Noise Trader Demand in Commodity Futures Markets

by

Dwight R. Sanders, Scott H. Irwin,

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Theoretical noise trader models suggest that uninformed traders can impact market prices. However, these models' conclusions depend on the assumed specification for noise trader demand. This research seeks to empirically determine the appropriate demand specification for uninformed traders. Using a commercial market sentiment index as a proxy for noise trader demand, a Granger causality model is estimated to examine the linear linkages between sentiment and futures returns. The results suggest that noise traders are positive feedback traders with relatively long memories.

INTRODUCTION

A large theoretical literature has developed that examines the impact of noise traders, i.e., uninformed speculators, on asset price behavior (e.g., De Long, Shleifer, Summers, and Waldmann). In these models, noise traders can impact market prices and social welfare; furthermore, they can profitably exist within the economy. However, the theoretical specification of noise trader demand is crucial to the models' predictions and subsequent empirical tests (Cutler, Poterba, and Summers, 1989). To date, little work has been done on rigorously describing and quantifying noise trader demand (e.g., Solt and Statman; De Bondt). The purpose of this research is to empirically examine the nature of noise trader demand in futures markets.

Noise traders take market positions based on nonfundamental information, i.e., technical signals, chart formations, or investment fads.[1] The theoretical demand structure of noise traders has been specified in numerous forms. For instance, Cutler, Poterba, and Summers (1989) specify noise trader demand as a function of past prices. That is, uninformed traders are purely trend-followers with extrapolative expectations. On the other hand, De Long *et al.* specify noise trader demand as a function of a random variable, sentiment. In this particular model, noise trader demand is driven by fads, social trends, and whims that stroke market sentiment. The demand function assumed in these models can alter their results. For instance, in Cutler *et al.*'s (1989) model positive feedback traders can create negative short-run autocorrelation in returns or long-

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[1]A particular type of noise trader is a positive feedback trader. Positive feedback traders buy after price increases; whereas, negative feedback traders sell. A feedback trader has a short-memory if demand is a function of very recent market returns. A feedback trader with a long-memory would utilize a longer history of returns in forming expectations. Clearly, long-memory is a relative term. In this paper, it refers to a trader using returns other than the most recent period's in forming expectations.

run mean reversion depending on the exact demand specification. Clearly, a realistic demand specification is vital for the correct interpretation and empirical testing of noise trader models. The following research seeks to provide empirical insights as to an appropriate characterization of this demand.

Noise traders are often categorized as retail or small speculators. There have been attempts to characterize the speculative demand or decision-making process of these investors; however, this research has focused almost exclusively on equity markets. For instance, Solt and Statman examine the sentiment of retail stock investors as captured in the Bearish Sentiment Index compiled by Investor's Intelligence. This gauge of market sentiment is constructed from surveys of market newsletters. Solt and Statman find that this market sentiment index contains no useful information for forecasting market returns. Furthermore, the aggregate sentiment among newsletters is positively correlated with past market returns. Similarly, De Bondt finds that the individual speculators surveyed by the American Association of Individual Investors demonstrate trend-following tendencies. That is, they are most bullish immediately following price increases. Collectively, this work suggests that the retail stock market speculator displays exptrapolative expectations.

The following research expands previous work by utilizing a comprehensive set of futures markets and explicitly examining the demand structure of noise traders: Is noise trader demand driven by past prices, i.e., extrapolative expectations, or is it a function of unobservable social variables? To confront this issue, the research relies on a measure of investor sentiment: Consensus' Index of Bullish Market Opinion.[2] The sentiment index essentially gauges the degree of bullishness (or bearishness) among retail futures speculators. Assuming that retail speculators do not have priority fundamental information, then their sentiment and, hence, the index serves as a proxy for noise trader demand. Using this data along with returns from a large cross-section of futures markets, the demand structure of noise traders is directly addressed.

MEASURING NOISE TRADER SENTIMENT

CONSENSUS' Index of Bullish Market Opinion

The methodology Consensus uses to compile its bullish sentiment index is quite simple. Consensus publishes a weekly market paper, *CONSENSUS: National Futures and Financial Weekly*, that contains a sampling of investment newsletters. From the sample of letters that Consensus receives, it compiles a sentiment index with a simple count of the number of bullish newsletters as a proportion all newsletters expressing an opinion. Consensus only considers those opinions which have been committed to publication. The Consensus bullish sentiment index at time t ($CBSI_t$) is expressed as:

$$CBSI_t = \frac{number\ of\ bullish\ newsletters}{number\ of\ newsletters\ expressing\ an\ opinion}.$$

[2]The analysis were also conducted using Market Vane's Bullish Consensus Index, and the results were not materially different from those presented.

For instance, if Consensus receives 100 newsletters that comment on the pork bellies market and 25 of those think that belly prices are going to increase, then the CBSI is 0.25 or 25 percent.[3] The CBSI is compiled each Friday, reflecting the opinions expressed in newsletters that were published during the week. It is released early the following week by recorded telephone message and published in the following Friday's edition of *CONSENSUS*.

Noise Traders and Information Sources

As a maintained hypothesis, it is assumed that the index compiled by Consensus reflects the sentiment of noise traders--not rational or informed market participants. That is, the market views subsumed within the indices are those of small retail speculators who are acting on noninformation: technical trading rules, extrapolation, or old news that is already incorporated into the market price. This maintained hypothesis is supported by reviewing the decision-making rules of small traders and sampling their information sources.

Surveys by the Chicago Board of Trade and *Barron's* suggest that small speculators do not behave in an entirely rational manner (see also Brennan; Nagy and Obenberger). Draper summarizes the surveys' findings. The surveys suggest that the average futures trader is highly educated, and they trade for the leverage and excitement. Furthermore, their important sources of information include: articles/publications, broker and newsletter recommendations, advisory services, and their own analysis. These findings are consistent with those of Smidt and Canoles. Collectively, these results suggest that retail speculators generally do not bring new information to bear on the markets, and they garnish much of their information from focused media sources such as those surveyed by Consensus.

Market advisors, brokers, and newsletters provide decision-making information for retail futures speculators; but, are they providing real information, or simply relaying old news and technical comments? Excerpts from an issue of *CONSENSUS* provide insight as to the information contained within advisors' recommendations and market newsletters. Many market advisors rely on technical indicators and simply pass along this information to their retail subscribers.

> The (soybean) market is in a sideways pattern between 563 and 547. If the 547 support is taken out, then the market could decline to 530....Charts suggest the market has confirmed the sideways pattern and thus we feel comfortable selling and did so today (Biedermann, Allendale, Inc.).

Each issue of *CONSENSUS* is filled with this type of technical commentary for nearly every futures market. Although rare, some newsletters are fundamental in nature, relaying government reports, seasonal tendencies, and pertinent cash market conditions. Even though they often contain detailed interpretations of relevant supply and demand factors, the fundamental analysis tends to reiterate public information.

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[3]Consensus, Inc. indicates that some interpretation is required for newsletters that do not explicitly make buy or sell recommendations.

The noninformational nature of the market newsletters, coupled with the evidence that retail investors rely on this advise, supports the maintained hypothesis: the sentiment indices are valid proxies for noise trader demand. To the extent that market opinion is correlated across the advisors, noise traders will act in concert (Shleifer and Summers).

DATA, METHODOLOGY, and RESULTS

Futures Data and Markets

Weekly futures returns are calculated for the closest to expiration contract where the maturity month has not been entered. To correspond with the release of the sentiment index, nearby contract returns (R_t) are calculated as the log-relative change in Friday-to-Friday closing prices, $\ln(p_t / p_{t-1})$. The data is available from May 1983 to September 1994 (591 observations).

A cross-section of twenty-eight futures markets is examined to strengthen the studies' general conclusions and to avoid erroneous implications based on the nuances of a particular market. Markets are chosen based on the availability of the futures and sentiment data. To facilitate the presentation of results and for relevant comparisons, related markets are designated into commodity groups: grain; livestock; food/fiber; financial; metal/energy. A complete listing of markets is provided in Table 1.[4]

Summary Statistics

The general characteristics of sentiment are explored with simple summary statistics presented in Table 1. The mean sentiment level (% bullish) tends to be less than a neutral 50. In fact, the mean CBSI is statistically less than 50 at the 1% level for all the markets except LC and SB.[5] The range of the mean CBSI is from a low of 38.5 for HU to a high of 51.5 for LC. Additionally, sentiment is quite volatile with large standard deviations and extremes of above 90 and below 10. The extreme values of sentiment along with its volatility suggest that the advisors that make-up the indices are reacting to correlated market signals. As an illustration of the sentiment behavior over time, the CBSI for coffee is plotted in Figure 1. Although not presented here for brevity, the sentiment data also displays a high level of cross-market correlation within commodity groups. For instance, the correlation between C and S sentiment is 0.63, and it is 0.78 between the BP and DM.[6] These type of correlations are indicative of systematic noise trader demand that covaries across traders and markets (see Shleifer and Summers).

Noise Trader Demand and Extrapolative Expectations

Solt and Statman as well as De Bondt document that retail stock market speculators exhibit extrapolative expectations--becoming more bullish after recent market increases. That is,

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[4]In the following discussion and tables, the commodities are referred to by their ticker symbols given in Table 1.

[5]Statistical significance is based on a two-tailed t-test. Note that with the large number of observations (591), the mean estimate is fairly precise. For example, the standard error for JO's estimated mean sentiment is 0.935.

[6]A detailed data description and market-by-market summary statistics are presented by Sanders.

their demand is an increasing function of past returns. A general method of exploring the linear linkages between and sentiment and price is within a "Granger causality" framework. Hamilton suggests the following direct or bivariate Granger test:

$$\rho_t = c_0 + \sum_{i=1}^{p} a_i \rho_{t-i} + \sum_{j=1}^{q} b_j R_{t-j} + e_t \ , \tag{1}$$

where, ρ_t and R_t represent noise trader sentiment and futures returns, respectively, and e_t is a white noise error term.

Causality from returns to sentiment in equation (1) is tested under the null of $b_j = 0 \ \forall \ j$. Specifically, equation (1) is estimated with OLS, and the null hypothesis that R_t does not lead ρ_t (i.e., $b_j = 0 \ \ \forall \ j$) is tested with a Chi-squared test (Hamilton, p. 305).[7, 8] The aggregate sign of causality (positive or negative) is addressed by summing the impact of lagged returns, $\sum b_j$, and testing if it equals zero using a two-tailed t-test. If $\sum b_j > 0$, then the noise traders are also positive feedback traders or trend-followers. That is, their demand is an increasing function of past prices.

Choosing the appropriate lag lengths (p,q) is of practical significance in performing the causality test. As suggested by Beveridge and Oickle, the order of an autoregressive system may best be determined by searching all possible lags for the combination that minimizes a model selection criterion. For example, in (1) the model is estimated by varying the own-lag length of ρ_t from $p=1,2,...p^{max}$, and the lag length of R_t from $q=1,2,...,q^{max}$ such that a total of (p^{max} x q^{max}) regressions are estimated. The p,q lag length combination that minimizes Akaike's information criteria (AIC) is chosen as the final model specification. For equation (1), all possible lag-length combinations are estimated with $p^{max} = q^{max} = 8$, and p,q is chosen to minimize AIC.[9]

The estimation results for each market are presented in Table 2. The results indicate that noise traders are predominately positive feedback traders, i.e., returns lead sentiment and the cumulative impact is positive. In each market examined, the null hypothesis that returns do not lead sentiment is rejected at the 0.01 level. The additive effect of lagged returns is statistically

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[7]Note, misspecification of equation (1) due to cointegration and an omitted error-correction term is not a problem with this data as sentiment is clearly stationary I(0) in levels.

[8]The causality test assumes that the two series, ρ_t and R_t, are covariance stationary, and e_t is an i.i.d. white noise error. This assumption is tested using White's general test for heteroskedasticity in the error term. If e_t is heteroskedastic, then the model is re-estimated using White's heteroskedastic consistent covariance estimator, and the appropriate test for the parameter restrictions is a Wald Chi-squared test (Greene, p. 392). A Lagrange multiplier test is used to verify that the residuals are serially uncorrelated. If, after choosing the optimal lag length, the residuals demonstrate autocorrelation, then additional lags of the dependent variable are added as explanatory variables (i.e., p is increased in equation 1) until the autocorrelation is eliminated.

[9]The time series models are estimated with data through August 1993. The remaining 54 observations were withheld for potential out-of-sample testing.

positive (1% level) for every market. Past returns and sentiment levels explain a fairly large portion of the variation in sentiment with the adjusted R-squared ranging from 0.53 to 0.78. These results are consistent with prior work on sentiment (Solt and Statman; De Bondt) and conjectures that noise traders are often trend-followers.

Close examination of Table 2 reveals that the degree of trend-following differs somewhat across the commodities. For a more general characterization of noise trader demand, the causality test in (1) is estimated by pooling the time series data across the designated commodity groups. The pooled cross-sectional time series models are estimated using the GLS procedure of Kmenta (pp. 616-635) correcting for cross-sectional correlation and heteroskedasticity. The lag-lengths for the pooled regressions are specified by choosing the maximum p and the maximum q from among the individual market specifications within each group. For instance in the grain group the maximum p is 2 (S and BO) and the maximum q is 2 (C, S, SM, BO); therefore, the pooled grain model's lag structure is 2,2. This specification procedure may over-specify lag structures at the expense of statistical power, but it assures that the model does not suffer from an under-specification bias.

The estimated pooled models are presented in Table 3. For each pooled regression, the null hypothesis that returns do not lead sentiment (i.e., $b_j = 0 \;\forall j$) is tested with a Wald Chi-squared test, and the cumulative impact of lagged returns is again tested with a two-tailed t-test (i.e., $\sum b_j = 0$). The pooled estimations reveal sentiment characteristics that are systematic across the markets. First, across all groups, sentiment follows a fairly strong positive autoregressive process with first-order coefficients around 0.65. Second, statistically significant positive extrapolation is demonstrated at one and two week lags for all the groups, i.e., positive feedback traders have relatively long memories. For instance, in grains, a one percent weekly return results in sentiment increasing by 1.26 percent the following week and 0.376 percent the week after that. For all the groups, the null that returns do not lead sentiment can be rejected at the 1% level, and the cumulative impact of lagged returns is significantly positive (1% level).

To illustrate the behavior of sentiment when driven by extrapolative expectations, the impulse response function for a one standard deviation shock to returns is calculated (see Harvey, p. 234).[10] Figure 2 shows the impulse response function for each pooled model. Looking at Figure 2, a standard deviation shock in weekly returns causes the greatest initial increase in food/fiber market sentiment.[11] Notably, the impact on metal/energy and financial market sentiment does not reach a peak until two weeks after the initial shock. All of the response functions decline rather smoothly and at similar rates, except for the livestock group where extrapolative effects are less pronounced. The varying level of extrapolation demonstrated across groups may arise from the relative proportion of uninformed traders or availability of public

[10]Implicitly, it is assumed that sentiment is endogenous and impacted by an exogenous shock to returns.

[11]The standard deviation of weekly returns (in parenthesis) for each group is as follows: grain (0.029), livestock (0.029), food/fiber (0.042), financial (0.013), and metal/energy (0.036).

fundamental information. In total, the pooled models strongly suggest that the noise traders subsumed within the sentiment index are long-memory positive feedback traders.

SUMMARY AND CONCLUSIONS

The presented analysis use the Consensus Index of Bullish Market Opinion to explore noise trader demand in futures markets. It is maintained that the market sentiment index adequately measures the demand of retail speculators. Furthermore, these small speculators rely on nonfundamental information in forming their expectations; thus, they are noise traders. The role of extrapolative expectations in noise trader demand is investigated within a Granger causality framework. The results suggest that noise trader demand (i.e., sentiment) is an increasing function of past returns. Furthermore, noise traders have long memories. That is, sentiment is influenced by returns over at least the previous two weeks. The sentiment index exhibits other characteristics of theoretical noise trader demand. Sentiment is very volatile with many extreme observations, and it covaries across related markets. These characteristics are consistent with systematic noise trader risk that can impact markets (see Shleifer and Summers).

Collectively, the findings suggest that the traders composing the index are long-memory positive feedback traders. Clearly, these traders respond to similar pseudo market signals (i.e., past returns), and as a result sentiment moves in unison and takes large swings to extreme values. These empirical findings have direct implications for the interpretation and testing of theoretical noise trader models. For instance, Cutler *et al.*'s (1989) model generates returns that are positively correlated if noise traders are short-memory negative feedback traders. The evidence presented here would shun that scenario in favor the results for long-memory positive feedback traders. For this type of noise trader, their model generates short-run positive autocorrelation and long-run negative autocorrelation in returns (i.e., mean-reversion). Perhaps not surprisingly, these are the anomalous characteristics of asset returns that are considered stylized facts (see Cutler *et al.*, 1991).

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Table 1. Summary Statistics, Consensus Sentiment Data: May 1983 - September 1994.

Group/Market	Mean	St. Dev.	Min.	Max.
Grain				
Corn(C)*	45.701	19.916	5	92
Wheat(W)	46.413	20.193	3	91
Soybeans(S)	46.783	17.882	12	90
Soybean Meal(SM)	42.501	20.012	5	95
Soybean Oil(BO)	43.992	21.861	5	96
Livestock				
Live Cattle(LC)	51.584	15.547	15	87
Feeder Cattle(FC)	46.998	19.617	6	95
Live Hogs(LH)	44.332	15.696	13	88
Pork Bellies(PB)	39.716	17.913	4	88
Food/Fiber				
Coffee(KC)	43.992	20.906	5	96
Sugar(SB)	51.279	22.112	5	94
Cocoa(CC)	41.755	20.455	4	94
Orange Juice(JO)	40.294	22.731	6	94
Cotton(CT)	45.981	21.331	7	96
Lumber(LB)	42.181	21.033	5	94
Financial				
Deutsche mark(DM)	46.876	21.822	4	89
Swiss franc(SF)	45.205	21.739	3	94
Japanese yen(JY)	42.701	20.821	3	91
British pound(BP)	42.870	22.017	0	96
Canadian dollar(CD)	41.591	19.899	0	92
Treasury bills(TB)	46.619	20.917	5	93
Treasury bonds(US)	44.406	17.525	9	86
Metal/Energy				
Gold(GC)	43.570	20.630	3	96
Silver(SI)	43.531	19.254	4	95
Platinum(PL)	44.450	21.641	6	95
Heating Oil(HO)	39.679	20.469	4	87
Crude Oil(CL)	40.401	18.471	3	86
Gasoline(HU)	38.551	20.674	5	93

*All of the markets have 591 weekly observations, except CL and HU which begin in April 1985 and have 494 observations. Ticker symbols are presented in parenthesis and used throughout the remainder of the tables when referring to the various markets.

Table 2. Granger Causality Test, Returns Lead Sentiment.

$$\rho_t = c_0 + \sum_{i=1}^{p} a_i \rho_{t-i} + \sum_{j=1}^{q} b_j R_{t-j} + e_t$$

The model is estimated with OLS, and the Wald Chi-squared statistic tests the null, H_0: $b_j=0\ \forall$ j. The cumulative impact of returns is calculated, $\sum b_j$ j=1,2,..,q., and tested against the null, H_0: $\sum b_j=0$, with a t-test.

Market	p,q	$\chi^2_{(q)}$	p-value	$\sum b_j$	t-stat.	p-value	adj. R^2
C*	1,2	39.56	0.000	152.6	4.94	0.000	0.761
W	1,1	63.83	0.000	140.7	7.98	0.000	0.741
S	2,2	23.70	0.000	135.3	4.17	0.000	0.701
SM	1,2	42.64	0.000	172.9	5.45	0.000	0.658
BO	2,2	45.70	0.000	178.5	6.29	0.000	0.653
LC	1,6	73.92	0.000	424.3	5.67	0.000	0.608
FC	4,1	43.17	0.000	266.1	6.57	0.000	0.531
LH	2.2	89.65	0.000	183.8	3.96	0.000	0.675
PB	2,3	54.17	0.000	79.3	3.96	0.000	0.630
KC	3,3	92.76	0.000	211.7	7.65	0.000	0.652
SB	3,2	60.91	0.000	90.2	6.75	0.000	0.782
CC	2,2	81.92	0.000	175.2	7.64	0.000	0.631
JO	5,2	37.82	0.000	175.6	5.71	0.000	0.693
CT	5,2	68.17	0.000	215.8	6.75	0.000	0.715
LB	1,2	63.92	0.000	155.6	6.52	0.000	0.608
DM	2,2	97.44	0.000	379.8	7.23	0.000	0.759
SF	2,3	100.5	0.000	460.7	7.42	0.000	0.769
JY	1,5	73.15	0.000	685.8	6.47	0.000	0.745
BP	4,3	81.07	0.000	466.3	6.52	0.000	0.759
CD	3,2	59.12	0.000	917.5	6.84	0.000	0.688
TB	4,1	66.43	0.000	2194	8.15	0.000	0.679
US	4,2	106.3	0.000	388.3	8.22	0.000	0.727
GC	2,2	71.74	0.000	282.5	7.59	0.000	0.795
SI	4,6	98.77	0.000	201.8	4.71	0.000	0.709
PL	2,2	73.41	0.000	213.4	7.91	0.000	0.703
HO	1,1	51.06	0.000	89.4	7.14	0.000	0.645
CL	4,1	40.55	0.000	65.5	6.36	0.000	0.683
HU	4,2	30.15	0.000	119.2	5.03	0.000	0.587

*All models are estimated over 536 weekly observations, except for those involving CL and HU which are estimated over 438 observations.

Table 3. Pooled Causality Test, Returns Lead Sentiment.

Independent Variables	Grain	Livestock	Food/Fiber	Financial	Metal/Energy
intercept	11.09 (16.9)*	12.03 (12.3)	10.45 (17.0)	10.33 (16.6)	10.02 (13.7)
ρ_{t-1}	0.664 (31.2)	0.617 (26.1)	0.645 (33.2)	0.692 (39.2)	0.685 (32.7)
ρ_{t-2}	0.091 (4.57)	0.049 (1.78)	0.028 (1.21)	0.021 (0.96)	0.026 (1.02)
ρ_{t-3}		0.022 (0.80)	0.044 (1.94)	-0.003 (-0.15)	0.029 (1.15)
ρ_{t-4}		0.053 (2.32)	0.011 (0.49)	0.052 (3.11)	0.022 (1.07)
ρ_{t-5}			0.026 (1.54)		
R_{t-1}	126.5 (14.6)	95.9 (11.6)	104.0 (18.8)	233.8 (17.5)	94.1 (13.8)
R_{t-2}	37.6 (4.44)	25.9 (3.03)	32.9 (5.64)	79.6 (5.67)	29.5 (4.15)
R_{t-3}		4.09 (0.47)	5.22 (0.90)	28.4 (2.01)	4.64 (0.65)
R_{t-4}		-5.76 (-0.78)		28.5 (2.11)	-1.95 (-0.28)
R_{t-5}		-7.65 (-0.94)		-5.93 (-0.44)	9.54 (1.38)
R_{t-6}		-4.67 (-0.58)			-3.37 (-0.50)
$\sum b_j$	164.1 (12.8)	107.8 (4.86)	142.2 (13.2)	364.6 (10.7)	132.4 (7.24)
$\chi^2_{(q)}$	221.6**	143.9	368.7	364.6	202.7
Buse R^2	0.667	0.545	0.683	0.671	0.653

*T-statistics in parenthesis test if the coefficient equals zero, with degrees of freedom equal to N*K-(p+q+1), where N=536 (438 for metal/energy) and K=number of markets in the group.
**All the $\chi^2_{(q)}$ statistics reject that the coefficients on lagged returns are zero at the 1% level.

Figure 1. Consensus Index of Bullish Market Opinion, Coffee: May 1983 - September 1994.

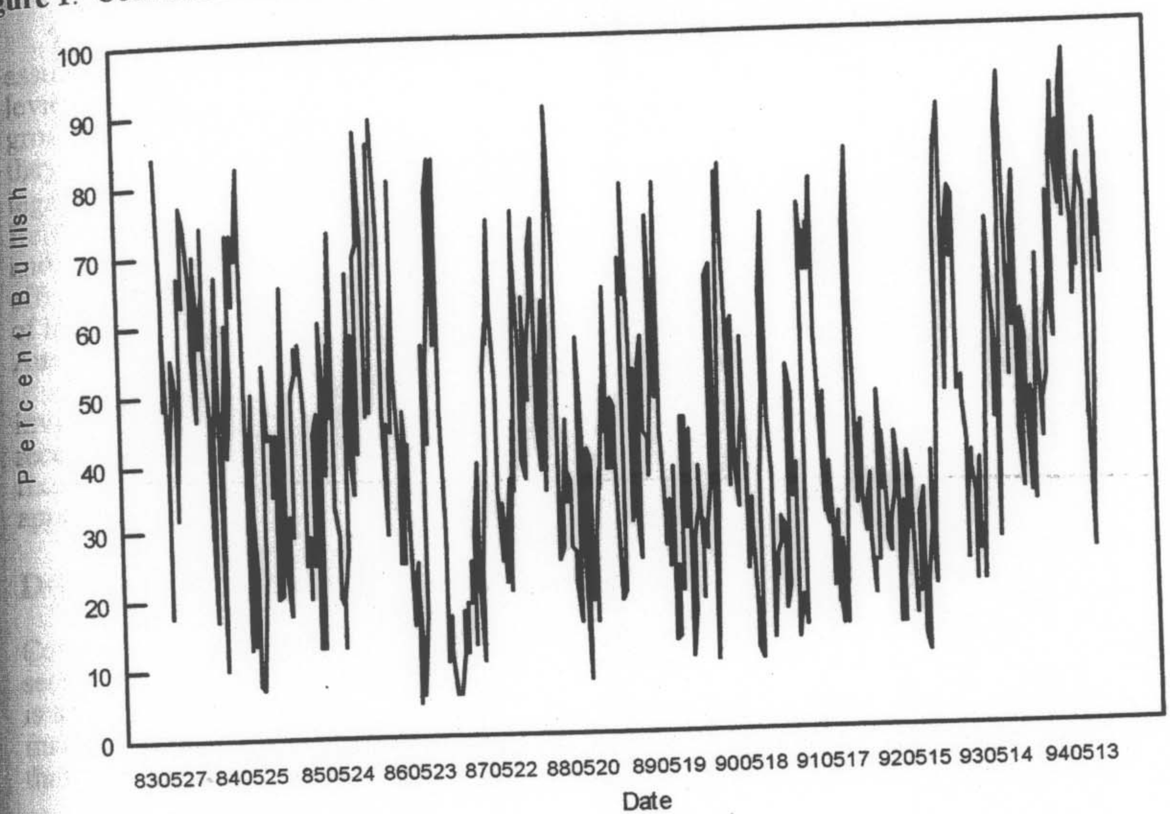

Figure 2. Extrapolative Expectations, Impulse Response Function, Consensus Data.