Journal of Banking and Finance 73 (2016) 147–164

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Stock return predictability and investor sentiment: A high-frequency perspective[☆]

Licheng Sun[a,*], Mohammad Najand[a], Jiancheng Shen[b]

[a] Department of Finance, Strome College of Business, Old Dominion University, Norfolk, VA 23529, US
[b] Department of Business, Leadership, and Management College of Arts and Sciences, Regent University, Virginia Beach, VA 23464, US

ARTICLE INFO

Article history:
Received 19 November 2015
Accepted 25 September 2016
Available online 1 October 2016

JEL Classification:
G11
G14

Keywords:
Intraday
Investor sentiment
High frequency
Stock return predictability
Noise trading

ABSTRACT

We explore the predictive relation between high-frequency investor sentiment and stock market returns. Our results are based on a proprietary dataset of high-frequency investor sentiment, which is computed based on a comprehensive textual analysis of sources from news wires, internet news sources, and social media. We find substantial evidence that intraday S&P 500 index returns are predictable using lagged half-hour investor sentiment. The predictive power is also found in other stock and bond index ETFs. We document that this sentiment effect is independent of the intraday momentum effect, which is based on lagged half-hour returns. While the intraday momentum effect only exists in the last half hour, the sentiment effect persists in at least the last two hours of a trading day. From an investment perspective, high-frequency investor sentiment also appears to have significant economic value when evaluated with market timing trading strategies. We find evidence that the return predictability is most likely driven by the trading activities of noise traders.

1. Introduction

It has been well documented that investor sentiment plays an important role in financial markets. For instance, from a theoretical perspective, De Long et al. (1990) show that, with limits to arbitrage, changes in noise traders' sentiment will result in excess market volatility as well as deviation in stock prices away from their fundamental values. Barberis, Shleifer, and Vishny (1998) present a model of investor sentiment that can produce both underreaction and overreaction to news.

Empirically, investor sentiment has also been shown to impact asset prices as well as have explanatory power on some well-known asset pricing anomalies. For example, Hirshleifer and Shumway (2003) find that upbeat investor mood associated with morning sunshine in the city of a country's leading stock exchange is significantly correlated with daily market index returns across 26 countries. Lemmon and Portniaguina (2006) explore the time-series relationship between sentiment and the small-stock premium and find that consumer confidence can forecast small stock returns. Antoniou et al. (2013) document that momentum profits arise only under investor optimism. Baker and Wurgler (2006) examine the cross-sectional effect of investor sentiment. They show that when sentiment is low (high), subsequent returns are relatively high (low) for small stocks, young stocks, high volatility stocks, and distressed stocks.

Given the significant impact from investor sentiment on asset prices, it is imperative that researchers use high-quality measures of aggregate investor sentiment in their studies. In the extant literature, there are at least three approaches that attempt to measure investor sentiment with accuracy.

First, investor sentiment could be captured using certain market-based variables. Lee et al. (1991) document that fluctuations in discounts of closed-end funds are driven by changes in investor sentiment. Baker and Wurgler (2006); 2007) construct a measure of investor sentiment that is based on several market-based variables such as closed-end fund discount, IPO first-day returns, IPO volume, and trading volume. Other popular market-based sentiment measures include: option implied volatility index, and market state as defined by the sign of lagged three-year or one-year market returns.

However, as argued by Qiu and Welch (2006) as well as Da et al. (2015), market-based measures of sentiment have the drawback of being the equilibrium outcome of many economic forces other than investor sentiment. Thus to get a "cleaner"

☆ We are grateful to Richard Peterson, Managing Director at MarketPsych, and Elijah DePalma from Thomson Reuters for providing us with the proprietary Thomson Reuters MarketPsych Indices data. We also thank two anonymous referees as well as seminar participants at Old Dominion University for helpful comments.

* Corresponding author.
E-mail addresses: lsun@odu.edu (L. Sun), mnajand@odu.edu (M. Najand), jshen@regent.edu (J. Shen).

http://dx.doi.org/10.1016/j.jbankfin.2016.09.010
0378-4266/

measure of sentiment, one can use survey-based measures of investor sentiment. Examples of this approach include: the University of Michigan Consumer Sentiment Index, the AAII investor sentiment survey, and the UBS/GALLUP Index for Investor Sentiments. Survey-based sentiment measures are not without their own weakness. Da et al. (2015) note that they are not available in high frequency and become increasingly less reliable when non-response rates in surveys are high or the incentive for truth-telling is low.

More recently, sentiment metrics based on textual analysis of media contents such as newspaper columns, messages boards, blogs, and google search results have gained popularity. We call these media-based investor sentiment measure. Using daily content from a popular *Wall Street Journal* column, Tetlock (2007) find that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume. He concludes that these results are consistent with theoretical models of noise and liquidity traders, and are inconsistent with theories of media content as a proxy for new information about fundamental asset values or market volatility. Antweiler and Frank (2004) study the effect of more than 1.5 million messages posted on internet message boards and find significant evidence that the stock messages help predict market volatility. Da et al. (2015) construct a sentiment index based on google search results using key words such as “recession”, “unemployment”, and “bankruptcy”. They find that this index can predict both short-term return reversals and temporary increase in volatility.

An important advantage of using media-based sentiment measures is their availability in high-frequency. Da et al. (2015) note that: “to date, high frequency analysis of investor sentiment is found only in laboratory settings.” For example, The FEARS index constructed by Da et al. is available in daily frequency. In contrast, many survey-based measures are only available in monthly or quarterly frequency. The popular Baker–Wurgler index is available in monthly and annual frequency.

In this paper, we study the predictive relation between investor sentiment and stock market returns at the intraday level. To the best of our knowledge, this article is the first to study the relation between ultra-high frequency investor sentiment and the predictability in intraday stock returns at the market index level. In our view, there at least three reasons to study investor sentiment at the intraday level. First, from a big picture perspective, progress in scientific subjects are often made by studying behavior at infinitesimal time increments (high frequency). In finance, for example, we have gained new knowledge about the behavior of market price and liquidity, among many other things, by studying market microstructure. In the case of modeling the volatility of asset prices, the predictive power of GARCH models have benefited from using high frequency data. Given the importance of understanding the nature of investor sentiment, it is our belief that studying investor sentiment at intraday level will shed new light on this subject, which cannot be gained by studying sentiment at lower frequency (monthly or daily) levels. Second, from a modeling perspective, if we view investor sentiment as governed by a continuous time process, then studying investor sentiment at intraday level will give us a more precise estimate of the real changes and movements in investor sentiment. For instance, suppose that policy makers would like to gauge investors’ real time response to a recent change in monetary policy. In this case, the ability to estimate the change in sentiment at intraday level will be invaluable whereas the low frequency alternatives will be inadequate. Third, from a practical perspective, investors could potentially use intraday investor sentiment as their model inputs and improve their trading strategies.

Our intraday sentiment measure is obtained from a proprietary dataset from Thomson Reuters, which is based on a commercial-strength comprehensive textual analysis of sources from news wires, internet news sources, and social media. We note the prior studies that focus on textual analysis of media contents almost exclusively rely on a single source. For example, Tetlock (2007) and Garcia (2013) use columns from *Wall Street Journal* and *New York Times* respectively. Chen et al. (2014) conduct textual analysis of articles published on *seekingalpha.com*. Compared with these studies in the extant literature, our sentiment measure is constructed from a much broader and more comprehensive collection of both traditional and social media sources. For example its sources include financial news, social media, earnings conference call transcripts, and executive interviews. In our view, given the goal is to obtain an accurate measure of investor sentiment, the all-encompassing nature of our sentiment measure is an important advantage over other single-source sentiment measures.

To match with the frequency of our sentiment data, we naturally choose to study stock return predictability at the intraday level. Heston et al. (2010) provide a comprehensive study of the cross-section stock return patterns at the intraday level. They identify an interesting pattern of return continuation at half-hour intervals that are exact multiples of a trading day. More recently, Gao et al. (2015) (henceforth GHLZ) document an intriguing intraday momentum pattern for the S&P 500 index ETF. They show that the first half-hour return on the market predicts the last half-hour return on the market.

We find convincing evidence that intraday S&P 500 index returns are predictable using lagged half-hour changes in investor sentiment. We document that this sentiment effect is independent of the intraday momentum effect of GHLZ, which is based on lagged half-hour returns. While the intraday momentum effect only exists in the last half hour, the sentiment effect persists in at least the last two hours of a trading day. From an investment perspective, high-frequency investor sentiment also appears to have significant economic value when evaluated with market timing trading strategies. In addition, similar results are also found in other large-cap, small-cap, and international stock ETFs.

While the overall evidence are supportive of the hypothesis that the predictive power of our intraday sentiment measure is attributable to the activities of noise traders, we are open to the notion that our results could potentially be driven by rational factors such as some (unidentified) state variables and/or market frictions. To help differentiate the behavioral and rational explanations, we have conducted a battery of empirical tests. We find no evidence that our results are driven lagged macroeconomic variables, macroeconomic news announcement effects associated with the non-farm payroll unemployment report, or FOMC (Federal Open Market Committee) meetings. In contrast, we do find evidence that our intraday sentiment measure is significantly correlated with alternative sentiment measures such as the University of Michigan consumer sentiment index. More importantly, we find that the predictive value of investor sentiment measure mainly shows up in days with high trading volume, which, according to Odean (1998) and Barber and Odean (2000), is an indication of noise trading. Thus we believe that our results are consistent with the noise trading hypothesis and more aligned with a behavioral explanation.

The rest of this paper is organized as follows. The next section describes the data. Section 3 documents the empirical relation between high-frequency investor sentiment and intraday S&P 500 returns using predictive regressions. Section 4 provides a battery of robustness checks by examining monthly and weekday seasonality, the effects of macroeconomic variables and alternative measures of investor sentiment such as market states, and CBOE’s volatility index. Section 5 evaluates the economic significance of investor sentiment using market timing trading strategies. Section 6 evaluates alternative explanations by exploring the relation between investor sentiment, trading volume, liquidity, and longer-horizon return reversal. Section 7 provides some concluding remarks.

2. Data description

Our intraday stock returns data are obtained from QuantQuote. The data vendor provides us with minute-by-minute price data starting from January 1998. Consistent with GHLZ (2015), we focus on the intraday returns of S&P 500 index ETF (ticker symbol SPY). According to Wikipedia, “for a long time, this fund was the largest ETF in the world.” According to Yahoo! Finance, its average daily trading volume is more than 147 million shares. Due to arbitrage forces, its intraday price movements are almost identical to the underlying cash index as well as the S&P 500 index futures. We first filter out price data outside the regular trading hours. Then we convert 1-minute price data to half hour returns. Thus we obtain thirteen half hour returns for each trading day.

Following GHLZ, the half hour returns are calculated on the close-to-close basis. Therefore the first half hour return should contain information during the overnight hours after the closing of the previous day. For example many of the economic news are released at 8:30 am, which is probably why GHLZ find the first half hour return informative. GHLZ show that both the first and (to a lesser extent) the 12th half hour returns can predict last half hour return. In this paper, our focus is broader than GHLZ. We are interested in knowing whether lagged changes in high frequency investor sentiment have predictive values for future market returns throughout the whole trading day, rather than just the last half hour.

Our intraday sentiment measure is based on the proprietary Thomson Reuters MarketPsych Indices (TRMI). Its website (https://www.marketpsych.com/data/) provides the following summary about the data.[1]

> “We have the world’s most comprehensive finance-specific sentiment data, covering all major countries, currencies, commodities, equity sectors, and individual US and non-US equities. The data is produced by distilling a massive collection of news and social media content though through an extensively curated language framework, which not only measures different emotions (optimism, confusion, urgency etc.), but also financial language (price forecasts etc.) and specific topics (interest rate, mergers etc.). TRMI is produced from 1998 to present, on both a daily and minutely basis.”

The construction of TRMI relies on the use of a patent-pending system to score sentiment-laden content in text. According to its documentation, TRMI’s text analytic techniques are designed to score business-specific language for quantitative financial applications. This is important because, as shown by Loughran and McDonald (2011), word lists that are not unique to finance might not correctly reflect tone in the financial context.

TRMI’s entire content set includes millions of articles and posts each day from various sources such as news wires, internet news sources, and social media. Due to the wide variety of content sources, cares have to be given when interpreting words or symbols that express emotions. For example, in social media someone may use an acronym such as “LOL” that is unlikely to be used in a formal news press lease. To account for these differences, TRMI uses differentiated models for news, social media forums, tweets, SEC filings, as well as earnings conference call transcripts.

Although TRMI covers a wide range of asset markets including equities, currencies, and commodities, we only have access to sentiment data that is linked to the S&P 500 index (SPY) and for the sample period from 1998 to 2011. The data granularity is at minute level and covers twenty-four hours a day. More specifically, the TRMI sentiment measure provides the 24 h rolling average score of total references in news and social media by counting overall positive references net of negative references. The scores are normalized so that its value ranges from -1 to 1. To match with our returns data, we convert the minute level data to half hour frequency and only focus on the regular trading hours. Perhaps due to the use of rolling average, we find that the levels of intraday investor sentiment are highly persistent, with first order autocorrelation larger than 99%. It is well known that highly persistent variables can caused biased inferences in predictive regressions. Therefore we focus on the lagged *changes* in investor sentiment rather than its levels.

While the TRMI sentiment data is based on textual analysis, we also evaluate the use of alternative market-based sentiment proxies as control variables. We focus on two measures: the Chicago Board Options Exchange (CBOE) volatility index (VIX) and market state. The VIX is inferred from S&P 500 index option implied volatility data and is widely regarded by the market as the so-called “fear index”. For example, Connolly et al. (2005) show that heightened levels of the VIX is associated with episodes of high stock market uncertainty and related to the flight-to-quality effect between stocks and bonds. Since intraday VIX data are not available to us, we rely on lagged values of the VIX from the previous trading day. Cooper et al. (2004) find that momentum profits occur exclusively in the UP market state, defined as the time periods when lagged three-year or one-year aggregate market return is non-negative. They attribute this result to increased levels of investor overconfidence in the UP market states. Since lagged market states are associated with investor overconfidence (or lack thereof), it may be viewed as a measure of investor sentiment as well. In this article we define the current market state as UP (DOWN) if the lagged return of the S&P 500 index during the past 250 trading days (approximately one year) is non-negative (negative).

In addition to the sentiment measures, we also look at the role of lagged macroeconomic variables in terms of predicting intraday return of the stock market. We focus on the following set of macroeconomic variables: term premium (TERM) defined as the spread between yields on 10-year and 1-year Treasury notes, default spread (DEF) defined as the spread between Moody’s BAA and AAA rated corporate bond yields, and short-term risk-free interest rate (Rate) using 3-month Treasury bills. All macroeconomic data are obtained from St. Louis Federal Reserve Bank. Since these macroeconomic variables are not available in intraday frequency, we use the daily values from the previous trading day.

In Fig. 1 we plot the means and standard deviations of SPY intraday returns as well as changes in investor sentiment in each of the half hours. The sample period is from January 2, 1998 to December 31, 2011. We note that for the SPY intraday returns, the mean returns are very close to zero. The volatility on the other hand seems to exhibit an interesting U-Shape pattern. The market is very volatile during the first half hour, appears to calm down during the lunch hours, and picks up steam again near the end of a trading day. Change in sentiment and especially its volatility also appear to be large during the first half hour, but it flattens out during the rest of the day.

To further cross-validate the interpretation of TRMI as a measure of investor sentiment, we run the following regressions:

$$\Delta Sent_t = \beta_0 + \beta_1 Proxy_t + \varepsilon_t, \tag{1}$$

where $\Delta Sent_t$, is the change in TRMI ($\times 100$) sentiment measure sampled at month *t*. *Proxy* denotes an alternative proxy for investor sentiment. We consider three such proxies: the Baker and Wurgler (2006) investor sentiment index (BW), the University of Michigan consumer sentiment index (UM), and the investor senti-

[1] The website also contains a more detailed description of the data in its user guide section. Please see https://www.marketpsych.com/guide/.

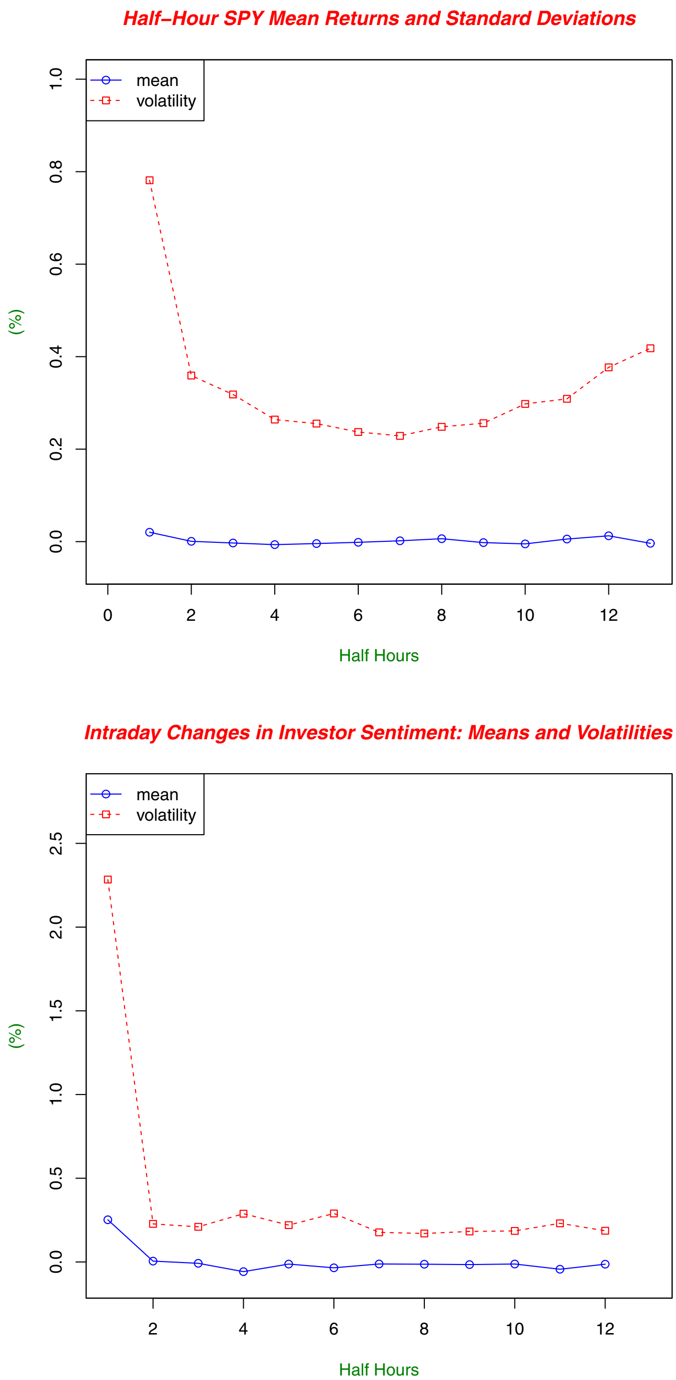

Fig. 1. Means and volatilities of half-hour SPY Intraday returns and changes in investor sentiment this figure plots the means and volatilities of half-hour SPY intraday returns as well as changes in investor sentiment. The sample period is from 01/1998 to 12/2011.

ment index proposed by Huang et al. (PLS). We note that the PLS sentiment index is derived from the BW index by eliminating a common noise component. Therefore in this sense, PLS could be viewed as an improved version of the BW index. We also run similar regressions but replace BW, UM and PLS with their counterparts ($BW^{\perp}$, $UM^{\perp}$, and $PLS^{\perp}$) that are orthogonal to a set of macroeconomic variables as in Baker and Wurgler (2006). The data set is in monthly frequency due to the fact that these regressors are only available in monthly format. The sample period is from January 1998 to December 2010 because the Baker and Wurgler dataset is only available up to 2010.

Table 1
Changes in TRMI vs. other sentiment proxies this table reports results from the following regression:
$\Delta Sent_t = \beta_0 + \beta_1 Proxy_t + \varepsilon_t$,
where $\Delta Sent_t$, is the change in TRMI ($\times$ 100) sentiment measure sampled at month *t*. *Proxy* denotes an alternative proxy for investor sentiment. We consider three sentiment proxies: the (Baker and Wurgler, 2006) investor sentiment index (BW), the University of Michigan consumer sentiment index (UM), and the investor sentiment index proposed by Huang, Jiang, Zhou, and Tu (2014) (PLS). We also run similar regressions but replace BW, UM and PLS with their counterparts ($BW^{\perp}$, $UM^{\perp}$, and $PLS^{\perp}$) that are orthogonal to a set of macroeconomic variables as in Baker and Wurgler (2006). The data set is in monthly frequency. Newey and West (1987) robust t-statistics are reported in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 1998 to December, 2010.

Raw sentiment proxies			
Sentiment proxy	β_0	β_1	adj. R^2 (%)
BW	−0.0235***	0.0049*	1.52
	(−7.677)	(1.790)	
UM	−0.0687***	0.0005***	13.62
	(−7.771)	(5.332)	
PLS	−0.0222***	0.0051***	4.54
	(−8.757)	(2.820)	
Orthogonalized Sentiment Proxies			
Sentiment proxy	β_0	β_1	adj. R^2 (%)
$BW^{\perp}$	−0.0232***	0.0035	0.40
	(−7.420)	(1.161)	
$UM^{\perp}$	−0.0227***	0.0006***	13.41
	(−9.905)	(4.951)	
$PLS^{\perp}$	−0.0232***	0.0046**	3.23
	(−8.516)	(2.125)	

Table 1 reports the results from these regressions. We find that the change in TRMI appears to have a significant and positive relation with all sentiment proxies except for $BW^{\perp}$, where the relation is nominally positive but lacks statistical significance. In particular we find that positive relations between both the raw and orthogonalized UM indexes and the change in TRMI are highly significant. We note that the change in TRMI has a correlation of about 40% with the UM index. In Fig. 2, we plot the time series of UM index against the change in TRMI sentiment variable. By visual inspection of the graph, we can see that the change in TRMI and UM sentiment index appear to move in similar patterns. Taken together, we conclude that overall the evidence is supportive of the notion that the change in TRMI captures investor sentiments.

3. Main empirical evidence

Following GHLZ (2015) among many others in the literature, we focus on the predictive regression approach to assess the predictive value of lagged high-frequency investor sentiment for intraday stock market returns.

3.1. Predictive regressions with high-frequency investor sentiment

First, we evaluate if lagged changes in investor sentiment can predict the future half-hour SPY returns of a given trading day. More formally, we consider the following predictive regression model:

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \epsilon_t, \quad i = 2, \ldots, 13, \tag{2}$$

where $r_{i,\,t}$ is the *i*th half-hour return on the S&P 500 index ETF on day *t*, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. Note that we do not run this regression for the

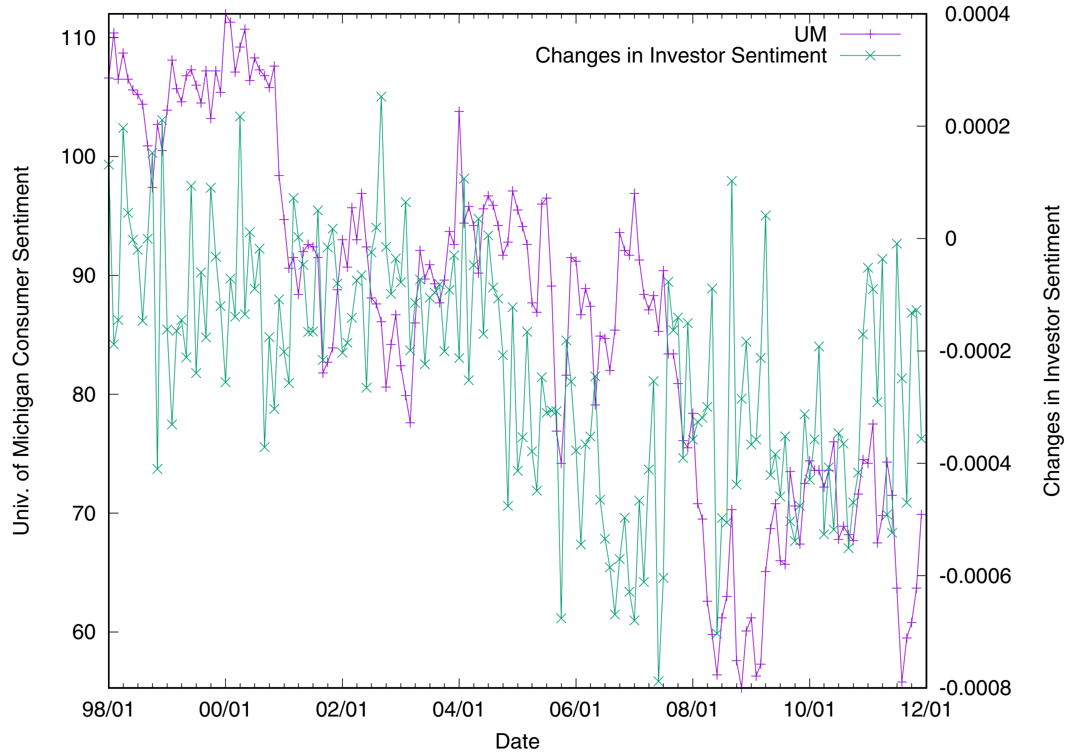

Fig. 2. Change in TRMI investor sentiment and University of Michigan consumer sentiment this figure plots the monthly time series of the change in TRMI investor sentiment vs. University of Michigan Consumer sentiment index. The sample period is from 01/1998 to 12/2011.

first half-hour market return because that will require the use of changes in investor sentiment from a previous trading day, but our focus in this paper is on the predictive value of intraday investor sentiment.

Table 2 reports results for the full sample period from 1998 to 2011. Newey and West (1987) robust t-statistics are shown in parentheses underneath the estimated coefficients. In Panel A, we find striking evidence that the change in investor sentiment variable Δs is significant in all half-hour periods except for the second half hour. In fact, other than the 3rd and 6th half hours where the significance are “only” at the 10% level, it is significant at the 1% level in all other cases. Most notably, for the last four half-hour periods, the t-statistics are all larger than 5. More interestingly, we find that the signs of estimated coefficient for the Δs are positive in all predictive regressions. The closer we are to the end of a trading day, the higher the estimated values of the coefficient β_1 become. We notice that the R^2 values also increase with the passage of trading hours, and eventually exceed the 1% level for the last two hours of a trading day. The R^2 values are 1.02%, 1.63%, 1.68%, and 1.43% for the 10th, 11th, 12th, and last half hour, respectively.

We note that these R^2 values are comparable to those reported by GHLZ (2015) on intraday momentum. In their study, GHLZ report that their most powerful predictor r_1, the first half-hour return, has a R^2 value of 1.6%. Their other predictor r_{12}, the 12th half-hour return, has a R^2 value of 1.1%. GHLZ also note that these numbers match or even exceeds the typical predictive R^2 at the monthly frequency found in the literature.

In Panels B and C of Table 2, we report the results for two subsample periods: the NBER-dated Recessions and Expansions. During our full sample period from 1998 to 2011, the U.S. economy has experienced two recessions: (1) from March 2001 to November 2001, and (2) from December 2007 to June 2009.[2]

Panel B shows that Δs is significant for the 4th, 7th, and the last four half hours of a trading day during the recessions. In terms of R^2 values, it exceeds the 1% level during 7th and the last three half hours. Similar results from Panel C indicates that during expansions, the change in sentiment variable is significant for the 4th, 5th, as well as the last five half hours of a trading day. In terms of R^2 values, it exceeds the 1% level during the last four half hours.

Overall we find the signs for estimates of Δs stay positive in all cases. In terms of t-statistics, the sentiment effect appears stronger during economic expansions than recessions. Since recessions (expansions) are more likely to be associated with low (high) investor sentiment, we conclude that this business-cycle related phenomenon appears consistent with the noise trader model of Yu and Yuan (2011), which predicts that noise traders are more likely to participate in the market when sentiment is high.

The evidence presented in Table 2 suggests much stronger sentiment effect later in the day than during morning hours of a trading day. Since the sentiment effect is strongest during the last four half-hour periods, our subsequent analysis will focus exclusively on them.

3.2. Predictive regressions with high-frequency investor sentiment and lagged returns

Next we run predictive regressions where both lagged changes in sentiment and lagged returns are included as predictors. The inclusion of lagged returns is motivated by the study on intraday momentum by GHLZ (2015).

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13, \quad (3)$$

where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t. Based on the results from Table 2, we focus on the last four half-hour returns. $r_{1,\,t}$ is the first half-hour return, which GHLZ find to be a powerful predictor of the last half-hour return. Since

[2] NBER business cycle dates are obtained from http://www.nber.org/cycles.html.

Table 2
Predictability of Intraday stock market returns with lagged change in investor sentiment this table reports results from the following predictive regressions:
$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \epsilon_t, \quad i = 2, \ldots, 13,$
where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. Panels A, B, and C report results for three periods: the whole sample period, the NBER-dated Recessions from March 2001 to November 2001 and from December 2007 to June 2009, and the NBER-dated Expansions, respectively. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

Half-hour return period	β_0	β_1	R^2(%)
Panel A: Full sample period from 1998 to 2011			
2nd Half-hour	−0.000	0.001	0.00
	(-0.14)	(0.41)	
3rd Half-hour	−0.000	0.040*	0.08
	(−0.42)	(1.70)	
4th Half-hour	−0.000	0.072***	0.33
	(−1.04)	(3.21)	
5th Half-hour	−0.000	0.049***	0.31
	(−0.32)	(2.81)	
6th Half-hour	−0.000	0.045*	0.18
	(−0.11)	(1.91)	
7th Half-hour	0.000	0.036***	0.20
	(0.52)	(2.65)	
8th Half-hour	0.000*	0.049*	0.12
	(1.71)	(1.71)	
9th Half-hour	−0.000	0.084***	0.31
	(−0.05)	(2.92)	
10th Half-hour	−0.000	0.165***	1.02
	(−0.56)	(5.46)	
11th Half-hour	0.000	0.213***	1.63
	(1.59)	(6.30)	
12th Half-hour	0.000***	0.212***	1.68
	(3.26)	(6.52)	
The Last Half-hour	0.000	0.269***	1.43
	(0.00)	(5.35)	
Panel B: Business Cycles - Recession			
2nd Half-hour	−0.000	0.005	0.05
	(−0.07)	(0.54)	
3rd Half-hour	0.000	0.104	0.23
	(0.48)	(1.52)	
4th Half-hour	−0.000*	0.116*	0.44
	(−1.85)	(1.73)	
5th Half-hour	−0.000	0.033	0.09
	(−0.82)	(0.77)	
6th Half-hour	0.000	0.093	0.23
	(0.30)	(1.32)	
7th Half-hour	−0.000	0.166***	1.27
	(−0.32)	(3.15)	
8th Half-hour	0.000	0.152	0.54
	(0.51)	(1.55)	
9th Half-hour	-0.000	0.086	0.15
	(-1.06)	(0.98)	
10th Half-hour	-0.000	0.211**	0.70
	(-0.20)	(2.25)	
11th Half-hour	0.001***	0.394***	2.29
	(2.95)	(2.95)	
12th Half-hour	0.000	0.412***	1.79
	(1.24)	(2.98)	
The Last Half-hour	0.000	0.476**	1.86
	(0.93)	(2.55)	
Panel C: Business Cycles - Expansion			
2nd Half-hour	-0.000	0.000	0.00
	(-0.07)	(0.09)	
3rd Half-hour	-0.000	0.029	0.06
	(-0.97)	(1.16)	
4th Half-hour	0.000	0.059**	0.28
	(0.14)	(2.57)	
5th Half-hour	0.000	0.053***	0.42
	(0.16)	(2.77)	
6th Half-hour	-0.000	0.039	0.19
	(-0.31)	(1.64)	
7th Half-hour	0.000	0.019	0.08
	(1.04)	(1.31)	
8th Half-hour	0.000*	0.027	0.05
	(1.79)	(0.97)	

(continued on next page)

Table 2 (*continued*)

Half-hour return period	β_0	β_1	R^2(%)
9th Half-hour	0.000	0.082***	0.41
	(0.78)	(2.88)	
10th Half-hour	-0.000	0.156***	1.27
	(-0.55)	(5.09)	
11th Half-hour	-0.000	0.176***	1.59
	(-0.27)	(5.85)	
12th Half-hour	0.000***	0.180***	2.04
	(3.37)	(6.21)	
The Last Half-hour	-0.000	0.216***	1.45
	(-0.72)	(5.16)	

Table 3

Predictability of Intraday stock market returns with lagged change in investor sentiment and lagged returns this table reports results from the following predictive regressions: $r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13,$ where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. Panels A, B, and C report results for three periods: the whole sample period, the NBER-dated recessions from March 2001 to November 2001 and from December 2007 to June 2009, and the NBER-dated expansions, respectively. Panel D shows the results for a similar regression after controlling for volatility: $r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 \sigma_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13,$, where $\sigma_{i-1,t}$ is the volatility calculated using a rolling window of 65 lagged half-hour returns. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

Half-hour return period	β_0	β_1	β_2	β_3	Adj. R^2(%)
Panel A: Full sample period from 1998 to 2011					
10th Half-hour	−0.000	0.170***	−0.001	−0.046	1.08
	(−0.55)	(5.52)	(−0.11)	(−1.14)	
11th Half-hour	0.000	0.208***	0.002	0.026	1.60
	(1.58)	(5.63)	(0.22)	(0.62)	
12th Half-hour	0.000***	0.207***	0.013	0.014	1.67
	(3.13)	(6.31)	(0.74)	(0.38)	
The last half-hour	−0.000	0.203***	0.066***	0.101**	3.66
	(−0.49)	(4.19)	(3.67)	(2.10)	
Panel B: Business cycles - recession					
10th Half-hour	−0.000	0.201**	0.005	0.018	0.21
	(−0.16)	(2.14)	(0.24)	(0.24)	
11th Half-hour	0.001***	0.367**	0.017	0.035	2.04
	(3.03)	(2.44)	(0.75)	(0.41)	
12th Half-hour	0.000	0.398***	0.017	0.002	1.36
	(1.33)	(2.82)	(0.41)	(0.04)	
The last half-hour	0.000	0.308*	0.096**	0.130	5.15
	(0.97)	(1.82)	(2.53)	(1.48)	
Panel C: Business cycles - Expansion					
10th Half-hour	−0.000	0.163***	−0.005	−0.091**	1.78
	(−0.43)	(5.19)	(−0.52)	(−2.22)	
11th Half-hour	−0.000	0.176***	−0.006	0.019	1.53
	(−0.21)	(5.74)	(−0.58)	(0.50)	
12th Half-hour	0.000***	0.176***	0.009	0.017	1.99
	(3.22)	(6.01)	(0.70)	(0.39)	
The last half-hour	−0.000	0.180***	0.046***	0.069*	2.63
	(−1.17)	(4.42)	(2.99)	(1.74)	

Panel D: Predictive regression with volatility						
10th Half-hour	0.000	0.173***	−0.001	−0.047	−0.043	1.21
	(0.49)	(5.52)	(−0.07)	(−1.22)	(−0.80)	
11th Half-hour	−0.000	0.197***	0.004	0.026	0.091	1.77
	(−1.32)	(5.72)	(0.34)	(0.65)	(1.54)	
12th Half-hour	−0.000*	0.204***	0.013	0.008	0.217**	2.78
	(−1.70)	(6.50)	(0.76)	(0.25)	(2.16)	
The Last Half-hour	0.000	0.205***	0.063***	0.089*	−0.009	3.33
	(0.03)	(4.57)	(3.68)	(1.89)	(−0.11)	

the returns are calculated on close-to-close basis, r_1 actually contains useful information from overnight. $\Delta s_{i-1,t}$ and $r_{i-1,t}$ are the lagged change in investor sentiment and lagged half-hour return respectively.

Panel A of Table 3 reports the results for the full sample period. Panels B and C of the same table report results for the NBER-dated recessions from March 2001 to November 2001 and from December 2007 to June 2009, and the NBER-dated expansions, respectively.

We find strong evidence that lagged changes in investor sentiment is the most predominant predictor even in the presence of the lagged return variables. For example, the estimated coefficients on Δs are significant in all cases. In fact they are highly significant at the 1% level both for the full sample and during the NBER-dated expansions. The results are slightly weaker during recession. But even in the weakest case, which is for the last half-hour during recessions, it is still significant at the 10% level.

In addition, we find that our results from the predictive regression for the last half-hour returns are remarkably consistent with the findings from GHLZ (2015). For example, based on a sample from 1993 to 2013, GHLZ report that in a predictive regression where the two lagged returns are the only two predictors, the estimated coefficient on r_1 is 0.068 with a Newey–West t-statistic of 4.14. Similarly, we find that the estimated coefficient on r_1 is 0.066 with a Newey-West t-statistic of 3.67. Note that we include the change in sentiment variable in the predictive regression and our sample is from 1998 to 2011. The results on the other predictor r_{12} are also very similar. GHLZ report a coefficient of 0.114 with a t-statistic of 2.60. We find the estimated coefficient to be 0.101 with a t-statistic of 2.10. GHLZ also report an R^2 value of 2.6% with the two lagged return predictors. We report an adjusted R^2 of 3.66% with the addition of our sentiment variable.

However, we also find that the predictive power of the lagged return variables are only limited to the last-half hour. In fact, for the 10th, 11th, and 12th half-hour predictive regressions, none of the lagged return variables are significant. The only exception is the r_9 variable in the 10th half hour during NBER-dated expansions, which is significant at the 5% level. However, its estimated coefficient is negative, which is inconsistent with the interpretation of intraday momentum as argued by GHLZ.

In Panel D of Table 3, we control for the volatility effect by running the following regression:

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 \sigma_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13, \tag{4}$$

where σ_{i-1} is the estimated volatility based on a rolling estimation window of 65 past half-hour returns. In comparison with the results from panels A, B, and C, we find that the results are almost identical. Estimates of β_1 remain highly significant in all cases. In contrast, β_4, the coefficient on volatility is mostly insignificant with the exception of the 12th half hour.

As an additional robustness check, we also run regressions based on whether the change in sentiment variable Δs is positive or negative. We find that the change in sentiment variable is highly significant regardless of its signs. We do not report these results in tabulated form because they are similar to the unconditional results shown in Panel A of Table 3.

Overall, the evidence presented here suggests that the sentiment effect is distinct from the intraday momentum effect. We find overwhelming evidence that impact from changes in investor sentiment on intraday market returns is much more pervasive than lagged return variables. The intraday momentum effect of GHLZ appears to exist only for the last half hour, whereas the sentiment effect persists in at least the last two hours of a trading day. Our results are robust after controlling for the volatility effect.

4. Robustness checks

In this section, we check the robustness of the sentiment effect by looking at its seasonality both monthly and by weekdays. We also check the roles of macroeconomic variables and alternative measures of investor sentiment.

4.1. Seasonality

Seasonality is often an important trait of an asset pricing anomaly. For example, Cooper et al. (2006) document that there exists a so-called the Other January effect for the US market indexes to differentiate it from the well-known small-firm in January effect. Da et al. (2015) also find that their sentiment index derived from Google search volumes exhibits weekly seasonality. Thus to alleviate concerns about seasonality, we first run the following predictive regression by calendar months to see if our results are driven by any particular month.

$$r_{i,mt} = \beta_0 + \beta_1 \Delta s_{i-1,mt} + \beta_2 r_{1,mt} + \beta_3 r_{i-1,mt} + \epsilon_{mt}, \quad i = 10, \ldots, 13, \tag{5}$$

where $m = January, February, \ldots, December$.

Table 4 report the results based on calendar months. We find that the change in sentiment variable is significant for a majority number of months in a year. For example, it is significant from April to October for both the 10th and 11th half hours, from May to October as well as in January and December for the 12th half hour, and from May to August as well as in January and October for the last half hour.

In contrast, we find that the lagged return variables are mostly insignificant for the 10th, 11th, and 12th half hours. For the last half hour, the r_1 variable is significant in January, March, May, and November. The r_{12} variable is significant in March, July, August, and November. Interestingly, we note that the intraday momentum effect is particular strong in November with an adjusted R^2 of 18.83%.

Next we run the following predictive regression to detect seasonality by weekdays.

$$r_{i,wt} = \beta_0 + \beta_1 \Delta s_{i-1,wt} + \beta_2 r_{1,wt} + \beta_3 r_{i-1,wt} + \epsilon_{wt}, \quad i = 10, \ldots, 13, \tag{6}$$

where $w = Monday, Tuesday, \ldots, Friday$.

We report the results in Table 5. Once again we find that the impact from investor sentiment is pervasive. It is significant in all weekdays except for Thursday in the 10th half hour, significant from Tuesday to Friday in the 11th half hour, Monday to Friday for the 12th half hour, and from Tuesday to Thursday in the last half hour. In contrast, the lagged return variables are mostly insignificant (or significant but have a negative sign) for the 10th, 11th, and 12th half hours. For last half hour, the lagged returns appear to have gained significance. The r_1 variable is significant for Monday, Wednesday, and Friday. r_{12} however is only significant on Tuesday.

To sum up, we find that the sentiment effect is a widespread phenomenon. It shows up during majority of the months and almost every weekday. In contrast, we find that the intraday momentum effect seems to be less pervasive.

4.2. The role of macroeconomic variables

We investigate the impact from a standard set of macroeconomic variables. Since intraday macroeconomic variables are typically not feasible, we rely on macroeconomic variables that are available at daily frequency. This leaves us with three commonly used macroeconomic variables: term premium (Term), default spread (Def), and short-term risk-free interest rate (Rate). For formal definitions of these variables, please see Section 2.

Table 6 reports results based on the following predictive regression model where lagged values (from the previous trading day) of the three macroeconomic variables are included:

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 Term_{t-1} + \beta_5 Def_{t-1} + \beta_6 Rate_{t-1} + \epsilon_t, \tag{7}$$

where $i = 10\text{th}, \ldots, 13\text{th}$ half hour.

We find that none of these macroeconomic variables can explain intraday sentiment effect. The only case that a macroeconomic variable is significant is the default spread during the 11th half hour. However even in that case, the estimated coefficient is extremely small (0.001). In all other cases, the estimated coefficients on macroeconomic variables are indistinguishable from zero.

Table 4
Robustness check: Monthly seasonality this table reports results from the following predictive regressions:
$r_{i,mt} = \beta_0 + \beta_1 \Delta s_{i-1,mt} + \beta_2 r_{1,mt} + \beta_3 r_{i-1,mt} + \epsilon_{mt}, \quad i = 10, \ldots, 13,$
where $m = January, February, \ldots, December$, r_i is the ith half-hour return on the S&P 500 index ETF, r_1 is the first half-hour return, and Δs_{i-1} denotes the change in investor sentiment in the $(i-1)$th half-hour. (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

Month	β_0	β_1	β_2	β_3	Adj. R^2(%)
Panel A: Predictive regressions for the 10th Half-hour					
January	0.000	−0.012	−0.026	0.046	−0.50
	(1.10)	(−0.13)	(−0.90)	(0.38)	
February	0.000	0.106	−0.004	−0.066	−0.65
	(0.70)	(0.94)	(−0.12)	(−0.72)	
March	−0.000	0.140	−0.014	0.007	−0.53
	(−0.23)	(1.46)	(−0.53)	(0.08)	
April	0.000	0.357***	0.004	−0.229*	7.35
	(0.16)	(2.62)	(0.14)	(−1.94)	
May	0.000	0.190**	0.008	−0.031	0.94
	(0.08)	(2.22)	(0.26)	(−0.34)	
June	−0.000	0.205*	−0.013	0.035	1.17
	(−0.38)	(1.67)	(−0.40)	(0.39)	
July	−0.000	0.246***	0.045**	−0.120	3.94
	(−0.99)	(3.36)	(1.98)	(−0.83)	
August	−0.000	0.269***	−0.013	0.125	2.91
	(−0.72)	(2.84)	(−0.64)	(1.06)	
September	−0.000	0.225**	0.029	−0.122	2.64
	(−0.28)	(2.36)	(1.55)	(−1.16)	
October	−0.000	0.415***	−0.018	−0.057	3.16
	(−0.98)	(4.05)	(−0.49)	(−0.66)	
November	0.000	0.036	−0.028	−0.019	−0.81
	(1.00)	(0.30)	(−0.58)	(−0.08)	
December	−0.000	−0.023	0.013	−0.135	0.17
	(−1.22)	(−0.56)	(0.28)	(−1.31)	
Panel B: Predictive regressions for the 11th half-hour					
January	0.000	0.066	0.095**	0.089	6.03
	(0.08)	(0.95)	(2.26)	(1.19)	
February	−0.000	0.059	0.010	0.010	−1.16
	(−1.00)	(0.45)	(0.21)	(0.09)	
March	0.000*	0.052	0.048*	0.106	1.93
	(1.86)	(0.41)	(1.80)	(1.03)	
April	−0.000*	0.383***	−0.001	0.074	7.14
	(−1.82)	(4.45)	(−0.03)	(0.71)	
May	0.000	0.192**	−0.035*	0.227*	7.27
	(0.35)	(2.47)	(−1.67)	(1.68)	
June	−0.000	0.203**	0.017	−0.071	2.07
	(−0.75)	(2.21)	(0.59)	(−1.18)	
July	0.000	0.296***	−0.031	0.080	3.12
	(0.69)	(3.02)	(−1.00)	(0.65)	
August	0.000	0.404**	−0.031	−0.135	3.33
	(0.24)	(2.46)	(−0.81)	(−1.13)	
September	0.000	0.358***	0.015	−0.109	4.07
	(1.57)	(3.06)	(0.72)	(−1.32)	
October	0.000**	0.349***	−0.024	0.077	2.58
	(2.02)	(2.72)	(−0.67)	(0.46)	
November	−0.000	0.070	0.022	0.097	0.12
	(−0.48)	(0.59)	(0.65)	(0.88)	
December	0.000	0.090	−0.063	−0.113	2.03
	(0.89)	(0.50)	(−1.61)	(−0.84)	
Panel C: Predictive Regressions for the 12th Half-hour					
January	−0.000	0.200*	0.004	−0.017	0.03
	(−0.21)	(1.67)	(0.09)	(−0.19)	
February	0.000**	0.065	−0.081*	−0.061	1.36
	(2.06)	(0.57)	(−1.73)	(−0.65)	
March	0.000	0.041	0.039	−0.053	−0.05
	(0.44)	(0.41)	(1.05)	(−0.55)	
April	−0.000	0.142	0.016	0.092	0.96
	(−0.49)	(1.24)	(0.46)	(0.61)	
May	0.000	0.160***	−0.045	−0.169	3.85
	(0.93)	(2.76)	(−1.29)	(−1.23)	
June	−0.000	0.076*	−0.046	0.228***	5.40
	(−1.32)	(1.92)	(−1.58)	(2.93)	
July	0.001**	0.298**	−0.040	0.035	3.22
	(2.35)	(2.05)	(−0.79)	(0.34)	
August	0.000**	0.287***	0.039	0.009	4.39
	(2.01)	(3.10)	(0.88)	(0.07)	
September	0.000*	0.298***	0.072**	0.001	7.09
	(1.66)	(2.72)	(2.16)	(0.01)	

(continued on next page)

Table 4 (*continued*)

Month	β_0	β_1	β_2	β_3	Adj. R^2(%)
October	0.001*	0.559***	−0.021	0.101	2.70
	(1.95)	(2.93)	(−0.25)	(0.90)	
November	0.000	0.122	0.055	−0.142	1.69
	(0.96)	(0.75)	(0.99)	(−1.33)	
December	−0.000	0.339***	0.092	0.073	7.21
	(−1.08)	(2.75)	(1.64)	(0.68)	
Panel D: Predictive Regressions for the Last Half-hour					
January	0.000	0.229**	0.096***	−0.016	5.57
	(0.51)	(2.02)	(3.46)	(−0.14)	
February	−0.000	0.133	0.015	0.038	−0.49
	(−1.05)	(1.14)	(0.39)	(0.27)	
March	−0.000*	0.097	0.108***	0.202*	8.69
	(−1.96)	(0.82)	(3.17)	(1.96)	
April	0.000	0.102	0.030	−0.059	−0.03
	(1.06)	(1.25)	(0.75)	(−0.71)	
May	0.000	0.372***	0.078***	0.074	7.46
	(1.40)	(3.37)	(2.75)	(0.90)	
June	−0.000	0.203**	0.031	0.049	1.24
	(−1.29)	(2.00)	(0.95)	(0.61)	
July	−0.000	0.252*	−0.036	0.152**	4.38
	(−0.32)	(1.89)	(−1.01)	(2.36)	
August	−0.000	0.322*	0.081	0.298*	10.20
	(−1.30)	(1.87)	(1.43)	(1.94)	
September	0.000	0.230	0.020	−0.096	0.08
	(0.22)	(1.20)	(0.53)	(−0.90)	
October	0.000	0.489*	0.093	0.040	4.02
	(0.33)	(1.88)	(1.11)	(0.44)	
November	−0.000	−0.050	0.164***	0.493**	18.83
	(−0.86)	(−0.23)	(3.81)	(2.22)	
December	0.000	−0.021	0.033	−0.027	−0.68
	(0.33)	(−0.19)	(0.48)	(−0.25)	

4.3. Alternative measures of investor sentiment

Next we investigate whether our main results are robust to the inclusion of alternative measures of investor sentiment. We consider three alternative measures of sentiment: the CBOE volatility index (VIX), change in VIX, and market state as defined by the sign of lagged 250-day (one-year) market return. Similar to the case of macroeconomic variables, we include only lagged values from the previous trading day in the predictive regressions. For details about the construction of these variables, please refer to Section 2.

Specifically, we estimate the following predictive regression models:

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 VIX_{t-1} + \beta_5 \Delta VIX_{t-1} + \beta_6 State_{t-1} + \epsilon_t, \quad (8)$$

where $i = 10\text{th}, \ldots, 13\text{th}$ half hour. *VIX* is the CBOE Volatility Index, ΔVIX refers to the change in VIX, and *State* is the Market State variable.

Results from Table 7 show that interestingly at least for the last hour of a trading day, these alternative sentiment measures do have some explanatory power. For example, in the 12th half hour, we find that lagged VIX and market state are significant at the 5% level. In the last half hour, the change in VIX appears highly significant at the 1% level.

In terms of adjusted R^2 values, the alternative sentiment measures also appear to be useful. For the 12th half hour, the adjusted R^2 increases from about 1.67% in Panel A of Table 3 to about 2.93%. For the last half hour, with ΔVIX, the adjusted R^2 also increases from about 3.66% in Panel A of Table 3 to about 4.76% in the current table.

However, in the other two half hours, these alternative measures do not appear to carry any significance. In contrast, our intraday sentiment variable remains highly significant in all cases.

5. Market timing trading strategies and discussion of empirical results

In this section, we study the performance of market timing trading strategies to evaluate the economic significance of sentiment-based intraday return predictability. We first describe these trading strategies, and then evaluate their performance based on two popular metrics: Sharpe ratio and certainty-equivalent return. We also briefly discuss why the predictive power is stronger later in the trading day than in the early trading hours.

5.1. Strategy formulation

Our results so far have established the predictability of intraday returns by high-frequency investor sentiment from a statistical perspective. In addition to statistical significance, it is also important to evaluate the economic value of investor sentiment when implemented on some trading strategies. To this end, we propose the following market timing trading strategies.

To begin with, consider the trading strategies used by GHLZ. Since they focus on the return variables only, GHLZ's strategy takes a long position in the SPY if r_1, the first half hour return, is positive, and a short position if r_1 is negative. In the case of two predictors r_1 and r_{12}, GHLZ's strategy will take a long (short) position if and only if both predictors are positive (negative). While this is a simple strategy to implement, it cannot be easily extended to cases where there are more than two predictors or when non-return predictors are used. For example, GHLZ report that their trading strategy with two predictors r_1 and r_{12} has a success rate of 77% compared to the 54% by the strategy that uses only r_1. However, the mean return of the two-predictor strategy is only 4.49% compared to the 6.19% by the one-predictor strategy. Presumably this is because the strategy with two predictors is more likely to stay out of the market when the two predictors give conflicting signals. Now if we extend their approach to three or four predictors, then

Table 5
Robustness check: Weekday seasonality this table reports results from the following predictive regressions:
$r_{i,wt} = \beta_0 + \beta_1 \Delta s_{i-1,wt} + \beta_2 r_{1,wt} + \beta_3 r_{i-1,wt} + \epsilon_{wt}, \quad i = 10, \ldots, 13,$
where $w = Monday, Tuesday, \ldots, Friday$, r_i is the ith half-hour return on the S&P 500 index ETF, r_1 is the first half-hour return, and Δs_{i-1} denotes the change in investor sentiment in the $(i-1)$th half-hour. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

Weekday	β_0	β_1	β_2	β_3	Adj. R^2(%)
Panel A: Predictive regressions for the 10th half-hour					
Monday	−0.000	0.263***	0.033*	−0.057	4.23
	(−0.86)	(3.70)	(1.87)	(−0.63)	
Tuesday	−0.000	0.207***	0.004	−0.048	1.07
	(−0.40)	(3.11)	(0.18)	(−0.51)	
Wednesday	0.000	0.176**	−0.047**	0.025	1.77
	(0.02)	(2.25)	(−2.07)	(0.40)	
Thursday	−0.000	0.049	0.003	0.081	0.11
	(−0.40)	(0.79)	(0.15)	(0.97)	
Friday	−0.000	0.116**	−0.011	−0.26***	6.18
	(−0.16)	(2.55)	(−0.55)	(−4.20)	
Panel B: Predictive regressions for the 11th half-hour					
Monday	0.000	0.066	0.019	0.050	0.70
	(0.19)	(1.08)	(0.81)	(0.64)	
Tuesday	0.000	0.150*	0.009	−0.029	0.30
	(0.12)	(1.68)	(0.24)	(−0.32)	
Wednesday	0.000	0.356***	0.027	−0.013	4.63
	(1.59)	(5.11)	(1.22)	(−0.24)	
Thursday	0.000	0.248***	0.002	0.075	2.69
	(0.01)	(2.94)	(0.07)	(1.05)	
Friday	0.000	0.238**	−0.055	0.099	3.27
	(0.97)	(2.56)	(−1.29)	(1.03)	
Panel C: Predictive regressions for the 12th half-hour					
Monday	0.000**	0.200***	−0.020	0.191*	3.56
	(2.45)	(2.87)	(−0.59)	(1.87)	
Tuesday	0.000**	0.248***	0.068**	−0.063	4.24
	(1.97)	(3.34)	(2.21)	(−0.81)	
Wednesday	−0.000	0.292***	0.024	0.078	3.57
	(−0.68)	(4.10)	(0.75)	(1.08)	
Thursday	0.000	0.327***	0.025	0.050	2.76
	(1.49)	(3.26)	(0.83)	(0.41)	
Friday	0.000	0.095*	−0.048	−0.113	1.31
	(1.38)	(1.92)	(−0.75)	(−1.58)	
Panel D: Predictive Regressions for the Last Half-hour					
Monday	−0.000	0.048	0.101***	0.61	4.19
	(−0.63)	(0.36)	(3.51)	(0.65)	
Tuesday	−0.000	0.350***	0.048	0.236***	10.28
	(−1.15)	(3.86)	(1.24)	(2.94)	
Wednesday	−0.000	0.303***	0.065**	−0.035	2.66
	(−0.98)	(2.71)	(2.03)	(−0.25)	
Thursday	0.000	0.191**	0.006	0.133	2.77
	(0.45)	(2.47)	(0.17)	(1.14)	
Friday	0.000	0.079	0.089**	0.094	3.13
	(1.07)	(0.98)	(2.52)	(0.71)	

the strategies are likely to stay out of the market for longer periods of time and therefore make them ineffective.

Instead we propose a market timing strategy where the setup is based on an out-of-sample predictive regressions approach. This allows us to implement the strategy where the number of predictors could be large and they are not necessarily return-based predictors. Specifically, given a sample of size T and a set of predictors that includes a constant $X \equiv [1, x_1, x_2, \ldots, x_n]$, we use an initial estimation window size of M, where $M < T$, and run the regression $r_i = X'\beta + \varepsilon$ to obtain the coefficient estimates $\widehat{\beta}$, where r_i is the market return at i-th half hour. Combined with the new observations at $t = M+1$ for the predictors, we can proceed to calculate the model predicted value for r_i at $t = M+1$, namely $\hat{r}_{i,M+1} = \widehat{\beta}' X_{M+1}$. This process is iterated by adding one more observation each time until we reach the end of the sample. Our trading signals are generated as follows: take a long position in the S&P 500 ETF if the predicted return for the i-th half hour is positive and otherwise take a short position. More formally, the strategy's return on day t based on the vector of predictors X is calculated as follows:

$$\eta(X) = \begin{cases} r_i & \text{if } \hat{r}_i > 0, \\ -r_i & \text{if } \hat{r}_i \le 0. \end{cases} \tag{9}$$

These returns are then used to calculate the performance evaluation metrics for the sample period from $t = M+1$ to $t = T$.

We consider the following three trading strategies: a benchmark model based on the sample mean, a model with Δs as the only predictor, and a model with lagged returns r_1 and r_{i-1} as predictors. Note that the benchmark strategy is equivalent to the case where only the constant term is included in the predictive regression. Thus from a Bayesian perspective, investors who have a dogmatic prior belief that none of the predictors are useful should implement this benchmark strategy.

5.2. Performance evaluation metrics

We consider two performance evaluation metrics. The first is the Sharpe ratio defined as follows:

$$\widehat{SR}_j = \frac{\hat{\mu}_j - r_f}{\hat{\sigma}_j}, \tag{10}$$

where $\hat{\mu}_j$ and $\hat{\sigma}_j$ are the sample mean and standard deviation of returns for strategy j and r_f is the risk-free rate. Following GHLZ, we set daily risk-free rate to zero.

To test whether the Sharpe ratios of different strategies are statistically distinguishable, we follow DeMiguel et al. (2009) (DGU) and report the p-value of the difference of the Sharpe ratios, using the approach suggested by Jobson and Korkie (1981) with adjustments proposed by Memmel (2003). Specifically, given two trad-

Table 6
Predictability of Intraday stock market returns: The role of macroeconomic variables this table reports results from the following predictive regressions:
$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 Term_{t-1} + \beta_5 Def_{t-1} + \beta_6 Rate_{t-1} + \epsilon_t, \quad i = 10, \ldots, 13,$
where $r_{i,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, $r_{1,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. We also include three lagged macroeconomic variables: term spread (*Term*), default spread (*Def*), and short-term interest rate (*Rate*). (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January 1998 to December 2011.

Half-hour return period	β_0	β_1	β_2	β_3	β_4	β_5	β_6	Adj. R^2(%)
10th Half-hour	−0.000	0.187***	−0.003	−0.051	−0.000	0.000	−0.000	1.13
	(−0.29)	(5.72)	(−0.28)	(−1.21)	(−0.01)	(0.70)	(−0.14)	
11th Half-hour	−0.001	0.207***	0.006	0.020	0.000	0.001**	0.000	2.26
	(−1.24)	(5.56)	(0.56)	(0.48)	(0.10)	(2.44)	(0.36)	
12th Half-hour	0.000	0.214***	0.011	0.020	0.000	0.000	0.000	1.62
	(0.20)	(6.28)	(0.56)	(0.47)	(0.02)	(0.02)	(0.35)	
The last Half-hour	0.000	0.219***	0.062***	0.108**	−0.000	0.000	−0.000	3.69
	(0.37)	(4.31)	(3.20)	(2.20)	(−0.94)	(0.75)	(−1.17)	

Table 7

Predictability of Intraday stock market returns: Alternative measures of investor sentiment this table reports results from the following predictive regressions:

$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \beta_4 VIX_{t-1} + \beta_5 \Delta VIX_{t-1} + \beta_6 State_{t-1} + \epsilon_t, \quad i = 10, \ldots, 13,$

where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. We also include three lagged values of the following three sentiment variables: CBOE's Volatility Index (*VIX*), change in VIX (ΔVIX), and Market State (*State*). (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is given by an ***, an ** or an *, respectively. The sample period is from January 1998 to December 2011.

Half-hour return period	β_0	β_1	β_2	β_3	β_4	β_5	β_6	Adj. R^2(%)
10th Half-hour	0.000	0.179***	−0.001	−0.048	−0.000	−0.000	−0.000	1.17
	(0.28)	(5.76)	(−0.10)	(−1.17)	(−0.33)	(−1.03)	(−0.25)	
11th Half-hour	−0.000	0.204***	0.003	0.027	0.000	0.000	−0.000	1.91
	(−0.92)	(5.85)	(0.29)	(0.65)	(1.39)	(0.07)	(−0.16)	
12th Half-hour	−0.001*	0.185***	0.013	0.007	0.00004**	0.000	0.0003**	2.93
	(−1.87)	(5.99)	(0.74)	(0.19)	(2.02)	(1.58)	(1.98)	
The last half-hour	−0.000	0.166***	0.066***	0.090*	0.000	0.0002***	−0.000	4.76
	(−0.30)	(3.51)	(3.71)	(1.92)	(0.41)	(3.23)	(−0.55)	

ing strategies j and k, denote the estimated means, standard deviations, and covariance of portfolio returns over a sample of size T as follows: $\hat{\mu}_j$, $\hat{\mu}_k$, $\hat{\sigma}_j$, $\hat{\sigma}_k$, and $\hat{\sigma}_{j,k}$ respectively. For the null hypothesis $H_0 : \hat{\mu}_j/\hat{\sigma}_j - \hat{\mu}_k/\hat{\sigma}_k = 0$, one can use the test statistic:

$$\hat{z}_{j,k} = \frac{\hat{\sigma}_k \hat{\mu}_j - \sigma_j \hat{\mu}_k}{\sqrt{\zeta}}, \tag{11}$$

where

$$\zeta = \frac{1}{T}\left(2\hat{\sigma}_j^2\hat{\sigma}_k^2 - 2\hat{\sigma}_j\hat{\sigma}_k\hat{\sigma}_{j,k} + \frac{1}{2}\hat{\sigma}_k^2\hat{\mu}_j^2 + \frac{1}{2}\hat{\sigma}_j^2\hat{\mu}_k^2 - \frac{\hat{\mu}_j\hat{\mu}_k}{\hat{\sigma}_j\hat{\sigma}_k}\hat{\sigma}_{j,k}^2\right) \tag{12}$$

which is asymptotically distributed as a standard normal.

The second performance evaluation metric is the certainty-equivalent return (CEQ) defined as the risk-free rate that an investor is willing to accept rather than adopting a particular risky strategy. Following DGU, it is computed as follows:

$$\widehat{CEQ}_j = \hat{\mu}_j - \frac{\gamma}{2}\hat{\sigma}_j^2, \tag{13}$$

where γ is the risk-aversion parameter. In our empirical results, we initially set $\gamma = 3$. This choice is based on a recent study by Guiso et al. (2014), who find that empirically the average risk aversion increases from 2.87 before the 2008 financial crisis to 3.28 after the crisis. As a robustness check, we also compute results based on $\gamma = 10$.

The CEQ metric defined in this manner actually refers to the level of expected utility of a mean-variance investor. DGU note that this is approximately the CEQ of an investor with quadratic utility. Therefore it measures the economic significance of a given strategy. To test whether the CEQ returns from two strategies are statistically different, we can compute the p-value of the difference following the procedure described in DGU. Specifically, given two trading strategies j and k, let v denote the vector of moments $v = (\mu_j, \mu_k, \sigma_j^2, \sigma_k^2)$, $\hat{v}$ its empirical counterpart obtained from a sample of size T. Further denote $f(v) = (\mu_j - \frac{\gamma}{2}\sigma_j^2) - (\mu_k - \frac{\gamma}{2}\sigma_k^2)$ the difference in CEQ of the two strategies. DGU note that the asymptotic distribution of $f(v)$ is $\sqrt{T}(f(\hat{v}) - f(v)) \to N\left(0, \frac{\partial f}{\partial v}^T \Psi \frac{\partial f}{\partial v}\right)$, where

$$\Psi = \begin{pmatrix} \sigma_j^2 & \sigma_{j,k} & 0 & 0 \\ \sigma_{j,k} & \sigma_k^2 & 0 & 0 \\ 0 & 0 & 2\sigma_j^4 & 2\sigma_{j,k}^2 \\ 0 & 0 & 2\sigma_{j,k}^2 & 2\sigma_k^4 \end{pmatrix}$$

Table 8 reports the annualized mean, standard deviation, Sharpe ratio, and CEQs for each strategy under consideration. Our initial estimation window size is $M = 250$ days. Panels A, B, C, and D report the results for the 10th, 11th, 12th, and the last half hour returns respectively.

Interestingly we find that the strategies have remarkably similar volatilities. For example, for the 10th half-hour returns, the volatility of all strategies are around 4.66%. For the last half hour, they are around 6.5%. On the other hand, the performance of each strategy shows significant disparity in terms of their mean returns. For example, in the 11th half hour, the strategy that uses Δs as the only predictor earns about 9.43%. In contrast, the benchmark strategy based on sample mean only has a mean return of approximately 1%.

We find that the best performer in all cases is the strategy that relies only on the predictive power of Δs. This conclusion is based on mean return, Sharpe ratio, as well as CEQs. For the 10th, 11th, and 12th half hours, the sentiment-based strategy significantly outperforms the two competitors. For example, in the 12th half hour, when evaluated based on the CEQ metric with a risk aversion parameter of 10, the sentiment strategy achieves a CEQ of about 8%, which is far superior to the 1% attained by the benchmark sample mean strategy. Interestingly, the strategy based on lagged returns has a negative CEQ, which means it is significantly worse than the benchmark strategy.

Consistent with GHLZ's finding, we find that, for the last half hour, the strategy based on lagged returns is much more competitive. In this case, its mean return is 8.17%, its Sharpe ratio is 1.26, and its CEQ returns are 7.54% ($\gamma = 3$) and 6.06% ($\gamma = 10$). This is comparable to the sentiment strategy where the numbers are 8.34% (mean return), 1.28 (Sharpe ratio), and 7.71% and 6.23%(CEQs) respectively. Both strategies significantly outperform the benchmark sample mean model.

Overall, the evidence from Table 8 confirms the economic value of utilizing the information from Δs to predict intraday market returns.

5.3. Discussion of empirical results

Our empirical results so far have presented a convincing case that investors sentiment have predictive value for intraday market returns during the last four half hours of a trading day. We call this phenomenon the "timing effect". But why is the timing effect appears stronger later in the day than during the earlier trading hours? In addition, Berkman et al. (2012) document that for individual firms, there appears to be a strong tendency for traders to chase relatively high opening prices. This phenomenon is concentrated among stocks that have recently attracted the attention of retail investors, and is more pronounced for stocks that are difficult to value, costly to arbitrage, and low in institutional owner-

Table 8
Evaluating the performance of market timing trading strategies this table reports the annualized mean returns, standard deviations, Sharpe ratio and CEQs for strategies that rely on various predictors to generate trading signals. The strategies enter a long (short) position in the S&P 500 ETF if the model predicted return is positive (non-positive). The benchmark strategy generates the trading signals if the historical sample average return is positive and *vice versa*. The second strategy uses the lagged change in investor sentiment as the only predictor. The third strategy relies on two lagged return variables: the first half hour return and the previous half hour return. The sample period is from January 1998 to December 2011 with an initial estimation window of 250 days. For CEQ returns, we use two risk aversion parameter values $\gamma = 3, 10$. We report the *p*-values in parentheses, which compares strategies that use predictor(s) with the benchmark strategy.

Strategies	Mean(%)	Std Dev (%)	Sharpe Ratio	CEQ (%) $\gamma = 3$	CEQ (%) $\gamma = 10$
Panel A: 10th Half-hour					
Benchmark	0.6795	4.6631	0.1457	0.3533	−0.4078
Δs	5.0219	4.6526	1.0794**	4.6972***	3.9396***
			(0.0123)	(0.0000)	(0.0000)
r_1, r_9	1.6241	4.6622	0.3483	1.2980***	0.5373***
			(0.5846)	(0.0000)	(0.0000)
Panel B: 11th Half-hour					
Benchmark	0.9981	4.8302	0.2066	0.6481	−0.1684
Δs	9.4336	4.7939	1.9678***	9.0888***	8.2845***
			(0.0000)	(0.0000)	(0.0000)
r_1, r_{10}	0.0342	4.8306	0.0071	−0.3158***	−1.1325
			(0.6119)	(0.0000)	(0.0000)
Panel C: 12th Half-hour					
Benchmark	2.7720	5.9352	0.4671	2.2436	1.0107
Δs	9.8335	5.9054	1.6652***	9.3104***	8.0899***
			(0.0001)	(0.0000)	(0.0000)
r_1, r_{11}	1.2084	5.9373	0.2035	0.6797***	−0.5541
			(0.4997)	(0.0000)	(0.0000)
Panel D: The last half-hour					
Benchmark	0.3605	6.5190	0.0553	−0.2770	−1.7644
Δs	8.3401	6.4978	1.2835***	7.7068***	6.2291
			(0.0015)	(0.0000)	(0.0000)
r_1, r_{12}	8.1715	6.4986	1.2574***	7.5380***	6.0598
			(0.0041)	(0.0000)	(0.0000)

ship. Given Berkman et al.'s finding, it appears to contradict the "timing effect" that we find in this article.

In our view, the difference between our results and the Berkman et al. paper is likely due to the fact that our focus is on the S&P 500 index ETF whereas their focus is on individual firms. In particular, note that their results are more pronounced for stocks that are difficult to value, costly to arbitrage, and low in institutional ownership, which certainly does not fit the profile of a large and liquid index ETF owned by many institutions.

More importantly, Berkman et al.'s results highlight the importance of idiosyncratic risk. In the case of individual firms, the opening prices are often influenced by overnight news events, such as earnings announcement, analyst upgrades and downgrades, new products, FDA approvals, and so on. In contrast, we find that our results are unlikely driven by news flows such as macroeconomic announcements.[3] Thus we argue that it is more appropriate to apply our investor sentiment measure on diversified portfolios / index ETFs than on individual firms.

With regard to the explanation why the timing effect is more prominent later in the day, we believe there could be two potential reasons.

First, there could be a time delay when investors decide to act on their sentiment due to risk aversion. We argue that investors who are attracted to the S&P 500 index ETF are probably more risk averse than those who chase the opening price of an individual stock. If so, then these investors find the S&P 500 index ETF a good investing vehicle presumably because they realize that it represents a diversified portfolio and thus is less risky than, say, a low-priced momentum stock. In other words, there is likely to be a "clientele effect", where investors with stronger risk aversion are more likely to trade the S&P 500 index ETF, whereas investors who are willing to take on more risk will chase individual stocks. Thus, the more risk averse investors are, the less likely that they will chase an excessively high or low opening price and probably prefer to wait until later in the day when the dusts are about to settle.

Second, if market makers (arbitrageurs) are risk averse (as assumed in the model of Subrahmanyam (1991)), they may be more willing to offset the actions of sentiment traders in the morning than later in the day. This is due to the uncertainty introduced by overnight news flows. As an example, suppose that noise traders are very bullish and they push the price above fair value at 3 pm. Market makers know that if they trade against the noise traders, then they will likely have to hold onto this short position overnight. However, there might be some pending news announcements during the overnight hours before the market opens tomorrow. Thus risk-averse market makers will likely delay trading against the noise traders until the next day. This also implies that the momentum in these sentiment-driven trades could last until the morning session of the next trading day.

In our view, the "timing effect" is likely driven by a combination of the above two factors. We will provide further evidence on the noise trading hypothesis in the Section 6.

6. Noise trading, liquidity, and alternative explanations

So far our results have shown that the high frequency TRMI sentiment measure has predictive values on intraday stock market returns. A natural explanation for the predictability is that it is driven by the actions of noise traders who are more susceptible to shifts in sentiment. However it is also possible that the pre-

[3] We provide more evidence on the impact of macroeconomic news in the Section 6.

dictability comes from other sources. Here we consider two alternative explanations. First, if the intraday sentiment variable proxies for the information content of the news flow of any given day, then it is possible that the documented predictability could come from the trading activities of investors who are "news-watchers" in the sense of Hong and Stein (1999). Second, it might be driven by the actions of some institutional traders who use sentiment proxies as inputs. In this section, we will shed light on these alternative explanations by studying the macroeconomic news announcement effect, as well as exploring the relation between investor sentiment, trading volume, market liquidity, and longer-horizon returns.

6.1. Macroeconomic announcement effects: Nonfarm payroll and FOMC meetings

To test for the "news-watcher" hypothesis, we study the impact from important macroeconomic news announcements. We focus on two important market moving events: non-farm payroll and FOMC meetings.

The non-farm payroll (NFP) employment report is released by the U.S. Bureau of Labor Statistics on the first Friday of each month. This news event appears to catch the attention of many investors and is typically announced at 8:30 am or about an hour before the opening bell rings at the New York Stock Exchange. To gauge the market's reaction to the NFP reports, we classify a given NFP report as "positive" if it surpasses market expectation and "negative" otherwise. We measure the expectation among market participants by using the consensus (median) forecast for the NFP numbers from the survey of professional forecasters from the Philadelphia Federal Reserve Bank. We augment our main predictive regression Eq. (3) with an additional "News" dummy variable that takes the value of 1 if the NFP report is positive and 0 otherwise. Due to data availability for the survey of professional forecasters, our sample period is from 2004 to 2011. We find that the "News" dummy variable is insignificant in all cases (based on the returns for the last four half hours of a trading day). In fact the only variable that is significant is the change in sentiment variable Δs for the 10th and 11th half hours. As a robustness check, we also replace the "News" dummy variable with a "Surprise" variable, which is defined as the difference between the actual NFP number and the consensus forecast. We find almost identical results with the only significant variables being Δs for the 10th and 11th half hours and lagged return in the 11th half hour. Therefore we conclude that the "news-watcher" hypothesis is likely to be invalid. Recall that our TRMI sentiment variable is constructed by analyzing the emotional content of a huge number of articles and posts from various sources each day. From this perspective, the results reported here is unsurprising because the diversification across a large number of sources makes it unlikely that our sentiment variable is just a proxy for the daily news headlines.

FOMC meetings are typically closely followed by market participants and considered to be market moving. For example, Lucca and Moench (2015) document that since 1994, the S&P500 index has on average increased 49 basis points in the 24 h before scheduled FOMC announcements, and about 80% of annual realized excess stock returns since 1994 are accounted for by the pre-FOMC announcement drift. In addition, FOMC policy announcements are released around 2:15 pm eastern US time, which appears to coincide with the timing of our main findings.

We obtain the FOMC meeting days from the Federal Reserve Bank's website. We split our sample into two parts: FOMC days vs. non-FOMC days. To account for potential pre-meeting and post-meeting drift effects, we count the FOMC window by including one day before and one day after the meetings. We re-run our main predictive regression model Eq. (3) using these two samples. The results are reported in Table 9. We find that investor sentiment is highly significant during the FOMC days for all the four half hour periods. The t-statistics range from 1.98 to 2.6. We also find that the other control variables are all insignificant except for the first half hour return during the last half hour. In Panel B, we report the results for non-FOMC days. We find that our main results are unchanged. Investor sentiments are still highly significant with t-statistics range from 5.9 to 4.18. Thus we conclude that our empirical results appear robust across both the FOMC and non-FOMC samples and are unlikely to be driven by the FOMC announcement effect.

6.2. Trading volume, liquidity and the noise trading hypothesis

Next, we provide evidence on the noise trading hypothesis by exploring the implications of noise trading on trading volume, liquidity, and longer-horizon returns.

To begin with, we notice that if the noise trading hypothesis is true, then we should expect to see the predictive value of investor sentiment mainly shows up in days with high trading volume. It is well known that high trading volume is an indication of noise trading. See, for example Odean (1998) and Barber and Odean (2000). Hence we propose to run the following regressions as a direct test of the noise trading hypothesis.

$$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 HighVol_t + \beta_3 \Delta s_{i-1,t} HighVol_t + \beta_4 r_{1,t} + \beta_5 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13, \tag{14}$$

where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. *HighVol* is a dummy variable that takes the value of 1 when detrended log trading volume is above the sample mean and 0 otherwise. It is well known that raw trading volume has a long run trend. Following Andersen (1996) among others, we first log transform the trading volume of the S&P 500 index ETF and then further de-trend the series by subtracting a 500-day moving average.

It is easy to see that this regression is very similar to Eq. (3). The key difference is that we now include a high trading volume dummy variable as well as an interaction term that multiplies the change in sentiment variable with the high trading volume dummy variable. The idea here is to capture the interaction between investor sentiment and high trading volume. If the noise trading hypothesis is true, then we should expected to see a positive and significant coefficient estimate for the interaction term (β_3).

Table 10 confirms that estimates for β_3 are significantly positive in three out of four cases: the 10th, 11th, and 12th half hours. The most significant result is from the 11th half hour with a t-statistic of 4.64. In the other two cases (the 10th and 12th half hours) the estimates for β_3 are significant at the 10% level. Even in the case of the last half hour, where the coefficient estimate is insignificant, the t-statistic is at a reasonable 1.60 (p-value = 11%). Interestingly, we also find the change in sentiment variable is mostly positive and significant. Thus the results reported here are consistent with our early findings without the inclusion of high trading volume dummy variable. Taken together, the evidence from Table 10 is consistent with the hypothesis that noise trading is the underlying reason for the return predictability by the TRMI sentiment variable.

Next, we explore the relation between market liquidity and investor sentiment. A number of theoretical models predict a positive relation between liquidity and noise trading. For example, Glosten and Milgrom (1985) present a model where a risk-neutral market maker will reduce liquidity (by widening the bid-ask spread) when faced with an increase in informed trading. However, the market makers will do exactly the opposite, namely increase market liquidity, when faced with an increase in noise

Table 9
Predictability of Intraday stock market returns with lagged change in investor sentiment: FOMC vs. Non-FOMC Days this table reports results from the following predictive regressions using the FOMC vs. non-FOMC samples: $r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13,$ where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t, $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. Panels A reports results for days where the Federal Open Market Committee (FOMC) has a meeting (including the day before and the day after the meetings). Panel B shows the results for the non-FOMC sample. (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The overall sample period is from January 2, 1998 to December 31, 2011.

Half-hour return period	β_0	β_1	β_2	β_3	Adj. R^2(%)
Panel A: FOMC Days					
10th Half-hour	0.0000	0.3045**	−0.0212	−0.0613	1.19
	(0.13)	(2.50)	(−0.51)	(−0.43)	
11th Half-hour	0.0004**	0.2270**	0.0327	0.0188	0.91
	(1.99)	(2.09)	(0.91)	(0.22)	
12th Half-hour	0.0000	0.2640***	0.0099	0.0503	2.39
	(0.00)	(2.60)	(0.30)	(0.47)	
The Last Half-hour	−0.0003	0.4669**	0.1742***	0.0217	10.40
	(−1.53)	(1.98)	(3.02)	(0.13)	
Panel B: Non-FOMC days					
10th Half-hour	−0.0001	0.1550***	0.0029	−0.0469	1.11
	(−1.39)	(5.31)	(0.28)	(−1.21)	
11th Half-hour	0.0000	0.1942***	−0.0016	0.0273	1.54
	(0.36)	(5.31)	(−0.14)	(0.66)	
12th Half-hour	0.0002***	0.2008***	0.0113	0.0080	1.51
	(3.10)	(5.90)	(0.59)	(0.21)	
The Last Half-hour	0.0000	0.1804***	0.0488***	0.0968**	2.77
	(0.00)	(4.18)	(2.80)	(2.04)	

Table 10
Trading volume and change in investor sentiment this table reports results from the following regression:
$r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 HighVol_t + \beta_3 \Delta s_{i-1,t} HighVol_t + \beta_4 r_{1,t} + \beta_5 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13,$
where $r_{i,\,t}$ is the ith half-hour return on the S&P 500 index ETF on day t , $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. *HighVol* is a dummy variable that takes the value of 1 when detrended log trading volume is above the sample mean and 0 otherwise. (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

Half-hour return period	β_0	β_1	β_2	β_3	β_4	β_5	Adj. R^2(%)
10th Half-hour	0.0000	0.1196***	−0.0001	0.1078*	−0.0004	−0.0453	1.23
	(0.68)	(4.02)	(−1.11)	(1.91)	(−0.04)	(−1.12)	
11th Half-hour	−0.0000	0.0506	0.0002*	0.2927***	−0.0013	0.0329	2.43
	(−0.35)	(1.47)	(1.94)	(4.64)	(−0.12)	(0.79)	
12th Half-hour	0.0002**	0.1436***	0.0001	0.0969*	0.0132	0.0133	1.71
	(2.21)	(4.10)	(0.96)	(1.68)	(0.72)	(0.36)	
The last Half-hour	0.0000	0.1188**	−0.0001	0.1425	0.0653***	0.1009**	3.66
	(0.16)	(2.37)	(−0.79)	(1.60)	(3.62)	(2.08)	

trading. Intuitively, an increase in noise trading mitigates a specialist's adverse selection problem, and therefore can help improve liquidity. The model of Admati and Pfleiderer (1988) also predicts a similar positive relation between noise trading and liquidity. However, theoretical predictions regarding the relation between noise trading and liquidity are not always in agreement. For example, in the Kyle (1985) model, liquidity is invariant to changes in the level of noise trading because in this model informed traders adjust their demands in proportion to noising trading. Thus the effects from informed trading and noise trading offset each other. Subrahmanyam (1991) presents a model where risk aversion by informed traders can cause a negative relation between liquidity and noise trading. Subrahmanyam shows that this result holds when market makers are either risk-neutral or risk averse. Given these diverse theoretical predictions, it is interesting to see which model is supported by our empirical evidence.

In Table 11, we study the relation between investor sentiment and market liquidity. We rely on a simple but commonly used measure of (il)liquidity proposed by Amihud (2002) (*Illiq*). It is defined as $Illiq(n) = \frac{1}{n}\sum_{i=1}^{n}\frac{|r_i|}{DVol_i}$, where $|r_i|$ is the absolute value of return on day i and $DVOL_i$ is the dollar volume. The original Amihud measure average over a whole year. In our case, since our focus is more high-frequency oriented, we set $n = 10, 20, 50$ days.

Panel A of this table reports estimates of the slope coefficient β_1 from the following linear regressions, $Illiq(n)_t = \beta_0 + \beta_1 \Delta Sent_t + \varepsilon_t$, where the dependent variable is the Amihud illiquidity measure on the S&P 500 index ETF. The explanatory variable is the change in TRMI investor sentiment measure. We use the change in sentiment variable at the 10th (Sent10), 11th (Sent11), 12th (Sent12), 13th (Sent13) half hour respectively as well as their average over the four half hours. We find a significant and positive relation with changes in investor sentiment during the 11th and 13th half hours for all measures of illiquidity. The relation is also significant when tested against the average change in sentiment. Taken together, these relations suggest that market liquidity and noise trading are negatively correlated, which appears inconsistent with Glosten and Milgrom's model but consistent with the prediction of Subrahmanyam (1991) model. Hence we caution the readers that our liquidity results are somewhat inconclusive as they are supportive of our hypothesis only under the model of Subrahmanyam (1991).

Table 11

Liquidity and investor sentiment panel A of this table reports estimates of the slope coefficient β_1 from the following linear regressions, $Illiq(n) = \beta_0 + \beta_1 \Delta Sent_t + \varepsilon_t$, where the dependent variable is the n-day moving average of the Amihud (2002) illiquidity measure on the S&P 500 index ETF. The explanatory variable is the change in investor sentiment at ith half hour, where we use sentiment levels at the 10th ($\Delta Sent10$), 11th ($\Delta Sent11$), 12th ($\Delta Sent12$), 13th ($\Delta Sent13$) half hour respectively as well as their average. Panel B reports estimates of the slope coefficient β_1 from the following linear regressions, $\Delta Illiq(n)_t = \beta_0 + \beta_1 \Delta LagSent_{t-j} + \varepsilon_t$, where $\Delta Illiq(n)$ is the change in the Amihud illiquidity measure and $\Delta LagSent_{t-j}$ denotes the change in investor sentiment with a lag of j days. We set $j = 5$. Heteroscedastic and autocorrelation consistent t-statistics are reported in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

	$\Delta Sent10$	$\Delta Sent11$	$\Delta Sent12$	$\Delta Sent13$	average $\Delta Sent$
Panel A: Contemporaneous relation between illiquidity and changes in sentiment					
$Illiq(10)$	0.3295	1.7445***	0.1952	1.3456***	2.2657***
	(0.76)	(4.92)	(0.46)	(3.75)	(3.92)
$Illiq(20)$	0.4297	1.7574***	0.1936	1.4150***	2.3631***
	(0.99)	(4.94)	(0.45)	(3.93)	(4.08)
$Illiq(50)$	0.4130	1.8174***	0.1929	1.4092***	2.3913***
	(0.93)	(5.04)	(0.44)	(3.86)	(4.06)
Panel B: Relation between changes in illiquidity and lagged changes in sentiment					
	$\Delta LagSent10_{t-5}$	$\Delta LagSent11_{t-5}$	$\Delta LagSent12_{t-5}$	$\Delta LagSent13_{t-5}$	Average $\Delta lagSent_{t-5}$
$\Delta Illiq(10)$	0.0448	−0.0055	−0.2214***	−0.0998**	−0.1498**
	(0.83)	(−0.12)	(−4.16)	(−2.24)	(−2.08)
$\Delta Illiq(20)$	−0.1497	−0.0335	−0.1138***	−0.0527**	−0.1272***
	(−1.56)	(−1.49)	(−4.22)	(−2.34)	(−3.49)
$\Delta Illiq(50)$	0.0033	−0.0046	−0.0304***	−0.0094	−0.0216
	(0.27)	(−0.48)	(−2.61)	(0.96)	(−1.37)

In Panel B of Table 11, we regress change in the illiquidity measure on lagged change in investor sentiment. We use a lag of 5 days. We find that there appears to be a negative relation between changes in illiquidity and lagged changes in sentiment especially for the average change in sentiment and sentiment in the 12th half hour. In other words, an increase in noise trading seems to induce a contemporaneous reduction in liquidity but a future improvement in liquidity, and *vice versa*. This appears to be consistent with the notion that noise trading can temporarily push prices away from the fundamental value, but informed traders and market makers will eventually step in, which leads to improvement in future liquidity.

Last, but not the least, we formally test the idea that if our findings are driven by noise trading, then we should expect to see a reversal at longer horizons. This is due to the fact that noise traders push price away from its fundamental value, which should eventually reverse. Table 12 reports results from the following predictive regressions at longer horizons:

$$r_{i+h,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{i-1,t} + \beta_3 r_{1,t} + \varepsilon_{i+h,t}, \quad i = 10, \ldots, 13, \tag{15}$$

where $r_{i+h,t}$ is the holding period return h half-hour periods after the ith half hour on the S&P 500 index ETF on day t. For example, $h = [i+6, i+30]$ denotes the interval from 6th half hour to 30th half hour after the ith half hour of day t. We have two major findings. First, there appears to be an initial continuation in returns. For the first five half hours, the coefficient estimates on the sentiment variable are significantly positive in all cases. It appears to be particularly strong for the 11th and the last half hours. This suggests that the momentum generated by the sentiment effect could last up to almost half a day and spill over to the early trading hours of the next trading day. This appears inconsistent with the notion that our results are driven by the end-of-day portfolio rebalancing effect. Second, we find that there appears to be some evidence of reversal at longer horizons. For example, we find that the coefficient estimates for β_1 at longer horizons are at least all nominally negative. It is significantly negative in the case of the 11th half hour.

Table 12

Predictability of longer-horizon returns with lagged change in investor sentiment and lagged returns this table reports results from the following predictive regressions:

$r_{i+h,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{i-1,t} + \beta_3 r_{1,t} + \varepsilon_{i+h,t}, \quad i = 10, \ldots, 13,$

where $r_{i+h,t}$ is the holding period return h half-hour periods after the ith half hour on the S&P 500 index ETF on day t. For example, $h = [i+6, i+30]$ denotes the interval from 6th half hour to 30th half hour after the ith half hour of day t. $r_{i-1,t}$ denotes the return for the $(i-1)$th half hour, $r_{1,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. Panels A, B, C, and D report results where regressions are run by choosing the value of i to be: the 10th Half-hour, the 11th Half-hour, the 12th Half-hour, and the last half-hour. Heteroscedastic and autocorrelation robust t-statistics are reported in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively. The sample period is from January 2, 1998 to December 31, 2011.

$r_{i+h,t}$	Constant	$\Delta s_{i-1,t}$	$r_{i-1,t}$	$r_{1,t}$
Panel A: 10th Half-hour				
$h = [i+1, i+5]$	0.0004**	0.1730**	−0.2343	0.0540
	(2.03)	(2.02)	(−1.39)	(0.99)
$h = [i+6, i+30]$	0.0004	−0.1692	−0.0707	0.0616
	(1.18)	(−1.40)	(−0.35)	(0.66)
Panel B: 11th Half-hour				
$h = [i+1, i+5]$	0.0004**	0.3033***	0.0716	0.0114
	(1.99)	(3.02)	(0.61)	(0.21)
$h = [i+6, i+30]$	0.0003	−0.2773**	−0.1530	0.0753
	(0.93)	(−1.97)	(−0.88)	(0.77)
Panel C: 12th Half-hour				
$h = [i+1, i+5]$	0.0002	0.1211*	0.0179	0.0072
	(1.04)	(1.77)	(0.18)	(0.14)
$h = [i+6, i+30]$	0.0005	−0.1270	−0.3293**	0.0630
	(1.39)	(−1.20)	(−2.08)	(0.67)
Panel D: The last half-hour				
$h = [i+1, i+5]$	0.0001	0.6821***	0.7986***	0.4157***
	(0.61)	(6.16)	(6.10)	(6.06)
$h = [i+6, i+30]$	0.0005	−0.1311	−0.2187	0.0719
	(1.26)	(−0.94)	(−1.37)	(0.75)

6.3. Predictive regressions using other ETFs

When viewed as a sentiment measure of the US stock market in general, the TRMI sentiment variables that we adopt in this paper

Table 13
Predictability of intraday returns with lagged change in investor sentiment: Other ETFs this table reports results from the following predictive regressions: $r_{i,t} = \beta_0 + \beta_1 \Delta s_{i-1,t} + \beta_2 r_{1,t} + \beta_3 r_{i-1,t} + \varepsilon_t, \quad i = 10, \ldots, 13,$ where $r_{i,\,t}$ is the ith half-hour return on one of the following ETFs on day t: DIA (Dow Jones Industrial Average), IWM (Russell 2000 Index), EFA (MSCI EAFE Index), and TLT (U.S. Treasury 20+ Year Bond Index). $r_{1,\,t}$ is the first half-hour return, and $\Delta s_{i-1,t}$ denotes the change in investor sentiment in the $(i-1)$th half-hour. (Newey and West, 1987) robust t-statistics are in parentheses and significance at the 1%, 5%, or 10% level is indicated by an ***, an ** or an *, respectively.

Half-hour return period	β_0	β_1	β_2	β_3	Adj. R^2(%)
Panel A: DIA (01/1998 to 12/2011)					
10th Half-hour	−0.0001*	0.1493***	−0.0038	−0.0891**	1.34
	(−1.69)	(4.99)	(−0.39)	(−2.03)	
11th Half-hour	0.0001	0.1965***	0.0029	−0.0137	1.49
	(2.51)	(5.52)	(0.30)	(−0.31)	
12th Half-hour	0.0001	0.1997***	0.0033	0.0119	1.50
	(1.56)	(5.46)	(0.18)	(0.29)	
The last half-hour	−0.0000	0.1742***	0.0387**	0.1312*	2.90
	(−0.03)	(3.84)	(2.08)	(1.90)	
Panel B: IWM (05/2000 to 12/2011)					
10th Half-hour	0.0000	0.1710***	−0.0046	-0.0114	0.59
	(0.17)	(4.08)	(−0.71)	(−0.24)	
11th Half-hour	0.0002**	0.2737***	0.0001	0.0210	1.60
	(2.31)	(4.63)	(0.01)	(0.45)	
12th Half-hour	0.0002**	0.2188***	0.0010	−0.0127	1.14
	(2.45)	(4.82)	(0.13)	(−0.23)	
The last half-hour	0.0001	0.4311***	0.0309	0.2248***	6.40
	(0.63)	(5.71)	(1.45)	(3.21)	
Panel C: EFA (08/2001 to 12/2011)					
10th Half-hour	0.0001	0.1237***	−0.0018	−0.0238	0.45
	(1.35)	(3.83)	(−0.54)	(−0.38)	
11th Half-hour	0.0002***	0.1627***	0.0009	0.0589	1.45
	(3.13)	(3.52)	(0.27)	(1.04)	
12th Half-hour	0.0001**	0.1452***	0.0064	−0.0432	1.15
	(1.99)	(4.18)	(0.88)	(−0.73)	
The last half-hour	0.0000	0.2406***	0.0214	0.1838**	5.46
	(0.02)	(3.87)	(1.40)	(2.25)	
Panel D: TLT (07/2002 to 12/2011)					
10th Half-hour	0.0001	−0.0513*	0.0365**	0.0295	0.75
	(1.26)	(−1.74)	(2.16)	(0.56)	
11th Half-hour	0.0000	−0.0693*	0.0530***	−0.1060	3.28
	(0.47)	(−1.80)	(4.33)	(−0.89)	
12th Half-hour	0.0000	−0.0151	−0.0002	0.0148	−0.04
	(0.67)	(−1.44)	(−0.03)	(0.57)	
The last half-hour	0.0000	−0.0165	0.0245**	−0.0438	0.48
	(0.90)	(−0.51)	(2.19)	(−0.87)	

should have explanatory power for other diversified portfolios and index ETFs in addition to the S&P 500 index ETF.

We choose four additional ETFs. These are: DIA (Dow Jones Industrial Average), IWM (Russell 2000 Index), EFA (MSCI EAFE Index), and TLT (U.S. Treasury 20+ Year Bond Index), which represents portfolios of large stocks, small-cap stocks, international stocks, and the Treasury bond market respectively. We report the results in Table 13. We find that investor sentiment retains its predictive power for the three stock ETFs: DIA, IWM, and EFA. The estimated coefficients for the TRMI sentiment variable are all positive and highly significant in all cases. It coefficients also appear larger in magnitude for small stocks (IWM) than for large stocks (DIA). The most interesting case is the bond ETF TLT. Here we find that the estimated coefficients for the sentiment variable is negative and significantly so for the 10th and 11th half hours. In other words, we find that TRMI sentiment is positively correlated with future stock returns but negatively correlated with future bond returns. In our view, this result is another piece of supportive evidence that TRMI captures investor sentiment. Recall that Connolly et al. (2005) document a negative relation between stock and bond market returns and they attribute this to the “flight-to-quality” effect. Baele et al. (2010) find that this phenomenon cannot be explained by rational asset pricing models based on economic factors. In other words, the negative stock-bond relation is likely driven by changes in investor sentiment. When investors becomes fearful, they dump stocks and buy bonds. When investors are greedy, they sell bonds and buy stocks. We find that the empirical results from these stock and bond ETFs are consistent with the interpretation that TRMI captures investors’ fear and greed.

To sum up, in this section we find that the macroeconomic news announcement effects cannot explain the documented return predictability. We also find that investor sentiment is associated with high trading volume, a reduction in contemporaneous liquidity but an improvement in future liquidity, short-term continuation in returns, and a longer horizon reversal. It also has predictive power for other stock and bond ETFs. Overall these findings are consistent with the hypothesis that sentiment-related return predictability is driven by noise trading.

7. Conclusion

In this article, we examine the predictability of intraday market return with changes in high-frequency investor sentiment. Our intraday investor sentiment measure is based on the proprietary Thomson Reuters MarketPsych index, which provides a commercial strength comprehensive textual analysis of various traditional as well social media sources. We focus on intraday high frequency measure of investor sentiment because it is likely to give us a more accurate gauge of the real-time fluctuations in investor sentiment. Our empirical findings can be summarized as follows.

First, we find strong evidence that changes in investor sentiment have predictive values for the intraday market returns. The predictability permeates throughout the whole trading day, but is particularly strong during the last two hours. In contrast, we find that the intraday momentum effect based on lagged returns is only significant for the last half hour. Thus the sentiment effect appears more pervasive than the intraday momentum effect. Moreover, we also find that intraday investor sentiment carries significant economic value as measured by both Sharpe ratio and certainty equivalent returns from market timing trading strategies.

Second, we show that the predictive value of high-frequency investor sentiment cannot be explained by lagged macroeconomic variables or the macroeconomic news announcement effects. It is related by not subsumed by alternative sentiment measures such as the CBOE volatility index.

Third, we find evidence that the sentiment-driven return predictability appears to come from noise trading. We document that predictability is much stronger during economic expansions and high trading volume days. In contrast, predictability is weaker during economic recessions and largely dissipates during low trading volume days. Thus the overall evidence presented in this article is consistent with the well-known phenomenon that noise traders' participation in the market increases when investor optimism is rising (Yu and Yuan (2011)) and when trading volume is high (Odean (1998) and Barber and Odean (2000)).

Our findings have important asset pricing implications. While prior studies have documented the impact from investor sentiment on asset prices, especially for small stocks, it has not been a consensus that sentiment can predict aggregate market index returns. We, on the other hand, provide strong evidence that indeed market index returns are predictable with investor sentiment at least at the intraday level. We attribute the predictability to the fact that, unlike prior studies that focus on a specific source, our sentiment measure is much more broadly based and constructed from all-encompassing traditional and social media sources. Thus it is able to pick up changes in investor sentiment with accuracy. With this improved measure of investor sentiment, our future research will continue to focus on the impact of investor sentiment on other important topics of asset pricing, such as its relation to asset pricing anomalies.

References

Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. Rev. Financ. Stud. 1, 3–40.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Markets 5 (1), 31–56.

Andersen, T.G., 1996. Return volatility and trading volume: an information flow interpretation of stochastic volatility. J. Finance 51 (1), 169–204.

Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. J. Financ. Quant. Anal. 48 (1), 245–275.

Antweiler, W., Frank, M.Z., 2004. Is all that talk just noise? the information content of internet stock message boards. J. Finance 59 (3), 1259–1295.

Baele, L., Bekaert, G., Inghelbrecht, K., 2010. The determinants of stock and bond return comovements. Rev. Financ. Stud. 23 (6), 2374–2428.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–157.

Barber, B.M., Odean, T., 2000. Trading is hazardous to your wealth: the common stock investment performance of individual investors. J. Finance 55 (2), 773–806.

Berkman, H., Koch, P.D., Tuttle, L., Zhang, Y.J., 2012. Paying attention: overnight returns and the hidden cost of buying at the open. J. Financ. Quant. Anal. 47 (04), 715–741.

Chen, H., De, P., Hu, Y.J., Hwang, B.-H., 2014. Wisdom of crowds: the value of stock opinions transmitted through social media. Rev. Financ. Stud. 27 (5), 1367–1403.

Connolly, R., Stivers, C., Sun, L., 2005. Stock market uncertainty and the stock-bond return relation. J. Financ. Quant. Anal. 40 (1), 161–194.

Cooper, M., Gutierrez, R.C., Hameed, A., 2004. Market states and momentum. J. Finance 59, 1345–1365.

Cooper, M.J., McConnell, J.J., Ovtchinnikov, A.V., 2006. The other january effect. J. Financ. Econ. 82 (2), 315–341.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. Rev. Financ. Stud. 28 (1), 1–32.

De Long, J.B., Shleifer, A., Summers, L., Waldmann, R.J., 1990. Noise trader risk in financial markets. Journal of Political Economy 98 (4), 703–738.

DeMiguel, V., Garlappi, L., Uppal, R., 2009. Optimal versus naive diversification: how inefficient is the 1/n portfolio strategy? Rev. Financ. Stud. 22, 1915–1953.

Gao, L., Han, Y., Li, S. Z., Zhou, G., 2015. Intraday momentum: The first half-hour return predicts the last half-hour return. Working paper, Washington University at St. Louis.

Garcia, D., 2013. Sentiment during recessions. J. Finance 68 (3), 1267–1300.

Glosten, L.R., Milgrom, P.R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Financ. Econ. 14 (1), 71–100.

Guiso, L., Sapienza, P., Zingales, L., 2014. Time varying risk aversion. Working paper, University of Chicago.

Heston, S.L., Korajczyk, R.A., Sadka, R., 2010. Intraday patterns in the cross-section of stock returns. J. Finance 65 (4), 1369–1407.

Hirshleifer, D., Shumway, T., 2003. Good day sunshine: stock returns and the weather. J. Finance 58 (3), 1009–1032.

Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. J. Finance 54 (6), 2143–2184.

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: a powerful predictor of stock returns. Rev. Financ. Stud. 28(3) 791–837.

Jobson, J.D., Korkie, B., 1981. Performance hypothesis testing with the sharpe and treynor measures. J. Finance 36, 889–908.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.

Lee, C., Shleifer, A., Thaler, R., 1991. Investors sentiment and the closed-end fund puzzle. J. Finance 46, 75–109.

Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: some empirical evidence. Rev. Financ. Stud. 19 (4), 1499–1529.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. J. Finance 66 (1), 67–97.

Lucca, D.O., Moench, E., 2015. The pre-fomc announcement drift. J. Finance 70 (1), 329–371.

Memmel, C., 2003. Performance hypothesis testing with the sharpe ratio. Finance Lett. 1, 21–23.

Newey, W.K., West, K.D., 1987. A simple positive semi-definite, heteroskedasticity and aurocorrelation consistent covariance matrix. Econometrica 51, 1233–1242.

Odean, T., 1998. Volume, volatility, price, and profit when all traders are above average. J. Finance 53 (6), 1887–1934.

Qiu, L., Welch, I., 2006. Investor sentiment measures. Working paper, Brown University.

Subrahmanyam, A., 1991. Risk aversion, market liquidity, and price efficiency. Rev. Financ. Stud. 4 (3), 417–441.

Tetlock, P.C., 2007. Giving content to investor sentiment: the role of media in the stock market. J. Finance 62 (3), 1139–1168.

Yu, J., Yuan, Y., 2011. Investor sentiment and the mean-variance relation. J. Financ. Econ. 100 (2), 367–381.