Original scientific paper

EXPLORING THE EPISTEMOLOGICAL ROLE OF THE DECOMPOSED S&P 500 SIGNAL COMPONENTS ON THE FORMATION OF INVESTORS' SENTIMENT

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Abstract
In this paper we address the question of whether the investor sentiment (optimism, neutrality, pessimism) and the decomposed S&P 500 signal components (irregularity, seasonality and trend) are dynamically, and Granger causally related on a temporal scale. The aim is to identify structural relationships between decomposed S&P 500 signal components and investors' sentiment that would defend our proposition that the formation of investors' sentiment has an epistemological nature, grounded on the epistemic properties of the decomposed S&P 500 signal components. The preliminary VAR and Granger causality results do indicate a dynamic unidirectional relationship between S&P 500 signal as a whole and investors' sentiment. While the secondary Granger causality results do indicate a bidirectional relationship between the decomposed S&P 500 signal components and investors' sentiment. These two results altogether suggest a structural relationship where the S&P 500 signal decomposition does have an epistemological role on the formation of investors' sentiment and vice versa investors' sentiment does impact the S&P 500 signal only on the level of its decomposed components, but not on the S&P 500 signal as a whole.

JEL Classification: G1

INTRODUCTION

The Standard and Poor's 500 (S&P 500) as a stock investor index is representing the stock performance of 500 largest corporations. It is a widely used index by investors during their investment decision process (Dichtl 2020). Whereas, investor sentiment (also related to investors' attention (Mbanga, Darrat, and Park 2019)) is the general attitude of the investors toward the future price developments in the financial investors expressed through the notions of optimism/pessimism (Baker and Wurgler 2007). Traditionally, there is a lot of research focus on how financial markets influence the investor sentiment and vice versa, how the investor sentiment influences the financial markets (Ahmed 2020). However, to our knowledge, there is lack of research on how the epistemology of each of the decomposed components of the financial time series individually influence the investor sentiment.

In general terms, epistemology is referred to as the theory of knowledge, because it is studying the nature of knowledge and information in all its facets: nature, source, and limits (Dretske 2008). The notion of epistemology is a widely applied concept in financial decision- making process (Robb 2013). By the epistemology of the decomposed components of the financial time series, we consider the nature, source and limits of knowledge that each of the decomposed financial time series components provides to the investor. Therefore, in this paper, we integrate the notion of epistemic utility, which is

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the utility of knowledge generated when the agents' learning process is focused not only on the target which is about to be learned, but it is also focused on the epistemological norms of the learning process itself (Pettigrew 2010; Carr 2017). For example, a financial analyst who has been dealing with extrapolation of highly noisy financial signals, would be more prepared to extrapolate compared to a financial analyst who has not been confronted with extrapolation of such highly noisy signals (Banerjee and Green 2015), because exposing a financial analyst to an uncertain, complex, and novel financial signal provides her with a more epistemologically rich environment compared toward exposing her to a simple signal without noise and which has only a clearly emphasized seasonal pattern.

The importance of this paper, we believe to rely on the crucial role that financial time series have on investment decisions, not only in the computational statistics perspective, but also on behavioral and perceptual perspectives. We aim to explore whether and how the epistemic properties of one aggregate financial time series as the S&P 500 index, influences the investors' aggregate attitude toward that same financial time series, by analyzing the role of the epistemic properties of each of the decomposed S&P 500 components on investors' sentiment. The time series decomposition is a very known and profound computational statistics process (Rios and de Mello 2012). Thus, we are not aiming to elaborate on the computational and theoretical underpinnings of the time series decomposition process, because that is also out of the scope of this paper. But we intend to use humbly only the epistemological contextualization that each of the decomposed time series components has, at this point, by assuming that there exists a behavioral tendency of investors when they visually extrapolate a financial time series graph based on visual feature extraction. In such case, the visual feature extraction would correspond (at least contextually) to visual time series decomposition into irregularity, seasonality, and trend component without any of computational statistics tools. Therefore, in the next section, we begin by exploring interpretatively the dynamic relationship between S&P500 time series and financial investor sentiment from epistemological perspective, and then we continue to explore statistically.

1. THE FORMATION OF INVESTORS' SENTIMENT, AN EPISTEMIC REASONING PROCESS?

The importance of epistemological addressing toward financial time series analysis relies on the extrapolation process itself, where the investor is forced to decide based on her previous beliefs generated by probabilism (Hoffmann and Post 2016). That is, an investor investing during a global economic recession period, can have the range of her stronger probabilistic beliefs generated from experience that in near future there might occur a "slight improvement" of the financial investor, compared to the range of weaker probability beliefs that there might be a "sharp improvement" in such short-run and this difference in the strength of investors' probabilistic beliefs when extrapolating is founded on the epistemological nature of past data evidence to which the investor has been exposed before (Lam, Liu, and Wong 2010). However, not all past financial evidence reveals information at first hand (Baltakys 2019). Indeed, investors' perceptual mechanisms identify and extract features and group the past evidence based on the similarity of the patterns (Hawaldar and Rahiman 2019).

The decomposition of time series in components of irregularity, seasonality and trend is a computational process whose product offers three components: irregularity, seasonality and trend component (Rios and de Mello 2012). However, these three components despite having a computational relevance, we propose that they serve also as three epistemic properties which an investor can approximately identify as visual features when she is visually prospecting the time series graph (as in Figure 1):

- **"Is the signal very noisy?" –** the irregularity component as increase of epistemic uncertainty of the signal
- **"Has the signal a repetitive pattern?" –** the seasonality component as decrease of epistemic novelty of the signal
- **"Is the signal in overall increasing or decreasing in the long term?" –** the trend component as decrease of epistemic complexity of the signal in long-term perspective

The epistemic nature of each of the decomposed time series components relies on the different epistemic value that each of the components provides to the investor. For example, irregularity in a noisy signal represents a risky and uncertain epistemic property which requires a careful addressing from the observer. Whereas a seasonality component expressed as a repetitive pattern in the signal is more predictable and it offers not much of epistemic novelty to the investor. The trend component has implications for summarizing the small long-term variations into a trend and thus it provides the feeling of decrease in complexity of the time series in long term cyclical context. Furthermore, these three epistemic properties correspond to three out of Daniel Berlyne's four stimulus collative properties, namely stimulus' uncertainty, novelty, complexity and conflict (Cupchik and Berlyne 1979). The notion of stimulus collative properties implies that the perceiver's curiosity (or the motivation to explore the environment and generate knowledge and seek information) depends strongly on the arousal potential of every stimulus ranging from abstract paintings up to musical melodies (Daniel E Berlyne and Lawrence 1964). Considering the behavioral finance level analysis of this paper, we dwell into each of the identified epistemic properties as to formulate our hypotheses on behalf of categorizing the S&P500 time series extrapolation as an epistemic reasoning process. This theoretical framework has also its psychobiological counterpart which is not primary subject of this paper, but for which we orientate the reader to additional literature (D. E. Berlyne 1970).

Epistemic uncertainty relates to the relative frequency (or probability) of encountering a given consequence, which would lead to an increase in the completeness/sufficiency of knowledge of the underlying processes involved in causing those given consequences. However, a decision making under risk and decision making under uncertainty are considered as two epistemically different categories (De Groot and Thurik 2018). Whereas in the former, the quantification and thus grasping of uncertainty is unavailable due to lack of epistemic reasoning ("not knowing what to know"), in the latter, uncertainty is quantifiable and as such probabilities are available enough as to apply the probability axioms. The epistemological nature of uncertainty is a central research topic of information theory, where uncertainty represents epistemologically rich environment which is represented quantitatively through the notion of Shannon's entropy (R. Zhou, Cai, and Tong 2013) and is considered a key learning factor in behavioral finance (Chen 2003). Considering the impact of uncertainty in investment decision making and risk and uncertainty perception of financial time series (Molgedey and Ebeling 2000; Darbellay and Wuertz 2000), we aim to test the following alternative hypothesis:

H1. The irregularity component of S&P500 time series will affect the investors' sentiment.

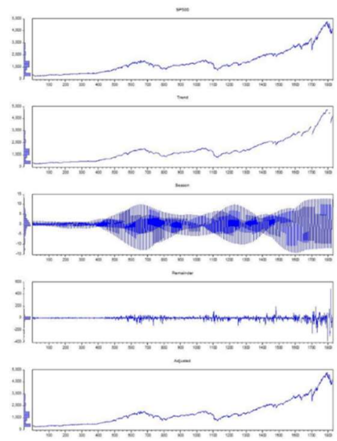

Figure 1. The decomposed S&P500 signal components

Investors are in continuous search of new or additional information that will provide them the edge over what the rest of the market knows. They try to overcome the market efficiency hypothesis by extracting and synthesizing new information that would lead them to new states of knowledge (Mishra and Kumar 2011). Therefore, the repetitive patterns in a financial time series are easily recognizable by the market and their epistemic value drops significantly. Furthermore, the repetitive patterns of time series provide the feeling of seasonality and assurance that what is currently increasing at a certain (known) point in time will decrease, and vice versa. Although this repetitive pattern lacks novelty in terms of knowledge generation, it provides the investor with the opportunity for contrarian trading, without specifically implying that the investor should be optimist or pessimist. But the predictability of such a repetitive pattern as they offer lower risk, yet returns are lower as well (Chang and Pinegar 1988). We consider that the lack of epistemic novelty of the seasonality component (and lack of epistemic value due to market efficiency hypothesis), would shift investors from a Neutrality sentiment either towards an Optimism sentiment or Pessimism sentiment, depending on the seasonality cycle. Therefore, we formulate our next alternative hypothesis as:

H2. The seasonality component of S&P500 signal, will decrease the investors' sentiment of neutrality.

Time series that do not provide the feeling of long-term average are to be considered as more complex, because they lack the generalization in terms of system memorability or long-term persistence (Tang et al. 2015). By generalization we mean the level of isolating small, short run signal variances as to gain the general long-term perspective of the signal evolution. It appears as a tradeoff, whether we are intending to deal with the short-term variances and lose the sense of signal direction (trend) or whether we are intending to deal with the signal direction in the long-run by averaging through the signal variances of the short-run. Here applies the same logic as central limit theorem within cross-sectional data. The normality of distribution of cross-sectional (both, discrete and continuous) data offers a feeling of order out of disorder (decreasing the complexity), because it generalizes the small deviances by providing a general representative measurement such as the sample mean. In time series' context, the long-term average provided by an increasing, uniform or a decreasing trend, is providing the feeling that the time series at least do have a direction (a long-term order out of short-term disorder), and as such this direction will serve epistemically when the investor performs a visual extrapolation, either through the lenses of optimism (expecting an increase of S&P500) or pessimism (expecting a decrease of S&P500). To test this proposition, we formulated the next alternative hypothesis as:

H3. The trend component of S&P500 signal will affect the investors' sentiment.

2. METHODS AND DATA

As to compare the effect of S&P 500 signal on investors' sentiment with the effect of individual components of S&P 500 signal on the investors' sentiment, we have tested two different VAR models. There are several direct and indirect measurement methods of the investor sentiment (G. Zhou 2018). We decided to rely on the American Association of Individual Investors (AAII) investor sentiment historical survey data (https://www.aaii.com/sentimentsurvey).

The AAII is providing an investor sentiment index generated by the AAII sentiment survey where the opinions of individual investors regarding the future price developments for the next six months are pooled directly on weekly basis. The data are time series of investor sentiments in terms of Bullish, Neutral and Bearish and time series of S&P500 in the period 1987-2020.

To explore the general dynamic relationship between the S&P500 signal and the investor sentiment components (optimism, neutrality and pessimism) we performed a vector autoregression modeling of the S&P500 and the AAII investor sentiment time series by considering both of them as endogenous variables. This bivariate time series analysis shall reveal the key interactions across time in between these two variables of interest without dwelling in the details of how such dynamic relationship prevails. However, it will serve us latter on to test our general proposition that the decomposed S&P500 time series components do indeed reveal the epistemological reasoning argument for the formation of investors' sentiment.

To identify the epistemic role of each individual decomposed S&P500 signal component on each of the investor sentiments we have built a second VAR model. Led by the latter exploratory aim of the first VAR modeling, we further continued to explore potential structural and temporal relationships within and between the decomposed S&P500 time series components and the investor sentiment components by using the VAR modeling approach. We remained open for any bi-directional relationships both in structural and temporal perspective.

3. RESULTS AND DISCUSSIONS

3.1. S&P500 signal and investors' sentiment

We started the VAR modeling procedure with tests of stationarity and the optimal lag length choice. From the VAR Lag order selection criteria, the lag 7 is proposed to be the most optimal lag length for performing VAR analysis on S&P500 and investor sentiment components time series (Table 1). From VAR of S&P500 signal and investor sentiment components results, there is an evident statistically significant relationship between S&P500 and investor sentiment components (Table 2). This relationship is unidirectional, that is, on temporal scale there is statistically significant evidence that S&P500 is driving the investor sentiment and not vice versa. At lag 1 the S&P500 time series signal is increasing the Bullish investor sentiment and increasing the Neutral investor sentiment, while decreasing the Bearish investor sentiment. Whereas at lag 2 the S&P500 time series signal is decreasing the Bullish investor sentiment and increasing the Bearish investor sentiment. There is no statistically significant effect of the S&P 500 signal of lag 2 on the Neutral investor sentiment.

Table 1. VAR Lag Order Selection Criteria

Endogenous variables: BULLISH BEARISH NEUTRAL SP500
Exogenous variables: C
Sample: 1 1825
Included observations: 1808

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3790.484	NA	1.78e-07	-4.188589	-4.176421	-4.184098
1	10906.17	14192.02	6.92e-11	-12.04223	-11.98139	-12.01977
2	11066.36	318.7682	5.90e-11	-12.20172	-12.09221*	-12.16130
3	11116.72	100.0005	5.68e-11	-12.23973	-12.08155	-12.18135*
4	11143.59	53.24342	5.61e-11	-12.25176	-12.04490	-12.17542
5	11159.24	30.93486	5.62e-11	-12.25137	-11.99584	-12.15707
6	11172.27	25.68668	5.63e-11	-12.24808	-11.94388	-12.13581
7	**11201.12**	**56.79281***	**5.55e-11***	**-12.26231***	**-11.90943**	**-12.13208**
8	11210.94	19.27853	5.59e-11	-12.25547	-11.85392	-12.10727

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 2. Vector Autoregression Estimates

Date: 09/01/22 Time: 11:52
Sample (adjusted): 8 1825
Included observations: 1810 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	BULLISH	BEARISH	NEUTRAL	SP500
BULLISH(-1)	-45.31230	47.39179	-2.065699	7521.448
	(27.7984)	(26.1580)	(21.2652)	(16358.5)
	[-1.63003]	[1.81175]	[-0.09714]	[0.45979]
BULLISH(-2)	1.665500	-2.151770	0.506709	1667.793
	(27.8265)	(26.1844)	(21.2867)	(16375.0)
	[0.05985]	[-0.08218]	[0.02380]	[0.10185]
BULLISH(-3)	11.76323	-7.408406	-4.341656	-6559.248
	(27.8153)	(26.1738)	(21.2781)	(16368.4)
	[0.42291]	[-0.28305]	[-0.20404]	[-0.40073]

BULLISH(-4)	-3.719031	17.49894	-13.76230	-8315.178
	(27.7777)	(26.1385)	(21.2494)	(16346.3)
	[-0.13389]	[0.66947]	[-0.64766]	[-0.50869]
BULLISH(-5)	30.83118	-28.20299	-2.597008	4990.168
	(27.7783)	(26.1390)	(21.2498)	(16346.7)
	[1.10990]	[-1.07896]	[-0.12221]	[0.30527]
BULLISH(-6)	-40.11857	49.80616	-9.683184	-17882.02
	(27.7684)	(26.1298)	(21.2423)	(16340.9)
	[-1.44475]	[1.90611]	[-0.45584]	[-1.09431]
BULLISH(-7)	-44.92272	43.49261	1.482880	4931.054
	(27.7881)	(26.1483)	(21.2573)	(16352.4)
	[-1.61662]	[1.66331]	[0.06976]	[0.30155]
BEARISH(-1)	-45.79309	47.85938	-2.052492	7504.467
	(27.7989)	(26.1584)	(21.2656)	(16358.8)
	[-1.64730]	[1.82960]	[-0.09652]	[0.45874]
BEARISH(-2)	1.508552	-1.998436	0.510281	1663.933
	(27.8276)	(26.1854)	(21.2875)	(16375.7)
	[0.05421]	[-0.07632]	[0.02397]	[0.10161]
BEARISH(-3)	11.72521	-7.349160	-4.362880	-6552.639
	(27.8164)	(26.1749)	(21.2790)	(16369.1)
	[0.42152]	[-0.28077]	[-0.20503]	[-0.40031]
BEARISH(-4)	-3.775275	17.53869	-13.74576	-8299.137
	(27.7788)	(26.1395)	(21.2502)	(16346.9)
	[-0.13591]	[0.67097]	[-0.64685]	[-0.50769]
BEARISH(-5)	30.83762	-28.21383	-2.592638	4980.910
	(27.7793)	(26.1400)	(21.2506)	(16347.3)
	[1.11009]	[-1.07933]	[-0.12200]	[0.30469]
BEARISH(-6)	-40.13130	49.82727	-9.691554	-17865.90
	(27.7695)	(26.1308)	(21.2431)	(16341.5)
	[-1.44516]	[1.90684]	[-0.45622]	[-1.09328]
BEARISH(-7)	-44.97903	43.59577	1.436060	4922.980
	(27.7892)	(26.1493)	(21.2582)	(16353.1)
	[-1.61858]	[1.66719]	[0.06755]	[0.30104]
NEUTRAL(-1)	-45.86938	47.53738	-1.654201	7495.613
	(27.7996)	(26.1591)	(21.2661)	(16359.2)
	[-1.65000]	[1.81724]	[-0.07779]	[0.45819]
NEUTRAL(-2)	1.523810	-2.173991	0.670633	1681.804
	(27.8281)	(26.1859)	(21.2879)	(16376.0)
	[0.05476]	[-0.08302]	[0.03150]	[0.10270]
NEUTRAL(-3)	11.75519	-7.486413	-4.255613	-6540.216

	(27.8169)	(26.1753)	(21.2793)	(16369.4)
	[0.42259]	[-0.28601]	[-0.19999]	[-0.39954]
NEUTRAL(-4)	-3.837407	17.53761	-13.68261	-8336.922
	(27.7793)	(26.1400)	(21.2506)	(16347.3)
	[-0.13814]	[0.67091]	[-0.64387]	[-0.50999]
NEUTRAL(-5)	30.87437	-28.28304	-2.560173	5002.180
	(27.7799)	(26.1406)	(21.2511)	(16347.6)
	[1.11139]	[-1.08196]	[-0.12047]	[0.30599]
NEUTRAL(-6)	-40.12696	49.80217	-9.670752	-17865.17
	(27.7700)	(26.1312)	(21.2435)	(16341.8)
	[-1.44498]	[1.90585]	[-0.45523]	[-1.09322]
NEUTRAL(-7)	-44.98898	43.47982	1.561909	4915.672
	(27.7893)	(26.1494)	(21.2583)	(16353.2)
	[-1.61893]	[1.66274]	[0.07347]	[0.30059]
SP500(-1)	**0.000218**	**-0.000285**	**6.65E-05**	**0.939232**
	(4.2E-05)	**(4.0E-05)**	**(3.2E-05)**	**(0.02489)**
	[5.15362]	**[-7.14957]**	**[2.05696]**	**[37.7422]**
SP500(-2)	**-0.000229**	**0.000219**	1.00E-05	**0.075887**
	(5.7E-05)	**(5.3E-05)**	(4.3E-05)	**(0.03342)**
	[-4.03499]	**[4.09995]**	[0.23109]	**[2.27094]**
SP500(-3)	-4.01E-06	6.67E-05	-6.27E-05	-0.046087
	(5.7E-05)	(5.4E-05)	(4.4E-05)	(0.03365)
	[-0.07004]	[1.24003]	[-1.43300]	[-1.36957]
SP500(-4)	3.06E-05	-1.51E-05	-1.55E-05	-0.032936
	(5.7E-05)	(5.4E-05)	(4.4E-05)	(0.03365)
	[0.53460]	[-0.28077]	[-0.35322]	[-0.97870]
SP500(-5)	-1.21E-05	4.29E-06	7.76E-06	**0.089049**
	(5.7E-05)	(5.4E-05)	(4.4E-05)	**(0.03382)**
	[-0.21001]	[0.07933]	[0.17659]	**[2.63318]**
SP500(-6)	7.16E-06	2.01E-05	-2.73E-05	**-0.088572**
	(5.8E-05)	(5.4E-05)	(4.4E-05)	**(0.03387)**
	[0.12437]	[0.37161]	[-0.61988]	**[-2.61537]**
SP500(-7)	-1.31E-05	-7.17E-06	2.02E-05	**0.064951**
	(4.3E-05)	(4.0E-05)	(3.3E-05)	**(0.02530)**
	[-0.30375]	[-0.17711]	[0.61533]	**[2.56701]**
C	90.70711	-120.3747	30.51417	13646.50
	(69.5327)	(65.4294)	(53.1911)	(40917.8)
	[1.30453]	[-1.83976]	[0.57367]	[0.33351]
R-squared	0.539757	0.557646	0.603315	0.998330
Adj. R-squared	0.532521	0.550692	0.597078	0.998304
Sum sq. resids	8.404853	7.442143	4.918464	2910566.

S.E. equation	0.068696	0.064642	0.052551	40.42562
F-statistic	74.59617	80.18538	96.73952	38033.42
Log likelihood	2293.628	2403.722	2778.539	-9249.691
Akaike AIC	-2.502352	-2.624002	-3.038165	10.25270
Schwarz SC	-2.414213	-2.535863	-2.950026	10.34084
Mean dependent	0.376683	0.308840	0.314477	1401.491
S.D. dependent	0.100474	0.096437	0.082789	981.6621
Determinant resid covariance (dof adj.)	5.19E-11			
Determinant resid covariance	4.87E-11			
Log likelihood	11216.74			
Akaike information criterion	-12.26601			
Schwarz criterion	-11.91345			
Number of coefficients	116			

From this VAR model of S&P500 signal and investor sentiment components we cannot infer what particularly is the reason that S&P500 time series influences the investor sentiment components across time (comparing lag 1 and lag 2) in two opposite directions. An increase in the S&P500 signal of lag 1 creates the investing euphoria and as such it would increase the investor sentiment of optimism; however we do see that this is not the case with the week before the last week (lag 2) where the increase of S&P 500 signal of lag 2 decreases optimism and increases pessimism. We might interpret this result as the investors' past week lack of optimism is decreasing significantly in the current week and investors start to become more of optimists.

The results from the Granger causality test confirm that it is S&P 500 signal the one that Granger causes investors' sentiment and not the vice versa (Table 3). This is statistical evidence that the S&P 500 signal might indeed serve the investors as an epistemological target. Furthermore, the results from the Granger causality test reveal causality of S&P500 signal on investor sentiments of Bullish and Bearish while does not reveal causality of S&P500 signal on investor sentiment of Neutral. What is interesting, is that the causality direction is from S&P500 signal towards the investor sentiment and not vice versa. This at first appears to diminish the value of investor sentiment for predicting S&P500 signal. However, at this point we remain open for additional addressing to how the investor sentiments relate not to the S&P500 signal per se, but to its decomposed time series components. Therefore, in the next sections, we continue to test the proposition that S&P500 signal extrapolation is indeed much more than computational endeavor and as such investor sentiments despite not relating to the S&P500 signal as a whole, they might relate to some of its decomposed time series components individually.

Table 3. Pairwise Granger Causality Test

Date: 09/03/22 Time: 18:35
Sample: 1 1825
Lags: 7

Null Hypothesis:	Obs	F-Statistic	Prob.
NEUTRAL does not Granger Cause BULLISH	1810	1.12242	0.3459
BULLISH does not Granger Cause NEUTRAL		1.68048	0.1094

BEARISH does not Granger Cause BULLISH	1810	1.12103	0.3468
BULLISH does not Granger Cause BEARISH		**4.75010**	**3.E-05**
SP500 does not Granger Cause BULLISH	**1810**	**3.72767**	**0.0005**
BULLISH does not Granger Cause SP500		0.49340	0.8399
BEARISH does not Granger Cause NEUTRAL	1810	1.68033	0.1094
NEUTRAL does not Granger Cause BEARISH		**4.75426**	**3.E-05**
SP500 does not Granger Cause NEUTRAL	1810	1.31590	0.2386
NEUTRAL does not Granger Cause SP500		0.59818	0.7579
SP500 does not Granger Cause BEARISH	**1810**	**8.22824**	**7.E-10**
BEARISH does not Granger Cause SP500		0.47153	0.8557

To gain insight into the scale of above identified statistically significant VAR relationships and Granger causalities both in short and long-run terms, we performed variance decomposition of S&P500 signal and investor sentiment components. We chose to analyze bilaterally the forecasting power of each of the components on 10 periods (2.5 months). Results indicated that both, in short and long-run the investor sentiments have very small forecasting power on the S&P500 signal, which in VAR modeling it showed to be statistically nonsignificant. The investor sentiment of Bearish in comparison with the other investor sentiments has considerably higher forecasting power on the S&P500 signal, on average 10% in both short and long-term. The previously identified VAR relationships and the statistically significant unilateral Granger causality S&P500 signal towards the investor sentiments, from the variance decomposition results shows S&P500 to have very small forecasting power on investor sentiment of Bearish (on average 2.7% in short and long-term), on investor sentiment of Neutral (on average 0.5% in short and long-term) and on investor sentiment of Bullish (on average 1.05% in short and long-term).

3.2. The decomposed S&P500 signal components and investors' sentiment

Considering that we have already performed the stationarity test earlier in our first VAR modeling, we started the second VAR modeling with selecting the optimal lag length for the VAR model. The most optimal lag length turns out to be 4, which in context of our data means four weeks or one month (Table 4). Results of VAR show both structural and temporal inter and intrarelationships between the decomposed S&P time series components and the investor sentiment components (Table 5).

Table 4. VAR Lag Order Selection Criteria

Endogenous variables: BULLISH NEUTRAL BEARISH IRREGULARITY SEASONALITY DTREND
Exogenous variables: C
Date: 08/20/22 Time: 21:49
Sample: 1 1825
Included observations: 1815

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1113.409	NA	1.19e-08	-1.220286	-1.202091	-1.213572
1	4450.171	6647.786	3.13e-10	-4.857489	-4.730127	-4.810495

2	5550.217	2184.333	9.69e-11	-6.029991	-5.793463	-5.942716
3	8032.571	4912.735	6.54e-12	-8.725698	-8.380002	-8.598141
4	31437.72	**46165.53***	**4.29e-23***	**-34.47683***	**-34.02197***	**-34.30899***

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 5. The Vector Autoregression Estimates for the decomposed S&P500 time series components and the investor sentiment components

Vector Autoregression Estimates
Date: 08/20/22 Time: 15:32
Sample (adjusted): 6 1825
Included observations: 1815 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	IRREGULARITY	DTREND	SEASONALITY	BULLISH	NEUTRAL	BEARISH
IRREGULARITY(-1)	-1.852450	-0.147550	0.000106	**-0.000663**	**-0.000348**	**0.001011**
	(0.01486)	(0.01486)	(0.00106)	**(0.00022)**	**(0.00017)**	**(0.00021)**
	[-124.637]	[-9.92756]	[0.09937]	**[-3.01276]**	**[-2.00128]**	**[4.91521]**
IRREGULARITY(-2)	-3.374312	0.374312	0.000413	**-0.000875**	-0.000528	**0.001403**
	(0.02471)	(0.02471)	(0.00177)	**(0.00037)**	(0.00029)	**(0.00034)**
	[-136.574]	[15.1502]	[0.23359]	**[-2.39257]**	[-1.82603]	**[4.10389]**
IRREGULARITY(-3)	-2.283316	0.283317	0.000573	-0.000199	-0.000453	0.000652
	(0.02547)	(0.02547)	(0.00182)	(0.00038)	(0.00030)	(0.00035)
	[-89.6355]	[11.1221]	[0.31426]	[-0.52763]	[-1.51802]	[1.84923]
IRREGULARITY(-4)	-1.285976	0.285976	0.000135	-0.000142	-0.000146	0.000288
	(0.01369)	(0.01369)	(0.00098)	(0.00020)	(0.00016)	(0.00019)
	[-93.9212]	[20.8863]	[0.13736]	[-0.69934]	[-0.91185]	[1.51979]
DTREND(-1)	-4.795785	1.795785	0.000201	-0.000192	-0.000656	0.000849
	(0.03329)	(0.03329)	(0.00238)	(0.00049)	(0.00039)	(0.00046)
	[-144.082]	[53.9516]	[0.08418]	[-0.39076]	[-1.68355]	[1.84304]
DTREND(-2)	3.634773	-0.634773	0.000539	**0.001202**	0.000512	**-0.001715**
	(0.03646)	(0.03646)	(0.00261)	**(0.00054)**	(0.00043)	**(0.00050)**
	[99.7030]	[-17.4120]	[0.20654]	**[2.22902]**	[1.19947]	**[-3.39879]**
DTREND(-3)	1.302696	-0.302696	-0.000885	-0.000595	0.000536	5.90E-05
	(0.05435)	(0.05435)	(0.00389)	(0.00080)	(0.00064)	(0.00075)
	[23.9675]	[-5.56912]	[-0.22741]	[-0.74011]	[0.84234]	[0.07839]

DTREND(-4)	-0.014402	0.014402	0.000165	0.000244	-0.000305	6.11E-05
	(0.02432)	(0.02432)	(0.00174)	(0.00036)	(0.00028)	(0.00034)
	[-0.59223]	[0.59223]	[0.09500]	[0.67682]	[-1.06951]	[0.18154]
SEASONALITY(-1)	0.009318	-0.009317	-0.516244	0.004077	**-0.007168**	0.003096
	(0.28864)	(0.28864)	(0.02067)	(0.00427)	**(0.00338)**	(0.00399)
	[0.03228]	[-0.03228]	[-24.9709]	[0.95459]	**[-2.12023]**	[0.77507]
SEASONALITY(-2)	0.038742	-0.038742	-0.100316	0.001397	-0.001009	-0.000386
	(0.15480)	(0.15480)	(0.01109)	(0.00229)	(0.00181)	(0.00214)
	[0.25027]	[-0.25027]	[-9.04759]	[0.60984]	[-0.55660]	[-0.18038]
SEASONALITY(-3)	0.021826	-0.021829	-0.900786	-0.003852	0.001926	0.001927
	(0.15506)	(0.15506)	(0.01111)	(0.00229)	(0.00182)	(0.00215)
	[0.14076]	[-0.14077]	[-81.1067]	[-1.67874]	[1.06075]	[0.89821]
SEASONALITY(-4)	0.031749	-0.031747	-0.485221	0.001857	-0.006102	0.004250
	(0.28888)	(0.28888)	(0.02069)	(0.00427)	(0.00338)	(0.00400)
	[0.10990]	[-0.10990]	[-23.4509]	[0.43440]	[-1.80354]	[1.06317]
BULLISH(-1)	800.6678	-800.6775	-165.4422	-51.30579	-4.490417	**55.80962**
	(1824.39)	(1824.39)	(130.670)	(26.9946)	(21.3674)	**(25.2477)**
	[0.43887]	[-0.43887]	[-1.26610]	[-1.90059]	[-0.21015]	**[2.21048]**
BULLISH(-2)	846.4450	-846.4369	63.97120	0.333907	-5.488168	5.177514
	(1827.46)	(1827.46)	(130.890)	(27.0401)	(21.4034)	(25.2902)
	[0.46318]	[-0.46318]	[0.48874]	[0.01235]	[-0.25642]	[0.20472]
BULLISH(-3)	-586.9524	586.9583	68.68206	12.34442	-6.573880	-5.753710
	(1826.13)	(1826.13)	(130.795)	(27.0204)	(21.3878)	(25.2718)
	[-0.32142]	[0.32142]	[0.52511]	[0.45686]	[-0.30737]	[-0.22767]
BULLISH(-4)	1849.467	-1849.472	-141.2767	-1.732540	-10.69366	12.44620
	(1825.12)	(1825.12)	(130.723)	(27.0054)	(21.3759)	(25.2578)
	[1.01334]	[-1.01334]	[-1.08074]	[-0.06416]	[-0.50027]	[0.49277]
NEUTRAL(-1)	799.2715	-799.2812	-165.3019	-51.85507	-4.056258	**55.92474**
	(1824.48)	(1824.48)	(130.676)	(26.9959)	(21.3684)	**(25.2489)**
	[0.43808]	[-0.43809]	[-1.26497]	[-1.92085]	[-0.18983]	**[2.21494]**
NEUTRAL(-2)	849.1896	-849.1814	63.57547	0.181029	-5.308235	5.150473
	(1827.57)	(1827.57)	(130.898)	(27.0417)	(21.4047)	(25.2917)
	[0.46465]	[-0.46465]	[0.48569]	[0.00669]	[-0.24799]	[0.20364]
NEUTRAL(-3)	-587.6989	587.7048	68.93642	12.32443	-6.468819	-5.838787
	(1826.23)	(1826.23)	(130.802)	(27.0219)	(21.3889)	(25.2732)
	[-0.32181]	[0.32181]	[0.52703]	[0.45609]	[-0.30244]	[-0.23103]
NEUTRAL(-4)	1848.287	-1848.292	-141.2559	-1.850131	-10.56222	12.43232
	(1825.20)	(1825.20)	(130.729)	(27.0066)	(21.3769)	(25.2589)
	[1.01265]	[-1.01265]	[-1.08053]	[-0.06851]	[-0.49409]	[0.49219]

BEARISH(-1)	800.9976	-801.0074	-165.5178	-51.79088	-4.481879	**56.28618**
	(1824.42)	(1824.42)	(130.672)	(26.9950)	(21.3677)	**(25.2480)**
	[0.43904]	[-0.43905]	[-1.26666]	[-1.91854]	[-0.20975]	**[2.22933]**
BEARISH(-2)	844.9449	-844.9367	63.99643	0.174740	-5.492593	5.341067
	(1827.53)	(1827.53)	(130.895)	(27.0411)	(21.4041)	(25.2911)
	[0.46234]	[-0.46234]	[0.48891]	[0.00646]	[-0.25661]	[0.21118]
BEARISH(-3)	-585.5085	585.5144	68.84353	12.29015	-6.604204	-5.669114
	(1826.21)	(1826.21)	(130.800)	(27.0215)	(21.3886)	(25.2728)
	[-0.32061]	[0.32062]	[0.52632]	[0.45483]	[-0.30877]	[-0.22432]
BEARISH(-4)	1847.907	-1847.912	-141.3977	-1.818866	-10.69519	12.53409
	(1825.20)	(1825.20)	(130.728)	(27.0065)	(21.3768)	(25.2588)
	[1.01244]	[-1.01245]	[-1.08162]	[-0.06735]	[-0.50032]	[0.49623]
C	-2909.307	2909.308	174.0621	41.24169	27.30144	-67.61662
	(3555.48)	(3555.48)	(254.658)	(52.6087)	(41.6420)	(49.2042)
	[-0.81826]	[0.81826]	[0.68351]	[0.78393]	[0.65562]	[-1.37421]
R-squared	0.950206	0.942916	0.797107	0.564538	0.596938	0.584957
Adj. R-squared	0.949539	0.942151	0.794386	0.558699	0.591534	0.579392
Sum sq. resids	36557.09	36557.09	187.5383	8.003677	5.014621	7.001302
S.E. equation	4.519176	4.519176	0.323682	0.066868	0.052929	0.062541
F-statistic	1423.269	1231.978	293.0152	96.69070	110.4587	105.1168
Log likelihood	-5300.405	-5300.405	-515.4776	2346.852	2771.147	2468.280
Akaike AIC	5.868215	5.868215	0.595568	-2.558514	-3.026058	-2.692319
Schwarz SC	5.944025	5.944025	0.671378	-2.482704	-2.950247	-2.616509
Mean dependent	-0.004723	2.107008	-0.000753	0.377083	0.314255	0.308661
S.D. dependent	20.11781	18.78932	0.713826	0.100659	0.082816	0.096433

Determinant resid covariance (dof adj.)	3.95E-23
Determinant resid covariance	3.63E-23
Log likelihood	31437.72
Akaike information criterion	-34.47683
Schwarz criterion	-34.02196
Number of coefficients	150

The irregularity component of the S&P 500 signal of lag 1 is negatively related to the Bullish and Neutral investor sentiments and positively related to the Bearish investor sentiment. This result is statistically significant; thus, it implies that the level of the observed irregularity component of the previous week in S&P time series diminishes optimism and neutrality while increasing the pessimism levels. Similarly, irregularity component of lag 2 is negatively related to Bullish investor sentiment and positively related to Bearish investor sentiment but does not affect the Neutral investor sentiment. Considering the impact of Irregularity on investor sentiment only up to lag 2, implies that Irregularity component of S&P500 time series after two weeks it loses significance for investor's decision making. Therefore, we reject our first null hypothesis.

The seasonality component of the S&P500 signal of lag 1 shows a statistically significant negative impact on Neutral investor sentiment only. This means that the seasonality component of the previous week in the S&P500 time series is decreasing the investor's neutrality and thus making them prone to move out of their comfort zone and become either optimists or pessimists. Furthermore, results of VAR imply that investors do have a sense of their investor sentiment across time. Being Bullish and being Bearish the last week they both increase the Bearish investor sentiment in the current week. Also, the Neutrality of the last week makes investors prone toward Bearish investor sentiment. Therefore, we reject our second null hypothesis.

The trend component of the S&P500 signal shows a statistically significant impact on investor sentiment only when we consider the trend component of lag 2. Results show that the trend component of lag 2 is positively related to the Bullish and negatively related to the Bearish investor sentiment. This is contrary to the common sense that the current increasing trend levels should lead the euphoria of investment. Indeed, it is the observed trend component of the week before last week the one that accounts for increasing the Bullish investor sentiment and decreasing the Bearish investor sentiment. Therefore, we reject our third null hypothesis.

Granger causality test results reveal that investor sentiments do indeed relate to decomposed S&P500 time series components (Table 6). The investor sentiment of Bullish is impacting the Irregularity and Trend component of the S&P500 signal. Whereas the investor sentiment of Bearish is impacting only the Trend component of the S&P500 signal. There is no statistically significant result that seasonality component is impacted by the investor sentiment. This is logical, considering that seasonality patterns emerge due to exogeneous natural cycles. These results add up to the argument that the extrapolation of S&P500 is indeed an epistemic reasoning process where the investors process the epistemic properties of the decomposed S&P500 time series components and as such the epistemically upgraded investors' sentiments impact individually the future decomposed S&P500 time series components.

Table 6. Pairwise Granger Causality Tests

Date: 09/03/22 Time: 18:30
Sample: 1 1825
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
NEUTRAL does not Granger Cause BULLISH	1820	2.69576	0.0678
BULLISH does not Granger Cause NEUTRAL		0.98537	0.3735
BEARISH does not Granger Cause BULLISH	1820	2.69305	0.0679
BULLISH does not Granger Cause BEARISH		5.64524	0.0036
IRREGULARITY does not Granger Cause BULLISH	1820	39.2796	2.E-17
***BULLISH does not Granger Cause IRREGULARITY		8.68671	0.0002
SEASONALITY does not Granger Cause BULLISH	1820	0.54702	0.5788
BULLISH does not Granger Cause SEASONALITY		0.21858	0.8037
DTREND does not Granger Cause BULLISH	1819	38.3710	5.E-17
***BULLISH does not Granger Cause DTREND		5.89265	0.0028
BEARISH does not Granger Cause NEUTRAL	1820	0.98550	0.3735
NEUTRAL does not Granger Cause BEARISH		5.65227	0.0036
IRREGULARITY does not Granger Cause NEUTRAL	1820	0.39181	0.6759

NEUTRAL does not Granger Cause IRREGULARITY		0.12737	0.8804
SEASONALITY does not Granger Cause NEUTRAL	1820	0.38890	0.6779
NEUTRAL does not Granger Cause SEASONALITY		0.18357	0.8323
DTREND does not Granger Cause NEUTRAL	1819	3.76699	0.0233
NEUTRAL does not Granger Cause DTREND		1.42666	0.2404
IRREGULARITY does not Granger Cause BEARISH	1820	49.7928	9.E-22
***BEARISH does not Granger Cause IRREGULARITY		11.1928	1.E-05
SEASONALITY does not Granger Cause BEARISH	1820	0.15853	0.8534
BEARISH does not Granger Cause SEASONALITY		0.22204	0.8009
DTREND does not Granger Cause BEARISH	1819	64.3135	1.E-27
BEARISH does not Granger Cause DTREND		11.9995	7.E-06
SEASONALITY does not Granger Cause IRREGULARITY	1823	0.00438	0.9956
IRREGULARITY does not Granger Cause SEASONALITY		0.00123	0.9988
DTREND does not Granger Cause IRREGULARITY	1822	413.649	9E-149
IRREGULARITY does not Granger Cause DTREND		1161.23	0.0000
DTREND does not Granger Cause SEASONALITY	1822	0.00046	0.9995
SEASONALITY does not Granger Cause DTREND		0.02381	0.9765

The variance decomposition results indicate that the percentage of forecast error variance of decomposed S&P500 on investor sentiments although statistically significant (as indicated above) it is still very low. All investor sentiment components (individually) have a forecasting power of 0.4% on the decomposed S&P500 signal components (individually) during 10 periods. Whereas the above statistically significant relationships of investor sentiments and S&P500 signal components show to increase in the long run. The power of Irregularity component to forecast the Bearish investor sentiment, in the long term (10 periods) is approximately 15%, which is considerably higher than the forecasting power of the Seasonal and Trend component. The power of Irregularity component to forecast the Bullish investor sentiment in long term (10 periods) is approximately twice as lower as the power to forecast the Bearish investor sentiment, approximately 8%.

According to (Lütkepohl and Poskitt 1991), the stability (stationarity) of the estimated VAR can be evaluated with the modulus (less than 1) of all roots and which lie inside the unit circle. Results indicate that both VAR models do have modulus less than 1 and all the roots do lie inside the unit circle (Figure 2).

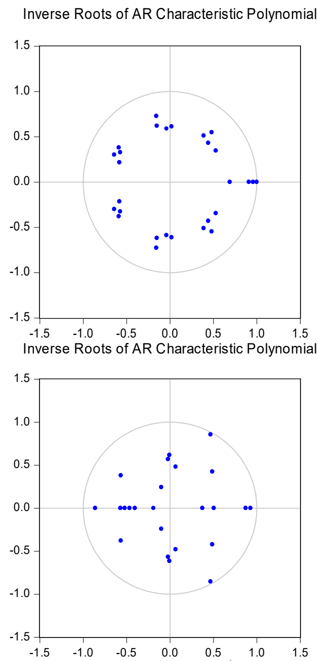

Figure 2. The 1st and 2nd VAR models stability

CONCLUSION

We conclude that the decomposition of time series into its three time series components, namely the irregularity (noise), seasonal and trend component, represents not only a computational endeavor, but also a strategic epistemological effort to address the individual role that each of these components play on the investors' sentiment formation process. From the interpretations of the decomposed time series' epistemic properties, we can conclude that the irregularity component increases epistemic uncertainty, seasonality component decreases epistemic novelty, whereas the trend component increases epistemic complexity. The epistemic uncertainty in the extrapolation process, increases the epistemic challenge of the extrapolation and as consequence the investors' optimism is decreased. Seasonal patterns are repeatable patterns which do not add up novelty to investors' knowledge, thus factoring out the seasonality component from the time series serves as an effort to isolate only the "novel" patterns for which investors do not have a previous knowledge. As consequence, the seasonality component decreases investors' sentiment of neutrality thus seasonality component is directing investors either towards the sentiment of optimism or pessimism. Whereas the extrapolation process of financial time series whose long-term average is inconsistent representative of short-term average in the logic of system-memorability, despite representing higher epistemic complexity, it increases investors' sentiment of optimism. Considering that the results of this paper represent the investors' behavioral level of extrapolation, this opens the door for future experimental research as to reveal on how the formation of investors' sentiment results from these three epistemic components of a decomposed financial time series in terms of investors' visual attention toward financial time series, and how it impacts the extrapolation process.

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