.008	0.002	0.002	0.000

Note: We aggregate ASVI, $ASVI_{15}$, and $ASVI_{67}$ across S&P 500 stocks and use them to predict the equally-weighted (left panel) and value-weighted (right panel) returns of the S&P 500 stocks in the subsequent month. Newey-West standard errors reported in parentheses control for autocorrelation and heteroscedasticity. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2004 to 2019.

Next, we used weekend ASVI to construct a cross-sectional trading strategy by sorting stocks on the previous weekend ASVI and formed long-short portfolios. Specifically, we created quintile portfolios based on weekly, weekday, and weekend ASVI. In Tables 5a-b, we report the portfolio abnormal returns and alphas further controlling for the Carhart four-factor model. Consistent with the results from the panel regressions, weekly and weekday ASVI could not predict stock returns in the cross-section. For the weekend ASVI, when we used the equally weighted scheme (Table 5a), the long-short portfolio generates an average return of 2.92% per annum with statistical significance. The results on portfolio alpha controlling for the Carhart four-factor model are essentially the same. For the weekend ASVI, when we used the value-weighted scheme (Table 5b), the long-short portfolio generated an average return of 2.09% per annum but without statistical significance. Again, smaller stocks within the S&P 500 seemed to generate stronger results—a common pattern in our findings.

Table 5a. ASVIs and Long-Short Portfolios—Panel A: Equally Weighted Portfolios						
	Lo	**2**	**3**	**4**	**Hi**	**Hi-Lo**
			Sorted by ASVI			
Mean	-0.61	-1.55	-0.64	-0.62	0.17	0.79
	(0.97)	(0.95)	(0.86)	(0.81)	(0.92)	(1.31)
Alpha	-0.54	-1.43	-0.41	-0.51	0.32	0.86
	(1.00)	(0.96)	(0.86)	(0.83)	(0.92)	(1.38)
			Sorted by $ASVI_{15}$			
Mean	-0.31	-1.65*	-0.20	-0.97	-0.18	0.14
	(1.04)	(0.98)	(0.89)	(0.91)	(0.89)	(1.26)
Alpha	-0.28	-1.52	0.01	-0.86	0.02	0.30
	(1.07)	(0.98)	(0.91)	(0.93)	(0.89)	(1.36)
			Sorted by $ASVI_{67}$			
Mean	-2.73***	-0.57	0.06	-0.11	0.19	2.92**
	(0.96)	(0.85)	(0.84)	(0.91)	(0.93)	(1.25)
Alpha	-2.62***	-0.38	0.22	0.07	0.23	2.85**
	(0.97)	(0.85)	(0.83)	(0.92)	(0.93)	(1.24)

Table 5b. ASVIs and Long-Short Portfolios—Panel B: Value-Weighted Portfolios						
	Lo	**2**	**3**	**4**	**Hi**	**Hi-Lo**
			Sorted by ASVI			
Mean	-1.54 (1.17)	-3.75*** (0.97)	-2.27** (1.04)	-2.39** (1.05)	-2.98* (1.63)	-1.44 (2.19)
Alpha	-1.66 (1.19)	-3.74*** (0.98)	-2.39** (1.08)	-2.44** (1.06)	-2.73* (1.65)	-1.07 (2.29)
			Sorted by $ASVI_{15}$			
Mean	-2.17* (1.28)	-3.58*** (1.15)	-1.70 (1.03)	-2.08* (1.11)	-3.45** (1.59)	-1.28 (2.25)

Alpha	-2.35* (1.31)	-3.51*** (1.16)	-1.67 (1.08)	-2.11* (1.11)	-3.47** (1.67)	-1.12 (2.42)
Sorted by ASVI$_{67}$						
Mean	-3.28*** (1.09)	-3.63*** (0.95)	-3.12** (1.22)	-1.81 (1.20)	-1.19 (1.24)	2.09 (1.56)
Alpha	-3.32*** (1.06)	-3.67*** (0.95)	-3.24** (1.25)	-1.78 (1.22)	-1.04 (1.25)	2.28 (1.57)

Note: We sorted S&P 500 stocks into quintile portfolios based on their ASVI, ASVI$_{15}$, and ASVI$_{67}$ and report the average abnormal returns (Mean) and alphas relative to the Carhart four-factor model. We also report the results for the long-short portfolio (Hi-Lo) that buys high ASVI stocks and short-sells low ASVI stocks. Panel A (Table 5a) is for the equally weighted portfolios and Panel B (Table 5b) is for the value-weighted portfolios. Returns and alphas are annualized. Newey-West standard errors reported in parentheses control for autocorrelation and heteroscedasticity. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2004 to 2019.

Next, we split the S&P 500 stocks based on the market cap size and conducted double sorts on size and ASVIs to examine the difference between small and large stocks within the S&P 500 stocks. For each size group, we created quintile portfolios based on weekly, weekday, and weekend ASVI, and formed the long-short portfolios from the highest and lowest quintiles. In Tables 6a-b, we report the long-short portfolio returns and alphas controlling for the Carhart four-factor model. Weekly and weekday ASVIs still could not predict stock returns in the cross-section. For the weekend ASVI, when we used the equally weighted scheme (Table 6a), the long-short portfolio from the small-size group generated an average return of 3.36% per annum with statistical significance, and the long-short portfolio from the large-size group did not generate any significant returns. The results on portfolio alpha controlling for the Carhart four-factor model are essentially the same. For the weekend ASVI, when we used the value-weighted scheme (Table 6b), the long-short portfolio from the small size group generated an average return of 3.53% per annum with statistical significance; interestingly, the long-short portfolio from the large size group generated an average return of 2.53% per annum with marginal statistical significance. Our analyses show that the weekend ASVI has strong cross-sectional predictive power for S&P 500 stocks with the value-weighted scheme, even for the largest among the S&P 500 stocks.

Overall, we found that weekend ASVI has predictive power for stock returns in both the time series and the cross-section; the results are stronger for smaller stocks among the S&P 500 stocks.

Table 6a. Portfolios Double-Sorted on Size and ASVIs—Panel A: Equally Weighted Long-Short Portfolios						
	ASVI		$ASVI_{15}$		$ASVI_{67}$	
	Mean	Alpha	Mean	Alpha	Mean	Alpha
Small	1.73 (1.36)	1.76 (1.38)	0.89 (1.34)	1.04 (1.37)	3.36** (1.36)	3.31** (1.36)
Large	0.37 (1.42)	0.46 (1.51)	0.37 (1.44)	0.44 (1.53)	0.53 (1.02)	0.44 (1.02)

Table 6b. Portfolios Double-Sorted on Size and ASVIs—Panel B: Value-Weighted Long-Short Portfolios						
	ASVI		$ASVI_{15}$		$ASVI_{67}$	
	Mean	Alpha	Mean	Alpha	Mean	Alpha
Small	1.68 (1.48)	1.75 (1.53)	0.94 (1.41)	1.08 (1.45)	3.53** (1.42)	3.51** (1.43)
Large	-0.50 (1.74)	-0.39 (1.81)	-0.31 (1.77)	-0.31 (1.85)	2.53* (1.48)	2.73* (1.50)

Note: We double-sorted S&P 500 stocks into 2-by-5 portfolios based on their lagged market value (size) and ASVI, $ASVI_{15}$, and $ASVI_{67}$, and report the average abnormal returns (Mean) and alphas relative to the Carhart four-factor model for the long-short portfolio that buys high ASVI stocks and short-sells low ASVI stocks within each size group. Panel A (Table 6a) is for the equally weighted portfolios and Panel B (Table 6b) is for the value-weighted portfolios. The rows labeled "Small" refer to the portfolios that are constructed using the stocks in the bottom half of the size distribution; the rows labeled "Large" refer to the portfolios that are constructed using the stocks in the top half of the size distribution. Returns and alphas are annualized. Newey-West standard errors reported in parentheses control for autocorrelation and heteroscedasticity. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample is from 2004 to 2019.

4.2 Google Search and Trading Activity

We next investigated whether ASVI from Google search leads to a retail order imbalance. We constructed novel retail order imbalance measures based on Boehmer et al. (2021). This measure builds on the fact that, owing to Regulation NMS in the U.S. and the resulting institutional arrangements, retail order flow, but not institutional order flow, can receive price improvements, measured in small fractions of a cent per share. This fact can help identify marketable retail price-improved orders from TAQ (trade and quote) transaction data. Most of these price-improved transactions take place off-exchange and are reported to a trade reporting facility (TRF). With the TRF data, retail buys (sells) are identified if the transaction price is slightly below (above) the round penny. For each stock and on each day, we computed the number of shares in marketable retail buys and sells and computed the marketable retail order imbalance (MROI) by dividing the difference between buy order and sell order volume by the sum of buy order and sell order volume. This retail order imbalance measure is between -1 (i.e., 100% sells) and 1 (i.e., 100% buys). We followed Boehmer et al. (2021) in focusing on the sample period from January 3, 2010, to December 31, 2015, in order to be conservative by choosing a start date after widespread adoption of this practice by brokerage firms began and an end date before the SEC adopted a tick size pilot program (TSPP) that affected tick size and brokers' ability to provide price improvement for many stocks.

Additionally, we investigated the relation between ASVI from Google search and future abnormal turnover among stocks. Abnormal turnover includes both retail and institutional trades. A comparison between retail trading activity and overall trading volume can help us examine whether price pressure is the channel for stock return predictability.

In Table 7, we ran a predictive regression similar to that in Tables 3a-b by replacing abnormal returns with the MROI, calculated as the difference between buying and selling volume. We discovered that weekday ASVI leads to a significant retail order imbalance; in contrast, weekend search has a limited impact on the retail order imbalance. Weekend search typically has a much smaller volume than weekday search, so it is possible that retail investors who search on weekends are a smaller group, relative to those who search on weekdays. It is thus not surprising that weekend search has a smaller impact on the retail order imbalance. On the other hand, weekday search significantly predicts the next week's retail order imbalance.

Table 7. ASVIs and Retail Order Imbalance

	(1)	(2)	(3)	(4)
ASVI	0.10577**			
	(0.0417)			
$ASVI_{15}$		0.12455***		0.12311***
		(0.04022)		(0.04041)
$ASVI_{67}$			0.03706	0.03185
			(.04484)	(.0449)
Cap	2.3709***	2.3704***	2.3703***	2.3696***
	(0.79094)	(0.79066)	(0.79173)	(0.79028)
IH	0.3389	0.339	0.33854	0.33932
	(0.21994)	(0.21984)	(0.22005)	(0.21965)
AD	0.21459	0.2134	0.2176	0.21331

	(0.71766)	(0.71742)	(0.71809)	(0.71775)
Number of news	-0.2637*** (0.05997)	-0.26524*** (0.06018)	-0.25521*** (0.05893)	-0.26594*** (0.06026)
NIP	-0.06871 (0.04714)	-0.06879 (0.04712)	-0.06828 (0.04711)	-0.06881 (0.04712)
MCQ	0.24934*** (0.05889)	0.24925*** (0.0589)	0.24962*** (0.05892)	0.24917*** (0.05889)
Number of analysts	0.45021* (0.24408)	0.44872* (0.2441)	0.45433* (0.24402)	0.44754* (0.24393)
AbsRet	-0.65584*** (0.05765)	-0.65618*** (0.05775)	-0.65351*** (0.05761)	-0.65647*** (0.05772)
Turnover	0.21227** (0.0927)	0.21072** (0.09254)	0.22018** (0.0929)	0.21044** (0.09262)
$MROI_{[t-1]}$	0.25174*** (0.01011)	0.25173*** (0.0101)	0.25181*** (0.01011)	0.25172*** (0.0101)
Fixed effect	Yes	Yes	Yes	Yes
Obs.	100,142	100,142	100,142	100,142
R^2	0.143	0.143	0.142	0.143

Note: The dependent variable is 100 times the marketable retail order imbalance in the following week. All explanatory variables are standardized and defined in Table 1. The firm fixed effects are included in the regression. The sample includes S&P 500 stocks from 2010 to 2015. Robust standard errors, reported in parentheses, are clustered at the stock level. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

In Table 8, we ran a predictive regression similar to that in Table 7 by replacing the retail order imbalance with abnormal turnover in the following week. We discovered that weekend ASVI leads to significant abnormal turnover and that, in contrast, weekday search has little predictive power. Our sample is S&P 500 stocks, and institutional trading usually dominates retail trading for large-cap stocks. It is thus possible that aggregate trading volume is stable even when retail trading is active. However, weekend search can predict aggregate trading volume even though it consists of a small group of retail investors, an indication that this small group of retail investors is able to predict aggregate trading activities from all of the market participants.

Table 8. ASVIs and Abnormal Turnover

	(1)	(2)	(3)	(4)
ASVI	-0.0003			
	(0.0015)			
$ASVI_{15}$		-0.0016		-0.0018
		(0.0015)		(0.0015)
$ASVI_{67}$			0.0048***	0.0049***
			(0.0013)	(0.0013)
Cap	-0.0276***	-0.0276***	-0.0277***	-0.0277***
	(0.0073)	(0.0073)	(0.0074)	(0.0074)
IH	0.0142**	0.0142**	0.0144**	0.0143**
	(0.0069)	(0.0069)	(0.0069)	(0.0069)
AD	-0.0061	-0.0061	-0.0062	-0.0061
	(0.0249)	(0.0249)	(0.0249)	(0.0249)
Number of news	-0.0276***	-0.0275***	-0.0277***	-0.0276***
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
NIP	-0.0018	-0.0018	-0.0018	-0.0018
	(0.0015)	(0.0014)	(0.0015)	(0.0015)
MCQ	0.0072***	0.0072***	0.0071***	0.0071***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Number of analysts	-0.0209***	-0.0208***	-0.0213***	-0.0212***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
AbsRet	-0.0405***	-0.0405***	-0.0406***	-0.0405***
	(0.0027)	(0.0027)	(0.0027)	(0.0027)
Lagged turnover	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
Obs.	263,467	263,467	263,467	263,467
R^2	0.667	0.667	0.667	0.667

Note: The dependent variable is turnover in the next week, and the lagged turnover is included in the control variables to capture the effects of ASVIs on abnormal turnover. Four lags of weekly turnover are included in the regression based on information criteria. All variables are standardized and defined in Table 1. The firm fixed effects are included in the regression. The sample includes S&P 500 stocks from 2004 to

2019. Robust standard errors, reported in parentheses, are clustered at the stock level. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Weekend ASVIs and Short-Horizon Trading Activities				
	MROI		**Abnormal Turnover**	
	Mon.	**Mon.&Tue.**	**Mon.**	**Mon.&Tue.**
$ASVI_{67}$	0.0168 (0.059)	-0.0608 (0.0504)	0.0034*** (0.0009)	0.0029** (0.0012)
Lagged Dep. Var	Yes	Yes	Yes	Yes
Lagged Abn. Ret	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
Obs.	92,788	92,068	231,323	231,323
R^2	0.061	0.088	0.651	0.643

Note: The dependent variable is the MROI or Turnover on Monday or Monday and Tuesday combined in the following week. All explanatory variables are standardized and defined in Table 1. The firm fixed effects are included in the regression. The sample includes S&P 500 stocks from 2010 to 2015 for the regression on MROI and from 2004 to 2019 for Turnover. In the regression on Turnover, the lagged Turnover is included in the control variables to capture the effects of ASVIs on abnormal turnover. The number of lags is determined based on information criteria. Robust standard errors, reported in parentheses, are clustered at the stock level. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

4.3 The Dynamics of ASVIs

Psychology studies (see Pashler & Johnston, 1998) have shown that retrieving information from long-term memory is the most significant constraint in more central cognitive analysis, such as analyzing stock price movements. In our setting, the formation of long-term memory requires deliberate searches with persistence rather than searches prompted by transitory stimuli. Our data do not afford us the distinction of whether the user of a search engine is deliberate and persistent, such as the identity or past performance of the user. Our approach to separating weekend and weekday search provides a simple-to-implement yet robust method. To examine whether weekend search is more persistent, we studied the dynamics of weekday and weekend search.

Table 10. The Dynamics of Weekday and Weekend Search				
	$ASVI_{15, t}$		$ASVI_{67, t}$	
	(1)	(2)	(1)	(2)
$ASVI_{15, t}$				0.037*** (0.003)
$ASVI_{15, t-1}$	0.068*** (0.003)	0.0656*** (0.003)		0.0155*** (0.003)
$ASVI_{15, t-2}$	0.0333*** (0.003)	0.0313*** (0.003)		0.0108*** (0.003)
$ASVI_{15, t-3}$	0.0039 (0.003)	0.0023 (0.003)		0.0109*** (0.003)
$ASVI_{15, t-4}$	-0.0108*** (0.003)	-0.0121*** (0.003)		0.0016 (0.003)
$ASVI_{67, t-1}$		0.0335*** (0.003)	0.0877*** (0.003)	0.0854*** (0.003)
$ASVI_{67, t-2}$		0.014*** (0.003)	0.0573*** (0.003)	0.0555*** (0.003)
$ASVI_{67, t-3}$		0.0151*** (0.003)	0.0303*** (0.003)	0.0285*** (0.003)
$ASVI_{67, t-4}$		0.0056** (0.003)	0.007** (0.003)	0.0058** (0.003)
Number of news	0.0841*** (0.002)	0.0834*** (0.002)	0.0257*** (0.002)	0.0222*** (0.002)
NIP	0.0085*** (0.002)	0.0085*** (0.002)	0.0026 (0.002)	0.0026 (0.002)
MCQ	0.0059** (0.002)	0.0055** (0.002)	0.0034 (0.002)	0.0032 (0.002)
Other controls	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes

Obs.	263,409	263,409	263,409	263,409
R^2	0.020	0.022	0.018	0.020

Note: The dependent variable is the standardized ASVIs in the current week. All variables are standardized and defined in Table 1. The sample includes S&P 500 stocks from 2004 to 2019. Newey-West standard errors with four lags robust to heteroskedasticity are reported in parentheses. The *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

In Table 10, we regress the weekday and weekend ASVIs on the list of control variables used in the return regression and the lagged ASVIs. The control variables are from the same week as the ASVIs since we tried to explore what prompts the search following existing studies (e.g., Liu & Ye, 2016). We included the lagged ASVIs so that we could examine their persistence. We included the weekday or weekend ASVI lags in Specification 1 and both lags in Specification 2. Our analysis yielded two major findings. First, we found weekend search to be more persistent than weekday search in that the lags of weekday ASVI were significantly positive up to two weeks and reverse in four weeks, whereas the lags of weekend ASVI were significant up to four weeks. Furthermore, the inclusion of same-week and lagged weekday ASVI did not change the persistence pattern for weekend ASVI. This evidence is inconsistent with the alternative view that weekend search simply represents the spillover from weekday search. Interestingly, weekday ASVI is significantly positively correlated with lagged weekend ASVI beyond two weeks, even though not this is not so with its own lags, an indication that weekend search captures the persistent component of overall ASVIs. Second, although both weekday and weekend search significantly correlate with news, we found weekday search to be more significantly associated with the news-based sentiment measures than weekend search. Interestingly, the news-based sentiment measures were able to predict stock returns, as shown in Tables 3a-b, but weekday ASVI could not predict stock returns with or without controlling for the sentiment measures, which indicates that weekday ASVI captures the components in the sentiment measures that do not predict returns. In contrast, we found weekend search to be less driven by sentiment overall. Both findings highlight the more persistent and less transitory nature of weekend ASVI.

Psychological studies (e.g., Pashler & Johnston, 1998) have found that intensive cognitive resources and long-term memory are necessary for processing complex tasks, as compared to simple tasks. From this perspective, weekend search stands out for its persistency, lending support to our main hypothesis.

5. Conclusion

Recent studies have proposed online search on stocks as a direct measure of investor attention, which can thereby predict stock returns. We study the heterogeneity in retail investor attention by comparing searches conducted on weekdays and weekends and the implications on stock return predictability. Weekends afford retail investors more time for the intensive cognitive analysis necessary to make better predictions. Therefore, we hypothesize that weekend search could have stronger predictive power for stock returns than weekday search.

Using the daily SVI from Google Trends on a sample of S&P 500 stocks from 2004 to 2019, we show that weekend search, rather than weekday search, predicts stock returns in both the cross-section and time series. Long-short portfolios based on weekend search can generate alphas of more than 3% per annum. The aggregate weekend search has strong predictive power for equally weighted market returns. These findings fill an important void in the existing studies on the predictive power of search on the returns of large-cap stocks, which make up the majority of U.S. stock market capitalization.

Additionally, we make an attempt to differentiate between two theoretical channels—information processing and price pressure—that might explain our empirical findings. We find that weekday search, rather than weekend search, is associated with the subsequent retail order imbalance. This finding together with the evidence that weekday search does not predict returns, is inconsistent with the price pressure channel for return predictability. In contrast, weekend search, rather than weekday search, predicts overall trading volume from both institutional and retail investors, as well as stock returns, supporting the information channel. While the price pressure channel typically works better for small-cap stocks, the information processing channel can work for large-cap stocks as well. Overall, our findings support the importance of the information channel over the price pressure channel in this context.

Our study makes the following contributions. First, we extend the literature on empirical asset pricing—more specifically, the recent stream of studies that visit the predictive power of internet search data. Second, our findings reveal the mechanism through which retail investor attention can help make better predictions in financial markets. The existing studies have focused on the price pressure channel, whereas we demonstrate the importance of the information processing channel. Third, our study adds to the fintech literature by extending the study of alternative data, especially with the arrival of the big data era (Ahsen et al., 2019; Song et al., 2019). Exploring heterogeneity in more granular internet usage data could provide insights into future improvements in investment management.

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