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1 Task 1

The analyzed paper [6] aims to investigate the relationship between the managers' sentiments[1] and its asset pricing implications with a focus on US stock markets. Managers are probably the most well-informed subjects about their companies but very often they incur behavioural biases which affect the financial performances of their firms. In this regard, there is evidence that they tend to take decisions pushed by the contingent financial framework they are facing; this fact makes them overly optimistic or pessimistic and can lead to irrational market outcomes. Through a newly developed manager sentiment index[2], the Authors investigate different research questions. First, they look for US stock market returns predictability to capture possible recurrent patterns between MS and stocks' returns. Second, they assess the portfolio implications (SR and CER[3]) coming from out-of-sample forecasted values obtained using MSI. Next, they have tried to find out possible relationships between managers' sentiments (often biased) and earnings surprises, overinvestment and difficult-to-value stocks. Finally, the paper aims to compare the achieved results and those predicted by other macroeconomic variables and investor sentiment indexes in the existing literature.

Since the MS are not extensively treated in the literature, the Authors decided to develop their own qualitative monthly index (S^{MS}) for capturing the managers' opinions and beliefs about their companies. This index is based on the textual tones in financial disclosures, measured as the difference between the number of positive and negative words scaled by the total word count (classification is based on financial word dictionaries); more in detail, it is computed as an equally weighted sum between the textual tones in conference calls and those in financial statements (10-Ks and 10-Qs). Because of the low correlation, the two components are complementary, not redundant. The main instruments used for carrying out the analysis are linear regression models (univariate or multivariate) together with inferential procedures (hypothesis testing). The main results consist of the estimates of the regression coefficients, their t-statistics (Newey-West ones to correct for heteroskedasticity- and autocorrelation-related issues) and the R^2 of the models.

The proposed MS index negatively predicts future stock returns and this turns out to be consistent with existing literature's findings: too optimistic views from managers are, on average, followed by lower future market returns. This kind of behaviour is highly persistent and long-term in nature. MS results to be a relevant variable in properly doing its predictive job, especially if compared to investor sentiment indexes or commonly used macroeconomic variables. As for the portfolio performance, the economic value forecasts of a mean-variance portfolio display far better results in terms of SR and CER than the ones recorded by the market over the same sample period. MS shows to negatively predict subsequent aggregate earnings surprise and to positively predict long-run overinvestment. This confirms that future over-optimistic beliefs can bias the decisions (misuse of resources) and the expectations of the managers, adversely affecting the companies' performances. Finally, the MSI proves to be good at forecasting returns of difficult-to-value stocks, which show a high sensibility to sentiment-driven mispricing.

[1] From here on, MS or managers' sentiments will be used interchangeably
[2] MSI
[3] Sharpe Ratio and Certainty Equivalent Return

2 Task 2

In Section 2 we reproduce Table 2 of Jiang et al. (2019) [6] and we further compare the results with those obtained by using as regressors three existing indexes of investor sentiment over literature:

- the Baker-Wurgler (2006) investor sentiment index (S^{BW});
- the Huang, Jiang, Tu and Zhou's (2015) aligned investors sentiment index (S^{HJTZ});
- the Conference Board consumer confidence index (S^{CBC}).

The estimation method consists of simple standard predictive regression models applied to seven different time horizons (1 month, 3 months, 6 months, 9 months, 1 year, 2 years and 3 years). From time to time, the dependent variables are the percentage cumulative excess market returns[4], while the only regressor is represented by the monthly indexes' values, both the *manager* sentiment index and the three *investors* sentiment indexes above mentioned. It is important to remark that all the independent variables[5] are standardized. The primary interests are the slope coefficients of the regressions, which can be interpreted as the percentage change in the aggregate market excess return given a one-standard-deviation positive shock in the considered investors' sentiment index.
The final aim of these models is to find out the forecasting power and the time-persistency of those indexes over the aggregate stock market returns. The predictive regression models used are the following:

$$R^m_{t\to t+h} = \alpha + \beta S^k_t + \epsilon_{t\to t+h} \qquad k = MS, BW, HJTZ, CBC \tag{1}$$

In Appendix A a reproduction of the original table and one version for each of the alternative investor sentiment indexes are reported; the outputs include the intercept coefficients, the slopes, the corresponding t-stats and the R^2 of the models. To check for statistical significance of the estimated coefficients, we use the Newey-West Heteroscedastic robust t-statistics: in particular, in the R function "NeweyWest" we impose the "lag" argument equal to the fourth-root of the number of observations, following the generally used rule of thumb[1].
For what concerns the predictive regression models with the MSI as a regressor, the results we obtained differ slightly with respect to those in [6]; more specifically, the estimated coefficients and the R^2 are the same, while the only discrepancies lie in the Newey-West t-statistics, which are probably due to different assumptions made by the Authors in their computations. Overall, as expected, we can assess that the manager sentiment is inversely related to the excess aggregate market returns in the next months.

The Baker and Wurgler investor sentiment index consists of the first principle component of six stock market-based sentiments proxies (closed-end fund discount, New York Stock-Exchange share turnover, number and average first-day IPO's returns, equity share in new issues and the dividend premium). Looking at Table 3, we can see that S^{BW} is a negative excess return predictor for future time periods: this is consistent with what we would expect given the wide literature in this regard. When comparing with MSI results (Table 2), we can assess that, the intercepts of the BW model are higher for all the maturities. The betas, instead, are lower at least for shorter time horizons. These facts suggest that, while the model predicts higher excess (cumulative) market returns (i.e. the αs), there is a lower negative influence of the BW investor

[4]The monthly excess returns are based on the market returns of the S&P 500 and the risk-free rate.
[5]This holds also for the analysis in following Sections 3 and 4.

sentiment on the future returns; put it in another way, S^{BW} is economically less significant than S^{MS} in predicting future cumulative returns and this is shown also by the t-statistics. This pattern reverts for longer time horizons (>9 months). Nevertheless, for both the indexes, as the time span increases the α makes even more positive and the β makes even more negative. This is coherent with the high correlation between the two indexes (approximately 0.5). Another similar trend can be retrieved from the R^2 of the models; these keep growing until they peak at a certain point in time (at 12 months for MSI and at 24 months for BW).

Huang et al. (2015) proposed an aligned investor sentiment index combining the same Baker and Wurgler's six investor sentiment proxies in a more efficient partial least square method. However, their index (S^{HJTZ}) shows a very poor predicting power especially for longer time horizons. The results are reported in Table 4 in Appendix A. This can be seen by looking at the very low R^2 for timespans equal to 6 and 9 months and 1 and 2 years. The same conclusion can be drawn also by analyzing the β which are satisfactory only for the one-month time horizon and for the 3 years one (when compared with the previous two models); in addition, they tend to increase with time and become positive as time horizon grows. This is somewhat controversial with respect to the previous indexes, which record even more negative βs. As for the Newey-West heteroskedasticity-adjusted t-statistics, they show to be quite close to 0 in medium time horizons, bringing us to question their statistical significance of the estimated slopes' coefficients. In conclusion, the HJTZ index proves to be much less satisfactory and powerful than the other two above mentioned peers.

The Conference Board consumer confidence index, S^{CBC}, is an investor sentiment proxy based on mail surveys on a random sample of U.S. households. Essentially, it reflects prevailing business conditions and likely developments for the months ahead. The index is computed on a monthly basis and reports details of consumer attitudes, buying intentions, vacation plans, consumer expectations for inflation, other than stock prices and interest rates. The results obtained are reported in Table 5. The key variable of interest in these models is again β; for a short time horizon, the betas are small in absolute value when compared to the results obtained for the first two indexes (i.e. S^{MS} and S^{BW}). Furthermore, their significance is very low, making us again question their predictive power in the short run. For longer time horizons, instead, they improve and show to be good negative cumulative excess returns predictors, consistently with the two indexes before mentioned. The same considerations can be made for the R^2; they are very low up to time horizon 12 when there is a fast increase in the goodness of fit of the results.

Finally, for the sake of completeness, Figure 1 displays the time series plot of the four indexes considered in our regressions:

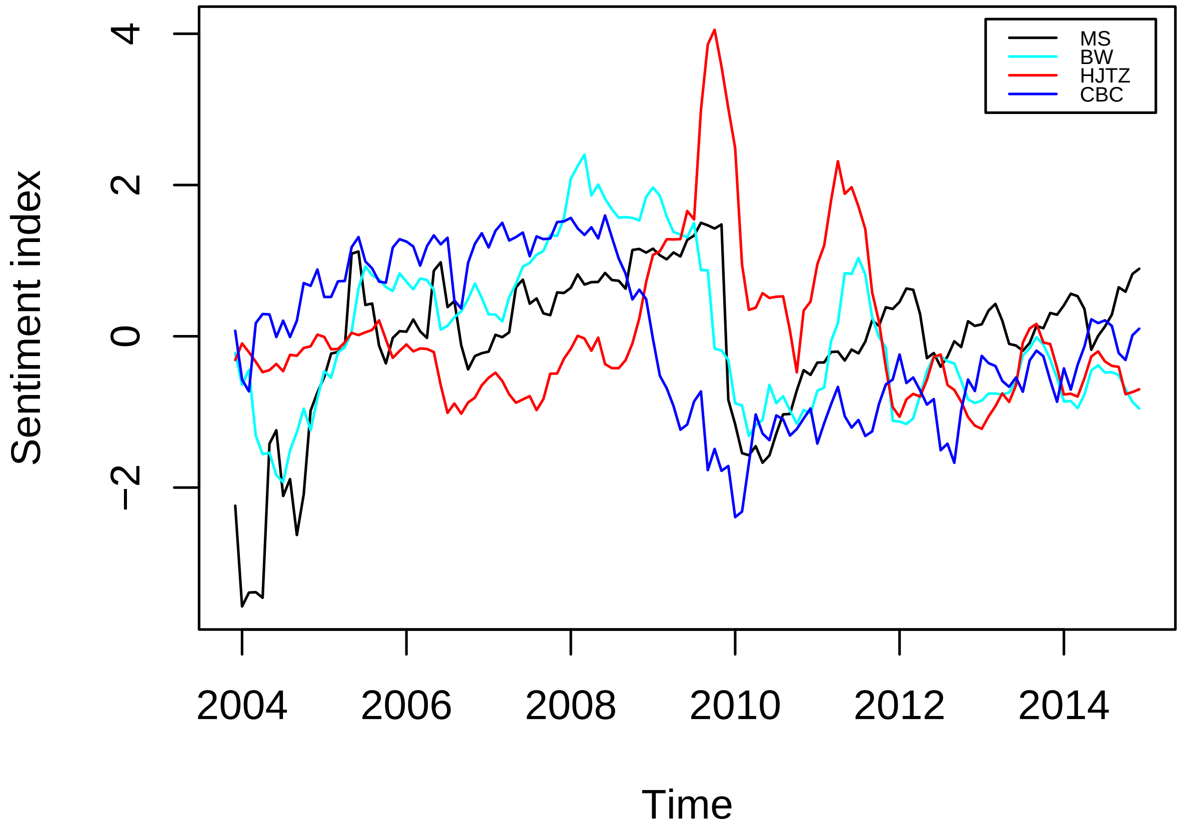

Figure 1: Time-series of Sentiment Indexes (2003:01 to 2014:12)

3 Task 3

The present Section wants to replicate the results of Table 5 in [6] and to further deepen the analysis by considering an all-encompassing multivariate regression with all the economic variables. The replicated results are included in Appendix B and more specifically in Table 6.
All the results here are based on the first principal component factor extracted from the individual economic variables (ECON) and on 14 commonly used variables, which relate to business-cycle fundamentals or changes in macroeconomic risks. Those are the following: log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), stock return variance (SVAR), book-to-market ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), and inflation rate (INFL). Moreover, only the one-month-ahead excess market return is considered as the dependent variable. First of all, we investigate the predictive power of each of the 14 variables taken separately. The estimated predictive regressions are expressed in Equation 2:

$$R^m_{t+1} = \alpha + \psi Z^k_t + \epsilon_{t+1} \qquad k = 1, \dots, 15 \tag{2}$$

where the ψ parameters are the main estimated objects. The final goal is then to compare the results achieved with the ones obtained with the MSI (S^{MS}). As it can be noted in Panel A of Table 6, the estimated ψs are exactly equal to the ones in the paper. The same holds for the R^2 but not for the Newey-West heteroskedasticity-corrected t-statistics. Out of the 15 variables only 2 result to be statistically significant (SVAR and LTY) in our estimations, two less than the obtained by the Authors in [6]. In any case, the goodness of fit of the models is globally very poor when considering the R^2. Overall, we can definitely conclude that the S^{MS} dominates the 15 variables in forecasting the monthly excess market returns in-sample ($R^2 = 9.75\%$).

Next, we repeat the previous procedure by adding the MSI to each predictive regression. In this way, we want to test if the predicting power of S^{MS} remains high even after controlling for this macroeconomic or business-cycle variable (singularly considered). The predictive regression models are, therefore, the following:

$$R^m_{t+1} = \alpha + \beta S^{MS}_t + \psi Z^k_t + \epsilon_{t+1} \qquad k = 1, \ldots, 15 \tag{3}$$

where β is the coefficient that represents the MSI. Also in this case the results for the estimated coefficients and the R^2 are (almost) identical to the ones in [6], while the major discrepancies are detectable in the t-statistics. All the βs obtained are included between -1.39 and -1.10, this value being very similar in sign and absolute value to the one obtained in Table 2 for the one-month time horizon. The R^2 of these bivariate predictive regressions greatly improve and the same is true for the t-statistics which are largely negative, suggesting that β is largely significant. All this put together signals that the dominant forecasting power is played by the MSI.

Finally, we run a last multivariate predictive regression including all the 15 variables together with the manager sentiment index S^{MS}. The following is the regression considered:

$$R^m_{t+1} = \alpha + \beta S^{MS}_t + \sum_{k=1}^{15} \psi_k Z^k_t + \epsilon_{t+1} \qquad k = 1, \ldots, 15 \tag{4}$$

Given this kind of regression and the nature of the independent variables themselves, it seems clear that multicollinearity could probably affect the coefficient estimates and invalidate the obtained results for the individual predictors. In general, we refer to multicollinearity when two or more explanatory variables are highly correlated, and not necessarily in a perfect way (see Table B for the complete correlation matrix), meaning that there is redundancy between those variables, which provide a similar predictive relationship with the outcome. Concerning the regression in (4), we investigated this problem by using, first, the `alias` R function (which allows finding linearly dependent terms) which detected DE, TMS and ECON[6] as the most correlated in our sample of economic variables (intuitively, this could also be noted seeing that `R` autonomously did not include these variables when calculating OLS regression, since they are redundant[7]). Once removed these variables, we relied on the Variance Inflation Function (`vif`) to investigate if and how much the standard errors of our coefficients are inflated by the presence of a high correlation between some predictors. The magnitude of this effect on each coefficient can be calculated as $VIF_j = (1 - R^2_j)^{-1}$, and we followed the general rule of thumb for which values above 10 suggest the exclusion of that variable from the model (see [3] [4] [5]). The results of the estimation before and after having checked for multicollinearity are included in Table 1 below.

[6]It seems quite logical since the ECON nature itself because it is definite as the first principal component extracted from the economic variables, to which it is strictly correlated by construction.

[7]This comes from the fact that the correlation matrix in Table 7 is not full rank, thus the system of the equation has infinite solutions and cannot be solved unless omitting those variables which values are obtainable as a linear combination of the others. In this particular case, the rank is 13<16, and the system is undetermined.

	Panel A: Suggested regression			Panel B: Restricted regression		
	ψ , β (%)	t-stat	VIF	ψ , β (%)	t-stat	VIF
MSI	-1.67	-3.72	2.34	-1.28	-3.82	1.86
DP	1.92	0.99	30.78	-	-	-
DY	1.29	0.59	29.05	-	-	-
EP	0.02	2.61	6.86	-0.27	-0.48	2.41
DE	-	-	-	-	-	-
SVAR	0.97	-1.71	2.91	-0.06	-1.73	2.03
BM	-0.42	-0.67	3.86	0.19	0.38	2.18
NTIS	0.49	0.68	5.27	0.24	0.54	2.79
TBL	0.47	0.91	2.99	0.06	1.25	2.85
LTY	0.09	0.11	6.05	-1.10	-2.02	3.83
LTR	0.84	2.03	1.45	0.66	1.83	1.38
TMS	-	-	-	-	-	-
DFY	-0.99	-0.96	10.37	-	-	-
DFR	0.68	1.08	1.89	0.52	0.96	1.51
INFL	0.51	1.26	1.42	0.63	1.35	1.24
ECON	-	-	-	-	-	-
$Adj.R^2$	20.8%			$Adj.R^2$ 16.7%		

Table 1: Summary statistics for the suggested and restricted model

Panel A shows the general multivariate regression with all the variables, without addressing possible effects arising from highly correlated variables. The R^2 is equal to 20.8%, but this must be taken with care since this regression is not much reliable, because it suffers from multicollinearity. In any case, also the t-stats are quite low, suggesting that only a few coefficients are statistically significant. Panel B depicts, instead, the updated version, after having removed the most correlated variables (by using the `vif` criterion). As reported in the table above, the obtained R^2 is equal to 16.7%, greater than the coefficients of determination of the regressions in Table 6 panel B; this provides evidence of a greater predictive power of the corrected regression. Although it is lower than 20.8%, we are now more sure about the reliability of the estimates, things that do not happen in the all-encompassing regression. The MSI β confirms to be the most relevant one and assumes a similar value to the previous models (-1.36%), with a stronger negative predictive power; also in terms of number of statistical significance, the latter regression performs better with respect to the suggested general model to be estimated. It is important to remark that dropping an independent variable can cause a correlation between the errors and one or more independent variables, which causes biasedness and inconsistency in all the estimators: in this case, with the restricted model, we assume that the "true" model does not include any of the dropped variables, so our results are, hopefully, unbiased. In any case, it is noticeable that, given high multicollinearity, having excluded some variables from the new restricted model has definitively decreased the variance of the estimators (see the VIF column in Table 1). For a sake of completeness, we checked if the restricted model is misspecified utilizing an F-test for multiple joint exclusion alternatives. Since squares and powers of the independent variables, if jointly significative, suggest the presence of some forme of misspecification, we included every economic variable squared in a new model and verified if the null hypothesis $H_0 : \delta_{MSI^2} = ... = \delta_{INFL^2} = 0$ against the alternative that at least one of the coefficient of the squared variables δ_q is greater than 0. The test resulted in an F-value of 2.01 and a p-value of 3.79%, which lead to rejecting the null at 5% level and allows to state that the restricted model overlooked some important nonlinearities and suffers from functional form misspecification.

4 Task 4

In this last Section 4 we replicate Table 7 in [6] and consider two additional regressions in which we use the University of Michigan Consumer Sentiment (MCS) Index in place of Baker and Wurgler's (2006) and Huang et al.'s (2015) indexes. The overall aim of these VAR (Vector Autoregressive) models is to test for potential feedback relationships between MSI and other investor sentiment indexes. For this purpose 5 lags for each index are considered in the models. The procedure consists of estimating them, firstly with the MSI as the dependent variable and the other chosen index as the independent variable and secondly reverting the roles of the two indexes. This is done in order to verify if those indexes contain unique and complementary information or if one of the two reacts to lagged information included in the other one. The estimated models are the following:

$$S_t^{MS} = \alpha + \sum_{i=1}^{5} \delta_i S_{t-i}^{MS} + \sum_{k=1}^{5} \beta_i S_{t-i}^{k} + \epsilon_t \qquad k = BW, HJTZ, MCS. \tag{5}$$

and

$$S_t^{k} = \alpha + \sum_{i=1}^{5} \delta_i S_{t-i}^{k} + \sum_{i=1}^{5} \beta_i S_{t-i}^{MS} + \epsilon_t \qquad k = BW, HJTZ, MCS. \tag{6}$$

The results obtained for the βs are reported in Appendix C, in Tables 8, 9 and 10; those related to the first two panels are exactly equal to the ones reported in the paper, with the only exception of the usual t-statistics. The Adjusted R^2 of the models are very high and ranges from 0.82 and 0.94, this meaning that Equations 5 and 6 explain greatly the dynamics of the MSI and the three different investor indexes (see the three Panels A, B and C). As recalled in the paper [6], the models in Equations 5 and 6 are "equivalent to Granger causality tests for a lead-lag relationship between manager sentiment and investor sentiment, after accounting for each variable's own autocorrelation[8]." The key concepts here are therefore the βs of all the models: those represent the coefficients of the lagged variables of the other index in the model, other than the dependent variable. By looking at them, we can infer that they are not statistically significant, meaning that the lagged values of the regressand are the strongest predictors of the current levels of the index considered. This holds especially for the first models estimated with S^{MS}, S^{HJTZ}, and S^{BW}. We can conclude that each of the three indexes captures a different kind of sentiment information with respect to the others (i.e. their information could be deemed as unique and complementary). As for the last additional models (S^{MCS} with S^{MS}), we can see that some of the estimated βs are statistically significant; this fact points to a somewhat different conclusion. Maybe, in the Equations with S^{MS} and S^{MCS}, some lags of the index other than the dependent variable ones could play some role in predicting the first one. This could also be interpreted as the fact that both MSI Granger leads the MCS index and the MCS index Granger leads the MSI.

[8]The model estimated are similar to Tetlock (2007) and Garcia (2013).

Appendices

A Appendix 1

Horizon	$\alpha(\%)$	t-stat	$\beta(\%)$	t-stat	$R^2(\%)$
1	0.76	2.29*	-1.26	-3.33**	9.75
3	2.35	2.63**	-3.85	-3.72***	24.91
6	4.59	2.97**	-6.03	-3.60***	25.80
9	6.69	3.28**	-7.72	-3.74***	27.12
12	8.47	3.41***	-8.57	-3.16***	25.36
24	15.27	3.54***	-11.63	-3.23**	20.38
36	20.16	3.43***	-12.41	-3.73***	16.16

Table 2: Manager sentiment and aggregate market return

Horizon	$\alpha(\%)$	t-stat	$\beta(\%)$	t-stat	$R^2(\%)$
1	0.76	2.17*	-0.91	-2.69**	5.11
3	2.39	2.48*	-2.64	-2.73**	11.78
6	4.75	3.04**	-5.20	-2.95**	19.30
9	7.19	3.80***	-8.23	-3.67***	30.66
12	9.53	4.78***	-11.25	-4.58***	43.31
24	18.78	5.97***	-19.26	-5.96***	53.88
36	25.57	5.22***	-20.10	-6.07***	38.97

Table 3: Baker-Wurgler Investor Sentiment Index

Horizon	α(%)	t-stat	β(%)	t-stat	R^2(%)
1	0.76	2.24*	-1.17	-2.42*	8.45
3	2.40	2.41*	-2.15	-1.43	7.87
6	4.73	2.64**	-1.33	-0.53	1.27
9	6.94	2.94**	-0.42	-0.14	0.83
12	8.93	3.21**	-0.26	-0.09	0.02
24	16.03	3.37**	3.45	0.93	1.83
36	19.80	3.17**	10.69	2.25*	11.39

Table 4: Huang, Jiang, Tu, and Zhou (2015) aligned investor sentiment index

Horizon	α(%)	t-stat	β(%)	t-stat	R^2(%)
1	0.76	1.97	-0.21	-0.46	0.26
3	2.39	2.25*	-0.66	-0.56	0.74
6	4.66	2.62**	-2.17	-1.15	3.32
9	6.81	2.97**	-3.95	-1.87	7.13
12	8.71	3.31**	-6.12	-2.85**	13.23
24	16.04	4.58***	-16.94	-5.22***	44.85
36	22.39	6.35***	-24.95	-8.83***	66.63

Table 5: Conference Board consumer confidence index

B Appendix 2

	Panel A: Univariate regression $R^m_{t+1} = \alpha + \psi Z^k_t + \epsilon_{t+1}$			Panel B: Bivariate regression $R^m_{t+1} = \alpha + \beta S^{MS}_t + \psi Z^k_t + \epsilon_{t+1}$				
	ψ (%)	t-stat	R^2 (%)	β (%)	t-stat	ψ (%)	t-stat	R^2 (%)
DP	0.11	0.17	0.08	-1.26	-3.34	0.11	0.23	9.83
DY	0.31	0.55	0.61	-1.24	-3.24	0.24	0.56	10.12
EP	-0.22	-0.45	0.30	-1.42	-3.03	0.38	0.72	10.50
DE	0.21	0.38	0.26	-1.34	-2.95	-0.25	-0.48	10.84
SVAR	-0.96	-2.71	5.72	-1.18	-3.66	-0.85	-3.05	14.17
BM	0.20	0.54	0.25	-1.33	-3.43	0.43	1.20	10.88
NTIS	0.84	1.52	4.33	-1.10	-3.14	0.45	0.9135	10.85
TBL	-0.41	-1.61	1.04	-1.22	-3.10	-0.15	-0.56	9.88
LTY	-0.54	-2.24	1.79	-1.37	-3.75	-0.75	-3.03	13.12
LTR	0.31	1.05	0.58	-1.29	-3.19	0.42	1.29	10.81
TMS	0.16	0.59	0.16	-1.39	-3.11	-0.36	-1.14	10.44
DFY	-0.26	-0.40	0.43	-1.31	3.39	-0.44	-0.92	10.91
DFR	0.57	0.85	2.02	-1.19	-3.39	0.36	0.5864	10.53
INFL	0.46	0.91	1.27	-1.26	-3.36	0.45	1.09	11.01
ECON	0.13	0.21	0.11	-1.29	-3.24	0.28	0.60	10.22

Table 6: Comparison with economic variables

	MSI	DP	DY	EP	DE	SVAR	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	ECON
MSI	1	0.01	-0.05	0.43	-0.34	0.09	0.17	-0.35	0.21	-0.15	0.08	-0.37	-0.13	-0.17	-0.01	0.16
DP	0.01	1	0.97	-0.62	0.78	0.60	0.29	-0.54	-0.40	-0.40	0.06	0.24	0.85	0.02	-0.28	-0.89
DY	-0.05	0.97	1	-0.66	0.80	0.49	0.25	-0.50	-0.42	-0.43	0.01	0.25	0.83	0.15	-0.28	-0.88
EP	0.43	-0.62	-0.66	1	-0.98	-0.30	0.31	0.31	0.17	-0.17	0.06	-0.34	-0.68	-0.23	0.14	0.69
DE	-0.34	0.78	0.80	-0.98	1	0.41	-0.17	-0.40	-0.25	0.02	-0.03	0.34	0.78	0.19	-0.19	-0.81
SVAR	0.09	0.60	0.49	-0.30	0.41	1	0.14	-0.44	-0.16	-0.03	0.18	0.18	0.66	-0.23	-0.28	-0.61
BM	0.17	0.29	0.25	0.31	-0.17	0.14	1	0.19	-0.36	-0.60	0.11	0.05	0.12	-0.07	-0.20	-0.11
NTIS	-0.35	-0.54	-0.50	0.31	-0.40	-0.44	0.19	1	-0.17	0.05	0.01	0.26	-0.59	0.11	0.04	0.54
TBL	0.21	-0.40	-0.42	0.17	-0.25	-0.16	-0.36	-0.17	1	0.64	-0.03	-0.85	-0.24	-0.09	0.19	0.60
LTY	-0.15	-0.40	-0.43	-0.17	0.02	-0.03	-0.60	0.05	0.64	1	-0.17	-0.13	-0.13	0.01	0.24	0.37
LTR	0.08	0.06	0.01	0.06	-0.03	0.18	0.11	0.01	-0.03	-0.17	1	-0.08	0.03	-0.42	-0.13	-0.05
TMS	-0.37	0.24	0.25	-0.34	0.34	0.18	0.05	0.26	-0.85	-0.13	-0.08	1	0.22	0.12	-0.08	-0.51
DFY	-0.13	0.85	0.83	-0.68	0.78	0.66	0.12	-0.59	-0.24	-0.13	0.03	0.22	1	0.13	-0.36	-0.86
DFR	-0.17	0.02	0.15	-0.23	0.19	-0.23	-0.07	0.11	-0.09	0.01	-0.42	0.12	0.13	1	-0.11	-0.13
INFL	-0.01	-0.29	-0.29	0.14	-0.19	-0.28	-0.20	0.04	0.19	0.24	-0.13	-0.08	-0.36	-0.11	1	0.33
ECON	0.16	-0.89	-0.88	0.69	-0.81	-0.61	-0.11	0.54	0.60	0.37	-0.05	-0.51	-0.86	-0.13	0.33	1

Table 7: Economic variables correlation matrix

C Appendix 3

	Panel A: IS $\Longrightarrow$ MS			
	$S^{BW} \Longrightarrow S^{MS}$		$S^{HJTZ} \Longrightarrow S^{MS}$	
β_1	-0.03	[-0.32]	-0.04	[-0.34]
β_2	0.22	[0.86]	0.20	[1.41]
β_3	-0.11	[-0.36]	-0.24	[-2.45]
β_4	0.19	[1.07]	-0.07	[-0.34]
β_5	-0.20	[-1.36]	0.07	[0.38]
$Adj.R^2$	0.83		0.82	

Table 8: Feedback between MS and BW

	Panel B: MS $\Longrightarrow$ IS			
	$S^{MS} \Longrightarrow S^{BW}$		$S^{MS} \Longrightarrow S^{HJTZ}$	
β_1	0.02	[0.19]	-0.01	[-0.13]
β_2	0.05	[0.45]	0.14	[1.36]
β_3	-0.01	[-0.13]	-0.14	[-1.00]
β_4	-0.06	[-0.74]	0.00	[0.04]
β_5	0.02	[0.42]	0.02	[0.49]
$Adj.R^2$	0.94		0.92	

Table 9: Feedback between MS and HJTZ

	Panel C: MCS $\Longleftrightarrow$ MS			
	$S^{MCS} \Longrightarrow S^{MS}$		$S^{MS} \Longrightarrow S^{MCS}$	
β_1	-0.12	[-1.97]	0.10	[1.51]
β_2	0.10	[1.25]	-0.18	[-2.27]
β_3	0.11	[0.88]	-0.18	[-1.97]
β_4	-0.23	[-1.59]	0.25	[2.45]
β_5	0.21	[2.60]	-0.08	[-1.16]
$Adj.R^2$	0.83		0.86	

Table 10: Feedback between MS and MCS

References

[1] Greene, W. H., Econometric Analysis, 7th edition, *Prentice Hall, Upper Saddle River (2012).*

[2] Guidolin, M., Pedio, M., Lecture Notes. Winter 2021.

[3] Vittinghoff E, Glidden DV, Shiboski SC, McCulloch CE. Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models. 2nd ed. 2012 edition. Springer; 2011.

[4] James G, Witten D, Hastie T, Tibshirani R. An Introduction to Statistical Learning: With Applications in R. 1st ed. 2013, Corr. 7th printing 2017 edition. Springer; 2013.

[5] Menard S. Applied Logistic Regression Analysis. 2nd edition. SAGE Publications, Inc; 2001.

[6] Jiang, F., Lee, J., Martin, X., Zhou, G. Manager Sentiment and stock returns. *Journal of Financial Economics*. 132 (2019) 126-146.

[7] Wooldridge, Jeffrey M., Introductory Econometrics: a Modern Approach. *Mason, Ohio: South-Western Cengage Learning.*, 2012.