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Abstract

We explore the relationship between investor, consumer, and business sentiment and the direction of excess stock market returns in the US. Our findings indicate that measures of investor sentiment are useful predictors, even after controlling for the predictive ability of commonly used predictors of stock returns and for the effects of recession. Measures of consumer and business sentiment do not hold similar predictive ability. The findings hold both in- and out-of-sample.

Keywords: Equity return, Probit model, Sentiment variable, Sign predictability

JEL classification: C22, G12, G17

1 Introduction

Traditionally, the majority of research on stock return predictability has focused on the use of macroeconomic and financial variables. However, investor psychology has also been found to be useful in explaining the behavior of financial markets, and already in the seminal paper of Kahneman and Tversky (1979) investor psychology is suggested to play a role in explaining asset returns. Based on this idea, various sentiment variables, aiming to catch market participant beliefs of future asset prices

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not justified by fundamentals, have been developed and found useful in predicting the future movements in asset prices.

Baker and Wurgler (2006, 2007) develop an investor sentiment index, which they find to have significant predictive ability for a large number of cross-sectional stock returns. Furthermore, Huang et al. (2015) build on the afomentioned studies and propose an aligned sentiment index from which a common noise component of sentiment proxies has been eliminated. Their findings indicate that the new index has superior predictive power over existing sentiment indices both in- and out-of-sample for both aggregate and cross-sectional stock returns. On the other hand, some studies have found contradictory evidence on the investor sentiment-return relationship. Brown and Cliff (2004) form an index of sentiment based on survey data and technical variables, and find that it has little predictive power for near-term future stock returns. Further research has suggested that the predictive ability of sentiment is strongest during recessionary periods (Garcia (2013) and Smales (2017)) and may also be asymmetric (Zhong-Xin et al. (2015)).

In addition to investor sentiment, the role of both consumer and business sentiment in stock return predictability has been studied in the literature. In a number of studies, consumer confidence indices have in fact been used in as proxies for investor sentiment (see, e.g., Qiu and Welch (2006), Lemmon and Portniaguina (2006), and Schmeling (2009)), as they arguably include a component related to investor sentiment. Furthermore, Campbell and Diebold (2009) find that expected business conditions affect excess stock returns in both statistically and economically significant counter-cyclical manner.

We contribute to the literature by considering the predictive ability of sentiment variables on the directional predictability of stock returns. The motivation in focusing on the sign component of the return is based on previous studies where the sign of the excess stock return to has been shown to be predictable even in the absence of mean predictability (see, e.g., Christoffersen and Diebold (2006) and Chevapatrakul (2013)). Also, forecasts based on binary dependent variable models have outperformed those based on conventional predictive regression models in a number of studies (see, e.g., Leung et al. (2000), Nyberg (2011), and Pönkä (2017)).

Our in-sample findings indicate that investor sentiment variables are indeed useful predictors of the direction of excess stock returns. Moreover, the results are consistent with previous findings that have found that stock returns tend to be lower after periods of high investor sentiment. However, we find that measures of consumer and business sentiment do not hold similar predictive ability. This suggests that the use of consumer confidence as a proxy for investor sentiment might not be justifiable, or atleast that it contains distinctive information compared to the other investor sentiment indices.

The out-of-sample results generally affirm the in-sample findings, using both statistical and economic measures of goodness-of-fit. In particular, we find evidence in favour of the aligned sentiment index of Huang et al. (2015) as a predictor of the future direction of excess stock returns. Finally, we find that while including an autoregressive structure in the probit model improves in-sample fit, the more parsimonious static probit models fare better out of sample.

The rest of the paper is organised as follows. In Section 2, we discuss the details of our methdology and goodness-of-fit measures. In Section 3 we discuss the data and in Section 4 we present our empirical findings. Finally, Section 6 concludes.

2 Methodology and data

We are interested in predicting the direction of the monthly excess US stock market return, where the excess return is defined as the difference between the market return RM_t and a risk-free rate RF_t (i.e. $RE_t = RM_t - RF_t$). The excess return is transformed into a binary indicator

$$y_t = \begin{cases} 1, \text{if the excess return is positive,} \\ 0, \text{otherwise.} \end{cases} \tag{1}$$

In order determine the conditional probability of a positive excess return (p_t), we employ the probit model

$$p_t = P_{t-1}(y_t = 1) = \Phi(\pi_t), \tag{2}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and π_t is a linear function of the lagged predictive variables. In the context of our study, we employ a static probit model where π_t is specified as

$$\pi_t = \omega + \gamma SI_{t-1} + \boldsymbol{\beta x}_{t-1}, \tag{3}$$

where ω is a constant term, SI_{t-1} is the first lag of the sentiment variable of interest, and $\boldsymbol{x}_{t-1}$ is a vector of control variables. We estimate the parameters of our model using the method of maximum likelihood and use Newey-West-type robust standard errors, similarly as in Kauppi and Saikkonen (2008).

We also consider a dynamic extension to the static probit model (3) to analyze potential improvements in predictive ability. Specifically, we employ the first-order autoregressive probit model of Kauppi and Saikkonen (2008).In the model, the lagged value of the linear function π_t is included in order to introduce an autoregressive structure

$$\pi_t = \omega + \alpha\pi_{t-1} + \gamma SI_{t-1} + \boldsymbol{\beta x}_{t-1}. \tag{4}$$

Various evaluation methods of probability forecasts for binary dependent variable models have been proposed in the literature, and we employ a number of these to evaluate the in-sample and out-of-sample performance of our models. These include the pseudo-R^2 of Estrella (1998), the Bayesian information criterion (BIC), and the success ratio (SR), which is simply the percentage of correct forecasts. In addition to these conventional measures, we employ the Area Under the receiver operating characteristic Curve (AUC). The AUC is a measure of overall predictive ability of a given model and it has recently gained popularity in economic applications, as discussed in Nyberg and Pönkä (2016). The AUC is of particular interest in our application, as a statistically significant improvement over the 0.5 benchmark implies sign predictability that may lead to economic gains. In this paper, we study these potential economic gains by means of simple market timing tests.

3 Data

There are a number of forward-looking sentiment indicators that may be used to analyze future business conditions and stock returns. In this study, we employ confidence indicators of various economic agents, including investor, consumer, and business sentiment indices. Specifically, we use the sentiment index of Baker and Wurgler (2006) (SIBW) and the aligned sentiment index of Huang et al. (2015) (SIHO) as measures for investor sentiment.[1] Furthermore, as a measure of consumer confidence, we include the University of Michigan consumer sentiment index for the US (CCI). Finally, as a measure of business confidence, we include the Purchasing Managers' Index (PMI)[2] that has been found to hold predictive power for future stock returns (Johnson and Watson (2011)) and recessions (Christiansen et al. (2014)). The consumer confidence index and the Purchasing Managers' Index are used in first differences to ensure stationarity.

The correlation coefficients between the sentiment variables are presented in Table 1. As expected, the correlation between the investor sentiment variables $SIBW$ and $SIHO$ is rather high 0.62. Otherwise, the correlations are close to zero, indicating that the measures contain unrelated information.

In terms of financial control variables, we follow a typical convention in the literature (see, e.g. Ang and Bekaert (2007) and Rapach et al. (2013)), and use the 3-

[1] We would like to thank the authors of these studies for making the data available. The data is obtained the website of Guofu Zhou: http://apps.olin.wustl.edu/faculty/zhou/.

[2] This monthly index is published by the Institute for Supply Management (ISM) https://www.instituteforsupplymanagement.org/. It is constructed using survey data for more than 400 manufacturing firms.

Table 1: Correlations between sentiment variables

	$SIBW_t$	$SIHO_t$	$DCCI_t$	$DPMI_t$
$SIBW_t$	1.00	0.62	-0.02	-0.07
$SIHO_t$		1.00	-0.08	-0.04
$DCCI_t$			1.00	0.20
$DPMI_t$				1.00

Notes: This table displays the correlation coefficients between the variables employed in the study.

month treasury bill rate (TB) and the dividend yield (DY) as additional predictors.[3]

4 Empirical findings

Our in-sample findings for single-predictor probit models (Table 2) indicate that two out of four studied sentiment variables are useful predictors for the direction of market movements. More precisely, we find that investor sentiment indices of Baker and Wurgler (2006) (SIBW) and Huang et al. (2015) (SIHO) are statistically highly significant predictors for the direction of excess market returns. The sign of the estimated coefficient for both indices are negative, which is in line with previous literature that has found stock returns to be lower after high levels of investor sentiment (see, e.g. Huang et al. (2015) and Smales (2017)). However, neither the measure of consumer confidence (DCCI) nor business confidence (DPMI) have statistically significant predictive ability in the single-predictor model.

In Table 3, where we include the two commonly used predictors of excess returns as control variables, we find that models including the investor sentiment index of Huang et al. (2015) (M2) and that of Baker and Wurgler (2006) (M1) perform the best according to all goodness-of-fit measures considered. However, of these two indices, we find that the model including the index of Huang et al. (2015) performs the best. The AUC for M2 is 0.607, while the baseline model (M5) that includes only the short term interest rate and the dividend yield delivers an AUC of 0.582.

[3]The 3-Month Treasury Bill: Secondary Market Rate (TB) and the University of Michigan Consumer sentiment index have been retrieved from FRED database, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/. Similarly, the S&P500 index and the dividend yield are obtained from the Goyal and Welch (2008) dataset, http://www.hec.unil.ch/agoyal/.

Table 2: In-sample results for single-predictor probit models

Sentiment variables, first lags						
	Variable	Coeff.	adj.psR^2	BIC	SR	AUC
1	$SIBW_{t-1}$	-0.240***	0.012	297.338	0.636	0.565***
2	$SIHO_{t-1}$	-0.242***	0.024	294.735	0.647	0.572***
3	$DCCI_{t-1}$	0.002	Neg.	301.041	0.613	0.496
4	$DPMI_{t-1}$	-0.001	Neg.	301.051	0.613	0.512

Notes: This table presents the findings from single-predictor probit models using sentiment variables as predictors using the in-sample period 1978M1-2014M12. The goodness-of-fit measures are described in Section 2. In the table, *, **, and *** denote the statistical significance of the estimated coefficients and the AUC at 10%, 5% and 1% significance levels, respectively. "Neg." refers to a negative value of the adjusted pseudo-R^2.

On the other hand, the models including the consumer confidence index (M3) and the Purchasing managers' index (M4) do not improve over the baseline model.

Table 3: In-sample estimation results of probit models with the benchmark predictors and sentiment variables.

	M1	M2	M3	M4	M5
$SIBW_{t-1}$	-0.150*				
	(0.089)				
$SIHO_{t-1}$		-0.202***			
		(0.067)			
$DCCI_{t-1}$			-0.001		
			(0.016)		
$DPMI_{t-1}$				-0.011	
				(0.030)	
$CONST$	1.905**	1.841**	2.323***	2.343***	2.320***
	(0.766)	(0.729)	(0.704)	(0.711)	(0.701)
TB_{t-1}	-4.928**	-4.258*	-6.891***	-6.991***	-6.879***
	(2.476)	(2.299)	(2.189)	(2.241)	(2.169)
DY_{t-1}	0.367**	0.365**	0.462**	0.466***	0.462***
	(0.184)	(0.176)	(0.170)	(0.172)	(0.170)
$logL$	-289.245	-286.680	-290.331	-290.255	-290.334
BIC	301.428	298.863	302.514	302.438	299.471
$adj.psR^2$	0.017	0.028	0.012	0.012	0.014
SR	0.624	0.649***	0.620	0.622*	0.622
AUC	0.585***	0.607***	0.582***	0.584***	0.582***

Notes: This table illustrates the predictive power of the sentiment variables, the three-month T-bill rate (TB), and the dividend yield (DY). Robust standard errors of the estimated coefficients are reported in brackets. The success ratio (SR) is based on a signal forecast $\hat{y}_t$ receiving the value 1 if $p_t > 0.5$ and 0 otherwise. In the table, *, **, and *** denote the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) PT predictability test for the success ratios, and the AUC at 10%, 5% and 1% significance levels, respectively.

In Table 4, we report the results for autoregressive probit models. The findings are similar to the ones obtained for the static probit model, as once again a model including the investor sentiment index of Huang et al. (2015) (AR2), performs the

Table 4: In-sample estimation results of autoregressive probit models with the benchmark predictors and sentiment variables.

	AR1	AR2	AR3	AR4	AR5
$SIBW_{t-1}$	-0.209*				
	(0.122)				
$SIHO_{t-1}$		-0.277**			
		(0.115)			
$DCCI_{t-1}$			-0.007		
			(0.013)		
$DPMI_{t-1}$				-0.026	
				(0.020)	
π_{t-1}	-0.447***	-0.428***	-0.622***	-0.793***	-0.923***
	(0.166)	(0.115)	(0.191)	(0.078)	(0.131)
$CONST$	2.837**	2.711*	3.824***	4.258***	4.383***
	(1.230)	(1.470)	(1.220)	(1.238)	(1.276)
TB_{t-1}	-7.491*	-6.470	-11.471***	-12.872***	-13.519***
	(3.938)	(4.365)	(3.787)	(3.910)	(4.127)
DY_{t-1}	0.548**	0.538*	0.761***	0.846***	0.862***
	(0.287)	(0.328)	(0.289)	(0.300)	(0.312)
$logL$	-289.067	-286.633	-289.853	-288.873	-289.855
BIC	304.295	301.861	305.081	304.101	302.028
$adj.psR^2$	0.015	0.026	0.012	0.016	0.014
SR	0.622	0.645***	0.629***	0.624**	0.627**
AUC	0.588***	0.609***	0.590***	0.601***	0.592***

Notes: This table illustrates the predictive power of the sentiment variables, the three-month interest rate (TB), and the dividend yield (DY) in an autoregressive probit model. The autoregressive term is denoted with π. Robust standard errors of the estimated coefficients are reported in brackets. The success ratio (SR) is based on a signal forecast $\hat{y}_t$ receiving value 1 when $p_t > 0.5$ and 0 otherwise. In the table, *, **, and *** denote the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) PT predictability test for the success ratios, and the AUC at 10%, 5% and 1% significance levels, respectively.

best. In general, the AUC is higher for the autoregressive models than their static counterparts, and the estimated coefficients for the autoregressive parameters π_{t-1} are statistically highly significant.

In addition the in-sample analysis, we study the predictive ability of the sentiment variables in a pseudo out-of-sample setting for the period 1989M1-2014M12. We employ an expanding window, but we evaluated the robustness of the results by using a rolling window.[4] The out-of-sample results for the static probit models in Panel A of Table 5 generally confirm the in-sample findings, as the model including the sentiment index of Huang et al. (2015) (M2) performs the best in terms of the AUC. We also employ a market timing test based on the forecasts of the models, similarly as in Nyberg and Pönkä (2016). The return of the trading strategy based

[4]These results based on the rolling window are available upon request.

on the forecasts of model M2 (11.37%) is higher than that of the baseline model M5. Furthermore, M2 is the only one that is able to outperform a buy-and-hold strategy, which yields an annual return of 10.47% and a Sharpe ratio of 1.67.

Table 5: Out-of-sample forecasts for static and autoregressive probit models.

	Panel A: static probit models				
	M1	M2	M3	M4	M5
SR	0.615	0.622	0.609	0.599	0.612
AUC	0.510	0.522	0.494	0.507	0.503
RET	10.35%	11.37%	10.06%	9.71%	10.24%
SHR	1.69	2.01	1.61	1.53	1.65
	Panel B: autoregressive probit models				
	AR1	AR2	AR3	AR4	AR5
SR	0.590	0.571	0.580	0.589	0.596
AUC	0.510	0.524	0.508	0.486	0.491
RET	9.12%	9.06%	8.88%	9.73%	9.78%
SHR	1.38	1.47	1.36	1.56	1.57

Notes: This table displays expanding window out-of-sample forecasting results for the period 1989M01–2014M12. The forecasts in Panel A are based on the static probit model (3) and in Panel B on the autoregressive probit model (4). RET referes to annualized returns of a simple trading strategy based on the model forecast and SHR refers to the Sharpe ratio.

The autoregressive probit models improved the in-sample performance of our models. However, the results in Panel B of Table 5 indicate that this result does not hold in an out-of-sample setting. Using both statistical and economic measures of goodness-of-fit, the forecasts of the autoregressive probit models are outperformed by the more parsimonious static probit model.[5] Among the autoregressive models, the model including the sentiment index of Huang et al. (2015) (AR2) outperforms the competing models based on the AUC, but the other measures do not confirm this finding.

5 Sentiment and the stock market during recessions

This section presents findings from further analysis regarding predictive power of sentiment variables during periods of economic growth and recession, as previous studies have suggested that the predictive ability of sentiment may be stronger

[5] A similar finding in favour of the static probit model was made by Pönkä (2017), who studied the directional predictability of US excess stock market returns by lagged excess returns from industry portfolios.

during recessionary periods (Garcia (2013) and Smales (2017)). To study this issue, we employ a dummy variable for NBER recessions defined as follows:

$$REC_t = \begin{cases} 1, \text{if the economy is in a recession,} \\ 0, \text{if the economy is in an expansion.} \end{cases} \tag{5}$$

This dummy variable is used together with each sentiment indicator (SI) in the following way:

$$\pi_t = \omega + \gamma SI_{t-1} + \delta SI_{t-1} REC_{t-1} + \boldsymbol{\beta x}_{t-1}, \tag{6}$$

where the interaction term $\delta SI_{t-1} REC_{t-1}$ captures the effect of the recession. However, in Table 6 the coefficients for the interaction term are not statistically significant, thus suggesting that the relationship between sentiment and the future direction of change in the stock market is not substantially dependent on the state of the economy.

Table 6: In-sample estimation results of probit models with the benchmark predictors and sentiment variables.

	M1R	M2R	M3R	M4R
$SIBW_{t-1}$	-0.127			
	(0.089)			
$SIHO_{t-1}$		-0.191***		
		(0.068)		
$DCCI_{t-1}$			-0.002	
			(0.016)	
$DPMI_{t-1}$				-0.015
				(0.030)
$SI_{t-1}REC_{t-1}$	0.107	0.156	-0.373	0.155
	(0.136)	(0.316)	(0.342)	(0.136)
$logL$	-288.896	-286.560	-289.617	-289.492
BIC	304.125	301.788	304.845	304.720
$adj.psR^2$	0.016	0.027	0.013	0.013
SR	0.629	0.645***	0.622	0.627
AUC	0.590***	0.608***	0.586***	0.585***

Notes: This table illustrates the predictive power of the sentiment variables, taking into account recession periods. The models M1R–MR4 also include a constant terms and the three-month T-bill rate (TB), and the dividend yield (DY), as predictors, but the coefficients for these are not presented here. Robust standard errors of the estimated coefficients are reported in brackets. The success ratio (SR) is based on a signal forecast $\hat{y}_t$ receiving the value 1 if $p_t > 0.5$ and 0 otherwise. In the table, *, **, and *** denote the statistical significance of the estimated coefficients, the Pesaran and Timmermann (2009) PT predictability test for the success ratios, and the AUC at 10%, 5% and 1% significance levels, respectively.

6 Conclusion

We investigate the predictive ability of sentiment variables on the directional predictability of excess stock returns in the US stock market. Our findings indicate that the investor sentiment index of Huang et al. (2015) is a powerful predictor, even after controlling for the predictive ability of commonly used predictors of stock returns and the effects of recession periods. Furthermore, we find that measures of consumer or business sentiment do not hold similar predictive ability as measures of investor sentiment. Finally, we find that although the autoregressive probit model improves the in-sample fit of the model, in an out-of-sample setting it is outperformed by the more parsimonious static probit model using both statistical and economic goodness-of-fit measures.

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