# Quarterly Earnings Estimates for Publicly Traded Agribusinesses: An Evaluation

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## Abstract

Decisions made by publicly traded agribusinesses impact suppliers, processors, farmers, and even rural communities. Professional analysts' estimates of earnings per share (EPS) provide a unique source of information regarding firm-level financial performance. Incorporating a battery of tests, this research examines the forecast properties of consensus analysts' EPS estimates reported in the Institutional Brokers Estimate System for a sample of publicly traded food companies. While the results are mixed among firms, they suggest 1) analysts forecasts are largely unbiased but inefficient, and may not encompass information in simple time series models, and 2) EPS may be becoming more difficult to estimate.

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## Introduction

As publicly traded agribusinesses strive to achieve wealth maximization through the value of their stock price, the decisions they make can considerably impact downstream players and even rural communities. "While closing a rural agricultural processing plant, or sourcing raw commodity inputs from abroad, may help bolster a food company's faltering stock price, these strategies may also adversely affect local farm production and marketing practices" (Vickner, 2002, pg. 11). Indeed, agribusinesses throughout the supply chain should consider the performance of publicly traded agribusiness firms. Professional analysts' earnings estimates provide a rare source of forward looking information regarding the financial performance of publicly traded firms.

A number of studies in the economics, finance, and accounting literature have examined the forecast properties of analysts' estimates for both domestic and foreign firms (Affleck-Graves and Mendenhall, 1990; Capstaff, Paudyal, and Rees, 1995; Ho, 1996; Keane and Runkle, 1998 Das, Levine, and Sivaramakrishnan, 1998; Barefield and Comiskey, 1975). Overall, these studies and others suggest that analysts' forecasts tend to be more accurate than alternative forecasts, yet are typically not formed in a rational manner.

Despite the insight from these studies, there is no known research which explicitly examines the forecast properties of analysts' earnings estimates for individual publicly traded agribusiness firms. Therefore, the objective of this research is to thoroughly examine the forecast performance of professional analysts' estimates for publicly traded agribusiness companies. Specifically, we focus on analysts' ability to forecast quarterly earnings per share (EPS).

Indeed, understanding the forecasting performance of professional stock analysts is important given that analysts' EPS estimates are one of the few forward looking estimates of a firm's financial performance. As well, many of the short- and long-term strategic business decisions made by publicly traded agribusiness companies have contributed greatly to the structural changes realized in the agribusiness sector (Vickner, 2002). Given the volatile commodity markets and globalization that are hallmarks of the agribusiness market environment, insight into the performance of analysts' estimates of earnings are vital, as they provide the only comprehensive estimate of future financial performance for these firms. This research also contributes to the vast literature which examines the performance of analysts' forecasts as it focuses on a single industry – agribusiness – and rigorously examines the performance of a group of single identified firms instead of summarizing the performance of numerous firms across SIC classifications. Furthermore, much of the insight garnered from studies in the accounting and finance literature were published in the 1970's, 1980's, and 1990's, hence this research provides a needed analysis of analysts' forecast performance during more recent times which have seen considerable volatility in corporate earnings and resulting stock prices. This research also introduces methods which have been used successfully in the agricultural economics literature in evaluating the performance of public forecasts to the problem of examining professional analysts' EPS forecasts. Thus, this paper helps bridge the accounting and finance literature with the body of knowledge in agricultural economics and agribusiness.

## Literature Review

Accurate, unbiased forecasts of future earnings of an organization greatly benefit investors and other decision makers. Accounting information provided through financial statements and disclosures provide decision makers with current and historical performance of the firm. However, operating in a world of uncertainty, greater accuracy of forecasted earnings or earnings expectations potentially allow decision makers to decrease their risk about future earnings performance and improve upon their assessments of firm valuation and the cost of capital. Thus, meaningful and accurate earnings expectations help investors, businesses downstream in the supply chain, and other entities in allocating scarce capital.

A rich literature exists in the fields of accounting and finance focusing on the performance of analysts' forecasts of earnings, as well as the performance of alternative forecasting models of earnings. The predictive accuracy of mechanical techniques, such as time-series forecasts of earnings, has often been found to be inferior to the predictive accuracy of earnings expectations forecasted by security analysts (Barefield and Comiskey, 1975; Brown and Rozeff, 1978; Hopwood, McKeown, and Newbold, 1981). While these and other studies have routinely found that analysts' forecasts tend to be more accurate, they have also been found to be not formed in a rational manner (Affleck-Graves et. al, 1990; Capstaff, Paudyal, and Rees, 1995; Ho, 1996; Keane and Runkle, 1998; Das, Levine, and Sivaramakrishnan, 1998).

Several studies have examined the various characteristics of analyst forecasts errors and the analyst themselves. The direction of analysts' earnings forecasts errors reveals systematic and time persistent optimistic bias about actual firm performance (Barefield and Comiskey 1981; Francis and Philbrick 1993; Das, Levine, and Sivaramakrishnan 1998; Clement 1999). For example, Das, Levine, and Sivaramakrishnan (1998) find that analysts' forecasts of earnings contain significantly more bias for low predictability firms (i.e., firms with high demands of non-public information). Studies suggest that analyst optimism is motivated by maintaining/building client relationships, personal compensation, and pleasing clients to obtain future access to management's private information (Francis and Philbrick 1993; Affleck-Graves et al., 1990; Hunton and McEwen, 1997). On the other hand, it is possible that analysts with unfavorable information, self select, and drop out of the pool of forecasters (McNichols and O'Brien, 1997). Many researchers have also found that analysts' predictive accuracy improves as the end of the forecast year approaches (Crichfield, Dyckman and Lakonishok, 1978; Sinha, Brown and Das, 1997). Many refer to this as the "recency" effect; hence, forecast recency is positively related to forecast accuracy.

However, not all analysts predict earnings with the same degree of accuracy. Sinha et al. (1997) document that forecast accuracy differs systematically among analysts. Clement (1999) finds that analysts' characteristics may be useful in predicting differences in forecasting performance including an increasing level of ability and skill of the analysts gained through experience, greater employer resources available to the analysts (employer size), and increasing degree of specialization. Clement (1999) states that forecast accuracy is important to researchers because they use analysts' forecast accuracy as a proxy for the capital markets' expectation of earnings.

Only a few studies provide evidence of analyst earnings forecast performance by industry. Barefield and Comiskey (1981) present the distribution of average forecast errors for nine industries for a 1967-72 sample period. Using a sample of only eight firms representing the combined food, beverage, and tobacco industry, they found that the coefficient of variation of forecast errors is positively related to the magnitude of the forecast error suggesting a greater volatility of earnings stream that is increasingly more difficult to predict. Sinha et al., (1997) present the distribution of average forecast errors for 14 industries made between a 1984 and 1990 sample period. Having sufficient data over 5 to 120 trading days, their sample contained eight firms, 45 to 28 individual analysts, and 865 to 428 forecasts made between 1984 and 1990 for the food and kindred industry. As the number of trading days increased the number of available analysts and forecasts decreased. The magnitude of forecast errors was not presented as they focused on F-statistics of forecast recency. Interestingly, each of the two studies included a total of eight firms, our study includes eleven firms.

A rich literature also exists in the agricultural economics and agribusiness fields devoted to the evaluation of publicly available forecasts of commodity prices and quantities (Sanders and Manfredo, 2002; Bailey and Brorsen, 1998, Carter and Galopin, 1998; Garcia et. al, 1997; Kastens, Schroeder, and Plain, 1998; among others). In many ways, analysts' forecasts are similar to forecasts made by public agencies as they are forward looking and often used by investors and businesses in decision making. However, forecasts provided by government agencies, such as the Hogs and Pigs Report, WASDE report, etc., are considered to be impartial sources of information. This may not always be the case with professional analyst forecasts of earnings as suggested by Francis and Philbrick (1993), Affleck-Graves et al. (1990), and Hunton and McEwen (1997). This research helps to bridge the gap between the accounting and finance literatures and the agricultural economics literature by incorporating methods used to evaluate public forecasts in analyzing the forecast performance of analysts' forecasts of earnings.

## Data

Consensus estimates of quarterly earnings per share, as well as realized quarterly earnings per share, from the Institutional Brokers Estimate System (I/B/E/S) are used in the analysis.[1] This data was accessed via the WRDS database maintained by the Wharton School at the University of Pennsylvania. I/B/E/S maintains an extensive database of analysts' forecasts of various financial performance measures, most notably EPS, for publicly traded companies on both domestic and international stock exchanges. More than 8,900 companies are covered for North America (U.S. and Canada), and over 12,000 for Latin America, Europe, and Asia combined. I/B/E/S provides this data to institutional money managers, brokers, financial intermediaries, and market news services. In their summary history files, I/B/E/S compiles a mean or consensus EPS forecast which is the simple average of all EPS forecasts submitted by participating analysts. The consensus forecasts are compiled on a monthly basis, specifically on the Thursday before the third Friday of every month (I/B/E/S). I/B/E/S refers to this as the "statistical period". Quarterly consensus estimates are estimated for the nearby quarter, up to 8 quarters ahead. In

[1] I/B/E/S is currently owned by Thompson Financial. Thompson Financial acquired I/B/E/S in 2000. For more information on the I/B/E/S database see http://www.thomsonreuters.com/products_services/financial/ibes#what_s_included

this study, we focus our efforts on the nearby quarter. That is, the forecasts that we specifically used corresponded to the last consensus forecast compiled prior to the forecast period end date which is the last day of the fiscal quarter. For example, for a firm that follows a calendar quarter fiscal year (March, June, September, December), the forecast period end date would be the last day of the month. For 1990 quarter 1 (1990.1), for example, the forecast period end date would be March 31, 1990. So, the consensus EPS estimate used would be the one calculated on March 15, 1990. Similarly, for the second quarter of 1990 (1990.2), the forecast period end date is June 30, 1990, and the consensus forecast used is the one calculated on June 15, 1990. For the particular sample that we use and discuss below, there were typically anywhere between 1 to 20 or more analysts that contributed to the consensus forecasts. If a particular analyst provides a forecast in a prior statistical period, and does not provide an update for the following statistical period, their original estimate carries over. Given the consensus estimates are estimated each month, additional analysts may be added to the consensus forecast and/or they may revise their estimates. Typically the last consensus estimates calculated prior to the forecast period end date have the largest number of analysts contributing to the consensus forecast.

According to I/B/E/S, the EPS estimates provided by analysts typically reflect earnings per share on a continuing operations basis where discontinued operations, extra-ordinary charges, and other non-operating items are removed. In cases where analysts do not report their EPS estimates in this manner, I/B/E/S adjusts the forecast to reflect this. As well, I/B/E/S does not force analysts to report fully diluted or basic EPS, but rather lets the majority of analysts following the stock to prevail. If one or more particular analysts do not follow the convention of the majority, I/B/E/S will adjust for a fully diluted or basic EPS depending on the majority of analysts' forecasts.

I/B/E/S compiles actual EPS from various market newswire services when the numbers are released to the public. I/B/E/S adjusts the actual earnings to match the estimates such that the estimates and actual EPS are reported in the same manner (e.g., fully diluted vs. basic, etc.). The release of actual EPS by individual firms to the public typically occurs anywhere from one to two months after the forecast period end date. Actual EPS are matched to the corresponding forecast period end date in the database for convenient analysis. Overall, I/B/E/S ensures that estimated and actual EPS are comparable. I/B/E/S also adjusts for mergers and acquisitions and any accounting changes which may occur. As well, when a stock splits, I/B/E/S adjusts all historical forecasts and realized EPS in the database history. At times, companies may also retroactively adjust their actual EPS numbers due to changes in the application of accounting principles, asset write-offs, etc. In these cases, however, I/B/E/S does not retroactively adjust historical estimates and actual EPS to reflect this, ensuring that the particular data point reflects the information when the estimate and actual EPS were released.

The agribusiness firms that we examine in this study reflect many of the well known publicly traded agribusiness firms in the United States. We constrained our sample to include only U.S. based firms with total market capitalization over two billion dollars (Table 1). The firms studied include Kellogg Co. (K), Hershey Co. (H), Flowers Foods Inc. (FLO), Archer-Daniels-Midland Co. (ADM), Sara Lee Corp. (SLE), William Wrigley Jr. Co. (WWY), HJ Heinz Co. (HNZ), Hormel Foods Corp. (HRL), Corn Products International Inc. (CPO), General Mills (GIS), and

ConAgra Foods Inc. (CAG). Each of these firms is traded on the New York Stock Exchange, and each falls within the general SIC code 20: Food and Kindred Products (Table 1).[2]

The sample spans from the end of the third quarter 1985 (1985.3) to end of the third quarter in 2007 (2007.3). This provides 89 observations of quarterly analysts' consensus forecasts and realized EPS used for estimating alternative (e.g., time series) forecasts and out-of-sample forecast evaluation. Given that the focus is on quarterly consensus estimates and actual EPS, the data tend to exhibit seasonality. As well, for many of the firms, the consensus estimates and actual EPS trend upward over the sample period, consistent with overall growth in earnings for most firms over the sample period. To account for this and to ensure stationarity of the data, we focus on quarterly differences in the data. Specifically, we define the forecast series as $FE_t = F_t - A_{t-4}$ where $F_t$ is the consensus forecast for quarter *t* and $A_{t-4}$ is the realized EPS for the same quarter of the previous year. We also define the actual series as $AE_t = A_t - A_{t-4}$ which is the difference between the realized EPS in quarter *t* and the realized EPS in the same quarter of the previous year.[3] Both $FE_t$ and $AE_t$ are unscaled series (Obrien, 1988).[4] In both cases, EPS and subsequently $FE_t$ and $AE_t$ are expressed as cents per share.[5]

Table 2 provides summary statistics (mean and standard deviation) for both the raw consensus forecasts and realized EPS ($F_t$ and $A_t$) as well as the quarterly difference series ($FE_t$ and $AE_t$) for the out-of-sample period (described in the next section) which covers 1993 quarter 3 (1999.3) through quarter 3 in 2007 (2007.3). For example, for ADM, the mean consensus estimate $F_t$ is \$0.2446 with a standard deviation of \$0.1645 while the mean realized EPS, $A_t$ is \$0.1346 with a standard deviation of \$0.1346. The mean seasonal difference $FE_t$ is \$0.0417 and the actual seasonal difference $AE_t$ is \$0.0330. Therefore, consensus analysts' forecasts over the out-of-sample period have estimated on average about a 4 cent increase in EPS from the same quarter of the previous year, while realized EPS have averaged about 3 cents from the same quarter of the previous year. The consensus estimates and actual EPS have been volatile as well with standard deviations for $FE_t$ and $AE_t$ for ADM at \$0.0683 and \$0.0960 respectively.

## Methods and Results

In this research, we examine several facets of forecast performance. These include both traditional forecast accuracy measures as well as tests exploring the optimal properties of forecasts as well as their improvement over time. In analyzing the performance of consensus

[2] Indeed, other agribusiness firms, such as Tyson Foods, have capitalizations greater than \$2 billion. However, for these firms, the I/B/E/S data files were incomplete or the histories of consensus and realized EPS were too short for meaningful analysis.
[3] Both the series $FE_t$ and $AE_t$ were found to be stationary using the Augmented Dickey Fuller (ADF) test.
[4] In many studies examining forecast performance, logarithmic changes (percent changes) are used in defining the forecast and actual series (see Sanders and Manfredo, 2002). However, when dealing with forecasted and actual EPS, there is the possibility for negative forecasted and realized EPS which makes the expression of percent changes problematic. These unscaled series are prone to asymmetry and heteroskedasticity. Several ad-hoc scaling procedures have been suggested and used in the accounting literature (see Obrien, 1998 footnote 6, pg. 60), but are largely unintuitive. Therefore, we focus on these unscaled series, and correct for heteroskedasticity if needed in our forecast evaluation tests.
[5] In evaluating forecast errors, the use of year-over-year differences, or difference in successive quarters, is equal. It can easily be shown that $e_t = AE_t - FE_t = (A_t - A_{t-4}) - (F_t - A_{t-4}) = A_t - F_t$.

EPS forecasts for agribusiness firms, a simple alternative forecast is developed for comparison. Here, we incorporate a simple time series model, namely an AR(4). An AR(4) specification has been used in other studies examining forecast performance utilizing quarterly data (Sanders and Manfredo, 2002). While the AR(4) is an admittedly simple alternative, it describes the data well and generally picks up the major time series properties of the data. While other specifications may be more appropriate than the AR(4) for some of the companies examined, the intention of this study is not to conduct a horserace of alternative forecasting methods of realized EPS. Rather, the AR(4) merely serves as a straw man to which the consensus forecasts can be compared. The data used to estimate the AR(4) are the actual earnings difference ($AE_t$) for each of the firms beginning with 1985.3 going through 1993.2 (30 observations), with the corresponding one-period ahead forecast made for 1993.3. Each quarter, the AR(4) model is re-estimated and the one-period ahead forecast made, which results in a growing sample over time to estimate the one-period ahead forecasts. Hence, the one-period ahead forecast of actual earnings changes ($AE_{t+1}$) corresponding to 2007.3 is estimated using data from 1985.3 to 2007.2 (88 observations). Each of the evaluation tests and subsequent results are outlined below.

*Forecast Accuracy Measures – RMSE and MAE*

Both the root mean squared error (RMSE) and mean absolute error (MAE) are used to evaluate the point accuracy of the consensus forecasts and the competing time series forecasts of quarterly EPS on an out-of-sample basis (Table 3). For both the consensus and time series forecasts, the forecast error is defined as $e_t = AE_t - FE_t$. Therefore, RMSE is $\sqrt{\sum e_t^2 / n}$ and MAE is $(\sum |e_t| / n)$ where $n$ is the number of out-of-sample observations. The out-of-sample period begins at 1993.3 and extends to 2007.3 for a total of 59 out-of-sample observations for evaluation.

In comparing the forecasts (Table 3), in every case the consensus forecasts have a smaller RMSE and MAE than that of the time series forecasts. This is consistent with the extant literature from the accounting field. That is, consensus forecasts tend to be more accurate than those provided from competing models. However, it may be the case that the differences in RMSE and MAE are not statistically significant (Diebold and Mariano, 1995). To test this hypothesis, we incorporate the Modified Diebold-Mariano (MDM) statistic for testing the differences in mean squared errors as suggested by Harvey, Leybourne, and Newbold (1997). The MDM test uses two time series of h-step ahead forecast errors, $e_{1t}$ and $e_{2t}$, ($t=1$ to $n$) and a specified loss function g($e$). In this case, $e_{1t}$ corresponds to the forecast errors of the consensus forecasts and $e_{2t}$ to the forecast errors of the time series forecasts. The null hypothesis of the MDM test is $E[g(e_{1t}) - g(e_{2t})]=0$, where the loss function, g($e$), is the squared operator in the case of RMSE and the absolute value operator in the case of MAE. Rejection of the null hypothesis suggests that there is a statistically significant difference between the accuracy of the compared forecasts. The null hypothesis that the sample mean ($\bar{d}$) of $d_t = g(e_{1t}) - g(e_{2t})$ equals zero is tested using the critical values from a t-distribution. The RMSE, MAE, and the MDM statistics are presented in Table 3.

While the consensus forecasts have a smaller RMSE and MAE in each case relative to the time series forecasts, not all of the differences are statistically significant. When considering RMSE, only the consensus estimates for K, HSY, SLE, WWY, GIS, and CAG are statistically smaller than the time series alternative at the 5% level (6 out of 11 instances). For MAE, however, only the consensus estimates for ADM and CPO are not statistically smaller than the time series alternative at either the 5% or 10% level. While certainly not unanimous, these results on average suggest that analysts provide more accurate forecasts than alternative forecasts than time series competitors which is consistent with findings in the accounting and finance literature. While understanding the point accuracy of a forecast is important, it is only one measure of overall forecast performance.

*Test for Forecast Bias*

An optimal forecast is one that is both unbiased and efficient (Diebold and Lopez, 1998). An optimal forecast utilizes all information available to the forecaster. It is also the most accurate forecast in a mean squared error framework. Typically, forecast optimality is tested using the following OLS regression framework:

$$ACT_t = \alpha + \beta FCST_t + \varepsilon_t \ , \quad (1)$$

where $ACT_t$ is the realized value and $FCST_t$ is the forecast. The joint null hypothesis for forecast optimality is that $\alpha$=0 and $\beta$ =1. Failure to reject the joint null implies that the forecast is indeed optimal in that it is both unbiased, $\alpha$=0, and efficient $\beta$ =1. This common test, however, is subject to interpretative problems (Holden and Peel, 1990; Granger and Newbold, 1986). Namely, the joint null is only a necessary condition for efficiency (Granger and Newbold, 1986) and a necessary, but not sufficient, condition for unbiasedness. A rejection of the null hypothesis, therefore, does not provide clear insight into the optimal properties of the forecast. Therefore, to avoid these interpretive problems, we use the methodology demonstrated by Pons (2000) which incorporates the suggestion by Granger and Newbold (1986, p. 286) that forecast optimality tests should be conducted using forecast errors (Holden and Peel, 1990).

The specific test for bias used here is an OLS regression of the forecast error, $e_t = AE_t - FE_t$, on an intercept term ($\gamma$) such that:

$$e_t = \gamma + \upsilon_t , \quad (2)$$

where $\upsilon_t$ is a random disturbance term (Pons, 2000). The null hypothesis of an unbiased forecast, one that does not consistently under- or over- estimate the actual value, is $\gamma$=0. The null hypothesis is tested using a two-tailed t-test.[6]

Table 4 shows the results of the forecast bias test outlined in equation (2). Of the 11 firms examined, only the consensus forecasts for K and SLE are found to exhibit a statistically significant bias at the 5% level. In both cases, the consensus forecasts systematically

[6] The data setup used in this study yields non-overlapping forecasts and actual values of quarterly EPS. Therefore, the OLS standard errors from this and all subsequent regression models are consistent (Brown and Maital, 1981; Clements and Hendry, 1998 pg. 57). In equation 2, and in all subsequent regression models, heteroskedasticity is tested using White's test. Serial correlation is tested using the Ljung-Box test. If heteroskedasticity is found, White's heteroskedastic consistent covariance estimator is used. If serial correlation is present, the Newey-West covariance estimator is used (Hamilton, 1994, p. 218).

underestimate the actual EPS ($\gamma > 0$). The magnitude of the bias, approximately 1 cent per share in both cases, appears rather small on a per share basis, but can represent a considerable degree of profitability on a company wide basis.[7] In the case of K and SLE, adding the constant $\gamma$ in each case could yield a statistically better forecast. For example, if the realized EPS in quarter *t-4* for K was $0.75 per share, and the consensus forecast for quarter *t* is $0.77 (a forecasted +$0.02 change from *t-4* to *t*), then the forecasted change should be adjusted by adding $0.0136 to yield an adjusted forecasted change of $0.0336. Thus, the adjusted consensus forecast would then be $0.7836 ($0.75 + $0.0336). However, for 9 out of 11 agribusiness stocks examined, this is not the case. That is, the majority of the consensus forecasts are unbiased. Likewise, as is expected, there is a failure to reject the null hypothesis of $\gamma = 0$ for the time series forecasts of EPS for each firm (5% level), illustrating that each of the time series forecasts are unbiased.

*Tests for Forecast Efficiency – Beta and Rho Efficiency*

Forecast efficiency is another critical component of forecast optimality. A forecast is said to be weakly efficient if forecast errors, $e_t$, are orthogonal to the forecasts themselves and orthogonal to past forecast errors (Nordhaus, 1987). Given this, the following regression framework is used to test for weak efficiency in the forecast errors $e_t = AE_t - FE_t$ of the consensus and time series forecasts of EPS (Pons, 2000):

(3) $$e_t = \alpha + \beta FE_t + \upsilon_t$$

and

(4) $$e_t = \alpha + \rho e_{t-1} + \upsilon_t\,.$$

Equation (3) is referred to as the beta efficiency test (Table 5). Here, the null hypothesis of forecast efficiency is $\beta=0$. If the null hypothesis is rejected, this suggests that the forecast is not a minimum variance forecast. That is, the forecast, $FE_t$, is not efficiently or optimally incorporating all information available regarding future EPS available at time period *t*. If $\beta > 0$, then the forecasts are systematically too conservative, and if $\beta < 0$, then the forecasts are systematically too optimistic or too extreme. If $\beta$ is found to be statistically significant via a two-tailed t-test, then the forecast can be scaled by a factor of $1+\beta$ to improve efficiency.

Equation (4) is the rho efficiency test (Table 6), which tests if forecast errors are systematically related to past forecast errors. If the null hypothesis of $\rho=0$ is rejected (two-tailed t-test), then forecast errors in time *t* are related to past errors. In the case that $\rho > 0$, this suggests that past forecast errors are repeated (e.g., positive autocorrelation). For example, an overestimate of $AE_t$

[7] Former Chairman of Securities and Exchange Commission, Arthur Levitt, gave a speech on September 28, 1998 at the New York University Center for Law and Business about his concern of motivated firms to meet Wall Street earnings expectations, and overriding common sense in their zeal to satisfy consensus earnings estimates. Levitt says that the market is unforgiving of companies that miss their estimates, even by one penny. Although this one cent per share may appear rather small on a per share basis, it matters to Wall Street as they assess the stock value of the firm. In this study, actual EPS exceeded consensus forecast EPS.

would likely be followed by another overestimate and visa-versa. If $\rho < 0$, then overestimates would be followed by underestimates and visa-versa.

Table 5 presents the results of the beta efficiency test in equation (3). The consensus forecasts for 5 of the 11 firms are rejected for beta efficiency (HSY, SLE, WWY, HNZ, and CPO) at the 5% level, and two (K and HRL) at the 10% level. This suggests that analysts are not efficiently using the information available regarding future EPS for these firms at the time the consensus forecast is computed. Interestingly, the consensus forecasts for both K and SLE were also found to be systematically biased as discussed earlier. Four of the seven firms (SLE, HNZ, HRL, and CPO) had $\beta < 0$, and three firms realized $\beta > 0$ (K, HSY, AND WWY). For example, $\beta$= -0.3007 for HNZ suggests that the forecast errors are negatively related to the consensus forecast such that a large positive forecast generates a large negative error, and that a large negative forecast generates a large positive error. Thus if the consensus forecast $FE_t$ is +\$0.05 per share, the forecast should be scaled down by a factor of 1+ $\beta$ (0.6993). So, the adjusted $FE_t$ would be \$0.05 x 0.6993 = +\$0.0349. Thus if the realized EPS in quarter *t-4* were \$0.50 per share, the consensus estimate would for EPS in quarter *t* would be \$0.5349. Interestingly, the time series forecasts for CPO, HNZ, WWY, and CAG were also found to be beta inefficient. This suggests that the AR(4) model used may not be the most appropriate for these firms. These results may also be illustrating the fact that time series models in general are inherently penalized in forecasting quarterly EPS given that time series models can only use data up to the prior quarter, while analysts can assimilate new information into their forecasts up to the last statistical period prior to the forecast period end date.

Results from the rho efficiency tests are presented in Table 6. The null hypothesis of $\rho$ =0 is rejected for the consensus forecasts of ADM and CPO at the 5% level (p-value = 0.0139 and 0.0002 respectively). In each case, the estimated $\rho > 0$, suggesting that past forecast errors are repeated. That is, there is some positive autocorrelation in the error terms. While it is difficult to determine the exact reasons underlying these findings, it may be that analysts are not adequately capturing structural changes or other phenomenon related to these firms. ADM and CPO are also firms that are directly involved in the grain trade. It may be that analysts are not adequately incorporating information regarding the volatility of commodity prices that may ultimately impact EPS of these firms. None of the time series forecasts reject the null hypothesis at the 5% level as expected given that the time series models rely on serial correlation in generating forecasts. Interestingly, however, the null hypothesis of the time series forecast for ADM and WWY are rejected at the 10% level (p-value = 0.0729 and 0.0912 respectively). Indeed, this at least somewhat suggests that time series behavior in the error terms is not adequately being captured by the AR(4) model. While it may be a matter of misspecification of the time series model (e.g., a more appropriate time series specification exists for ADM), it may also be systematic of structural changes or other phenomenon, such as volatility in commodity prices, that is causing forecast errors to be repeated regardless of how the forecast is formed. This finding may also be due to factors strictly unique to ADM and WWY.

Forecasts that are rho inefficient can be scaled to account for the tendency to repeat forecast errors. For example, if the forecast error in the previous period from the consensus forecast, *t-1*, for ADM is +\$0.02, then the current quarter forecast should be adjusted by subtracting \$0.0066 (\$0.02 x 0.3294). If the current quarter consensus forecast $FE_t$ is +\$0.04 relative to *t-4*, then the adjusted forecast would be $0.0334. Hence if the actual EPS in *t-4* were $0.30 per share, the consensus EPS forecast for *t* would be adjusted to $0.3334. Overall, the results from the rho efficiency test suggests that at least for the case of ADM and CPO, the consensus forecasts may not be capturing or reflecting some relevant time series behavior in the actual quarterly changes in EPS.

*Test for Forecast Encompassing*

A preferred forecast is said to encompass a competing or alternative forecast if there is no linear combination of forecasts (e.g. a composite forecast) that would yield a smaller mean squared error relative to the preferred (Mills and Pepper, 1999). If this is the case, then the competing forecast contains no useful information that is not already found in the preferred forecast (Harvey and Newbold, 2000).[8] Forecast encompassing is tested in the following regression framework (Harvey, Leybourne, and Newbold, 1998):

(5) $$e_{1t} = \alpha + \lambda(e_{1t} - e_{2t}) + \upsilon_t$$

where $e_{1t}$ are the errors from the preferred forecast, $e_{2t}$ are the errors from the competing forecast, $e_{1t}$ - $e_{2t}$ is the difference in the two forecast error series, and $\upsilon_t$ is a random disturbance term. The null hypothesis is $\lambda$=0. A rejection of the null hypothesis suggests that the preferred and competing forecasts can be combined to form a composite forecast that would result in a smaller squared error than the preferred forecast alone. In this case, the weight placed on the competing forecast would be the estimated $\lambda$ and the weight placed on the preferred forecast would be 1- $\lambda$. A failure to reject the null hypothesis suggests that the preferred forecast should be used by itself.

The OLS estimates corresponding to equation (5) are presented in Table 7. Table 7 is broken into two sections for comparative purposes. In the first set of results, the consensus forecast is designated as the preferred forecast. According to the encompassing test, the null hypothesis of forecast encompassing is rejected at the 5% level for K (p-value = 0.0004), HNZ (p-value = 0.0119), HRL (p-value = 0.0400), and CPO (p-value = 0.0006). This suggests that the consensus EPS forecasts for each of these companies could be combined with the time series forecasts to provide a forecast that has a smaller mean squared error relative to the preferred. Interestingly and not surprisingly the consensus forecasts for CPO, which was found to be rho inefficient earlier, could be improved by combining with a time series forecasts. However, this was not the case for the consensus forecasts for ADM which were also found to be rho inefficient at the 5% level. However $\lambda$ is significant at the 10% level (p-value = 0.0602) for ADM, providing at least some evidence that analysts are not adequately incorporating the time series properties of actual EPS when making their forecasts. In the case of CPO, the optimal weight to place on the time series forecast would be 0.5996 (1 - 0.4004), and the weight to place on the consensus forecast would be $\lambda$=0.4004. The composite weights for the other consensus forecasts where a significant $\lambda$ was found include 0.2367 and 0.7633 for HRL, 0.3129 and 0.6871 for HNZ, and -0.1923 and 1.1923 for K. In the case for K, a negative weight is placed on the consensus forecast while a

[8] Note that the use of the word "preferred forecast" does not insinuate that the particular forecast is indeed preferred to others. Rather, it is nomenclature typically used in the forecasting literature when comparing two forecasts in an encompassing framework.

positive weight is placed on the time series alternative. While the signs on these weights are somewhat unexpected, they are a result of the covariance relationship between the consensus forecast and the time series alternative.

When the preferred forecast is designated as the time series forecasts, the null hypothesis of $\lambda=0$ is rejected for each of the firms in the sample. This result confirms that the time series forecasts alone will not provide the smallest mean squared error. In the case of the consensus forecasts for GIS, for example, the null hypothesis of forecast encompassing ($\lambda=0$) cannot be rejected. This suggests that the consensus forecasts used on their own will provide the smallest mean squared error and that a composite forecast with the time series alternative will provide no improvement relative to the consensus forecast. When the preferred forecast is designated as the time series alternative, $\lambda=0$ is rejected at the 5% level with $\lambda=1.0654$. This suggests that in a composite forecast with the consensus forecast, that basically all weight should be placed on the consensus forecast and none on the time series alternative.

The fact that the consensus forecasts for more than half the firms in the sample are found not to encompass the simple time series alternative at either the 5% or 10% level suggests that professional analysts may not be doing a good job of incorporating the time series properties of past realized EPS. This result is especially compelling given that the time series alternative is inherently penalized relative to the consensus forecasts from an informational perspective. The time series forecasts only use information up to the quarter prior to the nearby quarter being forecasted (e.g., past EPS up to $t-1$ is used to forecast EPS at time $t$). Analysts, on the other hand, can adjust their forecasts up until the last statistical period, incorporating their informational advantage, which in the case of the consensus forecasts used in this study is approximately two weeks prior to the forecast period end date. Indeed, analysts following several of these firms may not be privy to the important information reflected in simple time series models.

*Tests for Forecast Improvement*

The final test used examines how the consensus forecasts have performed over the out-of-sample period. Namely, the question arises as to whether analysts' forecasts have improved over time. A test for forecast improvement is presented here following the methodology of Bailey and Brorsen (1998). Again, focusing on forecast errors, the test for forecast improvement is defined as:

(6) $$|e_t| = \delta_1 + \delta_2 Trend_t + \upsilon_t$$

where $|e_t|$ is the absolute forecast error and $Trend_t$ is a time trend. The null hypothesis is that $\delta_2 = 0$ which is tested with a two-tailed t-test. A failure to reject the null implies that there is not a systematic improvement nor deterioration in the absolute forecast errors over time. A rejection of the null hypothesis, on the other hand, suggests that forecast errors have become systematically smaller ($\delta_2 < 0$) or systematically larger ($\delta_2 > 0$) over time.

Results of equation (6) are reported in Table 8. For the consensus forecasts, $\delta_2$ is > 0 for all firms but HNZ and CPO. In 5 cases, nearly half of the sample firms, the null hypothesis of $\delta_2 =$

0 is rejected at the 5% level (K, FLO, SLE, WWY, and CAG). These results suggest that on average, consensus analysts' forecasts have not improved over time, but have actually become worse. Interestingly, similar results are found for the time series forecasts. In 7 out of 11 cases the null hypothesis of $\delta_2 = 0$ is rejected at the 5% level. In fact, the null hypothesis for both the consensus forecasts and time series forecasts are rejected for FLO, SLE, WWY, and CAG. The fact that there is systematic deterioration in both the consensus forecasts and time series forecasts implies that it may be getting increasingly difficult to forecast earnings for these firms. This particularly may be the case for the year 2000 and beyond.

Indeed, since year 2000, firm level profitability has become more variable for many agribusiness firms given volatility in commodity markets, increased financial reporting regulation and associated regulatory costs (e.g., Sarbanes-Oxley), consolidation in the food and agribusiness sector, globalization, among other systematic factors such as 911 and firm specific factors (e.g., mergers and acquisitions). As well, in the aftermath of Enron and other corporate scandals, many analysts that worked for investment banking firms quit, were fired, or were forced to separate their analysis work from the brokerage functions of the firms that they worked for. Therefore, there was likely a large turnover of analysts post 2000 that may have contributed to increased forecast errors over time. Figure 1 shows the plots of absolute forecast errors for consensus forecasts and time series forecasts for FLO, SLE, WWY, and CAG (companies for which there was statistically significant deterioration in both the consensus and time series forecasts). Indeed, a pattern of increasing and more volatile forecast errors over time is evident, in particular post 2000.

## Summary, Conclusions, and Ongoing Research

This research provides a comprehensive examination of the forecasting performance of professional analyst forecasts of EPS for a sample of publicly traded agribusiness firms. In particular, consensus estimates of EPS provided through the Institutional Brokers Estimate System (I/B/E/S), a division of Thompson Financial, were examined. As well, simple time series alternative forecasts generated by an AR(4) model served as a point of comparison to the consensus forecasts. The agribusiness firms examined represent some of the largest agribusiness firms listed on the New York Stock Exchange, each reflecting a market capitalization of more than $2 billion. Analysts' estimates of EPS provide a rare source of forward looking information regarding firm level financial performance. Indeed, the decisions made by large publicly traded agribusiness firms may impact downstream players and even rural communities (Vickner, 2002).

The results of the forecast accuracy tests (MDM tests for equality in forecast errors), test for forecast bias, test for beta efficiency, test for rho efficiency, forecast encompassing tests, and tests for forecast improvement are summarized in Table 9 for each of the agribusiness firms in the sample. Overall, while the results are mixed, there is considerable evidence suggesting that analysts may not be doing well in predicting EPS for these firms. For example, for Kellogg (K), consensus forecasts provide statistically more accurate point forecasts than the time series alternative, but are biased, beta inefficient, and forecast errors have systematically increased over time. As well, consensus EPS forecasts for K do not encompass time series information provided by the time series alternative. For HJ Heinz (HNZ), Hormel (HRL), and Corn Products

International (CPO), there is evidence that the consensus forecasts of EPS are not statistically more accurate than the time series alternative, are both beta and rho inefficient, and do not encompass the information in the time series forecasts. Overall, consensus forecasts for ConAgra (CAG) performed the best of the companies in the sample, but absolute forecast errors have systematically been increasing over time.

Indeed, there is some evidence that suggests quarterly EPS is becoming more difficult to forecast in the agribusiness industry. This may be the result of a number of issues including volatility of commodity prices, globalization, consolidation in the agribusiness industry, regulatory changes (e.g., Sarbanes-Oxley) which have modified the investment banking and analyst environment, as well as generalized EPS volatility due to systematic influences in the economy post year 2000 (e.g., 911, Enron, Iraq and Afghanistan wars, interest rate environment, and general economic conditions). Ideas for ongoing research include testing for structural changes in the regression based tests both prior to and after year 2000, as well as determining if consensus forecasts for a given firm encompass analysts forecasts for other firms in the industry (e.g., an agribusiness composite EPS forecast) as well as the broader market (forecast of quarterly EPS for the S&P 500).

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Table 1. Company Name, Ticker, SIC, Market Capitalization, and Fiscal Quarters

| Company Name | Ticker[a] | SIC - Major Group 20 Food and Kindred Products | Market Capitalization[b] | Fiscal Quarters[c] |
|---|---|---|---|---|
| Kellogg Co. | K | 2043 - Cereal Breakfast Foods | $22,291 | Mar, Jun, Sep, Dec |
| Hershey Co. | HSY | 2064 - Candy and Other Confectionary Products | $10,470 | Mar, Jun, Sep, Dec |
| Flowers Foods Inc. | FLO | 2053 - Frozen Bakery Products, Except Bread | $2,026 | Mar, Jun, Sep, Dec |
| Archer Daniels Midland Co. | ADM | 2075 - Soybean Oil Mills | $21,025 | Mar, Jun, Sep, Dec |
| Sara Lee Corp. | SLE | 2013 - Sausages and Other Prepared Meats | $11,831 | Mar, Jun, Sep, Dec |
| William Wrigley Jr. Co. | WWY | 2067 - Chewing Gum | $17,115 | Mar, Jun, Sep, Dec |
| HJ Heinz Co. | HNZ | 2033 - Canned Fruits and Vegetables | $14,565 | Apr, Jul, Oct, Jan |
| Hormel Foods Corp. | HRL | 2011 - Meat Packing Plants | $4,815 | Apr, Jul, Oct, Jan |
| Corn Products International Inc. | CPO | 2056 - Wet Corn Milling | $3,509 | Apr, Jul, Oct, Jan |
| General Mills Inc. | GIS | 2043 - Cereal Breakfast Foods | $19,464 | Feb, May, Aug, Nov |
| ConAgra Foods Inc. | CAG | 2099 - Food Preparations, Not Elsewhere Classified | $12,940 | Feb, May, Aug, Nov |

[a] Each company is listed on the New York Stock Exchange.
[b] Market capitalization is in millions of dollars as of 9/20/97.
[c] Fiscal quarters end on the last business day of the month. This corresponds to the forecast period end date. Actual earnings are typically released one month or more after the forecast period end date. For example, March = quarter 1 for the Mar, Jun, Sep, Dec fiscal year; April = quarter 1 for Apr, Jul, Oct, Jan fiscal year; February = quarter 1 for Feb, May, Aug, Nov fiscal year.

Table 2. Summary Statistics (cents/share), 1993.3 to 2007.3

| Ticker | Mean $F_t$ | Stdev $F_t$ | Mean $A_t$ | Stdev $A_t$ | Mean $FE_t$ | Stdev $FE_t$ | Mean $AE_t$ | Stdev $AE_t$ |
|---|---|---|---|---|---|---|---|---|
| K | 0.4398 | 0.1140 | 0.4534 | 0.1293 | 0.0094 | 0.0636 | 0.0230 | 0.0754 |
| HSY | 0.3558 | 0.1813 | 0.3563 | 0.1796 | 0.0256 | 0.0321 | 0.0261 | 0.0419 |
| FLO | 0.0778 | 0.0694 | 0.0768 | 0.0764 | 0.0158 | 0.0218 | 0.0148 | 0.0317 |
| ADM | 0.2446 | 0.1645 | 0.2532 | 0.1346 | 0.0417 | 0.0683 | 0.0330 | 0.0960 |
| SLE | 0.2824 | 0.0875 | 0.2898 | 0.0900 | -0.0062 | 0.0671 | 0.0013 | 0.0641 |
| WWY | 0.3192 | 0.1271 | 0.3192 | 0.1281 | 0.0290 | 0.0160 | 0.0290 | 0.0264 |
| HNZ | 0.5380 | 0.0875 | 0.5352 | 0.1015 | 0.0284 | 0.0674 | 0.0257 | 0.0597 |
| HRL | 0.3019 | 0.1362 | 0.3053 | 0.1486 | 0.0224 | 0.0403 | 0.0258 | 0.0472 |
| CPO | 0.3969 | 0.1521 | 0.3850 | 0.1776 | 0.0363 | 0.0967 | 0.0243 | 0.0790 |
| GIS | 0.5458 | 0.1864 | 0.5500 | 0.2125 | 0.0214 | 0.0963 | 0.0257 | 0.1099 |
| CAG | 0.3378 | 0.0939 | 0.3397 | 0.0977 | 0.0120 | 0.0528 | 0.0140 | 0.0739 |

Notes: $F_t$ is the consensus analyst forecast for earnings per share (EPS) reported to I/B/E/S for quarter t. $A_t$ is the actual EPS for quarter t from I/B/E/S. $FE_t$ is defined as $F_t – A_{t-4}$, and $AE_t$ is $A_t – A_{t-4}$. Quarters correspond to the appropriate fiscal year (see Table 1).

Table 3. Forecast Accuracy Measures, 1993.3 to 2007.3

| | RMSE[a] | | | MAE | | |
|---|---|---|---|---|---|---|
| Ticker | Consensus | Time Series | MDM test[b] | Consensus | Time Series | MDM test |
| K | 0.0306 | 0.0670 | -4.065 * | 0.0203 | 0.0498 | -5.126 * |
| HSY | 0.0182 | 0.0327 | -2.842 * | 0.0131 | 0.0242 | -3.972 * |
| FLO | 0.0256 | 0.0289 | -1.308 | 0.0157 | 0.0203 | -2.602 * |
| ADM | 0.0657 | 0.0796 | -1.595 | 0.0514 | 0.0600 | -1.308 |
| SLE | 0.0228 | 0.0605 | -2.829 * | 0.0124 | 0.0371 | -4.176 * |
| WWY | 0.0169 | 0.0269 | -2.000 * | 0.0124 | 0.0180 | -2.669 * |
| HNZ | 0.0417 | 0.0562 | -1.566 | 0.0245 | 0.0402 | -2.355 * |
| HRL | 0.0350 | 0.0452 | -1.585 | 0.0252 | 0.0327 | -1.901 ** |
| CPO | 0.0646 | 0.0762 | -0.793 | 0.0389 | 0.0535 | -1.329 |
| GIS | 0.0529 | 0.1030 | -4.639 * | 0.0273 | 0.0709 | -3.444 * |
| CAG | 0.0444 | 0.0816 | -2.676 * | 0.0262 | 0.0509 | -3.410 * |

[a] RMSE is root mean squared error ( $\sqrt{\sum e^2 / n}$ ) and MAE is mean absolute error ( $\sum |e| / n$ ) where $e_t = AE_t - FP_t$.

[b] The t-statistics are from the Modified Diebold-Mariano Test for equality in prediction errors (see Harvey, Leybourne, and Newbold).

*Significant at the 5% level.

*Significant at the 10% level.

Table 4. Test for Forecast Bias ( $e_t = \gamma + \upsilon_t$ ), 1993.3 to 2007.3

| | Consensus | | | Time Series | | |
|---|---|---|---|---|---|---|
| Ticker | $\gamma$ | t-stat | p-value | $\gamma$ | t-stat | p-value |
| K | 0.0136 | 3.7600 | 0.0004 | -0.0006 | -0.0703 | 0.9442 |
| HSY | 0.0005 | 0.2127 | 0.8323 | 0.0000 | 0.0067 | 0.9947 |
| FLO | -0.0010 | -0.3528 [a] | 0.7255 | 0.0081 | 1.9556 [a] | 0.0553 |
| ADM | -0.0087 | -0.7738 [a] | 0.4422 | 0.0132 | 1.2804 | 0.2055 |
| SLE | 0.0075 | 2.7353 [a] | 0.0083 | -0.0114 | -1.4548 | 0.1511 |
| WWY | 0.0000 | 0.0153 | 0.9879 | 0.0023 | 0.6395 | 0.5250 |
| HNZ | -0.0027 | -0.5002 | 0.6188 | -0.0002 | -0.0239 [a] | 0.9810 |
| HRL | 0.0035 | 0.8187 [a] | 0.4163 | 0.0033 | 0.5497 | 0.5846 |
| CPO | -0.0119 | -0.8407 [a] | 0.4040 | 0.0015 | 0.1521 | 0.8797 |
| GIS | 0.0042 | 0.6125 | 0.5426 | -0.0030 | -0.2255 | 0.8224 |
| CAG | 0.0019 | 0.2796 [a] | 0.7808 | -0.0045 | -0.5105 [a] | 0.6116 |

[a] Standard error estimated with Newey-West covariance estimator.

Table 5. Test for Beta Efficiency ( $e_t = \alpha + \beta FE_t + \upsilon_t$ ), 1993.3 to 2007.3

| | Consensus | | | Time Series | | |
|---|---|---|---|---|---|---|
| Ticker | β | t-stat | p-value | β | t-stat | p-value |
| K | 0.1078 | 1.9276 | 0.0589 | -0.1899 | -0.9074 | 0.3680 |
| HSY | 0.1907 | 2.4535 [b] | 0.0172 | -0.0372 | -0.2288 | 0.8198 |
| FLO | -0.1413 | -0.9091 | 0.3671 | -0.1423 | -0.6744 | 0.5028 |
| ADM | 0.0250 | 0.1622 [a] | 0.8717 | -0.2244 | -1.5942 | 0.1164 |
| SLE | -0.0962 | -2.4390 [a] | 0.0179 | -0.2839 | -1.4869 [a] | 0.1426 |
| WWY | 0.2860 | 2.1124 | 0.0390 | -0.5555 | -1.6871 [a] | 0.0971 |
| HNZ | -0.3007 | -2.0197 [a] | 0.0481 | -0.3728 | -1.8402 [b] | 0.0710 |
| HRL | -0.1941 | -1.7227 | 0.0904 | -0.3657 | -1.5021 | 0.1386 |
| CPO | -0.3853 | -2.3430 [a] | 0.0226 | -0.4323 | -2.2058 | 0.0314 |
| GIS | -0.0012 | -0.0168 | 0.9867 | -0.3157 | -0.9099 [b] | 0.3667 |
| CAG | 0.1217 | 1.1660 [a] | 0.2485 | -0.9161 | -3.6875 | 0.0005 |

[a] Standard error estimated with Newey-West covariance estimator.
[b] Standard error estimated with White's covariance estimator.

Table 6. Test for Rho Efficiency ($e_t = \alpha + \rho e_{t-1} + \upsilon_t$), 1993.3 to 2007.3

| | Consensus | | | Time Series | | |
|---|---|---|---|---|---|---|
| Ticker | ρ | t-stat | p-value | ρ | t-stat | p-value |
| K | 0.1274 | 0.9663 | 0.3381 | 0.1512 | 1.1482 | 0.2558 |
| HSY | 0.0582 | 0.4179 | 0.6776 | 0.0582 | 0.4179 | 0.6776 |
| FLO | -0.1182 | -0.8857 | 0.3796 | -0.1182 | -0.8857 | 0.3796 |
| ADM | 0.3294 | 2.5409 | 0.0139 | 0.25 | 1.8301 | 0.0726 |
| SLE | 0.0442 | 0.5424 [a] | 0.5897 | 0.0881 | 0.6616 | 0.5109 |
| WWY | 0.1517 | 1.1493 | 0.2553 | 0.2273 | 1.7184 | 0.0912 |
| HNZ | 0.3655 | 1.7688 [a] | 0.0824 | -0.1687 | -1.2688 | 0.2098 |
| HRL | -0.0884 | -0.984 [a] | 0.3293 | 0.032 | 0.2361 | 0.8142 |
| CPO | 0.7172 | 3.9177 [b] | 0.0002 | -0.0699 | -0.52 | 0.6051 |
| GIS | 0.2253 | 1.7308 | 0.089 | 0.1777 | 1.3626 | 0.1785 |
| CAG | 0.0967 | 0.4906 [a] | 0.6256 | -0.2713 | -1.1303 [b] | 0.2632 |

[a] Standard error estimated with Newey-West covariance estimator.
[b] Standard error estimated with White's covariance estimator.

Table 7. Test for Forecast Encompassing ($e_{1t} = \alpha + \lambda(e_{1t} - e_{2t}) + \upsilon_t$), 1993.3 to 2007.3

| | Preferred Forecast - Consensus | | | Preferred Forecast - Time Series | | |
|---|---|---|---|---|---|---|
| Ticker | λ | t-stat | p-value | λ | t-stat | p-value |
| K | -0.1923 | -3.7751 [a] | 0.0004 | 1.1923 | 23.4102 [a] | 0.0000 |
| HSY | -0.1002 | -1.0420 | 0.3018 | 1.1002 | 11.4420 | 0.0000 |
| FLO | 0.3327 | 1.9160 | 0.0604 | 0.6673 | 3.8427 | 0.0003 |
| ADM | 0.2551 | 1.9173 | 0.0602 | 0.7449 | 5.5989 | 0.0000 |
| SLE | 0.0640 | 1.3834 [a] | 0.1719 | 0.9360 | 20.2364 [a] | 0.0000 |
| WWY | -0.1853 | -1.5029 | 0.1384 | 1.1853 | 9.6126 | 0.0000 |
| HNZ | 0.3129 | 2.5992 [b] | 0.0119 | 0.6871 | 5.7073 | 0.0000 |
| HRL | 0.2367 | 2.1013 | 0.0400 | 0.7633 | 6.7762 | 0.0000 |
| CPO | 0.4004 | 3.6407 [b] | 0.0006 | 0.5996 | 5.4522 | 0.0000 |
| GIS | -0.0137 | -0.1714 | 0.8645 | 1.0137 | 12.6799 | 0.0000 |
| CAG | -0.0654 | -0.9538 [a] | 0.3442 | 1.0654 | 15.5479 | 0.0000 |

[a] Standard error estimated with Newey-West covariance estimator.
[b] Standard error estimated with White's covariance estimator.

Table 8. Test for Improvement over Time ($|e_t| = \delta_1 + \delta_2 Trend_t + \upsilon_t$), 1993.3 to 2007.3

| | Consensus | | | Time Series | | |
|---|---|---|---|---|---|---|
| Ticker | δ x $10^2$ | t-stat | p-value | δ x $10^2$ | t-stat | p-value |
| K | 0.0500 | 2.8515 | 0.0060 | 0.0000 | -0.0694 | 0.9449 |
| HSY | 0.0000 | 0.5073 | 0.6139 | 0.0400 | 2.5928 | 0.0121 |
| FLO | 0.0400 | 3.1969 [a] | 0.0023 | 0.0500 | 3.4440 [a] | 0.0011 |
| ADM | 0.0100 | 0.3380 | 0.7366 | 0.1500 | 3.6857 [b] | 0.0005 |
| SLE | 0.0600 | 4.2464 | 0.0001 | 0.1600 | 6.8464 [a] | 0.0000 |
| WWY | 0.0300 | 3.2837 | 0.0018 | 0.0600 | 3.7894 [b] | 0.0004 |
| HNZ | -0.0200 | -0.4377 [b] | 0.6633 | 0.0700 | 2.5080 | 0.0150 |
| HRL | 0.0200 | 1.2328 | 0.2227 | -0.0100 | -0.5763 | 0.5667 |
| CPO | -0.1200 | -1.6156 [a] | 0.1117 | -0.0300 | -0.6385 [a] | 0.5257 |
| GIS | 0.0300 | 0.7666 | 0.4465 | 0.0600 | 1.1548 [a] | 0.2530 |
| CAG | 0.1200 | 5.4108 [a] | 0.0000 | 0.1200 | 2.9439 [a] | 0.0047 |

[a] Standard error estimated with Newey-West covariance estimator.
[b] Standard error estimated with White's covariance estimator.

Table 9. Summary of Forecast Performance Tests for Consensus Forecasts

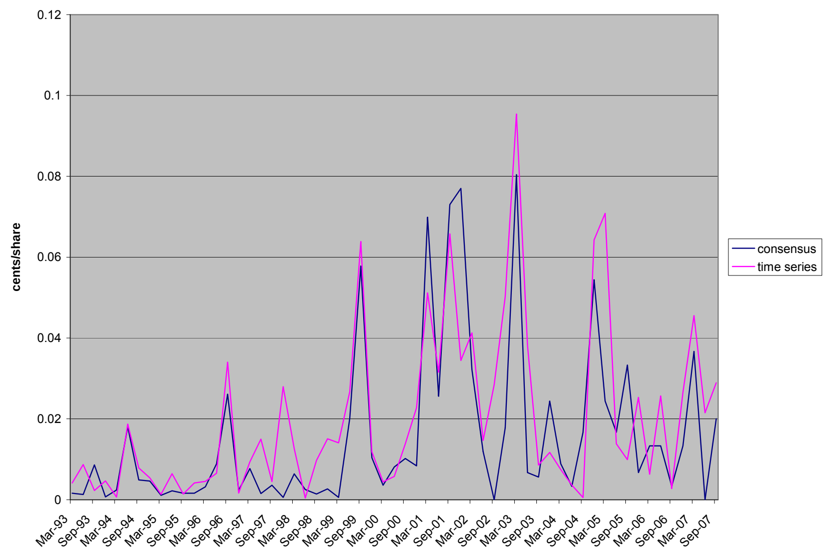
| Ticker | MDM[a] | Bias[b] $\alpha=0$ | Beta Efficiency $\beta=0$ | Rho Efficiency $\rho=0$ | Forecast Encompassing $\lambda=0$ | Forecast Improvement $\delta_2=0$ |
|---|---|---|---|---|---|---|
| K | | 5% | 10% | | 5% | 5% |
| HSY | | | 5% | | | |
| FLO | X | | | | 10% | 5% |
| ADM | X * | | | 5% | 10% | |
| SLE | | 5% | 5% | | | 5% |
| WWY | | | 5% | | | 5% |
| HNZ | X | | 5% | 10% | 5% | |
| HRL | X | | 10% | 5% | 5% | |
| CPO | X * | | 5% | 10% | 5% | |
| GIS | | | | | | |
| CAG | | | | | | 5% |

[a] X signifies that the MDM test for equality of RMSEs is not significant at the 5% level. Therefore, while the consensus forecast has a smaller RMSE than the time series alternative, it is not statistically significant. Similarly, * reflects that the MDM test for equality in MAEs is not significant. That is, the consensus forecast has a smaller MAE than the time series alternative, but it is not statistically significant at the 5% level.

[b] 5% reflects that the null hypothesis of the respective test was rejected at the 5% level. 10% represents that the null hypothesis of the respective test was rejected at the 10% level.

Figure 1 – Absolute Forecast Errors, 1993.3 to 2007.3[a]

FLO




SLE

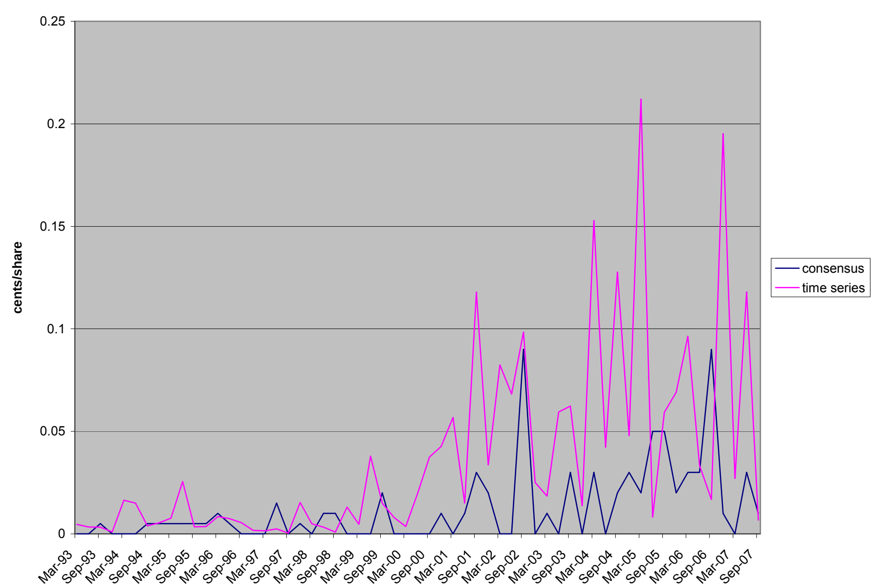
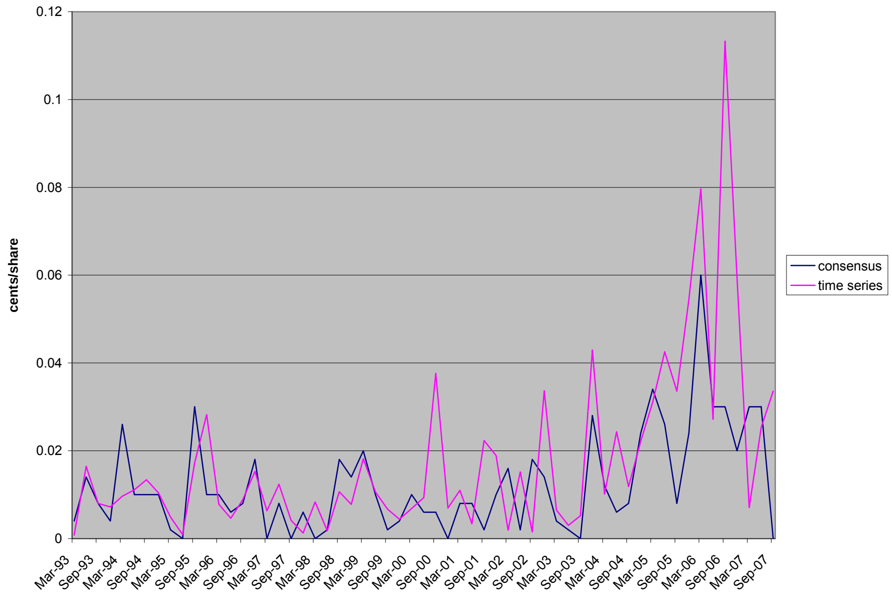
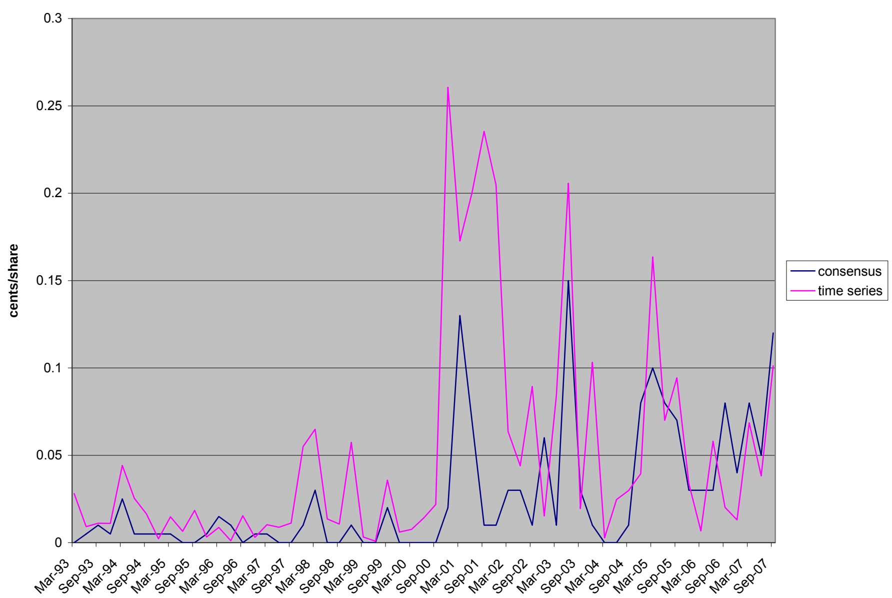


Figure 1 Continued – Absolute Forecast Errors, 1993.3 to 2007.3[a]

WWY




CAG




[a] Absolute forecast errors are defined as the absolute value of $e_t$ where $e_t = AE_t - FE_t$