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Anger in predicting the index futures returns

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Abstract

This paper aims to investigate how different emotions affect the subsequent index futures returns. We test the forecasting regressions which predict the S&P 500 index futures returns with lagged text-based emotion (anger, joy, fear, optimism, and gloom) indices and find asymmetric forecasting power exists between pessimism and optimism emotion indices. We show that only the text-based anger index could reliably perform at predicting index futures return in-sample and outperform the prevailing unconditional mean out-of-sample. Notably, the predictive power of the text-based anger index persists after controlling for other emotion indices, investor sentiment indices, and fundamental variables known to predict the futures market. And the asset allocation conditioning on text-based anger index can generate substantial economic benefits. Furthermore, the anger index influences the index futures return through both the discount rate and cash flow channels.

KEYWORDS

anger, emotions, index futures return predictability

JEL CLASSIFICATION

G12, G13, G17

1 | INTRODUCTION

A pioneering and well-known set of studies has explored the importance of investor sentiment in determining asset prices and explaining asset pricing anomalies (Brown & Cliff, 2004; Neal & Wheatley, 1998; Stambaugh et al., 2012). As pointed out by De Long et al. (1990), investors are subject to sentiment. That is, unlike the traditional rational expectations hypothesis, noisy traders act on the nonfundamental signals, and fluctuations in investor sentiment induce market prices to deviate from their fundamental values. More recently, Manela and Moreira (2017), Baker and Wurgler (2006), and Huang et al. (2015) construct the investor sentiment index in different ways and elucidate how the investor sentiment affects the stock market both theoretically and empirically.

To capture the variations in investor sentiment, most previous literature focuses on the one-dimensional sentiment indices, which deliver a single composite reading of investor sentiment. Specifically, when the overall investor sentiment index is high (low), the investor shows optimism (pessimism) about the future market. However, investor moods are complex and multidimensional. And when it comes to a particular mood, most literature focuses on the

The order of authors' names is alphabetical and all authors are co-first authors.

fear of investor and ignore the other moods, such as anger, gloom, and joy.[1] Motivated by Bodenhausen et al. (1994), other pessimistic moods, such as anger, can also lead to stereotypic judgments and generally make people more prone to impulsive and ill-considered decisions. That is, anger is also related to the mean–variance risk aversion of the market and future market returns.

Using a Thomson Reuters MarketPsych Index (TRMI) data set of text-based indices for different emotions of investors since 1990, this paper provides a novel insight into the expected futures return. Our paper, as far as we know, is one of the few first to make a thorough investigation of the relationship between lagged multidimensional market moods indices and the futures market. As pointed out by Han et al. (2022), the futures market plays a prominent role in the global market by providing market-wide information and leading the spot market in terms of price and return. This means that the fluctuations in investor sentiment, which affect risk-averse investors' preference for the spot market, such as the stock market, can also convey substantial information and pull down or up investors' demand for the futures market. Thus, this paper echoes the hypothesis by testing the forecasting regressions which predict the index futures returns with lagged text-based emotions (anger, fear, gloom, joy, and optimism) indices.

Our first set of results is related to the futures return predictability of the anger index. We find that the text-based anger index is the only one that could reliably perform at predicting index futures return both in-sample and out-of-sample. The average slope from the predictive regression of index futures return on the text-based anger index alone is 3.65% with a t statistic of 1.9389 over the full range of the observations. In addition, the explanatory power of the anger index is higher and more significant in the subsample period from January 2007 to December 2019. The t statistic is up to 2.5144, and the R^2 is up to 2.90%. This significant forecasting power of the anger index barely changes after controlling the range of observations and other primary factors. Turning to the out-of-sample exercise, the text-based anger index is valuable and outperforms the prevailing unconditional mean on a consistent basis over time. The encompassing test also elucidates the significance of the out-of-sample performance. Furthermore, the trading strategy based on the predictive model of the anger index generates significant economic gains. All the empirical evidence forcefully proves that the text-based anger index consistently delivers predictability on the futures market. Moreover, the microeconomic mechanism analysis reflects the anger index influences the futures market through the discount rate and cash flow channels.

Our second set of empirical evidence shows the different influences among investor moods indices on futures return. We first address the in-sample predictability of the anger index and compare it to the other investor moods indices. Adding other investor moods indices (joy, fear, optimism, and gloom) separately barely changes the statistical significance of the anger index. Especially when the anger index is combined with the joy, fear, and optimism index, it delivers more accurate forecasting power on futures return. Apart from the anger index, the optimism index is the only one that produces in-sample explanatory power consistently on index futures return across different ranges of observations. Turning to the out-of-sample exercise, however, the negative R^2_{OOS} value of the optimism index certifies that the optimism index fails to beat the average historical benchmark and does not generate explanatory power out-of-sample. Overall, the joy, fear, optimism, and gloom index do not help explain the futures return and are negligible for the 1-month ahead futures market.

This paper is in line with the literature that studies asset pricing implications of investor sentiment and makes several contributions. First, this paper distinguishes the overall investor sentiment into multidimensions and reveals the asymmetric predictability of multidimensional investor sentiment on the futures market. Concretely, we select the anger, fear, and gloom moods to represent the negative emotions and the joy and optimism moods for the positive ones. The remarkable predictability of negative emotion, anger, and the negligible predictability of positive emotions, joy, and optimism, imply the existence of asymmetric predictability. This asymmetric predictability between negative and positive emotions is supported as the investor shows more irrationality under the negative mood and needs a higher risk premium (Smales, 2014).

Second, we are the first of few to investigate the link between investor moods and index futures return and reveal anger matters in the futures market. The literature most relevant to this paper is proposed by Shen et al. (2021), which elucidates the explanatory power of fear on index futures return can last at lag up to 4 days by using the value at risk (VAR) model. Different from Shen et al. (2021), this paper focuses on the relatively longer predictive power of investor mood indices and provides empirical evidence that there exists a longer-lasting positive relationship between the anger

[1]Only Griffith et al. (2020) and Shen et al. (2021) investigate the predictive capability of fear, joy, gloom, and stress index on the stock market and bond market.

index and 1-month ahead index futures return. The positive relationship between anger index and 1-month ahead index futures return can be supported by Bodenhausen et al. (1994) and Nguyen and Noussair (2014). As documented by Bodenhausen et al. (1994), the subject, who displays an angry mood, renders more stereotypic judgments than does the sad subject, considered as the neutral mood subject. This means that anger mood will lead the investor more prone to impulsive and ill-considered decisions. Additionally, the experimental results provided by Nguyen and Noussair (2014) suggest that anger, considered as one of the negative emotions, can lower the risk appetite of investors.[2] Thus, angry investors tend to lose their confidence to the market and overreact more when they are hit by bad news, thereby reducing demand for stock more than the sad and fear investors. Further, the decreasing demand will pull down the contemporaneous stock asset price and lead to higher subsequent index futures return. Moreover, the statistical and economic evaluations of the out-of-sample forecasting performance reveal that the anger index contains meaningful information for index futures pricing and making trade strategy in real-time. This paper is the first, to the best of our knowledge, to provide empirical evidence that the anger index conveys meaningful and longer-lasting information on the futures market and delivers positive gains in both in- and out-of-sample.

Third, this paper is the first to explore the microeconomic mechanism of the forecasting capability of the anger index. With the VAR model, this paper elucidates that the anger index influences the index futures return through both the discount rate and cash flow channels. This economic mechanism analysis provides us with a new micro angle of view to understand the importance of investor emotions.

The rest of this paper is organized as follows. Section 2 discusses the data and construction of the investor mood indices. The in- and out-of-sample empirical forecasting results with robustness analysis are reported in Sections 3 and 4, respectively. Section 5 explores the microeconomic mechanism. Section 6 concludes.

2 | DATA AND MEASURING ANGER

We construct the monthly S&P 500 Index Futures returns based on the daily simple returns of S&P 500 Index Futures which are obtained from Datastream. The sample period is 1998:1–2019:12. From now on, $R_{m,t}$ denotes the S&P 500 Index Futures return in month t.

The TRMI anger index is based on enormous news and social media texts. The anger index is a unipolar index ranging from 0 to 1, indicating the average score of references to anger and disgust. Data is available for 1998:1–2019:12 and can be obtained from TRMIs database. The TRMI's emotional indicators, extracted by lexical analysis, reflect the aggregated corresponding emotion in the daily news and social media contents. The news sources cover the mainstream news from top businesses, regions, and industries. The social media sources include internet forums, such as finance-specific tweets. Then we construct the anger index by the following equation:

$$Anger_t = \frac{TRMIAnger_t - TRMIAnger_{t-1}}{TRMIAnger_{t-1}}. \tag{1}$$

More intuitively, we plot the time series of the anger index in Figure 1. The time trend in Figure 1 shows that the anger index fluctuates around 1.19%, which is consistent with the fact that the time series of the anger index is stationary. NBER recessions are represented by shaded bars. This figure shows that most large increases in the fluctuations of the anger index coincide with the NBER-dated recession. For example, the US stock market was through a crash in 2007 and there was a steep decline in US stock prices over a few days which definitely would result in fluctuations of investors' anger. This evidence implies that the anger index conveys useful information on economic conditions.

Similarly, we construct the joy index, fear index, optimism index, and gloom index by the same method to investigate the different emotions in predicting index futures returns. Also, we consider other predictors and control variables. First, the set of economic variables used in Sections 3.2 and 3.3 is directly downloaded from Amit Goyal's website, and data spans from January 1998 to December 2019. Then we also consider news implied volatility index (NVIX); (Manela & Moreira, 2017) and investor sentiment index (Baker & Wurgler, 2006; Huang et al., 2015) as the comparative variables.

[2]Ahn (2010) empirically confirms anger can lead investors more risk-averse and fear more risk-seeking. Kugler et al. (2012) also find those fearful participants are less risk-averse than angry participants in a two-person task involving person-based risk.

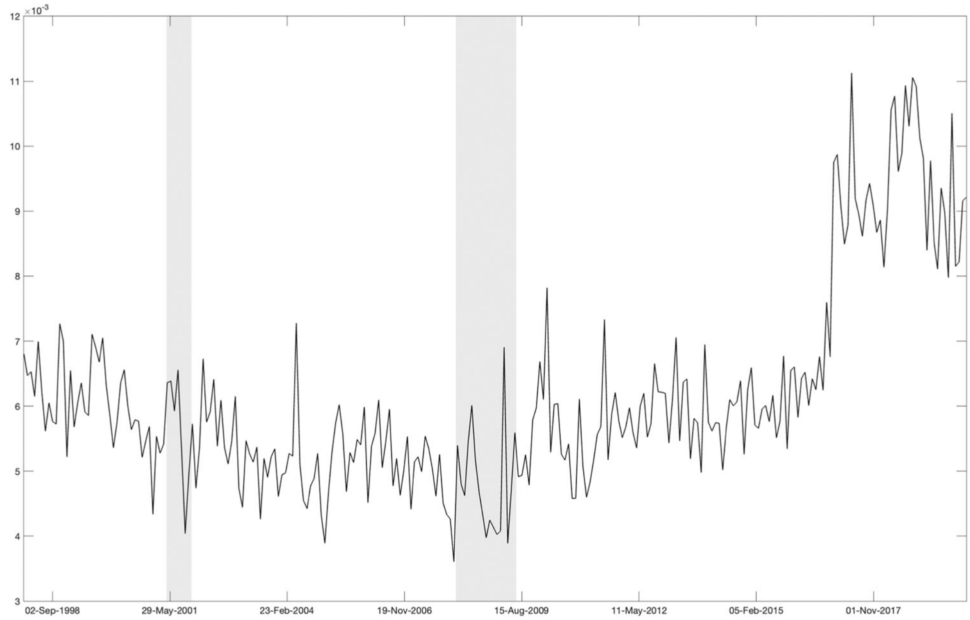

FIGURE 1 Dynamics of anger. This figure represents the dynamics of the anger index. The shadow parts mean that the United States is in a recession period.

TABLE 1 Summary statistics of variables

	Mean	Min	Median	Max	Std	Stationary process
$R_{m,t}$	0.0068	−0.1744	0.0114	0.1222	0.0483	1
Anger	0.0119	−0.4370	0.0040	0.6941	0.1471	1
Joy	0.0076	−0.2898	0.0023	0.8512	0.1323	1
Fear	0.0078	−0.3111	−0.0018	0.5054	0.1242	1
Optimism	−0.4748	−80.5373	−0.1550	32.0361	5.8951	1
Gloom	0.0022	−0.3392	−0.0057	0.5098	0.0983	1
NVIX	25.9334	13.6225	25.8322	57.8977	6.8756	0
S_{pca}	0.1271	−0.8939	0.0133	3.1974	0.6604	1
S_{pls}	−0.2679	−1.0848	−0.5593	2.4552	0.8170	0
$ECON_{avg}$	−0.7761	−0.8634	−0.7627	−0.6984	0.0427	0
$ECON_{pca}$	0.0000	−1.2872	−0.1051	4.7987	1.0000	0
DP	−4.0171	−4.5236	−3.9777	−3.2810	0.2063	0
DEF	0.0206	0.0103	0.0198	0.0549	0.0063	0
TERM	0.0222	−0.0041	0.0226	0.0453	0.0136	0
RREL	−0.0007	−0.0236	−0.0001	0.0097	0.0060	0

Note: This table reports the mean, minimum, median, maximum, standard error, and the ADF test result. The statistic value in column (6) equals 1 when the time series of the corresponding variable is stationary. The sample period is from January 1998 to December 2019.

Abbreviations: ADF, augmented Dickey–Fuller; DEF, default yield spread; DP, dividend–price ratio; NVIX, news implied volatility; RREL, detrended riskless rate; S_{pca}, investor sentiment index proposed by Baker & Wurgler (2006); S_{pls}, investor sentiment index proposed by Huang et al. (2015); TERM, term spread.

Additionally, we also report the summary statistics for the anger index and other alternative predictors in Table 1. The anger index fluctuates between −43.73% and 69.41%. And the mean and median of the anger index are positive (1.19% and 0.40%). The negligible standard error of the anger index (14.71%) and augmented Dickey–Fuller test confirm that the anger index is stationary.

3 | IN-SAMPLE PREDICTIVE PERFORMANCE

3.1 | Baseline regression

This section examines the predictive regression which forecasts the S&P 500 index futures return with lagged anger index by running the following regression:

$$R_{m,t+1} = \alpha + \beta Anger_t + \epsilon_{t+1}, \quad (2)$$

where $R_{m,t+1}$ is the monthly S&P 500 index futures return at month $t + 1$, $Anger_t$ is the measure of anger and disgust based on the news and social media text at month t.

Table 2 Panel A reports the empirical results from in-sample index futures return forecasting for the full 1998:1–2019:12 sample period. An increase in the anger index alone gives rise to the 1-month head index futures return with a regression slope of 3.65%. This positive link is consistent with Bodenhausen et al. (1994). The angry investors who render stereotypic judgments and ill-considered decisions, tend to lose their confidence to the market and overreact, thereby reducing their demand and hold for stock. And the decreasing demand will pull down the contemporaneous price and lead to the higher future return of index futures. Overall, angry investors need a premium to buy and hold the index futures which means there exists a positive link between the anger index and subsequent index futures return. And the t statistic value of the anger index (1.9389) indicates the rejection to the null hypothesis that the lagged anger index is not capable of explaining the dependent variable, the S&P 500 index futures return. The adjusted R^2 of the anger index, 1.24%, confirms that the anger index captures the investor's angry mood accurately and conveys useful market-level information to predict index futures.

Turning to the impact of different ranges of observations, we run the predictive regression of index futures return on anger index for a more recent period: 2007:1–2019:12 and present the regression results in Table 2 Panel B. It is worth noting that an increase of the anger index alone gives rise to the 1-month head index futures return with a higher regression slope of 5.53% and a more significant t statistic 2.5144. Moreover, the anger index explains 2.90% of the 1-month-ahead variation in index futures return. This explanatory power is higher than that reported in Table 2 Panel A, which can be attributed to the richer market-level information incorporated by the anger index. Overall, the anger index conveys accurate market-level information and consistent forecasting power on 1-month-ahead index futures return.

TABLE 2 Predictive regressions of S&P 500 index futures return—Baseline case

Variable	$R_{m,t+1}$
Panel A: 1998–2019	
Intercept	0.0050
	(1.5688)
Anger	0.0365
	(1.9389)
R^2 (%)	1.24
Panel B: 2007–2019	
Intercept	0.0052
	(1.1899)
Anger	0.0553
	(2.5144)
R^2 (%)	2.90

Note: This table reports results of the 1-month-ahead predictive regressions of the S&P 500 Index Futures return $R_{m,t+1}$. *Anger* is the score of references in news and social media to anger and disgust. Rows without brackets show the parameter estimates. Rows with brackets show the Newey–West adjusted t statistics (Newey & West, 1986). The last row presents the R^2 value. The sample periods are January 1998–December 2019 (Panel A) and January 2007–December 2019 (Panel B).

3.2 | Asymmetric predictive ability

We then address the asymmetric predictability between positive and negative emotions indices. We select the anger, fear, and gloom moods to capture the negative emotions and the joy and optimism moods for the positive emotions. We first explore the forecasting power of joy, fear, optimism, and gloom indices and compare them with the anger index by running the following regression:

$$R_{m,t+1} = \alpha + \beta Emotion_t + \epsilon_{t+1}, \tag{3}$$

where $R_{m,t+1}$ is the monthly S&P 500 index futures return at month $t + 1$, $Emotion_t$ is the set of emotions indices, joy, fear, optimism, and gloom indices.

Table 3 columns (1)–(5) represent the results of the single-variate models. Strikingly, only the anger index delivers consistent and substantial in-sample forecasting power. Neither the full range of the sample nor the subsample, the joy index, fear index, and optimism index demonstrate explanatory power on 1-month-ahead index futures returns with insignificant t statistic values and negligible in-sample R^2. Despite the gloom index generating superior explanatory power for the full sample 1998:1–2019:12 with a significant t statistic −2.2298 and a relative high in-sample R^2 2.00%, this forecasting power is no longer notable for the near term 2007:1–2019:12 with an insignificant t statistic value −1.6542. The negligible forecasting power of positive emotions indices and notable explanatory power of the negative emotion index, the anger index, imply the existence of asymmetric predictability. Consistent with Smales (2014), the passive investor is more irrational and needs a higher risk premium. Thus, the anger index, which captures the angry and disgust level of investors, conveys more predictive information than the positive emotions indices and generates superior explanatory power on futures return.

Additionally, we highlight that different predictive powers exist in negative emotions indices. The fear and gloom indices yield unrobust forecasting power as shown in columns (3) and (5) of Table 3. Consistent with Bodenhausen et al. (1994), the anger mood will lead the investor to stereotypic judgments and generally make people more prone to impulsive and ill-considered decisions compared with fear/gloom moods. This implies that angry investors tend to overreact more and the anger index captures greater information than fear/gloom indices.

Then we add the other emotions indices into the single-variate regression as control variables separately and elucidate the robust predictability of the anger index by running the following regression:

$$R_{m,t+1} = \alpha + \beta_1 Anger_t + \beta_2 Emotion_t + \epsilon_{t+1}. \tag{4}$$

As shown in columns (6)–(9), combining the other investor moods indices (joy, fear, optimism, and gloom) with the anger index barely changes the statistical significance of the anger index. Especially for the near sample period, when the joy, fear, and optimism index is added separately into the single-variate regression as the control variable, the anger index delivers more substantial and significant explanatory power with the more notable t statistic 2.7625, 2.7145, and 2.5779 and the greater R^2 3.26%, 3.09%, and 3.78%. Likewise, the explanatory power of the gloom index disappears for the near term 2007:1–2019:12. In summary, in this subsection we highlight the asymmetric predictability between positive and negative emotions indices on the futures market.

3.3 | Controlling for business cycle

Motivated by Welch and Goyal (2008), this paper tests whether the anger index contains any forecasting information beyond those already conveyed by the business cycling variables. We combine the anger index with a set of current cycling factors, D/P, DEF, $TERM$, and *detrended riskless rate (RREL)*, in the multivariate models.[3] The multivariate model is written as follows:

[3] D/P is the dividend ratio of the S&P 500 index, that is, the log of the S&P 500 index dividends minus the log of the S&P 500 index prices. DEF is the default yield spread, that is, yields of AAA corporate bonds minus that of BAA corporate bonds. *TERM* is the term spread, that is, yields of long-term (10-year) Treasury bond minus that of short-term (3-month) Treasury bill. RREL is the detrended riskless rate, that is, 1-month Treasury-bill rate minus its 12-month moving average. The order of the four business cycle variables below is the same as here.

TABLE 3 Predictive regressions of S&P 500 index futures return—Asymmetric predictive ability

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 1998–2019									
Intercept	0.0050	0.0054	0.0053	0.0056	0.0055	0.005	0.0049	0.0052	0.0052
	(1.5688)	(1.6900)	(1.6728)	(1.7772)	(1.8001)	(1.5299)	(1.5126)	(1.5957)	(1.6338)
Anger	0.0365					0.0373	0.0357	0.0346	0.0268
	(1.9389)					(2.0939)	(1.8886)	(1.8375)	(1.4458)
Joy		−0.0074				−0.0105			
		(−0.3069)				(−0.4617)			
Fear			0.0158				0.0125		
			(0.6315)				(0.4814)		
Optimism				0.0005				0.0004	
				(2.5700)				(1.9415)	
Gloom					−0.0656				−0.0564
					(−2.2298)				(−2.0620)
R^2 (%)	1.24	0.04	0.17	0.45	2.00	1.33	1.34	1.55	2.63
Panel B: 2007–2019									
Intercept	0.0052	0.0058	0.0062	0.0064	0.0064	0.0051	0.0054	0.0056	0.0057
	(1.1899)	(1.3250)	(1.4295)	(1.4806)	(1.5469)	(1.0888)	(1.1753)	(1.2102)	(1.2606)
Anger	0.0553					0.0539	0.0555	0.0528	0.0435
	(2.5144)					(2.7625)	(2.7145)	(2.5770)	(2.1502)
Joy		0.0342				0.0286			
		(0.8145)				(0.7482)			
Fear			−0.0166				−0.018		
			(−0.493-0)				(−0.5229)		
Optimism				0.0008				0.0007	
				(6.4221)				(5.1475)	
Gloom					−0.0803				−0.0607
					(−1.6542)				(−1.3824)
R^2 (%)	2.90	0.52	0.16	1.15	2.63	3.26	3.09	3.78	4.27

Note: This table reports results of the 1-month-ahead predictive regressions of the S&P 500 Index Futures return $R_{m,t+1}$. *Anger* is the score of references in news and social media to anger and disgust. *Joy* is the score of references in news and social media to happiness and affection. *Fear* is the score of reference in news and social media to fear and anxiety. *Optimism* is the score of references in news and social media to optimistic. *Gloom* is the score of references in news and social media to sadness. Rows without brackets show the parameter estimates. Rows with brackets show the Newey–West adjusted t statistics (Newey & West, 1986). The last row presents the R^2 value. The sample periods are January 1998–December 2019 (Panel A) and January 2007–December 2019 (Panel B).

$$R_{m,t+1} = \alpha + \beta_1 Anger_t + \beta_2 Cycle_t + \epsilon_{t+1}, \tag{5}$$

where $R_{m,t+1}$ is the monthly S&P 500 index futures return at month $t + 1$, $Anger_t$ is the measure of anger and disgust based on the news and social media text at month t. $Cycle_t$ is the set of business cycling variables.

Table 4 panel A shows the results of multivariate regressions over the sample period 1998:1–2019:12. Augmenting the predictive regression with business cycle factors barely reduces the prominence of the anger index, with more remarkable t statistics ranging from 1.8399 to 2.0005. Moreover, combining the anger index with the business cycle factor also gives rise to the explanatory power, with a more substantial R^2 from 1.33% to 2.99%. Note that, the business

TABLE 4 Predictive regressions of S&P 500 index futures return—Business cycle

Variable	(1)	(2)	(3)	(4)
Panel A: 1998–2019				
Intercept	0.0813	0.0119	0.0073	0.0057
	(0.7914)	(0.7841)	(1.5728)	(2.0243)
Anger	0.0351	0.0372	0.0370	0.0377
	(1.8399)	(1.9244)	(1.9798)	(2.0005)
DP	0.0190			
	(0.7553)			
DEF		−0.3380		
		(−0.4046)		
TERM			−0.1048	
			(−0.4169)	
RREL				1.0310
				(1.7492)
R^2 (%)	1.93	1.43	1.33	2.99
Panel B: 2007–2019				
Intercept	0.0437	0.0108	0.0089	0.0072
	(0.1738)	(0.5207)	(1.7590)	(2.1408)
Anger	0.0546	0.056	0.0558	0.0570
	(2.4081)	(2.5370)	(2.6967)	(2.7809)
DP	0.0099			
	(0.1551)			
DEF		−0.2494		
		(−0.2338)		
TERM			−0.1590	
			(−0.4749)	
RREL				1.9205
				(1.5486)
R^2 (%)	2.98	3.03	3.08	6.72

Note: This table reports results of the 1-month-ahead predictive regressions of the S&P 500 Index Futures return $R_{m,t+1}$. *Anger* is the score of references in news and social media to anger and disgust. DP_t is the dividend yield of the S&P 500 index. DEF_t represents the default spread, calculated as the difference between Moodys Baa corporate bond yields and 10-year Treasury bond yield. $TERM_t$ is the term spread, calculated as the difference between 10-year Treasury bond yields and 3-month Treasury-bill rates. $RREL_t$ is the detrended riskless rate, calculated as the difference between current Treasury-bill rate and its 12-month backward-moving average. Rows without brackets show the parameter estimates. Rows with brackets show the Newey–West adjusted t statistics (Newey & West, 1986). The last row presents the R^2 value. The sample periods are January 1998–December 2019 (Panel A) and January 2007–December 2019 (Panel B).
Abbreviations: DEF, default yield spread; DP, dividend–price ratio; RREL, detrended riskless rate; TERM, term spread.

cycle factors no longer contribute to predicting the subsequent index futures return once the anger index is introduced, even though these business cycle factors have been confirmed to convey fundamental information. That is, the anger index conveys valuable information which is not captured by primary business cycle factors.

Similarly, perhaps unsurprisingly, the anger index still conveys the complementary information source for the futures market over the sample period 2007:1–2019:12. As shown in column (1) of panel B, the t statistic value of the anger index, 2.4081, still reveals the rejection to the null hypothesis after combining the anger index with dividend–price (DP) in the two-factors model simultaneously. And the two-factors model augmented by the anger index and DP delivers more accurate forecasting power, with the higher R^2 2.98%. Likewise, when the other business cycle factors are introduced to the multivariate model separately, the anger index remains highly significant.

3.4 | Controlling for economic variables

The uncertainty and unstability can cause the primary factors to transfer more noisy information and induce insufficient in- and out-of-sample forecasts over time (Rapach et al., 2010). Applying the simple equal-weighted combination of the 14 essential economic factors proposed by Welch and Goyal (2008), the deterioration caused by uncertainty and unstability can be fixed.[4] Likewise, consistent with Baker and Wurgler (2006), this paper also removes the impairment of noisy information by employing the first principal component method. Then, we add the two combining factors into the single-variate regression as the control variable separately and test whether the anger index includes information beyond those contained in economic factors. The multivariate model is written as follows:

$$R_{m,t+1} = \alpha + \beta_1 Anger_t + \beta_2 ECON_t + \epsilon_{t+1}, \tag{6}$$

where $R_{m,t+1}$ is the monthly S&P 500 index futures return at month $t + 1$, $Anger_t$ is the measure of anger and disgust based on the news and social media text at month t, $ECON_t$ is the combination of 14 economic factors using the standardized first principal component (denoted by $ECON_{pca}$) and their equal-weighted average (denoted by $ECON_{avg}$).

The empirical evidence in Table 5 echoes the null hypothesis that the anger index contains complementary information to the economic factors. Columns (1)–(3) report the results of single-variate regression. Neither the $ECON_{avg}$ nor the $ECON_{pca}$ can yield a certain explanatory power on 1-month-head index futures return, with in-sample R^2 0.59%, 0.01% for the 1998:1–2019:12 period and 0.04%, 0.12% for 2007:1–2019:12 period. Columns (4) and (5) report the results of the two-factors models. Both the full sample and subsample anger index beat the $ECON_{avg}$ and the $ECON_{pca}$. Additionally, introducing the anger index into the predictive regression improves the explanatory power, increasing the R^2 up to 2.95%.

3.5 | Comparing with other sentiment indices

The NVIX should be considered as one of the potential competitors to the anger Index due to a pioneering set of studies suggesting that the NVIX indicator can capture the level of market pessimism (Liu et al., 2018; Manela & Moreira, 2017). Besides, the investor sentiment indices proposed by Baker and Wurgler (2006) and Huang et al. (2015) are also known as good indicators of the degree of market optimism (pessimism), implying the two investor sentiment indices should also be introduced as competitors. To test whether the anger index beats the other sentiment indices, we run the following regression:

$$R_{m,t+1} = \alpha + \beta_1 Anger_t + \beta_2 Sentiment_t + \epsilon_{t+1}, \tag{7}$$

where $R_{m,t+1}$ is the monthly S&P 500 index futures return at month $t + 1$, $Anger_t$ is the measure of anger and disgust based on the news and social media text at month t, $Sentiment_t$ is the set of competitive sentiment indices, $NVIX$, S_{pca}, and S_{pls}.

As in Table 6, across the panels, the NVIX barely delivers predictability, with negligible t statistic values −0.1047 for 1998:1–2019:12 period and −0.5255 for 2007:1–2019:12 period. As in panel A, although the coefficients of S_{pca} and S_{pls} are significantly negative, the S_{pca} and S_{pls} deliver insignificant forecasting power for the near term as in panel B. Besides, the results of multivariate regressions which combine the anger index and the competitive sentiment indices elucidate the robustness of the anger index. As in columns (5)–(7), the inclusion of S_{pca} and S_{pls} barely lower the significance of the anger index, indicating that the anger index captures complementary investor sentiment information, which has not been seized by the current sentiment indices.

[4]The 14 economic factors are the book-to-market ratio, the dividend–payout ratio, the default return spread, the default yield spread, the DP ratio, the dividend yield, the earnings–price ratio, the inflation rate, the long-term rate of return, the long-term yield, the net equity expansion, the stock variance, the Treasury-bill rate, the term spread. The order of the 14 economic variables below is the same as here.

TABLE 5 Predictive regressions of S&P 500 index futures return—Economic variable

Variable	(1)	(2)	(3)	(4)	(5)
Panel A: 1998–2019					
Intercept	0.0050	0.0713	0.0054	0.0703	0.0049
	(1.5688)	(1.1245)	(1.6587)	(1.0372)	(1.4858)
Anger	0.0365			0.0364	0.0369
	(1.9389)			(1.9599)	(1.9792)
$ECON_{avg}$		0.0853		0.0846	
		(1.0470)		(0.9722)	
$ECON_{pca}$			−0.0005		−0.0008
			(−0.0964)		(−0.1647)
R^2 (%)	1.24	0.59	0.01	1.82	1.27
Panel B: 2007–2019					
Intercept	0.0052	−0.0230	0.0062	−0.0145	0.0053
	(1.1899)	(−0.1678)	(1.3579)	(−0.0947)	(1.0951)
Anger	0.0553			0.0551	0.0547
	(2.5144)			(2.7847)	(2.5643)
$ECON_{avg}$		−0.0388		−0.0263	
		(−0.2142)		(−0.1304)	
$ECON_{pca}$			0.0014		0.0008
			(0.2797)		(0.1727)
R^2 (%)	2.90	0.04	0.12	2.92	2.95

Note: This table reports results of the 1-month-ahead predictive regressions of the S&P 500 Index Futures return $R_{m,t+1}$. *Anger* is the score of references in news and social media to anger and disgust. $ECON_{avg}$ is the equal-weighted average of 14 standard economic factors. $ECON_{pca}$ is the first principal component of 14 standard economic factors. Rows without brackets show the parameter estimates. Rows with brackets show the Newey–West adjusted t statistics (Newey & West, 1986). The last row presents the R^2 value. The sample periods are January 1998–December 2019 (Panel A) and January 2007–December 2019 (Panel B).

Overall, the in-sample results in this section imply that the anger index seizes the nonfundamental and complementary information that is not conveyed by current economic variables and sentiment indices, thereby generating outstanding forecasts on 1-month-head index futures return.

4 | OUT-OF-SAMPLE FORECASTS

4.1 | Out-of-sample methodology

To test whether the anger index still seizes the useful information in the real-time environment, we utilize the out-of-sample forecast methodology with recursive windows. The first M observations, $t = 1, ..., M$, constitute the initial training period. The rest $T - M$ observations, $t = M + 1, ..., T$, constitute the test period. We start the out-of-sample test by running the following regression:

$$R_{m,t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \quad t = 1, ..., M - 1, \tag{8}$$

where X_t is the predictive factor of interest. After obtaining the first two parameter estimations, $\hat{\alpha}_M$ and $\hat{\beta}_M$, we can obtain the estimation of $R_{m,M+1}$ by the following calculation formula:

TABLE 6 Comparison with other sentiment indices

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: 1998–2019							
Intercept	0.0050	0.007	0.0065	0.0021	0.0066	0.0046	0.0017
	(1.5688)	(0.3159)	(1.9667)	(0.5685)	(0.3057)	(1.8167)	(0.4632)
Anger	0.0365				0.0413	0.0348	0.0355
	(1.9389)				(1.9340)	(1.7616)	(1.8224)
NVIX		−0.0002			−0.0001		
		(−0.1047)			(−0.1092)		
S_{pca}			−0.012			−0.0113	
			(−2.7095)			(−2.6682)	
S_{pls}				−0.0108			−0.0107
				(−2.8479)			(−2.8487)
R^2 (%)	1.24	0.02	2.80	3.50	1.52	3.69	4.64
Panel B: 2007–2019							
Intercept	0.0052	0.0266	0.0037	−0.007	0.0271	0.0030	−0.0078
	(1.1899)	(0.6907)	(0.8460)	(−0.5874)	(0.7405)	(0.6737)	(−0.6609)
Anger	0.0553				0.0698	0.0539	0.0561
	(2.5144)				(2.5789)	(2.3095)	(2.5346)
NVIX		−0.0008			−0.0008		
		(−0.5255)			(−0.5883)		
S_{pca}			−0.0220			−0.0206	
			(−1.6132)			(−1.5195)	
S_{pls}				−0.0281			−0.0279
				(−1.3951)			(−1.4263)
R^2 (%)	2.90	0.91	2.33	4.29	5.17	4.97	7.17

Note: This table reports results of the 1-month-ahead predictive regressions of the S&P 500 Index Futures return $R_{m,t+1}$. *Anger* is the score of references in news and social media to anger and disgust. *NVIX*, S_{pca}, and S_{pls} are investor sentiment indices proposed by Manela and Moreira (2017), Baker and Wurgler (2006), and Huang et al. (2015), respectively. Rows without brackets show the parameter estimates. Rows with brackets show the Newey–West adjusted t statistics (Newey & West, 1986). The last row presents the R^2 value. The sample periods are January 1998–December 2019 (Panel A) and January 2007–December 2019 (Panel B).

$$\hat{R}_{m,M+1} = \hat{\alpha}_M + \hat{\beta}_M X_M. \tag{9}$$

Then we run the single-variate regression constantly, with an increment of one observation at a time, and increase the observation size to $T - 1$. Therefore, the last regression is as below:

$$R_{m,t+1} = \alpha + \beta X_t + \epsilon_{t+1}, \quad t = 1, \ldots, T - 2. \tag{10}$$

Likewise, we obtain the estimations of parameters, thereby the estimation of $R_{m,T}$. By expanding the estimation window, the out-of-sample forecasts of index futures return using the predictor of interest can be obtained and denoted by $\hat{R}_{m,t} = (\hat{R}_{m,M+1}, \ldots, \hat{R}_{m,T})$.

To gauge the value of the index futures return forecast model, this paper uses the prevailing mean of index futures return as the benchmark model, and denotes the forecasts using the prevailing mean by $\bar{R}_{m,M+1} = (\bar{R}_{m,M+1}, \ldots, \bar{R}_{m,T})$. Then, as in Welch and Goyal (2008), this paper calculates out-of-sample R^2 relative to the historical average benchmark model given as

$$R_{OOS}^2 = 1 - \frac{MSPE_P}{MSPE_N} = 1 - \frac{(1/T_{OOS})\sum_{t=M+1}^{T}(R_{m,t} - \hat{R}_{m,t})^2}{(1/T_{OOS})\sum_{t=M+1}^{T}(R_{m,t} - \bar{R}_{m,t})^2}. \tag{11}$$

A positive R_{OOS}^2 implies that the MSPE of the predictor of interest is lower than that of the prevailing mean model, indicating higher predictive accuracy.

As in Clark and McCracken (2001), we further conduct encompassing test to determine whether the difference in forecasts between the benchmark and predictive model of interest is statistically significant. The null hypothesis proposed in the encompassing test is $R_{OOS}^2 \leq 0$ and the *ENC* statistic is calculated as

$$ENC = \frac{T_{OOS} - k + 1}{T_{OOS}} \frac{\sum_{t=S_0+1}^{T}[(R_{m,t} - \bar{R}_{m,t})^2 - (R_{m,t} - \bar{R}_{m,t})(R_{m,t} - \hat{R}_{m,t})]}{RMSE_P}. \tag{12}$$

Additionally, the economic implication is also important for investors who rely on the predictive models to conduct the investment decisions. Thus, following Welch and Goyal (2008), this paper assumes the mean–variance investors construct the asset allocation with the out-of-sample forecasts, by allocating index futures and risk-free assets. The proportion of investors investing in index futures is given as

$$w_{m,t} = \frac{\hat{R}_{m,t}}{\lambda \hat{V}_{m,t}}, \tag{13}$$

where λ is the risk aversion and $\hat{V}_{m,t}$ is the variance of index futures returns. Consequently, the proportion of investors investing in risk-free assets is $1 - w_{m,t}$, and the portfolio excess return is given as

$$r_{p,t+1} = w_{m,t} R_{m,t+1} + R_{f,t+1}. \tag{14}$$

To underline whether the trading strategy based on predictors of interest has economic implication, this paper employs on the certainty equivalent return (*CE*) and Sharpe ratio (*SR*):

$$CE = \bar{r}_p - \frac{\lambda}{2}\sigma_p^2, \tag{15}$$

$$SR = \frac{\bar{r}_p}{\sigma_p}, \tag{16}$$

where the $\bar{r}_p$ and σ_p are the sample mean and variance of portfolio excess return. More intuitively, this paper denotes the *CEgain* (*SRgain*) as the difference between the *CE* (*SR*) of the trading strategy based on predictor of interest and that of based on historical average.

4.2 | Out-of-sample forecasting performance

This section concentrates on the out-of-sample performance of the anger index relative to the prevailing mean model and the current competitive predictors. The results of R_{OOS}^2 and *ENC* statistic values are shown in Table 7. Remarkably, the anger index performs well over all the emotions indices. Both the positive emotions indices, the joy index and optimism index, generate negligible out-of-sample predictability with negative R_{OOS}^2 values, −0.72% and −0.11%. And two of the three negative emotions indices, the anger index and gloom index, stand out with the positive and significant R_{OOS}^2 (1.24% and 1.87%). This once again elucidates that the positive and negative emotions have asymmetric predictive power on 1-month-ahead index futures return. Besides, although the R_{OOS}^2 of the gloom index is 1.87%, the gloom index generates lower near-term in-sample predictability than the anger index as shown in Table 3 which means the gloom index captures less nonfundamental information recently. The *ENC* statistic value of the anger index is 1.8121 and forcefully certifies the rejection to the null hypothesis that the anger index fails to encompass the forecasts for the prevailing mean. In another word, the anger index beats the unconditional benchmark.

TABLE 7 Out-of-sample forecasting results on index futures return

	$R^2_{OOS}(\%)$	*ENC*	*SRgain*	*CEgain*
Anger	1.24	1.8121	0.281	0.0721
Joy	−0.72	−0.4444	−0.1204	−0.0235
Fear	−2.57	−1.0025	0.2097	0.0513
Optimism	−0.11	−0.0074	0.0114	0.0069
Gloom	1.87	2.7768	0.7351	0.1722
DP	−4.23	−2.0461	0.127	0.0255
DEF	−4.08	3.0399	0.3702	0.0959
TERM	−0.27	−0.1097	0.0937	0.029
RREL	2.07	2.1783	0.5882	0.1405
$ECON_{avg}$	−2.39	−1.3584	0.042	−0.0038
$ECON_{pca}$	−5.40	−0.8489	0.3708	0.0927
NVIX	−3.70	−1.3762	−0.0678	−0.0182
S_{pca}	0.79	1.0988	0.4391	0.0881
S_{pls}	2.30	2.3615	0.6946	0.1622

Note: This table reports the out-of-sample results on S&P 500 index futures return. $R^2{}_{OOS}$ is the out-of-sample R^2 by Welch and Goyal (2008). ENC is the statistic by Clark and McCracken (2001). *SRgain* and *CEgain* are defined by Equation (16) and (15). The annual transaction fee is a 10-basis point fee. The out-of-sample period: 2007:1–2019:12.

Abbreviations: DEF, default yield spread; DP, dividend–price ratio; NVIX, news implied volatility; RREL, detrended riskless rate; TERM, term spread.

Besides, the columns (3) and (4) of Table 7 report the *SRgain* and *CEgain*. The trading strategy constructed with the S&P 500 index futures return forecasted by the anger index can beat that based on the prevailing mean with 0.2810 *SR* gain and 0.0721 *CE* gain. That is, the anger index also benefits for investors in real-time.

To confirm the stability of the out-of-sample forecast, this paper plots the difference between the cumulative sum of squared prediction errors (SSE) based on the prevailing mean and that based on the predictor proposed. Concretely, this paper denotes the difference with OOS_t, which is given as

$$OOS_t = \sum_{t=1}^{t}(R_{m,t+1} - \bar{R}_{m,t})^2 - \sum_{t=1}^{t}(R_{m,t+1} - \hat{R}_{m,t})^2, \quad t = M, ..., T1. \tag{17}$$

As confirmed by the equation, when the predictive model performs better than the prevailing mean, the SSE generated by the predictive model is lower than that produced by prevailing mean, thereby making the OOS_t positive. Additionally, the steady upward trend of the *OOS* measure elucidates that the predictive error between the historical average model and the predictive model is constantly stretched. That is, the predictive model generates progressively increasing out-of-sample gains over time.

Figure 2 plots the time series of *OOS* of the predictors of interest and allows us to have a more intuitive impression on the economic gains produced by predictors of interest. As shown in the first subfigure, the upward trend implies the anger index exceeds the historical average and delivers smooth out-of-sample predictability on 1-month-ahead index futures return. Additionally, the *OOS* of anger index soars during the period of subprime crisis, implying the anger index captures more beneficial informations in the terrible environment. However, the trends of *OOS* of the emotion indices (joy index, fear index, and optimism index), fundamental factors (*DP*, *DEF*, *TERM*, $ECON_{pca}$, $ECON_{avg}$), and other sentiment indices (*NVIX*, S_{pca}, S_{pls}) plummet when the subprime crisis occurs, revealing the invalidity of these competitive predictors.

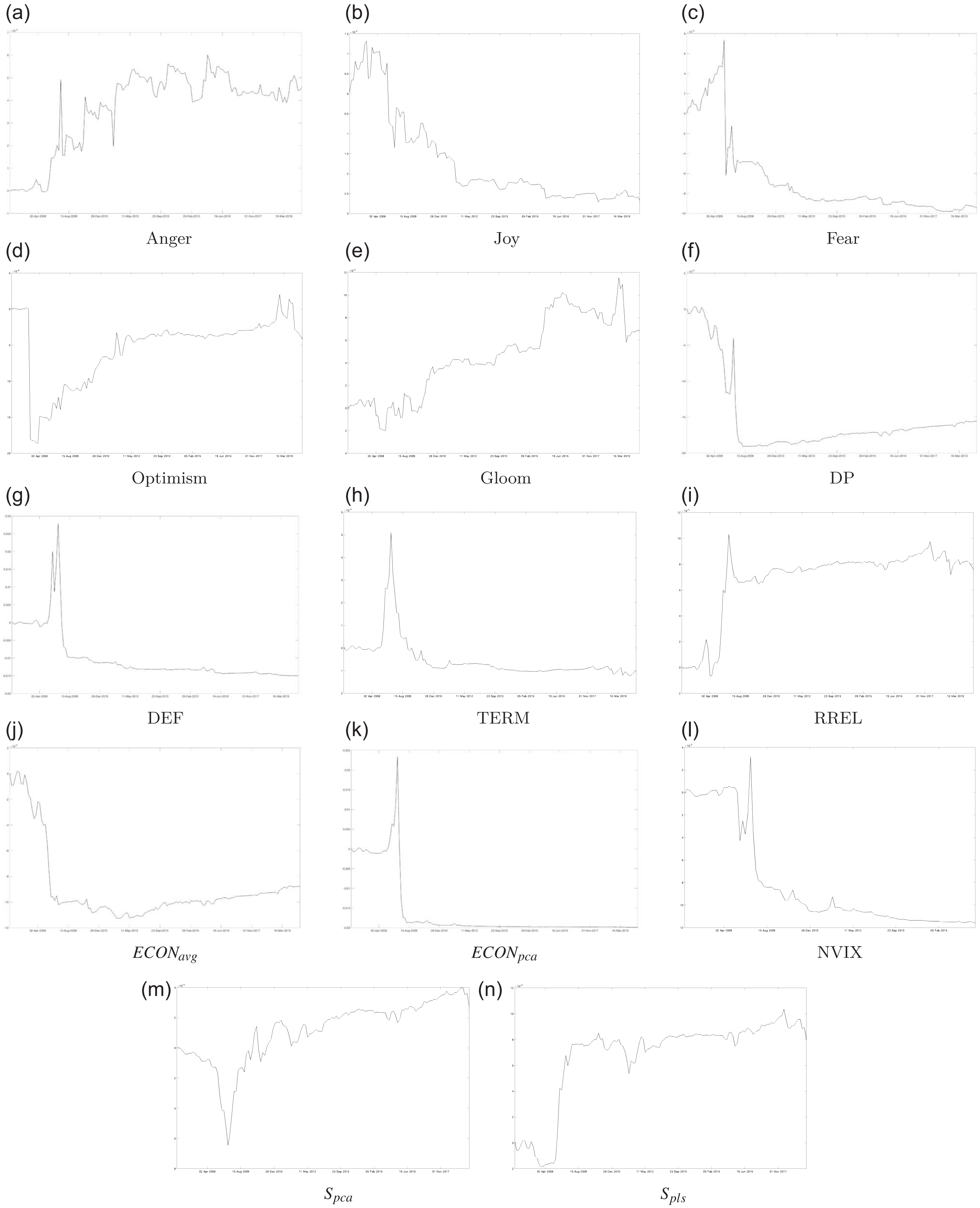

FIGURE 2 Monthly OOS performance of anger index and other predictors. These figures OOS of the anger index and the other alternative predictors, *Joy* index, *Fear* index, *Optimism* index, *Gloom* index, *DP*, *DEF*, *TERM*, *RREL*, $ECON_{avg}$, $ECON_{pca}$, *NVIX*, S_{pca}, S_{pls}. The OOS is defined by Equation (17). The OOS period: 2007:1–2019:12. OOS, out-of-sample.

4.3 | Conditional out-of-sample performance

This section explores whether the out-of-sample forecast of the anger index differs under different macroeconomic conditions. Investors are more likely to be angry in a downside market and make more irrational decisions. Therefore, the anger index should generate various out-of-sample predictive capabilities under different macroeconomic conditions.

Following Levine et al. (2018), this paper investigates the out-of-sample forecasting capability of the anger index under two pairs of macroeconomic conditions, recession/expansion and inflation down/up. As shown in Table 8, the forecasting power produced by the anger index is more pronounced in the periods of recession and falling inflation with the positive R^2_{OOS} and economic gains. Especially for the period of inflation down, the anger index produces a superior high R^2_{OOS} (2.05%). Additionally, the anger index produces substantial *SRgain* (1.1255) and *CEgain* (0.5016) in the period of recession.

5 | ECONOMIC EXPLANATION

The compelling evidence forcefully echoes the hypothesis that the anger index strongly forecasts the 1-month-ahead index futures return both in- and out-of-sample. In this section, this paper makes a thorough investigation on the microeconomic mechanism of this forecasting capability.

As argued by Campbell (1990), the stock price should be equal to the discounted value of expected future cash flows. Thus, we follow Campbell (1990) to investigate whether the anger index captures discount rate and/or cash flow risks. We use the VAR model to decompose the S&P 500 index futures return into three components: the expected return ($\hat{E}_t R^m_{t+1}$), the discount rate news ($\hat{\eta}^{DR}_{t+1}$), and the cash flow news ($\hat{\eta}^{CF}_{t+1}$). Then we regress the three components on the anger index separately with the single-variate predictive model, analyzing the mechanism of the anger index in forecasting index futures return. The single-variate regressions are given as

$$\hat{E}_t R^m_{t+1} = \alpha + \beta Anger_t + \epsilon_{t+1}, \tag{18}$$

$$\hat{\eta}^{DR}_{t+1} = \alpha + \beta Anger_t + \epsilon_{t+1}, \tag{19}$$

$$\hat{\eta}^{CF}_{t+1} = \alpha + \beta Anger_t + \epsilon_{t+1}. \tag{20}$$

Following Mele (2007) and Chen et al. (2022), we use the index futures return, DP ratio, and the volatility of index futures return to estimate the expected return $\hat{E}_t R^m_{t+1}$, discount rate $\hat{\eta}^{DR}_{t+1}$, cash flow $\hat{\eta}^{CF}_{t+1}$ by the VAR model. Concretely, the expected return is driven by DP ratio and volatility of return. Thus, the difference between real index futures return and expected return can be seen as the shock produced by the discount rate and/or cash flow news. Investigating the relationship between the anger index and discount rate and cash flow components, we can deeply comprehend the micro-mechanism of the anger index affecting index futures return.

TABLE 8 Conditional out-of-sample forecasting results on index futures return

	R^2_{OOS}(%)	*ENC*	*SRgain*	*CEgain*
Anger	1.24	1.8121	0.281	0.0721
Recession	1.05	1.2281	1.1255	0.5016
Expansion	1.37	2.1988	−0.0833	−0.0166
Inflation down	2.05	3.7131	0.6917	0.1862
Inflation up	0.35	1.3462	−0.255	−0.0763

Note: This table reports the conditional out-of-sample results on S&P 500 index futures return. R^2_{OOS} is the out-of-sample R^2 by Welch and Goyal (2008). ENC is the statistic by Clark and McCracken (2001). *SRgain* and *CEgain* are defined by Equation (16) and (15). The annual transaction fee is a 10-basis point fee. The out-of-sample period: 2007:1–2019:12.

TABLE 9 Return decomposition

	$\hat{E}_t R^m_{t+1}$	$\hat{\eta}^{DR}_{t+1}$	$\hat{\eta}^{CF}_{t+1}$
Panel A: 1998–2019			
Anger	−1.4897	−1.4588	2.1129
	(−1.6611)	(−1.6113)	(2.0522)
Joy	0.2970	0.7018	−0.3423
	(0.8640)	(0.6285)	(−0.2569)
Fear	−1.0011	−0.9152	1.6434
	(−4.1591)	(−0.6506)	(1.1045)
Optimism	0.0048	−0.0154	0.0315
	(1.1389)	(−1.3082)	(3.1948)
Gloom	−0.1943	3.1844	−3.2151
	(−0.5243)	(2.6802)	(−2.4913)
Panel B: 2007–2019			
Anger	−0.0041	−2.2097	3.1103
	(−0.0100)	(−2.6481)	(3.2158)
Joy	0.1723	−1.1527	1.8044
	(0.4274)	(−0.7025)	(0.8561)
Fear	−0.9126	1.2966	0.3827
	(−2.8904)	(0.8514)	(0.1834)
Optimism	0.0075	−0.0252	0.0465
	(1.8773)	(−3.1129)	(5.7111)
Gloom	0.1991	4.1856	−4.2010
	(0.4500)	(2.2290)	(−2.0599)

Note: This table reports the regression results of the three estimated components of the S&P 500 index futures return for month $t + 1$ on the anger index. $\hat{E}_t R^m_{t+1}$ is the expected return. $\hat{\eta}^{DR}_{t+1}$ is the discount rate news. $\hat{\eta}^{CF}_{t+1}$ is the cash flow news.

Table 9 reports the regression results of the three estimated components of index futures return on the anger index. As in panel A, the anger index mainly influences the index futures return through the cash flow channel with the remarkable t statistic 2.0522. However, for the near period, both coefficients of the anger index are statistically remarkable, implying that the predictive capability of the anger index comes from the discount rate and cash flow channels. That is, the anger index predicts the time-varying index futures returns through both channels. And this is essential for studying the micro-influence mechanism of the anger index on asset returns.

6 | CONCLUSION

This paper makes a thorough investigation on the different impacts of all emotion indices and empirically confirms that there exists asymmetric predictability between negative emotion indices and positive emotion indices. Among the negative emotion indices, the anger index consistently delivers superior predictability on 1-month-ahead index futures return as the impulse plays a role. In the future studying, it is interesting to investigate the implusive negative emotion indices. Additionally, the profitable trading strategy based on the anger index also demonstrates its strong economic importance.

Another concern in asset pricing is the microeconomic mechanisms that drive the variations of index futures return. We use the VAR model to decompose the index futures return into three components and confirm that the anger index drives index futures return through the discount rate and cash flow channels both.

The importance of the anger index takes several key takeaways and implications for both investors and policy makers. In the downside market, the policy makers should make effort to stabilize investor sentiment fluctuations, reducing the ongoing shock to the market and decreasing demand caused by the extreme anger of investors. Also, the market participants and investors need correctly understand the decision-making significance of emotions and avoid the irrational investment decisions when they are in anger.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in figshare at https://doi.org/10.6084/m9.figshare.21080947.

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