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Abstract

This paper contributes to the understanding of the non-linear causal linkage between investors' sentiment dynamics and stock returns for the US economy. Employing the sentiment index developed by Baker and Wurgler (J. Econ. Perspect. 16: 129-151, 2007) and within a non-linear causality framework, we found that sentiment embodies significant predictive power with respect to stock returns.

JEL Classification: G11, G14, C14, C22.
Keywords: Investors' sentiment; Stock returns; Non-linear Granger causality.

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1 Introduction

The discussion on the effectiveness of the standard finance model to explicate in a tolerable way the commonly cited stylized facts in the stock markets, has dominated the academic scene in the last two decades. There is convincing evidence in literature that investors are prone to exogenous sentiment waves, a fact that contests the rationality hypothesis. Behavioral finance researchers have provided a considerable impetus towards the quantification of investors' sentiment (see e.g., Barberis et al., 1998; Baker and Wurgler, 2007; Huisman et al., 2012). Investors' sentiment predictive content with respect to the future market movements may act as an invaluable tool for the market participants in forming successful trading strategies (Baker and Wurgler, 2007).

In recent years there is increasing empirical literature devoted to the investors' sentiment and stock returns nexus. Overall, the results are by no means uniform. The lack of uniformity can be attributed to several factors including; the approach followed to construct the sentiment index and the development level of the markets' institutions. Brown and Cliff (2004) concentrating on market aggregates for the US economy found limited evidence to support the predictive power of sentiment with respect to the stock returns. Kling and Gao (2008) showed that investors' sentiment does not influence stock returns for China. Schmeling (2009) found, for 18 industrialized countries, that investors' sentiment acts, on average, as a significant predictor for stock returns. More recently, Lux (2011) focusing on the German stock market, validated the predictive content hypothesis of the sentiment index with respect to stock returns. Common feature of all the abovementioned studies is that the causality inference adheres to the linear causality paradigm.

In contrast to extant literature, our analysis is much broader given that causality is examined from a non-linear perspective. The results in the majority of previous studies suffer from the assumption of linearity (Lux, 2011), a fact that may act as a limiting factor in cases where the true relationship between the variables might be non-linear. Baek and Brock (1992) noted that the standard causality testing procedure is inappropriate to detect non-linear relationships. Consequently, our attention shifts to the two non-linear causal testing procedures proposed by Hiemstra and Jones (1994) (H&J, hereafter) and Diks and Panchenko (2006)(D&P, hereafter).

The paper is structured as follows: section 2 presents the data sources and the methodology, section 3 continues with the empirical findings and finally, section 4 concludes.

2 Data and Methodology

2.1 Data sources

This study makes use of monthly time series data for the US economy over the period 1965:7 to 2007:12. The US stock prices index (2005=100) has been obtained from the Main Economic Indicators database of OECD, with the returns to be computed as the monthly percentage change (figures 1 and 3, respectively).[1] The US investor sentiment index along with its monthly change (figures 2 and 4, respectively) is taken from the study of Baker and Wurgler (2007).[2] The shaded areas in all figures below depict the US recession periods as defined by the National Bureau of Economic Research (NBER).

Figure 1: U.S. stock price index

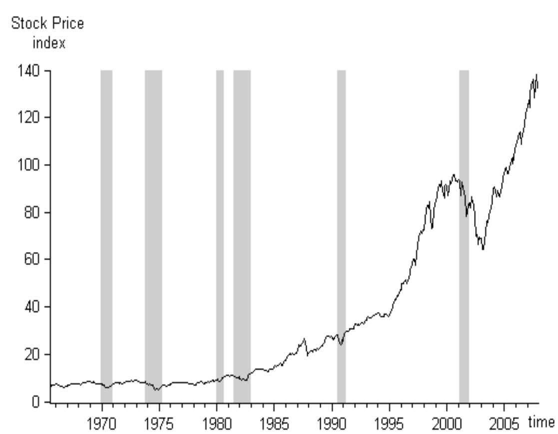
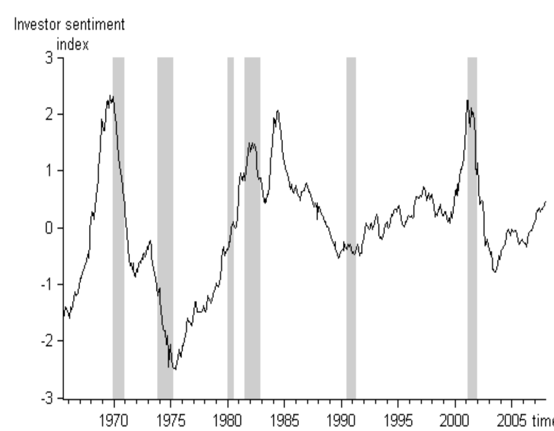


Figure 2: U.S. investors' sentiment index



[1]Available at: http://www.oecd-ilibrary.org/statistics
[2]Available at: http://people.stern.nyu.edu/jwurgler

Figure 3: U.S. stock returns

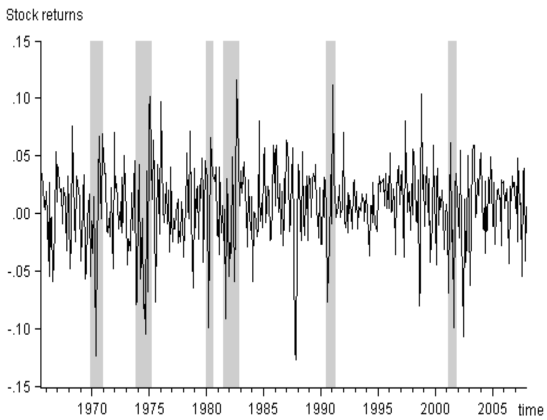
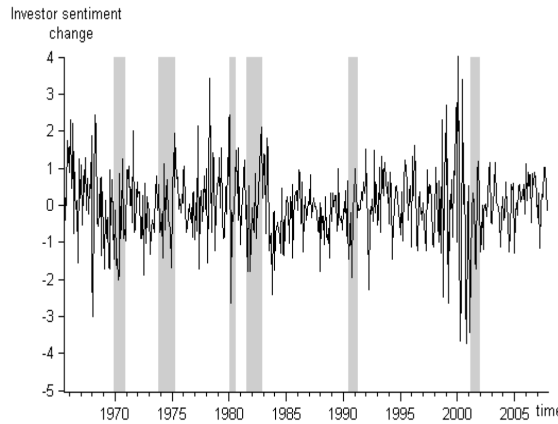


Figure 4: U.S. investor sentiment change



2.2 Methodology

For two strictly stationary and weakly dependent time series, R_t and S_t, consider the following: let $\mathbf{Z}_t^{\kappa}$ be the κ-length lead vector of R_t, $\mathbf{S}_t^{l_s}$ the l_s-length lag vector of S_t and finally, $\mathbf{R}_t^{l_r}$ the l_r-length lag vector of R_t, with $l_s, l_r \geq 1$. Given that the null hypothesis is actually a proposition about the invariant distribution of the $(l_s + l_r + \kappa)$-dimensional vector $\mathbf{X}_t = (\mathbf{S}_t^{l_s}, \mathbf{R}_t^{l_r}, \mathbf{Z}_t^{\kappa})$, the time subscript is dropped.[3] Under the null hypothesis, the joint probability density function $f_{S,R,Z}(s, r, z)$ along with its marginals, should satisfy:

$$\frac{f_{S,R,Z}(s, r, z)}{f_{S,R}(s, r)} = \frac{f_{R,Z}(r, z)}{f_R(r)} \tag{1}$$

H&J assess the discrepancy between the two sides of (1), by utilizing correlation integrals. For any arbitrary multivariate vector $\mathbf{W}$ taking on values in $\mathbb{R}^{d_{\mathbf{W}}}$, the correlation integral $(C_{\mathbf{W}}(\theta))$ is the probability of identifying two independent realizations of $\mathbf{W}$ within a distance smaller than or equal to θ. The general formula for $C_{\mathbf{W}}(\theta)$ is:

[3] As a common empirical practise, it is assumed that κ is equal to 1 and also for presentation purposes, we set $l_s = l_r = 1$.

$$
\begin{aligned}
C_W(\theta) &= P\left[\|\mathbf{W}_1 - \mathbf{W}_2\| \leq \theta\right], \mathbf{W}_1, \mathbf{W}_2 indpen. \sim \mathbf{W} \\
&= \int \int I\left(\|m_1 - m_2\| \leq \theta\right) f_N(m_1)\, f_N(m_2)\, dm_1 dm_2
\end{aligned}
\tag{2}
$$

where, $P[\bullet]$ denotes probability, $\|\bullet\|$ is the maximum norm and $I(\bullet)$ is an indicator function which takes on the value of 1, if $\|m_1 - m_2\| \leq \theta$ and 0 otherwise.

In line with the H&J testing approach, for a small positive value of θ (typical values range between 0.5 and 1.5), equation (1) implies the subsequent joint probabilities:

$$
\frac{C_{S,R,Z}(\theta)}{C_{S,R}(\theta)} = \frac{C_{R,Z}(\theta)}{C_R(\theta)} \tag{3}
$$

To assess statistically the above non-causality condition, H&J used sample estimators for the approximation of $C_{\mathbf{W}}(\theta)$. These estimators are:

$$
\hat{C}_{W,n}(\theta) = \frac{2}{n(n-1)} \sum_{i<j} \sum I_{ij}^W \tag{4}
$$

The ratios in (3) can be substituted by their respective estimators adjusting equation (4) accordingly. Finally, the subsequent T Statistic is shown in H&J to follow the normal distribution:

$$
T = \left[\frac{\hat{C}_{S,R,Z}(\theta, n)}{\hat{C}_{S,G}(\theta, n)} - \frac{\hat{C}_{R,Z}(\theta, n)}{\hat{C}_R(\theta, n)}\right] \sim N\left(0, \frac{1}{\sqrt{n}} \sigma^2(\kappa, \mathrm{l}_s, \mathrm{l}_r, \theta)\right) \tag{5}
$$

The major shortcoming of the H&J test is that it over-rejects, in certain situations, the null hypothesis (Diks and Panchenko, 2005, 2006). D&P remedy this shortcoming by introducing a modified Statistic. The null hypothesis is restated as:

$$q \equiv E\left[f_{S,R,Z}(S,R,Z)\, f_R(R) - f_{S,R}(S,R)\, f_{R,Z}(R,Z)\right] = 0 \tag{6}$$

with the proposed estimator for q to be:

$$T_n(\theta_n) = \frac{(2\theta)^{-d_S-2d_R-d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq ij} \sum_{j\neq i} \left(I_{ik}^{SRZ} I_{ij}^{R} - I_{ik}^{SR} I_{ij}^{RZ}\right)\right] \tag{7}$$

where, $I_{ij}^X = I\left(\|\mathbf{X}_i - \mathbf{X}_j\| \leq \theta\right)$, with $I(\bullet)$ to be the indicator function and θ_n the bandwidth which depends on the sample size. Hence, if we denote as $\hat{f}_X(\mathbf{X}_i)$ the local density estimator of the vector $\mathbf{X}$ at $\mathbf{X}_i$, that is:

$$\hat{f}_X(\mathbf{X}_i) = (2\theta_n)^{-d_X} (n-1)^{-1} \sum_{j,j\neq i} I_{ij}^X \tag{8}$$

Then, the $T_n(\theta_n)$ Statistic can be expressed as:

$$T_n(\theta_n) = \frac{(n-1)}{n(n-2)} \sum_i \left(\hat{f}_{S,R,Z}(S_i,R_i,Z_i)\, \hat{f}_R(R_i) - \hat{f}_{S,R}(S_i,R_i)\, \hat{f}_{R,Z}(R_i,Z_i)\right) \tag{9}$$

D&P demonstrated that if $\theta_n = Cn^{-\beta}$ with $\left(C > 0, \frac{1}{4} < \beta < \frac{1}{3}\right)$, then $T_n(\theta_n)$ converges to the standard normal:

$$\sqrt{n}\frac{(T_n(\theta_n) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{10}$$

where, S_n is the estimated standard error of $T_n(\bullet)$. Overall, the risk of over-rejecting the null is reduced with the D&P approach.

3 Empirical results

In this section, we focus on the stock returns and the change of investors' sentiment. To identify the integration order of these variables, we compute the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1979), the Generalized Least Squares detrending Dickey-Fuller test (GLS-DF) proposed by Elliott et al. (1996), the Breitung unit root test (Breitung, 2002) and finally, the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) developed by Kwiatkowski et al. (1992). All tests are implemented with and without the inclusion of a time trend. Table 1 illustrates the results of the unit root and stationarity tests. In every case, we reject the null hypothesis for the three implemented unit root tests, while the opposite holds for the KPSS test. Clearly, both variables appear to be I(0).

Table 1: Unit root and stationarity tests.

Variable	ADF test		GLS-DF test	
	no trend	trend	no trend	trend
	t-Stat.	t-Stat.	t-Stat.	t-Stat.
R	-17.505^{***}	-17.544^{***}	$-\ 4.924^{***}$	-15.551^{***}
S	-19.736^{***}	-19.718^{***}	-19.265^{***}	-19.644^{***}

Variable	Breitung test		KPSS test	
	no trend	trend	no trend	trend
	$B(n)/n$-Stat.	$B(n)/n$-Stat.	LM-Stat.	LM-Stat.
R	0.000^{***}	0.000^{***}	0.195	0.061
S	0.000^{***}	0.000^{***}	0.068	0.066

Notes: The lag-length (ADF and GLS-DF) was selected based on the Schwarz criterion. The bandwidth for the KPSS test was chosen according to the Newey-West selection procedure (spectral method: Bartlett kernel). For the Breitung test simulated p-values based on 5000 replications have been calculated in order to determine the level of significance. Finally, $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively.

The testing procedure for the H&J and the D&P is carried out in two sequential steps. In the first step both tests are implemented directly onto the raw series, while in the second step both tests are reapplied on the delinearized (through a bivariate VAR specification) series.[4] The testing results are presented in panels A and B of Table 2.

[4]The second step is considered of essential importance in order to ensure that the identified causality is purely non-linear in nature.

Table 2: Non-linear causality tests.

l_s=l_r	$R \rightarrow S$				$S \rightarrow R$			
			θ=1.5				θ=1.5	
	H&J(p-value)		D&P(p-value)		H&J(p-value)		D&P(p-value)	
Panel A:Without filtering (step one)								
1	0.202	(0.420)	0.299	(0.383)	1.959**	(0.025)	2.084**	(0.019)
2	0.605	(0.273)	0.560	(0.288)	1.346*	(0.089)	1.411*	(0.079)
3	0.904	(0.183)	0.644	(0.260)	0.868	(0.193)	0.894	(0.186)
4	0.755	(0.225)	0.539	(0.295)	2.168**	(0.015)	1.961**	(0.025)
5	0.306	(0.380)	0.286	(0.387)	1.946**	(0.026)	1.640**	(0.049)
Panel B:With VAR filtering (step two)								
1	0.071	(0.472)	−0.103	(0.541)	1.397*	(0.081)	1.422*	(0.077)
2	0.032	(0.374)	0.156	(0.438)	1.025	(0.153)	1.044	(0.148)
3	0.750	(0.227)	0.440	(0.330)	0.200	(0.421)	0.178	(0.429)
4	0.618	(0.268)	0.285	(0.388)	1.997**	(0.023)	1.904**	(0.028)
5	0.038	(0.485)	−0.186	(0.574)	1.702**	(0.044)	1.744**	(0.041)

Notes: $*$, $**$ and $***$ denote rejection of the null hypothesis at the 10%, 5% and 1% significance level, respectively. The selected VAR lag-order, based on the Akaike information criterion, is equal to 4.

The results reveal significant unidirectional causality running from investors' sentiment change to stock returns. The null hypothesis of no non-linear causality running from returns to sentiment is never rejected for both tests and both steps. For the null hypothesis of the opposite direction, there is sufficient evidence in favor of its rejection. For the raw series both tests reject the null hypothesis at the nominal level of 0.05 for the first, fourth and fifth lag and the test rejects at the nominal level of 0.1 when the lag-length is set equal to two. Only for the third lag we fail to reject the null at the conventional levels of significance. Finally, for the delinearized series both tests reveal an indistinguishable pattern. The null hypothesis is rejected at the 0.05 nominal level for the fourth and fifth lag, while the rejection level rises at the 0.1 when the lag-length was set equal to one. Overall, it can be argued that there is reasonable statistical evidence to support that sentiment acts as a useful tool in predicting stock returns.

4 Conclusions

The linear causality framework is widely adopted in the behavioral finance literature when evaluating the predictive content that sentiment may have upon stock returns. The salient feature of this study is the fact that the analysis is carried out, employing an extended dataset, within a non-linear framework. The non-linear causality tests implemented are the well established H&J test and the D&P test. The advantage of the D&P test over the H&J is that it corrects for the observed over-rejection of the null hypothesis. Our empirical findings reveal that there is reasonable statistical evidence to support that sentiment embodies significant predictive power with respect to stock returns.

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