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### Sentiment and sign predictability of stock returns

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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.

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# 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 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 aforementioned 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 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 at least 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

methodology. In Section 3, we discuss the data and in Section 4 we present our empirical findings. In Section 5, we analyse the effects of recession periods on the predictive power of sentiment variables. Finally, Section 6 concludes.

## 2 Methodology

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 a 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

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

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

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

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

$$\pi_t = \omega + \gamma SI_{t-1} + \beta \mathbf{x}_{t-1}, \quad (3)$$

where  $\omega$  is a constant term,  $SI_{t-1}$  is the first lag of the sentiment variable of interest, and  $\mathbf{x}_{t-1}$  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 analyse 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  $\pi_t$  is included in order to introduce an autoregressive structure

$$\pi_t = \omega + \alpha \pi_{t-1} + \gamma SI_{t-1} + \beta \mathbf{x}_{t-1}. \quad (4)$$

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 analyse 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.<sup>1</sup> 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)<sup>2</sup> 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 I. 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.

Table I. Correlations between sentiment variables

	SIBW <sub>t</sub>	SIHO <sub>t</sub>	DCCI <sub>t</sub>	DPMI <sub>t</sub>
SIBW <sub>t</sub>	1.00	0.62	-0.02	-0.07
SIHO <sub>t</sub>		1.00	-0.08	-0.04
DCCI <sub>t</sub>			1.00	0.20
DPMI <sub>t</sub>				1.00

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

The dependent variable is a binary indicator of the sign of the excess stock return, as defined in (5). We employ the monthly excess stock market returns from the Center for research in Security Prices (CSRP), available at Kenneth French's data library<sup>3</sup>, where the returns are based on a value-weighted market portfolio in excess of the one-month treasury bill rate. 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-month treasury bill rate (TB) and the dividend yield (DY) as additional predictors.<sup>4</sup>

### 4 Empirical findings

Our in-sample findings for single-predictor probit models (Table II) 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

<sup>1</sup>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/>.

<sup>2</sup>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.

<sup>3</sup>[http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

<sup>4</sup>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 data for the dividend yield are obtained from the Goyal and Welch (2008) dataset, <http://www.hec.unil.ch/agoyal/>.

of excess market returns. The sign of the estimated coefficient for both indices are negative, which is in line with financial theory and 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). Sentiment is thought to affect returns, since investor optimism or pessimism may cause mispricing in the stock markets in the short run. However, this mispricing does not tend to persist for long, hence creating a negative relationship between investor sentiment and future stock returns.

Table II. In-sample results for single-predictor probit models

<b>Sentiment variables, first lags</b>						
	Variable	Coeff.	adj.psR <sup>2</sup>	BIC	SR	AUC
1	SIBW <sub>t-1</sub>	-0.240***	0.012	297.338	0.636	0.565***
2	SIHO <sub>t-1</sub>	-0.242***	0.024	294.735	0.647	0.572***
3	DCCI <sub>t-1</sub>	0.002	Neg.	301.041	0.613	0.496
4	DPMI <sub>t-1</sub>	-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<sup>2</sup>.

However, neither the measure of consumer confidence (DCCI) nor business confidence (DPMI) have statistically significant predictive ability in the single-predictor model. This would imply that the consumer confidence index is not a powerful proxy for investor sentiment, although it may contain valuable information on future consumption and more general economic conditions. Also, since these two indices are based on survey data, it is possible that the information contained in them is already reflected in the stock prices.

In Table III, where we include the two commonly used predictors of excess returns as control variables, we find that models including the investor sentiment index of Baker and Wurgler (2006) (M1) and that of Huang et al. (2015) (M2) 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.<sup>5</sup> 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. 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. These findings lend support to the idea that the measures of investor sentiment of Baker and Wurgler (2006) and especially Huang et al. (2015) capture the optimism or pessimism that may cause mispricing in the stock markets in the short run, and that this information is not captured by the control variables.

In Table IV, 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 (AR2) including the investor sentiment index of Huang et al. (2015), performs the best. In general, the AUC is higher for the autoregressive models than their static counterparts, and the estimated coefficients for the autoregressive parameters  $\pi_{t-1}$  are statistically highly significant.

In addition to 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 ex-

<sup>5</sup>The robustness of these findings have been tested by adding the term spread and various credit spread measures as further control variables. However, the coefficients for these variables were not statistically significant, and therefore were left out from the final results. These findings are available upon request.

Table III. 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** (0.766)	1.841** (0.729)	2.323*** (0.704)	2.343*** (0.711)	2.320*** (0.701)
$TB_{t-1}$	-4.928** (2.476)	-4.258* (2.299)	-6.891*** (2.189)	-6.991*** (2.241)	-6.879*** (2.169)
$DY_{t-1}$	0.367** (0.184)	0.365** (0.176)	0.462** (0.170)	0.466*** (0.172)	0.462*** (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.

panding window, but we evaluated the robustness of the results by using a rolling window.<sup>6</sup> The out-of-sample results for the static probit models in Panel A of Table V 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 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.

The autoregressive probit models improved the in-sample performance of our models. However, the results in Panel B of Table V 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.<sup>7</sup> Among the autoregressive models, the model (AR2) including the sentiment index of Huang et al. (2015) outperforms the competing models based on the AUC, but the other measures do not confirm this finding.

<sup>6</sup>These results based on the rolling window are available upon request.

<sup>7</sup>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.

Table IV. 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)	
$\pi_{t-1}$	-0.447*** (0.166)	-0.428*** (0.115)	-0.622*** (0.191)	-0.793*** (0.078)	-0.923*** (0.131)
$CONST$	2.837** (1.230)	2.711* (1.470)	3.824*** (1.220)	4.258*** (1.238)	4.383*** (1.276)
$TB_{t-1}$	-7.491* (3.938)	-6.470 (4.365)	-11.471*** (3.787)	-12.872*** (3.910)	-13.519*** (4.127)
$DY_{t-1}$	0.548** (0.287)	0.538* (0.328)	0.761*** (0.289)	0.846*** (0.300)	0.862*** (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  $\pi$ . 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.

Table V. 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).  $RET$  refers to annualized returns of a simple trading strategy based on the model forecast and  $SHR$  refers to the Sharpe ratio.

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

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

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

$$\pi_t = \omega + \gamma SI_{t-1} + \delta SI_{t-1} REC_{t-1} + \beta \mathbf{x}_{t-1}, \quad (6)$$

where the interaction term  $\delta SI_{t-1} REC_{t-1}$  captures the effect of the recession. However, in Table VI 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. This finding contradicts those of e.g. Smales (2017), whose results suggest that sentiment has a greater influence on market returns during recession.

Table VI. 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 (0.136)	0.156 (0.316)	-0.373 (0.342)	0.155 (0.136)
$\log L$	-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–M4R 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. This



finding is in line with financial theory that suggests that high investor sentiment may represent overly optimistic beliefs of future cash flows, which are followed by lower returns when these expectations are not materialized (see, e.g., Baker and Wurgler 2006, and Huang et al. 2015). Our findings also show that the results of Huang et al. (2015) hold while using an alternative methodology, thus lending support to the robustness of their findings.

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. From a practical viewpoint, the findings of our study are relevant for investors and financial practitioners, as they lend further evidence that investor sentiment has an effect on stock returns.

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