Does the Market Drive the Animal Spirits?
A Cointegration Analysis

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ABSTRACT

This paper studies different relationships in the US between consumer sentiment and stock returns. The study adds to the existing literature by exploring the long run relationship between consumer sentiment and stock returns while expanding on previous research. The paper shows that short-term changes in consumer sentiment are caused by changes in stock returns, and not vice versa. Additionally, causality tests suggest that stock returns drive consumer sentiment in the long run. It appears that US consumers' assurance in the economic condition depend on their future belief in one of the leading economic indicators.

Keywords: Stock Returns, Consumer Sentiment, Cointegration, Causality

INTRODUCTION

The link between the stock market and consumer sentiment has intrigued many researchers. Initially, Keynes (1936) suggested that animal spirits were driving the market. He not only hinted to the relationship between sentiment and stock returns but also the causal direction. Otoo (2000) demonstrated for the US that changes in equity values and changes in consumer sentiment are indeed contemporaneously related. However, positive changes in consumer sentiment had no effect on changes in equity prices although Otoo found strong evidence indicating the reverse in the short run. Otoo used the Michigan Survey Research Center's Consumer Sentiment Index (CSI) and Conference Board (CB) data as direct measures of consumer sentiment. Although other researchers have used proxies to measure consumer sentiment (Lee, Shleifer, & Thaler, 1991; Elton, Gruber, & Busse, 1998; Hirshleifer & Shumway, 2001), the CSI has the most significance. The CSI is closely watched by individual investors, as well as economists, and is based on a direct survey of public perceptions about current economic conditions.

Some of the previous studies have used Granger-causality methodology to capture the short run relationship between consumer sentiment and stock returns.

This seems to be a reasonable choice of statistical procedure since causality testing within the vector autoregressive (VAR) framework is rather straightforward for short-term research. But a problem arises within the unrestricted VAR procedure if the underlying long run data are integrated or non-stationary and cointegrated. The contribution of this study is the investigation of the long run relationship between sentiment and stock returns. In this case, an error-correction model (ECM) is a more appropriate specification. Two reasons make the ECM a better choice for model specification. First, if the data are cointegrated and the VAR is estimated in first differences (or growth rates) then the model is misspecified and will lead to biased estimates. If the VAR is estimated in levels without imposing the cointegration restrictions, the estimates are consistent but the well-known downward bias in the autoregressive parameters will be present, again yielding biased results.

DATA AND METHODOLOGY

Data

The relationship between consumer sentiment and stock returns is investigated with aggregate data. Logged monthly data of the CSI and the S&P 500 is used to identify the changes in sentiment and stock returns, as well as the relationship between the two variables. The monthly data of the CSI started in January 1978 and is matched with the monthly closing aggregate stock prices (S&P 500 index) from January 1978 to September 2005. Monthly data is used in order to focus on the relationship at the highest available frequency.

Methodology

Long run relationship are typically researched via cointegration, given the time-series characteristics of the data. Cointegration is the concept whereby non-stationary time series share common unit roots or stochastic trends. This allows the elimination of the common unit roots through a suitable linear combination. These linear combinations have been given the economic interpretation as long run static equilibria. Simply, two (or more) time series may trend (stochastically) over time, but the equilibrium error of the system will revert to its mean given sufficient time. The first step is to determine whether the series are stationary and, if not, whether they are integrated of the same order. Perron (1989) suggests that structural breaks in time-series data may bias conventional unit root procedures toward acceptance of the unit root null hypothesis. Zivot and Andrews (ZA) (1992) specify a test that allows the breakpoint, if one does exist, to be determined endogenously. The following equation (1) sets forth the ZA condition used in this analysis:

$$X_t = \mu + \theta DU_t(\lambda) + \beta t + \alpha X_{t-1} + \sum_{j=1}^{k} c_j \Delta X_{t-j} + \varepsilon_t \tag{1}$$

where $DU_t(\lambda)$ is a dummy variable that takes on a value of 1.0 when t (trend) is greater than Tλ and zero otherwise, and λ is $\in [0.1, 0.9]$. ZA provide critical values for the t-statistic that test the null hypothesis of $\alpha = 1$. ZA tests as well as the Augmented Dickey-Fuller (ADF) (1981) are used to check for stationarity.

The estimation of the cointegrating relationship between consumer sentiment and stock returns is carried out using the maximum likelihood procedure of Johansen (1988, 1991). The Granger Representation Theorem (GRT) (1981), Engle and Granger (1987), provides the link between cointegrated systems and error-correction models (ECM). Johansen (1991) has generalized the GRT.

Consider a vector autoregression of known order,

$$X_t = \Pi_1 X_{t-1} + \dots + \Pi_k X_{t-k} + \mu + \varepsilon_t \tag{2}$$

where X_t is a pX1 vector of non-stationary [specifically I(1)] variables and k is the minimum lag length that reduces serial correlation in residuals to zero statistically to zero in each equation in the VAR based on the Ljung-Box (LB) Q-statistics.

In order to 'deal with' the non-stationarity, the system is usually in differenced form. If there exists a linear combination of the X's such that less than p unit roots remain, then the first differenced system will have a non-invertible moving average representation, and no finite VAR approximation will exist. The system in equation (2) can be rewritten as in equation (3),

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{k-1} \Delta X_{t-k+1} - \Pi X_{t-1} + \mu + \varepsilon_t \tag{3}$$

where $\Gamma_i = -I + \Pi_1 + \dots + \Pi_i$, for i = 1,...,k-1, and $\Pi = I - \Pi_1 - \dots - \Pi_k$. All long-run information is contained in the impact matrix Π. Three possibilities exist, 1) the matrix Π has full column rank, implying the X_t was stationary to begin with, 2) the matrix Π has zero rank, in which case the system is a traditional first differenced VAR, and 3) the rank of Π is intermediate or rank $(\Pi) = r < p$, implying there exists r linear combinations of X_t that are stationary or cointegrated.

If condition 3) prevails, then Π can be decomposed into two pxr matrices, α and β, such that $\Pi = \alpha\beta'$. The vectors of β represent the r linear cointegrating relationships such that $\beta' X_t$ is stationary. The loading matrix α represents the error-correction parameters, which can be given the interpretation as speed of adjustment parameters.

The estimation of the model in equation (3) can be conducted by reduced rank regression e.g. Johansen (1988) and Ahn and Reinsel (1988). This is done by regressing X_{t-1} and ΔX_t on lagged values of $\Delta X_t, \dots, \Delta X_{t-k+1}$, and μ. Defining the residuals from these regressions as R_{0t} and R_{kt} respectively, the residual product moment matrices are calculated as $S_{ij} = T^{-1}\Sigma R_{it}R_{jt}'$, for $i,j = 1,k$. The cointegrating relations are then estimated as the eigenvectors corresponding to the r largest eigenvalues of equation (4).

$$|\lambda S_{kk} - S_{k0} S_{00}^{-1} S_{0k}| = 0 \qquad (4)$$

Johansen (1988, 1991) has derived two test statistics to test for the number of cointegrating vectors. The first tests the null of r cointegrating vectors versus the alternative of r+1. This statistic is based on the maximum eigenvalues and thus is denoted $\lambda_{\max}$. The form of this test is given in (4).

$$\lambda_{\max} = -T \ln(\hat{\lambda}_{r+1}) \qquad (5)$$

The likelihood ratio test of the null of r cointegrating vectors versus the general null of p cointegrating vectors is given by the trace statistic, which is computed as,

$$Trace = -T \sum_{i=r+1}^{p} \ln(1-\lambda_i) \qquad (6)$$

The term μ captures the deterministic drift in the series that is eliminated by the cointegration vector(s). Treatment of these terms is important, since the asymptotic distribution of the test statistics for cointegration depend upon the specification of the deterministic components, as demonstrated in Johansen (1988, 1991). A procedure for testing for the appropriate deterministic specification is provided in Johansen (1994). Johansen (1994) demonstrates that the distribution of these tests is mixed Gaussian and can be analyzed within the standard likelihood ratio framework using the standard χ^2 distribution. Tests of linear restrictions on the elements of β can also be conducted using the likelihood ratio framework. This is done by estimating equation (3) freely and under the restriction on β. The form of the test statistic is,

$$G_{\beta} = -T \sum_{i=1}^{r} \ln\left[(1-\hat{\lambda}_i)/(1-\hat{\lambda}_i^{*})\right] \qquad (7)$$

where λ_i^{*}'s are the eigenvalues from the restricted model. The statistic G has an asymptotic χ^2. Examining the statistical significance of the parameters on the lagged terms in each equation usually tests causality within the VAR framework. But within the context of the vector error correction model (VECM), causality testing also includes tests on the error-correction coefficients. Granger and Lin (1995) interpret these tests as tests of long-run causality. Since the causality tests hinge on the validity of the conventional Johansen procedure, the recursive stability test of the cointegrating parameter will be conducted (Hansen & Johansen, 1999).

EMPIRICAL RESULTS

The ADF statistics indicate non-rejection of the null hypothesis of a unit root at the 5% significance level for the S&P 500 data as well as for the CSI data. The statistics are –1.12 and –2.83, respectively whereas the critical value for the ADF statistic is –2.86 at the 5% significance level (MacKinnon, 1996). The ZA procedure, which allows for the existence of a statistically significant structural break is performed to verify the robustness of the unit root tests.[1] The results are shown in Figure 1 where, if the data values normalized by a 5% critical value were greater than 1, a structural break would be indicated. There is no indication of a structural break in the monthly consumer sentiment data or the stock return data at the 5% significance level.

Table I shows the conventional Johansen statistics, which indicate the null of one cointegrating vector cannot be rejected at the 10% significance level. The appropriate lag length that reduces the serial correlation in the residuals of the VAR is 2. The lag length k is based on the LB Q-statistic, which is χ^2 distributed. Figure 2 shows the recursive tests of the stability of the cointegrating parameter. As indicated by the plot of the normalized recursive likelihood statistics below the critical value line of one, the cointegration vector is stable over the entire sample data, ensuring that the causality test statistics are robust.

Table 2 sets forth the long run and short run causality test statistics. The second column of Panel A presents LR test statistic of the hypothesis that $\hat{\alpha}_1 = 0.0$ is tested without restricting the β matrix. The associated p-value is this test is displayed in column 3. The fourth column of Panel A shows the LR test statistic of the hypothesis that $\hat{\alpha}_Y = 0.0$ is tested without restricting the β matrix. The associated p-value of this test can be found at the 5[th] column. The LR test statistics are distributed as a $\chi^2(1)$. The evidence of these LR test statistics suggest that changes in stock prices lead changes in consumer sentiment but that changes in sentiment has no effect on changes in stock returns.

Panel B sets forth the short-run causality tests. The second column presents the F-statistics of the standard Granger-causality hypothesis that lagged changes in sentiment Granger-causes stock returns, where the 3[rd] column presents the associated p-values. The fourth column presents the F-statistics of the standard Granger-causality hypothesis that lagged changes in stock prices causes consumer sentiment, where the 5[th] column presents the associated p-values. The evidence

[1] The CSI data and the S&P 500 data show a significant break in the data in mid-1998, coinciding with the documented fall in sentiment and stock market returns.

from the standard Granger-causality tests appear to indicate that stock returns Granger-causes consumer sentiment, and that the reverse does not hold.

CONCLUDING REMARKS

This paper studies the long run and the short run relationship in the US between consumer sentiment and stock returns, as proxied by the S&P 500 index over the years 1978-2005. The study adds to the existing literature by exploring the long run relationship between consumer sentiment and stock returns while expanding on the documented findings by Otoo (2000). I also found that short-term changes in consumer sentiment are caused by changes in stock returns, and not vice versa. The Johansen causality tests suggest that stock returns also drive consumer sentiment in the long run. It appears that US consumers' confidence in the economic state in the short run as well as in the long run depend on their future perceptions of the S&P 500 index, even if some of the consumers do not actively invest in stocks.

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APPENDIX

Table I: Cointegration Results

H_0	λ_{trace}^{a}
r=0	13.64*
r=1	1.41

k= 2, as indicated by the L-B Q-statistics.

[a] compared against critical values from Table B.2 in Johansen (1995) and Osterwald-Lenum (1992).

* denotes statistical significance at 10% level.

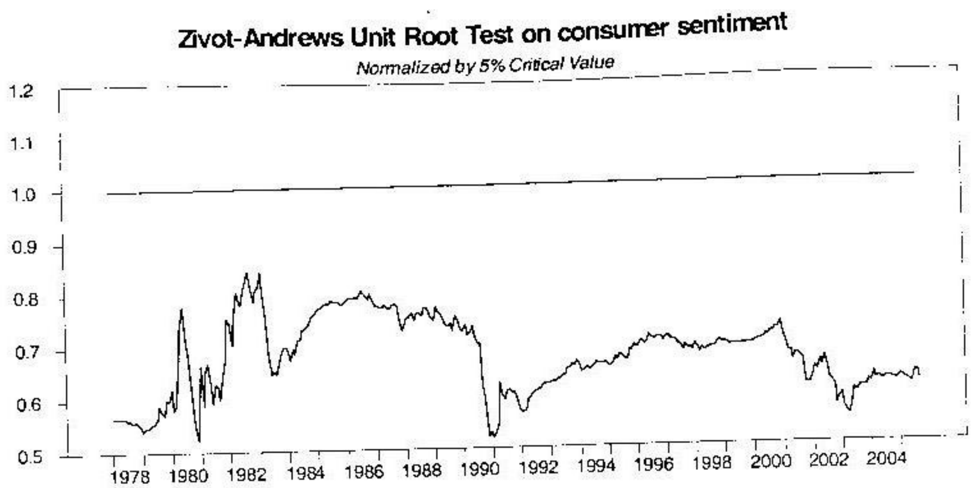
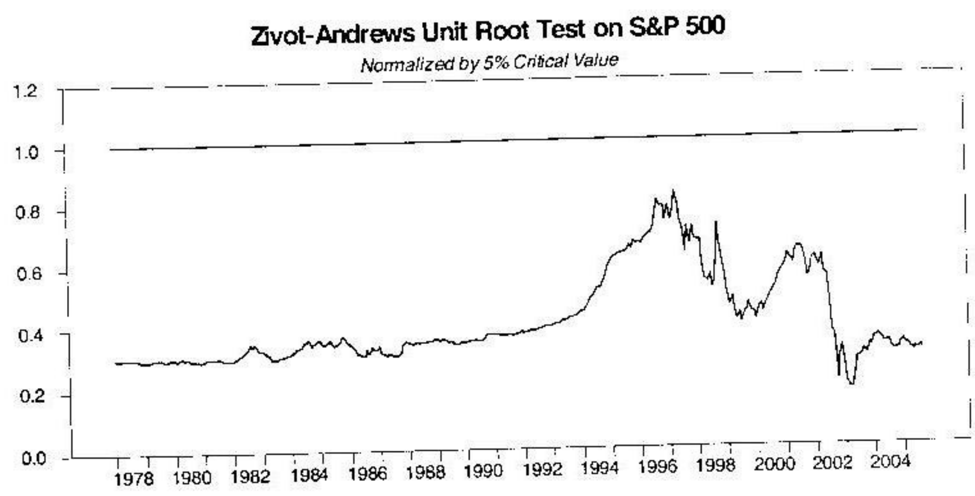


Figure – 1: Zivot-Andrews Unit Root Test Graphs

Note: If the data values normalized by a 5% critical value were greater than 1, a structural break would be indicated.



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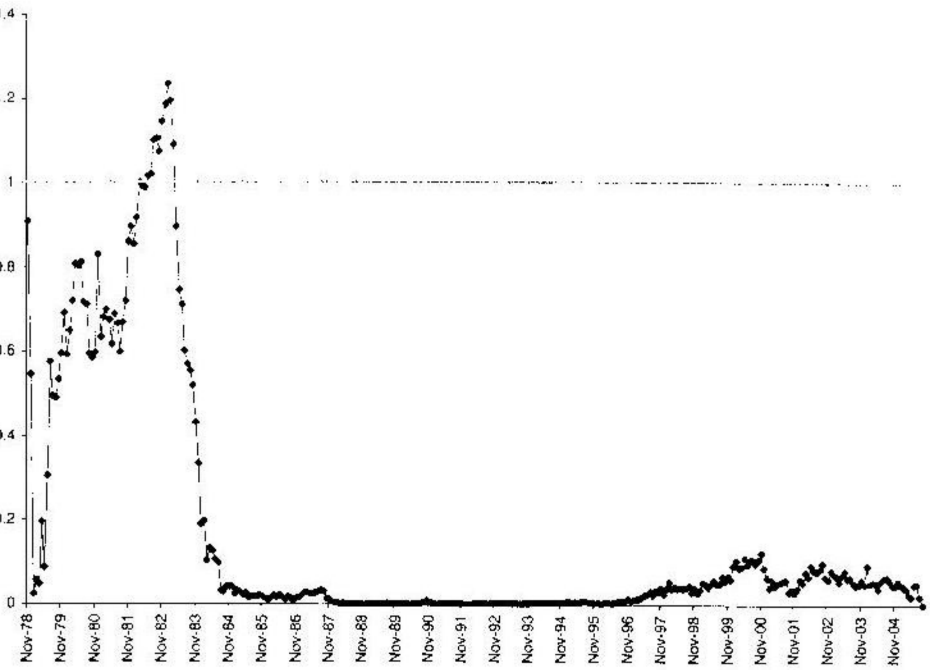

Figure – 2. Recursive Stability Tests

Note: Conditional on the cointegrating vector, the plot shows the recursive likelihood statistics scaled by a 5% critical value against the passage of time. The 1978:01-1978:11 period is the base, which is recursively increased until the last estimation period covering the full sample. The values below one indicate non-rejection of the null hypothesis that the cointegration parameter estimates for the recursive period are not statistically different from the ones for the entire sample at the 5% significance level.

Table II: Tests of Long Run and Short Run Causality between Sentiment and Stock Price

Long Run

Panel A	Sentiment → Stocks [a]	p-value [b]	Stocks → Sentiment [c]	p-value [d]
	0.16	0.69	10.75	0.00

Short Run

Panel B	Sentiment → Stocks [e]	p-value [f]	Stocks → Sentiment [g]	p-value [h]
	0.08	0.93	15.77	0.00

Notes: a – LR test of the hypothesis that $\alpha\gamma = 0.0$. b – P-value of test in a. c – LR test of the hypothesis that $\alpha = 0.0$. d – P-value of test in c. e – F-test of the standard Granger-causality hypothesis that lagged changes in Investment causes Output. f – P-value of test in e. g – F-test of the standard Granger-causality hypothesis that lagged changes in Output causes Investment. h – P-value of test in g.