Positive Feedback Trading: Google Trends and Feeder Cattle Futures

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ABSTRACT

What do investors' searches for public information reveal about their subsequent trading strategies? Does their search for information support the hypothesis of market efficiency or does it lend support to the idea that investors have behavioral biases. Using Google Trends, we find that the volume of Google searches about feeder cattle is associated with re-enforcement of momentum trading in a manner consistent with a positive feedback mechanism. Further, we find evidence that search volume for "cattle" is associated with higher volatility and thus amplifies the positive feedback trading mechanism, while the search volume for "corn", a major input to cattle production, is associated with a reduction in volatility.

Keywords: Momentum Trading; Positive Feedback Trading; Public Information; Market Efficiency; Futures; EViews7

INTRODUCTION

That many traders of assets, in this particular instance traders of feeder cattle futures, believe that assets can be traded profitably using simple rules based on past public information is an idea that is very old both in the popular and academic literature. In the academic literature, Leuthold (1972), for example, documents profitability in trading cattle futures using a simple mechanical filter rule. Anderson and Trapp (2000a, 2000b) found that feeder cattle market responds to changes in corn prices as corn represents over 60% in grain (feed) costs for cattle and has a 22% effect on the profitability of feeder cattle.

It is now widely accepted that asset prices can reflect the information used by well-informed investors as well as the trades of investors who trade on noise (Black, 1986, and Thaler, 1999, and the references therein). Noise traders, while supplying liquidity to asset markets, also make markets riskier. Consequently, informed traders may not take positions to fully eliminate arbitrage opportunities. De Long, Shleifer, Summers and Waldman (1990a) show that noise traders can pull prices away from fundamental values. Perversely, the arbitrage opportunities created by noise trading may not be exploited because of the increase in risk that can accompany noise trading. Thus noise traders can sometimes earn a higher expected return by bearing this increase in risk.

Faulty data can also make markets riskier for well-informed and astute investors who otherwise might have a sound strategy (Pleven & McGinty, 2011). Follow-up reporting with large changes in the initial reporting's estimates/predictions can also generate additional noise and uncertainty in strategy (Pleven & Polansek, 2011). Intentional bogus information can cause well-read investors to make incorrect decisions as illustrated in the 1983 movie *Trading Places* whose plot centered on a doctored report on expected orange juice supplies. Entertaining as the movie was supposed to be, it is referenced in insider trading legislation Section 136 of the Wall Street Transparency and Accountability Act and referred to as "the Eddie Murphy Rule" (Carton, 2010).

Positive feedback trading is claimed to be a particularly destabilizing form of noise trading that involves buying when prices move up and selling when prices move down. Positive feedback trading can be a result of extrapolative expectations, technical analysis, stop-loss orders and portfolio insurance. The interaction of feedback traders and rational speculators moves prices away from fundamentals as rational traders jump on the "bandwagon".

Eventually, speculators liquidate their positions and prices move back towards their fundamental values (See DeLong, Shleifer, Summers and Waldman, 1990b). Evidence supporting the presence of this effect is found by Sentana and Wadhwani (1992), Koutmos (1997), Antoniou, Koutmos and Pericli (2005) and Koutmos and Saidi (2001) amongst others. During low volatility periods, positive feedback trading leads to positive autocorrelation in asset prices, but during high volatility, the autocorrelations can turn negative, presumably because higher volatility means high risk and leads to greater selling and short-selling activity. In futures markets, Antoniou, Koutmos and Pescetto (2011) have documented the effect in index futures.

In this work, we propose to measure the activity of a subset of noisy traders by using the change in the volume of Google searches for information about cattle futures. We implicitly assume that only rational traders would want to update their information set, both by using public information and private. To measure this updating, we make use of Google Trends (GT), which tracks search terms volume. Millions of investors worldwide search online for investment related information making web search queries a valuable tool on investment trends. Examples include Bollen, Mao and Zeng (2011) predicting stock market trends based on Twitter keywords and Ito and Odenheimer (2012) discussing Israeli banks tracking customer Google search terms. The Google Trends tool, available at http://google.com/trends/, allows users to enter search queries the see the relative volume of these queries. GT analyzes a fraction of total Google searches over time and extrapolates to estimate total search volume invoking the query. GT data is scaled in two ways: fixed and relative. For fixed scaling, the data are normalized using the extrapolated data as a fixed point in time. Since the denominator does not change, values relate the volume of searches for a particular term to the volume at the beginning of the trends search series. In relative scaling, data are scaled using the average search volume over the entire time period selected. For this work, relative scaling was used with the Google Trends data.

FUTURES MARKETS, POSITIVE FEEDBACK TRADING AND INFORMATION SEARCHING

We assume that there are three groups of investors. Group A investors are risk-adverse and maximize their expected utility. The demand for feeder cattle futures contracts by Group A is determined by risk-return considerations along the lines of the dynamic capital asset pricing model.

The dynamic conditional capital asset pricing model for futures can be written as

$$E_{t-1}\left(R_{F,t}\right) = \beta_t[E_{t-1}\left(R_{m,t}\right) - \alpha] \tag{1}$$

where E_{t-1} is the conditional expectations operator, $\beta_t$is the conditional measure of exposure to systemic risk, $R_{F,t}$ is the ex-post return on cattle futures, $R_{m,t}$ the ex-post return on the market index and $\alpha$is the return on the risk free asset, or the zero-beta portfolio. We can rewrite Equation (1) as

$$E_{t-1}\left(R_{F,t}\right) = \lambda Cov_{t-1}\left(R_{m,t}, R_{F,t}\right) \tag{2}$$

where $\lambda = E_{t-1}\left(R_{m,t}\right) - \alpha / Var_{t-1}\left(R_{m,t}\right)$ which is the conditional price of systemic risk. We assume this to be time-invariant. $Var_{t-1}(*)$ and $Cov_{t-1}(*)$ are the conditional variance and co-variance operators.

We assume Group A investors have a demand function for feeder cattle futures of

$$D_A = E_{t-1}(R_{F,t}) / \lambda Cov_{t-1}\left(R_{m,t}, R_{F,t}\right) \tag{3}$$

where the numerator of Equation (3) is the expected futures returns and the denominator the required return. If the expected rate of return for Group A investors on feeder cattle futures is greater than the required rate of return, they will increase their demand of future contracts.

The second and third groups are noise traders who follow positive feedback trading strategies. They buy when prices move up and sell when prices move down. While models by Sentana and Wadhwani (1992) and

Antoniou, et al. (2005) allow for only one lag in the feedback mechanism, we follow Antoniou, et al. (2011) and allow for multiple lags in the demand function of noise traders. Demand by Group B traders is modeled as

$$D_B = \varphi_B(w^0 R_{F,t-1} + w^1 R_{F,t-2} + w^2 R_{F,t-3} + \cdots) \tag{4a}$$

$$= \varphi_B \sum_s w^s R_{F,t-s-1}, \text{ where s =0,1,2,3,….} \tag{4b}$$

where φ_B is elasticity of demand and w^s is a weighting parameter.

Group C traders are essentially a sub-group of Group B, except that prior to trading, they do an Internet search using a search engine, like Google, to determine price trends.

$$D_C = \varphi_C \Delta GT_{F,t-1}(w^0 R_{F,t-1} + w^1 R_{F,t-2} + w^2 R_{F,t-3} + \cdots) \tag{5a}$$

$$= \varphi_C \Delta GT_{F,t-1} \sum_s w^s R_{F,t-s-1}, \text{ where s =0,1,2,3,….} \tag{5b}$$

We assume that Group C noisy traders have less efficient access to public information than other noise traders, and as a result, attempt to overcome this by using Google to find such information. We assume that the results they come up with are similar to other searches being made by Group B investors, so that we can write

$$D_{B+C} = (\varphi_B + \varphi_C \Delta GT_{F,t-1})(w^0 R_{F,t-1} + w^1 R_{F,t-2} + w^2 R_{F,t-3} + \cdots) \tag{6a}$$

$$= (\varphi_B + \varphi_C \Delta GT_{F,t-1}) \sum_s w^s R_{F,t-s-1}, \text{ where s =0,1,2,3,….} \tag{6b}$$

That is, we implicitly assume that an increase in the magnitude of relative GT indices reflects increased interest and then increased demand for cattle futures. Such a demand function is consistent with technical trading rules based on moving averages, with an increase in Google searches reflecting an increase in people searching for public information to determine past trends.

Assuming that the feeder cattle futures contract is in zero net supply, then market clearing requires that $D_A + D_B + D_C = 0$. It then follows from Equations (3) and (5a) that

$$E_{t-1}(R_{F,t}) = ,\lambda Cov_{t-1}(R_{m,t}, R_{RF,t})(\varphi_B + \varphi_C \Delta GT_{t-1}) \sum_s w^s R_{F,t-s-1} \tag{7}$$

To reformulate in terms of observable variables, we make the following assumptions

$$R_{F,t} = E_{t-1}(R_{F,t}) + \varepsilon_t \tag{8a}$$

$$Corr(R_{F,t}, R_{m,t}) = \rho \tag{8b}$$

$$Var_{t-1}(R_{F,t}) = \delta Var_{t-1}(R_{m,t}) \tag{8c}$$

$$E_{t-1}(\Delta GT_{F,t}) = 0 \tag{8d}$$

$$Var_{t-1}(\Delta GT_{F,t}) = \theta \delta Var_{t-1}(R_{m,t}) \tag{8e}$$

$$Corr(R_{F,t}, \Delta GT_{F,t}) = r \tag{8f}$$

Most researchers have associated the presence of positive feedback trading with the existence of positive return autocorrelation (See Shiller, 1981, 1989). However, as Shiller demonstrates, this need not be the case. Therefore we will measure the effect of the presence of positive feedback trading in the conditional mean of returns as:

$$R_{F,t} = \beta_0 + \beta_1 Var_{t-1}(R_{F,t}) R_{F,t-1} + \varepsilon_t \tag{9}$$

where $Var_{t-1}(R_{F,t})$ is the conditional variance of the feeder cattle futures. Note that β_0 is a regression coefficient that is expected to be insignificantly different from zero, and β_1 is a product reflecting the market risk premium, the conditional correlation of feeder cattle futures returns with the market index, the proportionality of feeder cattle return variance to the market index variance and the demand elasticity of noise traders. The presence of positive feedback trading implies that $\beta_1 < 0$.

Letting the change in the Google Indices for feeder cattle be represented as $\Delta GT_{F,t}$, then we also measure the extent of positive feedback taking place as:

$$R_{F,t} = \beta_0 + \beta_1 Var_{t-1}(R_{F,t})R_{F,t-1} + \beta_2 Var_{t-1}(R_{F,t})R_{F,t-1}\Delta GT_{F,t} + \varepsilon_t \tag{10}$$

where the coefficient β_2 measures the extent to which noise traders searching public information using Google affect the degree of positive feedback trading taking place. If $\beta_2 < 0$, this means that the change in the GT index is associated with increases in positive feedback trading.

The specification of the process for the variance of feeder cattle futures returns follows the asymmetric GARCH(1,1) process given by:

$$Var_{t-1}(R_{F,t}) = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 + \alpha_2 Var_{t-2}(R_{F,t}) \tag{11}$$

where, again, $Var_{t-1}(R_{F,t})$ is the conditional variance of the feeder cattle futures, ε_t is the innovation at time *t* and where the coefficients α_0, α_1, α_2, and δ are non-negative parameters. The coefficient δ captures the sign effect, the asymmetric impact of positive and negative innovations. The variable S_{t-1}takes on a value of one if the innovation is negative and zero otherwise.

Estimation of the GARCH model requires specification of a density function for the innovations. Several specifications have been used in the previous literature. Generally, innovations are found to be leptokurtopic, so that Student's t or GED distributions are used. In this paper, we employ the GED. It's density function is:

$$f(\mu_t, \sigma_t, v) = v/2[\Gamma(\tfrac{3}{v})]^{\frac{1}{2}}[\Gamma\left(\tfrac{1}{v}\right)]^{-\frac{3}{2}}\left(\tfrac{1}{\sigma_t}\right)\exp\{xp\Gamma(\tfrac{3}{v})/\Gamma\left(\tfrac{1}{v}\right)]^{\frac{v}{2}}|\varepsilon_t/\sigma_t|^{v}\ \} \tag{12}$$

Given the above, the parameter vector can be estimated using the following log-likelihood function over the sample period:

$$L(\Theta) = \textstyle\sum_{t=1}\log f(\mu_t, \sigma_t, v) \tag{13}$$

The method of estimation used is the Berndt et al. (1974) method.

EMPIRICAL FINDINGS

The data include weekly returns of feeder cattle futures and corn futures traded on the Chicago Mercantile Exchange (CME). The data covers the era from January 9, 2004, through January 21, 2011. Returns are calculated on a weekly basis to correspond with the weekly GT index changes. Table 1 provides statistics on feeder cattle futures, feeder cattle futures volume, corn futures, and the changes in the GT indices for "cattle" and "corn".

Table 1 Descriptive Statistics

	Mean	Standard Deviation	Skewness	Kurtosis
Feeder Cattle	0.00081	0.00101	-0.00474	0.43398
FC Volume	0.11509	0.03017	2.82789	17.30875
FC Google	0.00112	0.00381	0.29706	5.67220
Corn	0.00101	0.00182	-0.11638	2.53595
Corn Google	0.00766	0.00650	1.48423	20.15628

In order to evaluate the presence of one-lag autocorrelation in feeder cattle futures returns, an autoregressive (AR) model was run. Table 2 estimates an AR(1) model for the feeder cattle futures returns. The absence of positive autocorrelation is sometimes interpreted as evidence against positive feedback trading. However, this can be misleading as this assumes that all investors are feedback traders. Antoniou, et al. (2011) propose a model of positive feedback trading that does not imply positive first-order autocorrelation; similarly, Shiller (1989) suggests that little or even negative autocorrelation could be a result of positive feedback trading.

Table 2 AR(1) Model of Weekly Feeder Cattle Futures Returns

Variable	Estimate (Standard Error)
Constant	0.000786
	(0.000999)
FC_{t-1}	-0.128241*
	(0.051512)
R^2	0.014003
F-stat	6.1977876*
D-W	1.998276

Numbers in parentheses are the standard errors of the estimates. R^2=coefficient of determination adjusted for degrees of freedom; F-Stat is the standard regression test of the significance of the deterministic variables; D-W=Durbin Watson statistic. ***significant at 1% level; **significant at 5% level; *significant at 10% level.

The AR(1) model provides little explanatory power on weekly futures returns, with an R^2 of 0.014. There is very little additional autocorrelation as attested by the Durbin-Watson statistic.

As a first test of the impact of Google searches on feeder cattle futures returns, we modify the AR(1) model to include lagged changes in the GT indices for feeder cattle futures and corn futures. The result, shown in Table 3, is that lagged changes in the amount of Google searches for "cattle" result in a lower return on feeder cattle futures, while an increase in searches for "corn" results in an increase in feeder cattle futures returns. The negative coefficient on the "cattle" search index change is reflective of positive feedback trading if it induces higher volatility so that arbitrage using the spot asset is riskier. The positive coefficient on the "corn" searches reflects traders trying to take advantage of arbitrage.

Table 3 Autoregressive Stepwise Regression Model of Weekly Feeder Cattle Futures Returns

Variable	Estimate (Standard Error)
Constant	0.000621
	(0.0009986)
FC_{t-1}	-0.120096**
	(0.050780)
FCG_{t-1}	-0.025145*
	(0.013489)
CG_{t-1}	0.023706***
	(0.007900)
R^2	0.051533
F-stat	6.574314***
D-W	2.005853
BPG	1.019821

Numbers in parentheses are the standard errors of the estimates. R^2=coefficient of determination adjusted for degrees of freedom; F-Stat is the standard regression test of the significance of the deterministic variables.; D-W=Durbin Watson statistic; BPG= Breusch-Pagan-Godfrey statistic. ***significant at 1% level; **significant at 5% level; *significant at 10% level.

As a formal test of the positive feedback hypothesis, we employ the model of Antoniou, et al. (2011) as outlined above. The estimation results for the two specifications of the conditional mean equations are exhibited in Table 4. The positive feedback model, as shown in Equation (9), predicts that the coefficient β_1 (a product reflecting the market risk premium, the conditional correlation of feeder cattle futures returns with the market index, the proportionality of feeder cattle return variance to the market index variance and the demand elasticity of noise traders) will be negative and significant if positive feedback trading as described in the model takes place, and the estimates here agreed with these predictions at a greater than a 2% significance level.

The second conditional mean specification, Equation (10), is then tested. In this modification of the test for positive feedback trading, we also test if changes in the level of Google searches for "cattle" might proxy for noisy traders looking at public information and then indulging in positive feedback trading. If true, then the coefficients β_1 and β_2 (the extent to which noise traders searching public information using Google affect the degree of positive feedback trading taking place) will both be negative and significant. And in fact, both are at the 5% level of significance. Essentially, Google searches are associated with higher volatility and thus amplify the positive feedback trading mechanism when the number of searches of "cattle" on Google increases. On the other hand, decreases in the number of searches leads to a diminished positive feedback trading effect. Therefore, we conclude that the changes in the GT index for "cattle" is a suitable proxy for positive feedback trading by some noisy traders.

To further test this result, we add three variables to the conditional mean Equation 10 (see Table 4): the change in the index for Google searches on "corn", the lagged weekly volume of cattle futures and the lagged return on corn futures. The coefficients β_1 and β_2 remain negative and significant. However, the significance of the lagged change in the searches for "corn" on Google means that not all public search information is captured by the first two variables. In fact, given the positive coefficient, the significance of the changes in searches on Google for "corn" may be indicative of a different group of traders in that its effects differ from the searches from "cattle". We leave this to future research.

Table 4 Maximum Likelihood Estimates Using One Lag in the Feedback Function

	Eq 9 for Mean	Eq 10 for Mean	Eq 10 and Control Variables
$\boldsymbol{\beta_0}$	0.0006 (0.0010)	0.0007 (0.0009)	0.0005 (0.0009)
$\boldsymbol{\beta_1}$	-302.3015** (118.8100)	-333.6668*** (112.8078)	-336.3205*** (116.7037)
$\boldsymbol{\beta_2}$		-2683.8281** (1125.4617)	-2324.2913** (1075.4956)
$\boldsymbol{\beta_3}$			0.0238*** (0.0055)
$\boldsymbol{\beta_4}$			-0.0297 (0.0331)
$\boldsymbol{\beta_5}$			0.00001 (0.00156)
$\boldsymbol{\alpha_0}$	0.00002* (0.0001)	0.00002** (0.00001)	0.0002*** (0.00001)
$\boldsymbol{\alpha_1}$	0.0522* (0.0271)	0.0511* (0.0267)	0.0529** (0.0244)
$\boldsymbol{\alpha_2}$	0.8795*** (0.0502)	0.8841*** (0.0473)	0.8791*** (0.0458)
$\boldsymbol{\delta}$	0.0368** (0.0165)	0.0344*** (0.0073)	0.0451** (0.0181)
v	1.0653*** (0.1106)	1.0566*** (0.1241)	1.0981*** (0.1324)

***significant at 1% level; **significant at 5% level; *significant at 10% level.

CONCLUSIONS

Examining the returns of the cattle futures market from January 2004 to January 2011, we find evidence supporting the positive feedback trading model. We additionally find evidence that changes in the Google search volume index for "cattle" proxy for searches for public information of noisy traders and help to increase the positive feedback trading effect in this futures market.

We also find evidence of a countervailing effect from searches for "corn". Increases in the number of these searches are associated with an increase in the returns on cattle futures, suggesting that they are connected with a factor that lowers risk perception in the cattle futures market.

There are a number of questions left for future research. First, while the change in the Google Trends index does seem to proxy for some searching for information that results in positive feedback trading, it doesn't have a very large economic impact. Second, other search terms may broaden the capture of the phenomenon. Third, modeling the time series features of changes in Google search trends may aid in our understanding of how public information is collected and used by investors.

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