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Institutional investor sentiment and aggregate stock returns

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Abstract

This paper examines the equity market return predictability of institutional investor sentiment, in comparison to individual investor sentiment. Our findings suggest that institutional traders are informed and that their sentiment helps to tilt stock prices towards the intrinsic value. This is because the sentiment of institutions encompasses news regarding expectations on future cash flows of underlying firms that impounds itself into future price expectations. In this study, we add to the large number of studies that investigate the role and implications of investor sentiment, which has long been viewed as a pure behavioural phenomenon, on market efficiency and price discovery.

KEYWORDS

cash flows, institutional investors, retail traders, return predictability, sentiment

JEL CLASSIFICATION

G14; G40; G41

1 | INTRODUCTION

How investor sentiment can predict aggregate stock returns has drawn much attention both in academia as well as in the investing community. It has been shown in many academic studies that the Baker and Wurgler (2006) type of sentiment measure (S^{BW} hereafter), often interpreted

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as indirectly representing individual investors' emotions, possesses some negative predictive power on stock market returns (e.g., Baker & Wurgler, 2007; Baker et al., 2012; Doukas & Milonas, 2004; Huang et al., 2015). Besides this market-activity-based BW composite, other more direct sentiment proxies based on survey or textual data are employed by Brown and Cliff (2004), Schmeling (2009), Garcia (2013), and Jiang et al. (2019), among others, to test the predictability of retail investor sentiment. They also find a clear negative relationship between individual investor sentiment and aggregate stock returns, especially over much longer horizons of 2–3 years.[1] The explanation for these results is that investor sentiment affects returns by driving stock prices away from the intrinsic value.

Institutional investor sentiment should do a much better forecasting job here, as it is recognized by many that institutions have a clear information advantage over retail investors. The reason is twofold. First, theoretically, retail investors are assumed to lack a cohesive level of information that could have been allowing them to extract economic rents familiar to well-informed institutions. Second, practically, retail investors are often beaten by professional institutions in terms of the pool of resources at disposal and the amount of time available to perform intensive analysis. The information-advantage argument is also consistent with investment thumb rules.

Clearly, one can tell that the literature on irrational sentiment (mostly focusing on individual investors) and the literature on sophisticated institutions have conflicting implications for the informativeness of investor sentiment. To reconcile them, we need to understand more about the collective attitude among financial institutions and the unique message contained within it. Unfortunately, extant studies shed some light on such issues. Brown and Cliff (2005) and Schmeling (2007) provide some evidence supporting comovement between institutional investor sentiment and medium- to long-run stock market returns, but mixed results are reported with regard to the short-run return predictability brought in by institutional investor sentiment (e.g., Brown & Cliff, 2004; Lee et al., 2002; Wang et al., 2006). In addition, the precise mechanism of institutional investor sentiment having predictive power for aggregate stock returns is unclear as well.

As a result, several research questions remain open, including: Can the sentiment of institutional investors forecast the future return of the market portfolio? Does institutional and individual sentiment behave differently? And most importantly, why institutional investor sentiment has return predictability?

The present paper addresses all these questions. Using an institutional investor sentiment index published by the SENTIX (S^{INS} hereafter), we find that S^{INS} is able to positively predict aggregated market returns over the next month. Moreover, this forecasting power is found to be economically significant. Specifically, one standard deviation increase in sentiment leads to an increase of 83 basis points in future stock returns.

One may worry that the forecastability of institutional investor sentiment is due to institutions utilizing a contrarian approach to bet against retail investor sentiment. To mitigate this concern, we validate our results by controlling for a list of common sentiment indices for individuals, such as the Baker and Wurgler (2006) investor sentiment (S^{BW}), the Huang et al. (2015) aligned investor sentiment (S^{HJTZ}), the American Association of Individual Investor sentiment (S^{AAII}), the SENTIX individual investor sentiment (S^{IND}) and the University of

[1]Several studies find that sentiment based on qualitative information positively predicts future firm returns (e.g., see Gu & Kurov, 2020; Tetlock et al., 2008).

Michigan consumer sentiment (S^{MCS}). We show that this is not the case. Actually, coefficients on S^{INS} remain significantly positive with other proxies being controlled for. Moreover, when compared to those retail investor sentiment indices, S^{INS} is the only sentiment measure whose return predictability can easily survive the Kitchen-sink type of regression. All these findings suggest that S^{INS} provides unique information relative to retail investor sentiment indices in terms of meaningful stock return forecasting. This conclusion remains robust if we perform out-of-sample forecasts, as S^{INS} generates the second-highest out-of-sample R^2 and offers a significant incremental out-of-sample explanatory power for future returns.

Then, we continue to explore the more fundamental question: Where does the predictive power of institutional investor sentiment come from? To answer this question, we conduct three different types of investigation.

First, we compare S^{INS} with 14 economic return predictors from Welch and Goyal (2008) to see whether S^{INS} could provide incremental information on stock markets beyond what has already been included in economic variables. If institutional investors' opinions about the future market performance originate from other economically relevant information, the predictive power of S^{INS} would be subsumed to that of economic variables. Our findings show that S^{INS} still performs well in terms of forecasting returns, after controlling for any one of those 14 economic return predictors or the first principal component of the entire set of economic variables (PC thereafter). In comparison, S^{BW} only exhibits limited negative predictive power when the PC is present. These results seem to indicate that the information advantage displayed by institutional investor sentiment is not driven by documented economic return predictors.

Second, we follow Rapach et al. (2016) to decompose returns into both the discount rate and cash flow component, based on the VAR approach developed by Campbell (1991) and Campbell and Ammer (1993), to find out the economic source of institutional investor sentiment's forecasting power. This exercise is inspired by the idea that the intrinsic value of stocks is determined by the expected discount rate and cash flow. Hence, if institutional investor sentiment indeed contains information about fundamentals, the sentiment-on-future-return effect should operate through either the channel of anticipated discount rate or that of expected cash flows or both. We show that S^{INS}'s forecasting power can be arguably attributed to the fact that the sentiment of institutions contains cash flow information. In other words, the positive return predictability of institutional investor sentiment is potentially driven by institutions' well-founded projections of favourite aggregate earnings growth in the future, which is in turn reflected by their high sentiment. However, S^{INS} lacks information about movements in the future discount rate. In contrast, we find that neither the discount rate news nor cash-flow news is related to the return predictability of S^{BW}.

Third, as Stambaugh et al. (2012) have found the association of stronger market anomalies (i.e., more profitable long–short strategies) following higher retail investor sentiment, one may also think that institutional investor sentiment just captures the effect of institutions ready to exploit opportunities created by mispricing. If this argument is true, we should observe a prominent correlation between the sentiment of institutions and anomaly-related excess returns on long–short strategies. Hence, we explore whether the forecasting power of S^{INS} is related to asset mispricing. To test this possibility, we investigate the role of investor sentiment in eleven anomalies in cross-sectional stock returns from Stambaugh et al. (2012). Our empirical tests show that S^{INS} is irrelevant to these anomaly strategies' aggregate returns, let alone on returns obtained from the short or long legs. As a comparison, S_t^{BW}'s negative impact on future returns is related to asset mispricing with short-sale constraints.

All in all, this paper adds to the wide body of sentiment literature in several ways. We begin by providing a deeper insight into sentiment and by questioning the role of individuals in dominating the emotional force, or in affecting sentiment's return predictability. That is to say, previous works construe broadly-defined investor sentiment as fully irrational; whereas our findings suggest that, at least, the sentiment of institutions is driven by rationality. As sentiments formed by retail traders and institutional investors reflect their respective expectations on future prices, each party's sentiment contains specific contents related to those expectations. For retail traders, the content includes psychological biases or information that has already been impounded into prices—their sentiment is unlikely to contain additional information on the determinants of future stock prices (Ben-Rephael et al., 2012; Neal & Wheatley, 1998). But for institutional investors, their content contains future cash flow information related to the determinants of future stock prices, as is documented in the extant literature (Ben-Rephael et al., 2017). Consequently, the sentiment of individuals will drive prices away from stock intrinsic values, whereas institutional investor sentiment can tilt prices towards the fundamentals. This is our first and foremost contribution to extant studies.

Furthermore, this paper has implications for whether sentiment affects the profitability of investment strategies. To mention a few examples, Antoniou et al. (2013) discover that momentum profits arise only under optimistic sentiment periods. Massa and Yadav (2015) show that mutual funds with sentiment contrarian strategies can attain superior performance. Though portfolios in their studies are constructed based on individual sentiment movement, our results indicate that managers could read from institutional investor opinions and employ portfolio strategies incorporating the sentiment of institutions.

On top of these contributions, works done here are also complementary to exercises conducted by Stambaugh et al. (2012, 2014) and Stambaugh and Yuan (2016) on the relationship between investor sentiment, market anomalies, and return determination. Our paper argues that the results produced by them are primarily driven by retail traders rather than institutional investors. In particular, we can show that retail traders are responsible for moving prices away from future values as their sentiment is related to anomalies of the market but is unrelated to fundamentals; institutional investor sentiment appears to exhibit no such relationship with anomalies.

In addition, our paper has a position in linking sentiment to corporate finance issues. For example, Brunnermeier and Nagel (2004) document that hedge funds exploit predictable investor sentiment during technology bubbles so that they can capture the upturn and avoid much of the downturn in financing startups. Arif and Lee (2014) consider the aggregate corporate investment to contain an overlapping substance with market-wide investor sentiment. Antoniou et al.'s (2016) study how sentiment impacts a firm's cost of equity capital. Like them, our paper establishes linkages between institution sentiment proxy and company earnings and discount rates. However, we depart from them as our paper highlights the exact informational contents rather delivered by institutional investor sentiment than behavioural deviations.

Last but not least, these findings contribute to the literature attempting to demonstrate the informational role of institutional investor behaviour. Chakravarty (2001) and Sias et al. (2006) argue that stock price moves depend on decisions implemented by these institutions. Using proprietary institutional trading volume data, Hendershott et al. (2015) provide direct evidence institutions are informed about news, such as quarterly earnings announcements. In support of their findings, our study confirms the existence of valuable information not only in the financial institutions' actual behaviours but also in their stated sentiment.

The remainder of this paper is organized as follows: Section 2 describes our data; Section 3 identifies the predictability of institutional investor sentiment; Section 4 explores the sources of the predictive power; followed by Section 5 with concluding remarks.

2 | DATA DESCRIPTION

2.1 | Sentiment measures

The raw data utilized to compute our preferred measure of institutional investor sentiment is sourced from the official website of SENTIX, which provides a rolling account of sentiment produced by surveying institutional investors' perceptions about future stock market prices in the next 1 month (short-term in the return-horizon context) and the next 6 months (long-term in the return-horizon context). The 6-month expectation is referred to as the strategic bias of institutional investors by SENTIX, and is preferred over its 1-month counterparty by us throughout this paper. Our choice of this longer expectation is inspired by previous findings that short-term sentiment measures tend to be noisy (Brown & Cliff, 2004, 2005; Schmeling, 2007).[2]

To participate in SENTIX surveys, a potential respondent has to open an account online first, with a business e-mail address belonging to some acknowledged investment firm, such as a commercial/investment bank, an asset management company, or a broker–dealer firm, and so forth. Though these registered firm representatives are not forced to respond to each round of surveys, SENTIX, namely, the survey organizer and the index releaser, do provide effective incentives intended to convert first-time users into frequent participants. Although there exist indirect proxies (e.g., the state street investor confidence index[3]) and other direct databases (e.g., Investors Intelligence's investment newsletter survey, the NAAIM investment advisors' exposure, the Yale ICF institutional investors' confidence) on the stock market all claim that they can assess institutional investor sentiment, we believe SENTIX institutional investor sentiment is an appropriate choice because (1) the respondents to SENTIX surveys must be verified representatives of institutions before they can record their perceptions on future market prices, and (2) SENTIX sticks to the rule that sentiment of institutions should not be confused with the sentiment of individuals who work or provide services for institutions.

The SENTIX started releasing a list of sentiment indices for different countries and asset classes in February 2001. In this study, we focus on the effects of sentiment on the U.S. stock market. Hence, our final institutional investor sentiment data is the SENTIX strategic bias index for U.S. equities, covering a period from February 2001 to December 2018 and constituting a sample of 215 observations.

Following previous studies that construct sentiment measures on the basis of surveys, we utilize the SENTIX strategic bias index to calculate our sentiment proxy S^{INS} as the spread between the percentage of all participants who express bullish views for future returns and the percentage who convey bearish views in the survey for the same set of returns. As a result,

[2]Like in these listed references, in our data set, we also find that institutional investors' expectations on the stock market within a 1-month horizon do not have any predictability on future returns.

[3]This new index measures investor confidence quantitatively by analyzing the actual buying and selling patterns of institutional investors. It assigns a precise meaning to changes in investor risk appetite: Greater the percentage allocation to equities, higher the confidence. It differs from survey-based measures in that it is based on actual trades, as opposed to opinions, of institutional investors.

a positive (negative) S^{INS} indicates that responding institutional investors, on average, are optimistic (pessimistic) about the prospective performance of the stock market. One thing we need to point out is that the SENTX sentiment data is originally recorded on a weekly frequency, but the frequency of other well-known sentiment measures, including the BW index (hereafter S^{BW}), is published every month. We, therefore, transform the weekly S^{INS} into a monthly index by taking the average of weekly sentiment levels within a given month.

We incorporate the S^{BW} index into all analyses conducted in this paper, and it is used as the major benchmark to derive comparison results between the effects of individual versus institutional investor sentiment on the stock market. Recall its methodology, S^{BW} is formed from the first principle component of six sentiment indicators of market activities: Closed-end fund discount, NYSE share turnover, number of IPOs, average first-day returns, percentage of equity issues over total equity, and debt issues and dividend premium. The BW index is a natural benchmark here because of two reasons. First, it is the most prominent measure for sentiment in the recent two decades in the academic world, academic studies centred around finance topics in particular. Second, S^{BW} is often viewed as a proxy for retail investor sentiment, which is widely applied to forecast future returns at both the firm level and the index level and to explain a variety of persistent mispricing phenomena prevailing in the market, the so-called anomalies. See Jacobs (2015) for a comprehensive study on this issue. Given those being said, and given our aim of establishing a contrasting concept of rational institutional investor sentiment, it is crucial to differentiate between S^{BW} and S^{INS} by testing their respective effects in empirical specifications like return prediction, anomaly explanation, and return decomposition. We believe that such investigations would help to foster understanding of the underlying causes for different effects in theoretical senses.

Figure 1 plots the time series of both the S^{INS} and S^{BW} indices over our sample period As can be seen in the figure, it is somewhat surprising that institutional investors were pretty optimistic about future stock market performance when individual investors were extremely pessimistic in 2001, that is, near the end of the internet bubble crisis. This large divergence,

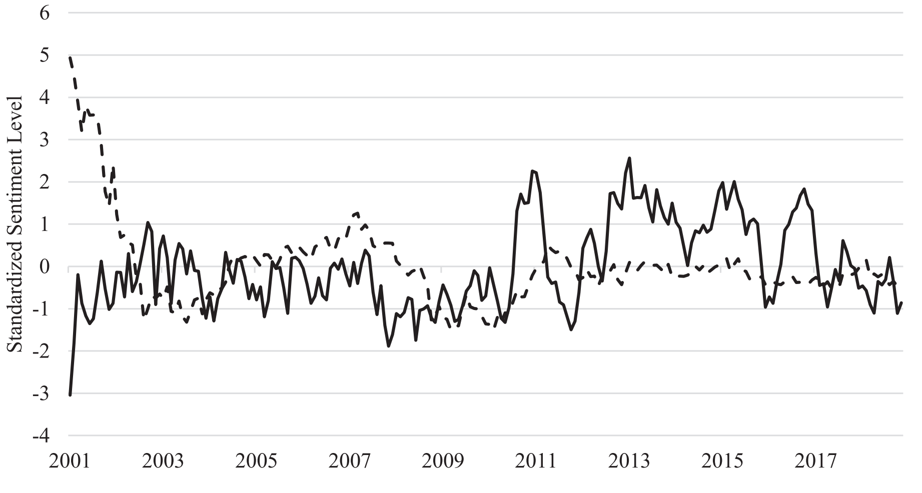

FIGURE 1 Institutional investor sentiment (INS)and BW (Baker and Wurgler) sentiment. The solid line depicts the SENTIX institutional investor sentiment index (S^{INS}). The dashed line is the Baker and Wurgler (2006) sentiment index (S^{BW}). The sample period is from February 2001 to December 2018. Both indices are scaled to have unit standard deviation and zero mean

together with many smaller ones occurred afterward, may indicate institutional investors indeed formulating perceptions differently than individuals. Subsequently, from 2001 to 2004, S^{INS} declined sharply. Then, it rose slightly and dropped significantly during the 2008 financial crisis. During the postcrisis period until the end of our sample period, S^{INS} was relatively stable. Overall, S^{INS} tends to be negatively correlated with S^{BW} and is much less volatile compared to S^{BW}. These suggest that the sentiment of institutions may have distinct impacts on the stock market than individual sentiment.

Besides S^{BW}, we adopt alternative sentiment indices to validate the uniqueness and robustness of the effect of the institutional investor sentiment on returns of stock markets. These alternatives include the Huang et al. (2015) aligned investor sentiment (S^{HJTZ}), the American Association of Individual Investor sentiment (S^{AAII}), the SENTIX individual investor sentiment (S^{IND}), and the University of Michigan consumer sentiment (S^{MCS}). These indices are widely used in the finance literature,[4] and using them as either benchmark or control variables does not change our main results. Section 3 is devoted to in-sample and out-of-sample tests on the predictability of institutional investor sentiment.

Table 1 reports the correlation coefficients for all the pairs of sentiment indices used in the current paper. Consistent with the visual evidence found in Figure 1, the correlation between S^{INS} and S^{BW} is negative and relatively small in absolute value. As expected, S^{INS} is also negatively related to S^{HJTZ}, a modified version of the BW index; but note that S^{INS} is positively associated with S^{AAII}, S^{IND}, and S^{MCS}. Among those positive coefficients, S^{INS} has the highest degree of correlation with S^{IND} as they are both prepared by the same vendor SENTIX and the lowest degree of correlation with S^{MCS} which represents sentiment from consumers instead of investors. Again, the wide range of coefficient values in this correlation table indicates that implications of S^{INS} on the stock market are likely to be different from insights gained by analyzing other well-known sentiment measures.

2.2 | Fourteen economic predictors as in Welch and Goyal (2008)

To provide solid evidence for the informational role played by institutional investor sentiment, in the following Subsection 4.1 we compare the predictive power of our intuitional investor sentiment proxy to that of 14 good predictors examined by Welch and Goyal (2008) due to their substantial economic meanings. Below, we list those predictors one by one, accompanied by their applications in the literature for reference (if there exist) and their first moments calculated from our sample data: (1) DP denotes the natural log of the dividend-to-price ratio and has a mean (median) of −3.96 (−3.96); (2) DY denotes the natural log of dividend yield and has a mean (median) of −3.96 (−3.95) (Ang & Bekaert, 2007; Campbell & Yogo, 2006; Fama & French, 1988). (3) EP denotes the natural log of the earnings-to-price ratio as in Campbell and Shiller (1988) with a mean (median) of −3.13 (−3.04); (4) DE denotes the natural log of the dividend-payout ratio with a mean (median) of −0.83 (−0.95); (5) RVOL denotes the volatility of excess stock returns sampled over a 60-month window with a mean (median) of 0.14 (0.13) (French et al., 1987; Guo, 2006); (6) BM denotes the book-to-market ratio for the Dow Jones Industrial Average (DJIA) Index, which is used in Kothari and Shanken (1997) and Pontiff and Schall (1998) with a

[4]See Zhou (2018) for a recent review on this matter.

TABLE 1 Sentiment index correlations

This table reports correlations between all pairs of six sentiment indexes, including the SENTIX institutional investor sentiment (S^{INS}), the Baker and Wurgler (2006) investor sentiment (S^{BW}), the Huang et al. (2015) aligned investor sentiment (S^{HJTZ}), the American Association of Individual Investor sentiment (S^{AAII}), the SENTIX individual investor sentiment (S^{IND}), and the University of Michigan consumer sentiment (S^{MCS}). All sentiment indices are standardized using their respective sample means and sample standard deviations. The sample period for all indices is identical from February 2001 to December 2018.

	S^{INS}	S^{BW}	S^{HJTZ}	S^{AAII}	S^{IND}
S^{BW}	−0.22				
S^{HJTZ}	−0.22	0.74			
S^{AAII}	0.19	0.07	−0.01		
S^{IND}	0.71	0.21	0.18	0.28	
S^{MCS}	0.11	0.19	−0.13	0.35	0.03

mean (median) of 0.29 (0.30). (7) NTIS denotes net equity expansion from Baker and Wurgler (2000) with a mean (median) of 0.00 (0.00)[5]; (8) TBL denotes the interest rate on a 3-month Treasury Bill with a mean (median) return of 1.35% (0.90%) (Ang & Bekaert, 2007; Breen et al., 1989; Fama & Schwert, 1977); (9) LTY denotes the long-term (30-year) government bond yield with a mean (median) of 3.90% (4.14%); (10) LTR denotes the return on long-term (30-year) government bonds with a mean (median) of 0.55% (0.81%); (11) TMS denotes the long-term government (30-year) bond yield minus the 3-month Treasury Bill rate, thus forming a term-yield spread with a mean (median) of 2.55% (2.64%) (Campbell, 1987; Fama & French, 1988); (12) DFY denotes the difference between the Moody's BAA-rated and AAA-rated corporate bond yields, thus creating a high-yield spread with a mean (median) of 1.07 (0.94); (13) DFR denotes the long-term corporate bond returns minus the long-term government bond return, thus producing a corporate default-risk spread with a mean (median) of 3% (5%); and finally (14) INFL denotes the inflation rate with a mean (median) of 0.17% (0.18%) per month (Campbell & Vuolteenaho, 2004; Fama & Schwert, 1977).

Panel (A) of Table 2 documents the summary statistics of the above 14 number listed predictors along with those of S^{INS} and S^{BW}. Note that S^{INS} has a mean (median) value of 0.09 (0.07), which is positive and means over-time on-average bullish institutional investors outnumber bearish ones. In contrast, the median of S_t^{BW} is slightly below zero, that is, −0.02, when averaged across time between 2001 and 2018. Panel (B) of Table 2 tells us that the S^{INS} is most negatively correlated with LTY (i.e., the long government bond yield) at the level of −0.43, but most positively correlated with BM (i.e., the book-to-market value ratio for the DJIA index) at the level at 0.37. Conversely, S^{BW} has the biggest negative correlation coefficient with DY (i.e., dividend yield) at the level at −0.61. As for positive correlations, the relation between S^{BW} and TBL (i.e., the interest rate on a 3-month Treasury bill) turns out to be taking the highest coefficient value, 0.51.

[5]This predictor is also called the "corporate issuing activity".

TABLE 2 Economic predictors anomaly returns summary statistics

Panel (A) shows correlation coefficients for 14 predictors from Welch and Goyal (2008), SENTIX institutional investor sentiment index (S^{INS}), and the Baker and Wurgler (2006) sentiment index (S^{BW}). DP is the log dividend-price ratio, DY is the log dividend yield, EP is the log earnings-price ratio, DE is the log dividend-payout ratio, RVOL is the volatility of excess stock returns, BM is the book-to-market value ratio for the Dow Jones Industrial Average Index, NTIS is net equity expansion, TBL is the interest rate on a 3-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA-rated and AAA-rated corporate bond yields, DFR is the long-term corporate bond returns minus the long-term government bond return, and the INFL is the inflation rate. Panel (B) reports summary statistics for all predictors. The sample period is from February 2001 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(A) Summary statistics																
Mean	−3.96	−3.96	−3.13	−0.83	0.14	0.29	−0.00	1.35	3.90	0.55	2.55	1.07	0.03	0.17	0.09	0.07
Median	−3.96	−3.95	−3.04	−0.95	0.13	0.30	−0.00	0.90	4.14	0.81	2.64	0.94	0.05	0.18	0.07	−0.02
P1	−4.36	−4.38	−4.81	−1.24	0.06	0.12	−0.05	0.01	1.84	−7.66	−0.16	0.59	−6.26	−0.84	−0.17	−0.89
P99	−3.38	−3.40	−2.66	1.29	0.31	0.42	0.03	4.97	5.93	8.06	4.46	3.09	6.02	0.91	0.41	2.93
SD	0.17	0.17	0.41	0.48	0.06	0.06	0.02	1.54	1.14	3.18	1.24	0.44	1.93	0.31	0.15	0.63
(B) Predictor variable correlations																
(1) DP	1.00															
(2) DY	0.97	1.00														
(3) EP	−0.25	−.25	1.00													
(4) DE	0.56	.55	−0.94	1.00												
(5) RVOL	0.25	.25	−0.63	0.62	1.00											
(6) BM	0.56	.55	0.41	−0.16	−0.09	1,00										
(7) NTIS	−0.51	−0.49	0.14	−0.30	0.15	0.04	1.00									
(8) TBL	−0.48	−0.50	0.09	−0.24	−0.38	−0.43	−0.04	1.00								
(9) LTY	−0.53	−0.55	−0.25	0.03	0.21	−0.50	0.36	0.61	1.00							

(Continues)

TABLE 2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(10) LTR	0.07	−0.00	0.05	−0.02	0.03	0.09	0.06	−0.01	−0.08	1.00						
(11) TMS	0.11	0.12	−0.34	0.33	0.66	0.08	0.39	−0.69	0.16	−0.06	1.00					
(12) DFY	0.67	0.63	−0.58	0.73	0.59	0.18	−0.38	−0.22	0.01	0.06	0.29	1.00				
(13) DFR	−0.02	0.11	−0.21	0.17	0.15	−0.07	0.06	−0.08	−0.00	−0.47	0.10	0.10	1.00			
(14) INFL	−0.21	−0.21	0.12	−0.18	−0.12	−0.11	0.04	0.18	0.17	−0.09	−0.07	−0.32	−0.10	1.00		
(15) S^{INS}	0.07	0.13	0.29	−0.22	−0.16	0.37	0.16	−0.39	−0.43	−0.21	0.09	−0.24	0.007	−0.05	1.00	
(16) S^{BW}	−0.57	−0.61	−0.07	−0.14	−0.06	−0.56	0.05	0.51	0.38	0.02	−0.28	−0.22	−0.06	.07	−0.22	1.00

2.3 | Eleven anomalies as in Stambaugh et al. (2012)

According to our empirical strategy that is about to be implemented in the next two sections, after confirming the ability or inability of S^{INS} and S^{BW}, we will proceed to use data on market anomalies to further differentiate the distinct effects of institutional and retail investor sentiments on future stock market returns. In line with Stambaugh et al. (2012), we investigate eleven distinctive asset-pricing anomalies that cannot be explained by the three classical systematic factors proposed by Fama and French (1993). In specific, the 11 anomalies are: (1) Total accruals; (2) asset growth; (3) composite equity issues; (4) failure probability; (5) gross profitability; (6) investment-to-assets; (7) momentum; (8) net operation assets; (9) Ohlson's *O* (distress); (10) return on assets; and (11) net stock issues.[6] At last, we complement these anomalies with the construction of a twelfth anomaly, (12) combination, by taking the average of all above eleven anomalies. The aim of adding this newly constructed variable is to capture the overall effect of interdependent anomalies.

For each anomaly, investors could establish long and short positions on both sides of the market to benefit from security mispricing. In other words, a weighted portfolio that values the long-leg should contain stocks in the potentially higher-performing decile; whereas a short-leg valued weighted portfolio should consist of stocks in the potentially lower-performing decile. To make our intentions clearer, consider the momentum effect (Jegadeesh & Titman, 1993) according to which stocks that perform better in the past tend to continuously outperform in the future. On the basis of this momentum sorting variable (e.g., returns in the past 12 months), long (short) leg portfolios would include stocks with the highest (lowest) returns in the previous 12 months. Hence, our expectation is that long-leg valued portfolios would earn positive abnormal returns, while short-leg valued portfolios would generate negative excess returns. How this anomaly setup helps to answer questions raised by the current study is as follows. Ideally, following high retail investor sentiment, we will observe higher profitability in the short-leg due to short-sale impediments. However, higher institutional investor sentiment, if as we argued that it contains useful information related to stock market pricing in the future, should be associated with higher profits in neither long-leg nor the short-leg valued portfolios. We use anomaly data to perform these tests in Subsection 4.3.

3 | THE PREDICTIVE POWER OF INSTITUTIONAL INVESTOR SENTIMENT ON AGGREGATE STOCK RETURNS

3.1 | In-sample test

As a first step, we conduct in-sample tests with the following specification of standard bivariate predictive regression. Our explanatory variables of interests are the proxy for institutional investor sentiment, denoted by S_t^{INS} in the following equation, and other well-known investor sentiment indices, denoted by S_t^{δ} in the following equation,

$$R_{t+1} = a + bS_t^{\mathrm{INS}} + cS_t^{\delta} + u_{t+1}, \delta = \mathrm{BW, HJTZ, AAII, IND, MCS}, \quad (2)$$

[6]Detailed descriptions about the eleven anomalies' definitions are also available in Stambaugh et al. (2012).

where R_{t+1} is the log excess return for the S&P 500 within month $t+1$. The six sentiment indices include the SENTIX institutional investor sentiment (S_t^{INS}), the Baker and Wurgler (2006) investor sentiment (S_t^{BW}), the Huang et al. (2015) aligned investor sentiment (S_t^{HJTZ}), the American Association of Individual Investor sentiment (S_t^{AAII}), the SENTIX individual investor sentiment (S_t^{IND}), and the University of Michigan consumer sentiment (S_t^{MCS}). All sentiment indices entering into the regression are standardized using their respective sample means and sample standard deviations. Concerning estimation bias correction, the regressions run are estimated using a Newey and West (1987) heteroskedastic and autocorrelation robust covariance matrix. The corresponding results are presented in Table 3.

Column 1 of Table 3 reports the capability of S_t^{INS} in positively forecasting the return of the market portfolio in the next month's return. And this predictive power is not just statistically significant at some conventional level, but it is also economically valuable—practitioners can exploit profits by timing the market. The coefficient b's estimate of 0.83 indicates that if S_t^{INS} increases by one standard deviation in the current month, then the next-month market return tends to rise by 83 basis points. An R^2 of 4.10% in turn means that S_t^{INS} alone can explain 4.10% of the total variations in stock market returns over the next month. This R^2 number is substantial in terms of monthly return forecasting as monthly returns are usually believed to contain a huge proportion of unpredictable components (Campbell & Thompson, 2008).

In Column 2 of Table 3, we find that a higher S_t^{BW} foreshadows lower future returns, and $S_t^{\mathrm{BW}}$by itself can only explain 4.22% variations in next-month stock market prices. For one thing, the opposite return forecasting directions of S_t^{INS} versus S_t^{BW} have the implications that S_t^{INS} contains a different set of market-moving factors than S_t^{BW}. This observation is consistent with the negative correlation between these two sentiment indices.

In Column 3 of Table 4, we re-run the predictive regression with both S_t^{INS} and S_t^{BW} included. One can think of S_t^{BW} as a control variable if the focus is on S_t^{INS}, and vice versa. The purpose of having the bivariate regression is to detect whether the forecasting power of S_t^{INS} is driven by S_t^{BW}. This supposition is likely to be true as institutional investors could rely solely on factors determining S_t^{BW} when expressing their own opinions about the market's future performance, and hence S_t^{INS} would lose its predictive ability if $S_t^{\mathrm{BW}}$is around. But it is clear from results presented in Column 3 that S_t^{INS}'s return predictability is not dominated by S_t^{BW}—the estimated coefficient before S_t^{INS} stays statistically significant, and its magnitude remains fairly large. It is S_t^{BW} that becomes a barely insignificant return predictor after controlling S_t^{INS}. In sum, as long as predictability is concerned, S_t^{INS} becomes unaffected by S_t^{BW}, whereas S_t^{BW} is, to some extent, subsumed by S_t^{INS}. Together, S_t^{INS} and S_t^{BW} can raise the portion of variations in the next-month stock price explained by sentiment from 4.10% or 4.22% to a higher level of 5.58%.

In Column 4 and 5 of Table 3, we repeat exercises in Column 2 and 3 but with S_t^{BW} replaced by S_t^{HJTZ}. Column 4 shows that S_t^{HJTZ} is as strong as S_t^{BW} in terms of predicting returns and can explain about 3.30% of next-month return fluctuations. Column 5 reveals that, similar to the case of S_t^{BW}, S_t^{HJTZ} becomes a barely insignificant predictor after controlling for S_t^{INS}. S_t^{INS} survives in an alternative bivariate regression setting.

For Columns 6 to 11 of Table 3, we compare S_t^{INS} with S_t^{AAII}, S_t^{IND}, and S_t^{MCS}, and find that they all provide little explanatory power for prospective stock market performance, thus none of their presence would have weakened the forecasting power of S_t^{INS}. In Column 12 of Table 4, we employ a kitchen-sink method which puts all sentiment measures into one single predictive regression. The conclusion is that S_t^{INS} stands out as the only index that can still provide gains with respect to forecasting returns in our sample in a statistically significant and economically valuable way. The estimated coefficients on other sentiment indices are all insignificant at the

TABLE 3 Predictive power of investor sentiment

This table reports regression results for the following model:

$$R_{t+1} = a + bS_t^{INS} + cS_t^{\delta} + u_{t+1}, \delta = \text{BW, HJTZ, AAII, IND, MCS},$$

where R_{t+1} is the log excess return for the S&P 500 in month $t+1$. The six sentiment indices include the SENTIX institutional investor sentiment (S^{INS}), the Baker and Wurgler (2006) investor sentiment (S^{BW}), the Huang et al. (2015) aligned investor sentiment (S^{HJTZ}), the American Association of Individual Investor sentiment (S^{AAII}), the SENTIX individual investor sentiment (S^{IND}), and the University of Michigan consumer sentiment (S^{MCS}). All sentiment indices are standardized using their respective sample means and sample standard deviations. The regressions are estimated using the Newey–West heteroskedastic and autocorrelation robust covariance matrix. T statistics are reported in parentheses. The sample period is from February 2001 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
S^{INS}	0.83		0.72		0.70		0.86		1.40		0.86	1.27
	(3.04)***		(2.45)**		(2.84)***		(3.26)		(4.15)***		(3.41)***	(2.70)***
S^{BW}		−0.86	−0.54									0.32
		(−3.38)***	(−1.73)*									(0.52)
S^{HJTZ}				−0.75	−0.59							−0.65
				(−2.27)**	(−1.81)*							(−1.17)
S^{AAII}						0.03	−0.13					0.10
						(0.33)	(−0.40)					(0.32)
S^{IND}								0.20	−0.80			−0.67
								(0.76)	(−2.94)***			(−1.45)
S^{MCS}										−0.13	−0.23	−0.44
										(−0.29)	(−0.58)	(−0.36)
R^2(%)	4.10	4.22	5.58	3.30	6.09	0.00	4.20	0.24	5.92	0.10	4.42	7.42

*, **, ***Statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE 4 Out-of-sample tests

Panel (A) reports the proportional reduction in mean square forecast error (MSFE) (R^2_{OS}) for predictive regression for stock returns based on the prevailing mean benchmark vis-à-vis competing forecast based on the sentiment indices. Panel (B) reports the proportional reduction in mean square forecast error (R^2_{OS}) for predictive regression for stock returns based on a univariate regression including a retail investor sentiment vis-à-vis competing forecast based on a bivariate model by adding the institutional investor sentiment to the baseline regression. Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the MSFE of the baseline model is less than or equal to the competing model MSFE against the alternative hypothesis that the MSFE of the baseline model is greater than the competing model MSFE. The six sentiment indices include the SENTIX institutional investor sentiment (S^{INS}), the Baker and Wurgler (2006) investor sentiment (S^{BW}), the Huang et al. (2015) aligned investor sentiment (S^{HJTZ}), the American Association of Individual Investor sentiment (S^{AAII}), the SENTIX individual investor sentiment (S^{IND}), and the University of Michigan consumer sentiment (S^{MCS}). All sentiment indices are standardized using their respective sample means and sample standard deviations. The full sample period is from February 2001 to December 2018. The out-of-sample period is from January 2010 to December 2018.

(A) Out-of-sample R^2 statistics	
S^{INS}	2.22***
S^{BW}	2.50**
S^{HJTZ}	1.63*
S^{AAII}	0.15
S^{IND}	−0.62
S^{MCS}	1.90
(B) Incremental out-of-sample R^2 statistics from S^{INS}	
S^{BW}	1.38***
S^{HJTZ}	2.52***
S^{AAII}	1.74***
S^{IND}	5.08***
S^{MCS}	1.33***

*, **, ***Statistical significance at 10%, 5%, and 1% levels, respectively.

10% level. The six sentiment indices combined can absorb about 7.42% of the variations in the aggregate market, confirming that investor sentiment deserves the title of an essential market-moving factor.

3.2 | Out-of-Sample test

As in-sample forecast gains cannot guarantee a predictor's performance out of sample[7], in this subsection, we conduct a standard out-of-sample test to see whether our proxy for institutional investor sentiment can generate additional forecasting powers for next-month returns relative to the historical average benchmark. If yes, then our proxy is a robust predictor out of the sample.

Following Rapach et al. (2016), we take three steps to evaluate the out-of-sample performance of our predictor of interest. In the first step, we employ a recursive expanding estimation window to calculate out-of-sample forecasts of future aggregate stock returns:

$$\hat{R}_{m+1} = \hat{a}_{0,m} + \hat{a}_{1,m} S_{m+1}, \tag{3}$$

where m is the number of observations in the chosen estimation window, $\hat{a}_{0,m}$ and $\hat{a}_{1,m}$ are the coefficient estimates obtained from regressing $\{R_t\}_{t=1}^{m}$ on $\{S_t\}_{t=1}^{m}$ with an intercept. As usual, R_t represents the aggregate stock return, whereas S_t is some investor sentiment index. We choose the first half of our entire sample period (i.e., from February 2001 to December 2009) as the initial in-sample estimating window. Dividing the whole sample into half–half is standard; nonetheless, other arbitrary choices on subsample length make no big change to our results.

In the second step, we calculate the out-of-sample R^2 statistic, denoted by R^2_{OS}, as the proportional reduction in the mean square forecast error (MSFE) of predictive regression for Equation (3) based on a sentiment measure of our choice vis-à-vis the prevail mean benchmark forecast:

$$R^2_{\text{OS}} = 1 - \frac{\sum_{k=q_0+1}^{q} (R_{m+k} - \hat{R}_{m+k})^2}{\sum_{k=q_0+1}^{q} (R_{m+k} - \bar{R}_{m+k})^2}, \tag{4}$$

where $\bar{R}_{m+k}$ is the historical average of the stock return before the point in time $m + k$. q_0 and q represent the end dates of the initial in-sample period and the full sample period, respectively.

In the third step, we implement the out-of-sample MSPE-adjusted statistic proposed by Clark and West (2007) to test the null hypothesis that $R^2_{\text{OS}} \leq 0$ against the alternative hypothesis that $R^2_{\text{OS}} > 0$. A positive significant R^2_{OS} suggests that the sentiment index outperforms the prevailing mean return when forecasting returns out-of-sample.

Table 4 lists R^2_{OS} from the competing forecasting model featured by the other five sentiment indices along with the institutional investor sentiment index S_t^{INS}. We can tell from the table that S_t^{INS} significantly beat the mean benchmark as S_t^{INS}'s R^2_{OS} is both positive and statistically significant at the 1% level. Its R^2_{OS} of 2.22% is also economically important, as Campbell and Thompson (2008) state that, a monthly out-of-sample R^2 of 0.5%, just one-eighth of our statistic, is already large enough to produce significant economic value. Among the rest five sentiment measures, $S_t^{\text{BW}}$and S_t^{HJTZ} also provide significant out-of-sample forecasting gains.

Computing R^2_{OS} for each single sentiment measure does not reveal that whether institutional investor sentiment offers incremental return forecasting power out-of-sample relative to alternative sentiment measures. To explore the question, we next calculate R^2_{OS} for a univariate predictive regression for stock returns based on a retail investor sentiment vis-à-vis competing forecast based on a bivariate regression by adding the institutional investor sentiment to the baseline univariate regression. A positive and significant R^2_{OS} would indicate that inclusion of the institutional investor sentiment improves return predictability of regressions with a retail investor sentiment measure. The results are reported in Panel B of Table 4. As seen in the panel, all R^2_{OS} is significantly positive, suggesting that SENTIX institutional investor sentiment

[7]Welch and Goyal (2008) find that, in the setup of forecasting aggregate stock returns, popular predictors came out of in-sample tests cannot significantly outperform an unconditional prevailing mean return.

provides some unique information for next period returns relative to all other sentiment indices.

4 | INSIDE THE BLACK BOX OF THE INSTITUTIONAL INVESTOR SENTIMENT'S PREDICTIVE POWER

In Section 3, we verify that our proxy for institutional investor sentiment S_t^{INS} possesses significant forecasting powers on aggregate stock returns from both in-sample and out-of-sample perspectives. Moreover, S_t^{INS} positively affects the next month's returns. In contrast, the BW Investor sentiment index and other common sentiment measures forecast future returns adversely. In this section, we attempt to decipher the mechanism of S_t^{INS} being a positive predictor. By comparing S_t^{INS} with 14 nonsentiment and economic predictors, by linking S_t^{INS} to components of aggregate returns, and by investigating the role played by S_t^{INS} in market anomalies, we aim to provide a further economic rationale to explain the positive relationship between institutional investor sentiment and future stock market returns.

4.1 | A comparison with economic predictors

In this subsection, we validate the forecasting power of our institutional investor sentiment measure against that of a variety of economic market return predictors. By doing so, we intend to assess the extent to which S_t^{INS} provides incremental information relevant to the future stock market, more than that has already been contained in identified economic variables. If it contains some extra piece of information, then the significance of the reported return predictability of the institutional sentiment index should survive after controlling for the economic predictors.

We choose 14 economic return predictors from Welch and Goyal (2008), as described in Section 2, and compute the first principal component of the 14 variables to capture the overall effect of a complete set of economic predictors on how our institutional investor sentiment proxy can predict stock market returns.[8]

In the first 14 rows in Table 5, we tabulate statistics representing the predictive power for each of the 13 economic predictors (Welch & Goyal, 2008) in our sample period. To facilitate comparisons, all economic predictors are standardized to have a mean of zero and a standard deviation of one. It can be seen that most economic variables are in lack of significant explanatory powers for next month's aggregate returns. Only the coefficient estimates on DY, BM, TBL, and LTY are significant at a conventional significance level. Among these four significant ones, the LTY has the largest estimate (i.e., 0.71) and the highest R^2 (i.e., 2.95%). Nevertheless, these two statistics are smaller than S_t^{INS}'s (i.e., coefficient estimate = 0.83 and $R^2 = 4.10\%$) and S_t^{BW}'s (i.e., coefficient estimate = 0.86 and $R^2 = 4.22\%$). These comparisons demonstrate S_t^{INS} as a better and ignored predictor than other individual predictors previously discovered from the literature.

[8]As for robustness checks, we also compute the first two and first three principal components. The corresponding results are similar.

TABLE 5 Comparison with economic predictors

This table reports ordinary least squares regression results for the following model:

$$r_{t+1} = \alpha + \beta P_{i,t} + \varepsilon_{t+1},$$

where r_t is the log excess return for S&P 500 in month t, $P_{i,t}$ is the value of predictor i for month t, and |PC indicates that regressions include the first principal component extracted from the 14 predictors from Welch and Goyal (2008). The two sentiment indices include the SENTIX institutional investor sentiment (S^{INS}) and the Baker and Wurgler (2006) investor sentiment (S^{BW}). All predictors are standardized to have a mean of zero and a standard deviation of 1. The regressions are estimated using the Newey–West heteroskedastic and autocorrelation robust covariance matrix. T statistics are reported as a separate column. The sample period is from February 2001 to December 2018. The last two rows report partial R^2 of our two main sentiment indices.

	β	T statistic	R^2R^2(%)
DP	0.53	1.08	1.61
DY	0.68*	1.58	2.66
EP	0.18	0.39	0.18
DE	0.03	0.07	0.01
RVOL	0.15	0.49	0.13
BM	0.52*	1.61	1.54
NTIS	−0.37	−0.82	0.78
TBL	0.49**	2.00	1.41
LTY	0.71***	−2.88	2.95
LTR	0.21	0.70	0.26
TMS	−0.04	−0.16	0.01
DFY	−0.31	−0.58	0.54
DFR	0.47	0.89	1.30
INFL	−0.39	−1.11	0.89
S^{INS} |PC	0.82***	2.75	3.87
S^{BW} |PC	−0.62	1.40	1.57

In the last two rows of Table 5, we report estimates on S_t^{INS} and S_t^{BW} after controlling for the first principal component extracted from the 14 economic variables, and we also report partial R^2 of sentiment measures. Comparing to the regressive regression results without economic variable as controls in Column 1 Table 3, the estimate on S_t^{INS}|PC changes only a bit (from 0.83 to 0.82). Moreover, a 3.87% partial R^2 indicates that S_t^{INS} retains substantial market explanatory even in the presence of the principal component of 14 economic predictors. In contrast, the retail investor sentiment proxy S_t^{BW} performs much worse after we control for the same principal component. The coefficient of S_t^{BW}|PC is not statistically significant, and the partial R^2 is less than 2%. In short, we are confident to conclude that the predictive power of S_t^{INS} is unaffected by that of other frequently used economic predictors from the previous literature.

This conclusion implies that S_t^{INS} contains different aspects of information about future stock market performance compared to existing popular economic predictors.

4.2 | Return decomposition

In this subsection, given that the established predictability of institutional investor sentiment, we attempt to find the linkages between the sentiment of institutions with the exact information about fundamentals contained in it. As the stock intrinsic value is determined by the expected discount rate and cash flow, then the sentiment effect of institutions should affect future stock market returns through either the anticipated discount rate channel or the expected cash flow channel, or both. We follow Rapach et al. (2016) to further decompose market returns into the discount rate and cash flow components using the VAR approach developed by Campbell (1991) and Campbell and Ammer (1993). Their approach enables us to pin down the exact economic channel through which institutional investor sentiment's forecasting power functions.

The return decomposition process starts with the log stock return equation below:

$$r_{t+1} = \log\left[\frac{P_{t+1} + D_{t+1}}{P_t}\right], \tag{5}$$

where r_{t+1} is the stock return during month $t+1$, and P and D represent the stock price and dividends, respectively. Using the Campbell and Shiller (1988) log-linear approximation of return, Equation (5) can be linearized and hence rewritten as the following formula:

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t, \tag{6}$$

where $\rho = 1/[1 + \exp(\overline{d-p})]$, $k = -\log(\rho) - (1-\rho)\log\left[\left(\frac{1}{\rho}\right) - 1\right]$, $p_t = \log(p_t)$, and $d_t = \log(d_t)$, and $\overline{d-p}$ is the average value of $p_t - d_t$. Equivalently, Equation (6) can be presented in the form as follows,

$$p_t \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - r_{t+1}, \tag{7}$$

Next, note that successfully transforming Equations (5) to (6) requires the imposition of the no-bubble transversality condition,

$$p_t = \sum_{j=0}^{\infty} p^j (1-\rho)d_{t+1+j} - \sum_{j=0}^{\infty} p^j r_{t+1+j} + k/(1-\rho). \tag{8}$$

Putting expectation operators on both sides of Equation (6), we get,

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} p^j \Delta d_{t+1+j} - (E_{t+1} - E_t)\sum_{j=0}^{\infty} p^j r_{t+1+j}. \tag{9}$$

As can be seen in Equation (9), the stock return innovation element (i.e., $r_{t+1} - E_t r_{t+1}$) is influenced by both cash flow news (i.e., $\delta_{t+1}^{\mathrm{CF}} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} p^j \Delta d_{t+1+j}$) and discount rate news (i.e., $\delta_{t+1}^{\mathrm{DR}} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} p^j r_{t+1+j}$). Campbell (1991) and Campbell and Ammer (1993) devise a VAR framework to extract the two components of cash flow and discount rate news out of stock return innovations. The final regressions are:

$$\hat{\delta}_{t+1}^{\mathrm{CF}} = \beta_{\mathrm{CF}} S_t + \varepsilon_{t+1}^{\mathrm{CF}}, \tag{10}$$

$$\hat{\delta}_{t+1}^{\mathrm{DR}} = \beta_{\mathrm{DR}} S_t + \varepsilon_{t+1}^{\mathrm{DR}}, \tag{11}$$

$$\hat{E}_t r_{t+1} = \alpha_{\hat{E}} + \beta_{\hat{E}} S_t + \varepsilon_{t+1}^{\hat{E}}, \tag{12}$$

where β_{CF} captures the sentiment effect on cash flow news, β_{DR} captures the sentiment effect on discount rate news, and $\beta_{\hat{E}}$ captures the sentiment effect on the part of returns that is unrelated to discount rate and cash flow news. S_t is either the SENTX institutional investor sentiment index or the BW retail investor sentiment index. Following Rapach et al. (2016), we extract empirically cash flow news ($\hat{\delta}_{t+1}^{\mathrm{CF}}$), discount rate news ($\hat{\delta}_{t+1}^{\mathrm{DR}}$), and expected return ($\hat{E}_t r_{t+1}$) based on VAR models incorporating stock returns, log dividend price ratio, and one from the Welch and Goyal (2008) list of economic predictor variables. The corresponding results for the above system of regressions are reported in Table 6.

Columns 1 and 2 of Table 6 report that almost all estimates of $\beta_{\hat{E}}$ and β_{CF} for S_t^{INS} are statistically significant. The size of β_{CF} estimates is much bigger than that of $\beta_{\hat{\mathrm{E}}}$ estimates. When including PC in the VAR return decomposition model, the $\beta_{\hat{\mathrm{E}}}$ estimate only takes a value of 0.15 and is insignificant, whereas the β_{CF} estimate is at 0.58 and maintains its statistical significance. In contrast, the β_{DR} estimates in Column 3 of Table 6 are all trivial and insignificant. These findings suggest that most of the predictive power for S_t^{INS} originates from its association with future cash flows, and the remaining tiny portion of its predictive power is related to neither cash flow news nor discount rate news.

Columns 4–6 show estimates on $\beta_{\hat{E}}$, β_{CF}, and β_{DR} for S_t^{BW}. Most β_{CF} and β_{DR} estimates are insignificant, whereas all $\beta_{\hat{E}}$ estimates are negative and sizeable. This pattern indicates that the negative predictive power of S_t^{BW} is not driven by the cash flow and discount rate channels. Put it another way, S_t^{BW} does not contain any information about fundamentals—it is all about emotions.

4.3 | Asset mispricing

This subsection considers the possibility that the return predictability of institutional investor sentiment might originate from asset mispricing. To rule out this possibility, we investigate the role of investor sentiment in eleven anomalies that appeared in cross-sectional stock returns suggested by Stambaugh et al. (2012). Intuitively, If institutional investor sentiment is related to price deviations caused by nonfundamental factors, then we should observe that the sentiment of institutions would be able to predict returns of portfolios picking stocks based on anomaly sorting variables, and short-leg portfolios should be more sensitive to sentiment than long-leg

TABLE 6 Return decomposition analysis

This table reports ordinary least squares regression results for the following model:

$$y_{t+1} = \alpha_y + \beta_y S_t + \varepsilon_{t+1}, \text{for } t = 1, 2, ..., T - 1,$$

where y_{t+1} is one of three estimated components of the S&P 500 log return for month t and S_t is either SENTIX institutional investor sentiment (S^{INS}) or Baker & Wurgler index (S^{BW}). The three components of the S&P 500 log return are the expected return ($\hat{E}(r_{t+1})$), cash flow news ($\hat{\gamma}^{\text{CF}}_{t+1}$), and discount rate news ($\hat{\gamma}^{\text{DR}}_{t+1}$). See the text for the construction methods for these three components. In the first column, "r"indicates the S&P 500 log return, and "PC" indicates the first principal component extracted from 14 predictors from Welch and Goyal (2008). See notes to Table 1 for all other variable definitions and sample selections. The regressions are estimated using the Newey–West heteroskedastic and autocorrelation robust covariance matrix. T statistics are reported in parentheses. The sample period is from February 2001 to December 2018.

	Institutional investor sentiment SENT			**Retail investor sentiment BW**		
	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{CF}$	$\hat{\beta}_{DR}$
VAR variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
r, DP	0.19 (2.74)***	0.49 (3.42)***	−0.13 (−1.07)	−0.43 (−7.78)***	−0.22 (−1.26)	−0.05 (−0.36)
r, DP, DY	0.19 (2.73) ***	0.49 (3.43)***	−0.13 (−1.08)	−0.43 (−8.00)***	−0.22 (−1.27)	−0.06 (0.38)
r, DP, EP	0.30 (4.22)***	.52 (2.04)**	0.01 (0.10)	−0.50 (−9.20)***	−0.65 (−2.13)**	−0.55 (−2.92)***
r, DP, DE	0.30 (4.22)***	0.52 (2.04)**	0.01 (0.10)	−0.50 (−9.20)***	−0.65 (−2.13)**	−0.55 (−2.92)***
r, DP, RVOL	0.20 (2.81)***	0.60 (3.07)***	−0.01 (−.12)	−0.43 (−7.90)***	−0.33 (−1.40)	−0.16 (−1.58)
r, DP, BM	0.28 (3.97)***	0.49 (2.71)***	−.04 (−.37)	−0.49 (−9.64)***	−0.33 (−1.24)	−0.22 (−1.53)
r, DP, NTIS	0.34 (3.51)***	0.46 (2.92)***	−0.01 (0.07)	−0.61 (−9.41)***	−0.10 (−0.59)	−0.10 (−0.48)
r, DP, TBL	0.21 (3.08)***	0.46 (3.07)***	−0.14 (−1.22)	−0.44 (−8.10)***	−0.14 (−0.72)	0.02 (0.14)
r, DP, LTY	0.33 (5.16)***	0.25 (1.27)	−0.23 (−1.36)	−0.44 (−8.87)***	−0.30 (−1.61)	−0.14 (−0.66)
r, DP, LTR	0.14 (1.81)*	0.51 (3.45)***	−0.17 (−1.40)	−0.43 (−7.39)***	−0.23 (−1.29)	−0.06 (−0.42)
r, DP, TMS	0.18 (2.58)**	0.46 (2.75)***	−0.18 (−1.14)	−0.38 (−6.81)***	−0.47 (−3.04)***	−0.26 (−1.14)
r, DP, DFY	0.50 (5.90)***	0.38 (1.75)*	0.06 (0.31)	−0.59 (−8.07)***	−0.25 (−1.23)	−0.23 (−0.77)
r, DP, DFR	0.18 (2.53)**	0.49 (3.42)***	−0.14 (−1.20)	−0.41 (−7.42)***	−0.22 (−1.26)	−0.04 (0.28)

TABLE 6 (Continued)

VAR variables	Institutional investor sentiment SENT $\hat{\beta}_{\hat{E}}$ (1)	$\hat{\beta}_{CF}$ (2)	$\hat{\beta}_{DR}$ (3)	Retail investor sentiment BW $\hat{\beta}_{\hat{E}}$ (4)	$\hat{\beta}_{CF}$ (5)	$\hat{\beta}_{DR}$ (6)
r, DP, INFL	0.17	0.52	−0.13	−0.46	−0.24	−0.10
	(2.06)**	(3.52)***	(−1.02)	(−7.33)***	(−1.39)	(−0.65)
r, DP, PC	0.15	0.58	−0.09	−0.46	−0.30	−0.15
	(1.57)	(3.54)***	(−0.66)	(−6.43)***	(−1.84)*	(−0.78)

*, **, ***Statistical significance at 10%, 5%, and 1% levels, respectively.

portfolios due to the existence of many short-selling constraints which prevent arbitrage. Conversely, if the institutional investor sentiment proxy S_t^{INS} does not have any influence on stock misevaluations, there would exist no significant relationship between S_t^{INS} and anomaly-related portfolio returns, supporting our argument that sentiment of institutions contains valuable information about fundamentals.

We use the following model to analyze the sentiment effect on asset mispricing:

$$R_{\mathrm{i,t}} = a + bS_{t-1} + c\mathrm{MKT}_t + d\mathrm{SMB}_t + e\mathrm{HML}_t + \sum_{j=1}^{4} m_j X_{j,t} + u_t, \tag{13}$$

where $R_{i,t}$ is the excess return for anomaly i in month t on either the long leg, the short leg, or the long minus short difference.[9] As defined in Subsection 2.3, long (short) leg portfolios contain the highest (lowest) 10% performance stocks based on a certain anomaly sorting variable, and these portfolios are expected to earn positive (negative) excess returns over the next period. In Equation (13), S_t is either the standardized institutional investor sentiment proxy S_t^{INS} or the BW retail investor sentiment index S_t^{BW}. We control for four macro-related variables here, the default premium, the term premium, CPI, and the unemployment rate so that major disturbances from macroeconomic indicators are mitigated. These regressions are estimated by using a Newey and West (1987) heteroskedastic and autocorrelation robust covariance matrix.

Columns 1, 3, and 5 of Table 7 show the regression results for S_t^{INS}. We can easily tell that S_t^{INS} is by and large irrelevant to returns of the portfolio constructed based on anomaly-sorting variables. Most S_t^{INS} estimates for the long leg, short leg, and long–short spread are not significant, especially for the short-leg oriented portfolios that should have been significant were S_t^{INS} to be correlated with irrational trading activities. In contrast, a high S_t^{BW} typically leads to a higher long–short return difference for nine out of 12 anomalies in Column 2. The positive abnormal returns of long–short strategies mainly come from abnormal negative returns of short-leg portfolios following high S_t^{BW}. In sum, this subsection provides evidence that the return predictability of institutional investor sentiment is not associated with asset misevaluation, unlike S_t^{BW} whose negative impacts

[9]The sample period of Table 7 ends in December 2016, because data on the eleven anomaly returns have not been updated after 2016 on Robert F. Stambaugh's personal website (http://finance.wharton.upenn.edu/~stambaug/).

TABLE 7 Anomaly return analysis

The table reports regression results for the following model:

$$R_{i,t} = a + bS_{t\text{-}1} + c\text{MKT}_t + d\text{SMB}_t + e\text{HML}_t + \sum_{j=1}^{4} m_j X_{j,t} + u_t,$$

where ($R_{i,t}$) is the excess return for anomaly i in month t on either the long leg, the short leg, or the long minus short difference. (S_t) is either SENTIX institutional investor sentiment (S^{INS}) or Baker and Wurgler index (S^{BW}). We control for four macro-related variables: The default premium, the term premium, CPI, and the unemployment rate. The regressions are estimated using the Newey–West heteroskedastic and autocorrelation robust covariance matrix. T statistics are reported in parentheses. The sample period is from February 2001 to December 2016.

	Long–Short		Short leg		Long leg	
	S^{INS}	S^{BW}	S^{INS}	S^{BW}	S^{INS}	S^{BW}
Anomaly	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Total accruals	0.05	−0.16	0.02	−0.04	0.08	−0.20
	(0.24)	(−0.69)	(0.17)	(−0.28)	(0.52)	(−1.27)
Asset growth	0.25	0.51	−0.03	−0.39	0.22	0.17
	(0.97)	(2.52)**	(−0.17)	(−2.49)**	(1.74)*	(1.24)
Composite equity issues	−0.19	0.47	0.01	−0.34	−0.18	0.15
	(−1.25)	(2.63)***	(0.07)	(−3.31)***	(−1.82)*	(1.17)
Failure probability	0.00	0.95	−0.12	−0.91	−0.12	0.04
	(0.01)	(3.06)***	(0.61)	(−3.76)***	(−1.40)	(0.28)
Gross profitability	−0.47	0.16	0.35	0.01	−0.12	0.17
	(−2.35)**	(0.61)	(2.18)**	(0.08)	(−0.94)	(0.82)
Investment-to-assets	0.13	0.41	−0.13	−0.22	−0.01	0.19
	(0.57)	(1.86)*	(−0.75)	(−178)*	(−0.08)	(1.20)
Momentum	0.31	0.46	−0.35	−0.36	−0.04	0.10
	(0.90)	(1.09)	(−1.43)	(−1.28)	(−0.21)	(0.55)
Net operation assets	0.25	0.47	−0.03	−0.30	0.22	0.17
	(1.17)	(3.42)***	(−0.23)	(−2.85)***	(1.69)*	(1.86)*
Ohlson's O (distress)	−0.35	0.42	0.16	−0.30	−0.18	0.11
	(−2.07)**	(1.80)*	(1.43)	(−1.55) **	(−2.05)**	(1.15)
Return on assets	−0.41	0.78	0.20	−0.55	−0.21	0.23
	(−2.23)**	(4.39)***	(1.34)	(−2.78)***	(−2.26)**	(2.01)**
Net stock issues	−0.12	0.56	0.03	−0.32	−0.09	0.24
	(−0.74)	(3.56)***	(0.25)	(−2.69)**	(−1.72)*	(3.05)***
Combination	−0.05	0.46	0.01	−0.33	−0.04	0.13
	(−0.423)	(4.07)***	(0.11)	(−3.90)***	(−0.97)	(2.44)**

*, **, ***Statistical significance at 10%, 5%, and 1% levels, respectively.

TABLE 8 International evidence on the predictive power of institutional investor sentiment

This table reports regression results for the Euro Area, Germany, Japan, and China based on the following model:

$$R_{t+1}^{\delta} = a + bS_t^{\mathrm{INS},\delta} + u_{t+1}, \text{ for } \delta = \text{EUR, DEU, JPN, CHN},$$

where R_{t+1}^{δ} is the log excess return for STOXX50, DAX, Nikkei225, and Shanghai composite index in month $t+1$. The sentiment indices include the region-specific SENTIX institutional investor sentiment ($S_t^{\mathrm{INS},\delta}$) for the Euro area (EUR), Germany (DEU), Japan (JPN), and China (CHN). All sentiment indices are standardized using their respective sample
means and sample standard deviations. The regressions are estimated using the Newey–West heteroskedastic and autocorrelation robust covariance matrix. T statistics are reported in parentheses. The sample period is from February 2001 to December 2018 for EUR, DEU, and JPN. Due to sentiment date availability, the sample period for CHN is from October 2009 to December 2018.

	Intercept	Sent	R^2(%)
Euro Area	−0.19 (−0.65)	0.72 (2.26)**	2.37
Germany	0.25 (0.60)	1.01 (2.48)**	2.31
Japan	0.20 (0.54)	0.93 (2.31)**	2.33
China	−0.17 (−0.29)	1.56 (2.42)**	5.91

***Statistical significance at 5% level.

on future returns are closely related to the inability of asset mispricing reversion in the short leg dimension.

4.4 | International evidence

In this subsection, we continue to validate our results in different geographical regions around the world. Specifically, we compile SENTIX institutional investor sentiment indices for the Euro area (EUR), Germany (DEU), Japan (JPN), and China (CHN) and then investigate return predictability for each region. The results are summarized in Table 8. Similar to the institutional investor sentiment for the U.S. stock market, our array of institutional investor sentiment proxies for international markets again display positive and significant forecasting power for their corresponding region-specific future returns.

5 | CONCLUSION

In this paper, we find that the institutional investor sentiment serves as a statistically and economically significant predictor for aggregate stock returns. More specifically, one standard deviation increase in our institutional investor sentiment measure leads to a rise of 83 basis points in the performance of the stock market. This forecasting power stays robust after we control for various popular economic indicators and other well-known retail sentiment measures that can also predict returns. What is more, we find that institutional investors are able to forecast future cash flow levels for the aggregate stock market, and this ability contributes to a large portion of institutions' return predictability.

We use the BW sentiment index as a proxy for retail investor sentiment, and as a placebo for testing the institutional investor sentiment in terms of forecasting returns. The finding is that the BW retail investor sentiment index lacks cash flow information and discount rate information, both of which are considered to be major determinants of the fundamental level of stock market prices. The BW sentiment's negative predictability is mainly related to asset mispricing instead of fundamentals. A high BW sentiment index would make stock prices float away from their intrinsic values.

Our results would attract the attention of academics, practitioners, and regulators for good reasons. From an academic perspective, on the one hand, the consensus of the current literature surrounding investor sentiment is on how sentiment adversely associates with the market, but this view can partially be ascribed to retail traders who sometimes behave irrationally. On the other hand, retail investor sentiment may be responsible for driving prices away from fundamentals, a phenomenon often placating sentiment analysis, and hence inducing the relegation of sentiment to some irrational component of market dynamics. Our results lay bare the problem of the above two misperceptions: It is not the sentiment that is irrational that matters but the identity of traders expressing sentiment matters, a reconciling opinion which is coherent with both the efficient market theory and the principles in behavioural finance.

From a practical investment professional point of view, it is greatly beneficial to understand the market dynamics when the sentiment of institutional traders fluctuates. A skillful practitioner could engineer a number of instruments to take advantage of the positive relationship between current institutional investor sentiment and future aggregate stock returns.

From the regulatory standpoint, regulators would perform well by noting the effects of different investors' sentiment on the efficiency of market dynamics. Retail investor sentiment could be responsible in large part for temporary security price distortions as well as failures of market correction dynamics by acting upon their own expectations of market prices—even though these are faulty in the sense of irrelevance to fundamentals. Institutional investor sentiment, contrarily, assumes the responsibilities of tilting prices towards fundamentally determined values through the information contained in the sentiment of institutions on reasonable expectations on future cash flows. Therefore, to further increase market efficiency, regulators should improve the intensity and diversity of communications between individual investors and financial institutions.

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