The Accuracy of USDA's Export Forecasts

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November 1992

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Abstract

USDA's quarterly forecasts of fiscal year agricultural exports by commodity and region were examined for their reliability *in* predicting annual changes during 1977-89. Most of the forecasts were strongly correlated with actual exports. Most obvious exceptions probably stemmed from rounding errors. Bias was not a problem for the forecasts of total exports in any quarter, nor for most of the commodity forecasts. There was some upward bias in the forecasts for less developed countries, and downward bias for some developed countries. The USDA forecasts were conservative; they were more likely to underestimate the magnitude of change than to overestimate it.

Keywords: Exports, fore casting, accuracy, export programs, commodities, high-value products.

Acknowledgments

The author would like to thank Carlos Arnade, Linwood Hoffman, Mark Smith, David Stallings, Ronald Trostle, and Thomas Warden for helpful comments, and Kelly Kirby-Flowers for historical data.

Washington, DC 20005-4788 November 1992

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Introduction

The U.S. Department of Agriculture's (USDA) short-term forecasts are probably the most widely disseminated agricultural forecasts in the world. They are generally believed to be accurate, and, while specific forecast1s are occasionally questioned, they remain the benchmark against which alternative forecasts are compared. The accuracy of USDA's forecasts is, therefore, of vital concern. This report examines the accuracy of the fiscal year forecasts of U.S. agricultural exports that USDA publishes quarterly in its Outlook for U.S. Agricultural Exports.

USDA's quarterly export forecasts were found to be largely efficient and unbiased, although they showed signs of being consistently cautious. The forecasts for grain exports were the most accurate of the group. They generally had the smallest percentage error and the best correlation, but the magnitude of change was conservatively forecast. Given the importance of grain to total exports, this led to conservative forecasts of change for total U.S. agricultural exports. Cotton exports were also accurate, matching grains in correlation, but showing upward bias and larger average errors.

In addition to cotton {'value), USDA's forecasts were determined to be upwardly biased for Eastern Europe, South Asia, East and Southeast Asia, the Middle East, and North Africa. Forecasts were determined to be downwardly biased for rice (volume), animal fats, sugar and tropical products, the former soviet Union, and Latin America. USDA's forecast for livestock products was also biased downward, but that was probably due to a tendency to underestimate change coinciding with a period of rapidly rising exports. Although the result of this tendency was a set of forecasts that averaged significantly lower than actual exports, such bias would probably not have appeared if livestock exports had trended downward or tended not to grow.

It *is* desirable to eliminate systematic errors from any forecast, but increasing forecast reliability is likely to entail costs. Any desire to improve forecast accuracy must be balanced by considerations of how costs compare with benefits. In any case, the first step is discovering systematic errors. Unforeseeable events will always result in some forecast error, but when errors fall into discernible patterns, they represent behavior that can be altered to improve forecast accuracy.

USDA's Forecasts

Each month USDA publish• s forecasts of the annual levels of production, consumption, trade, and stocks for key commodities and countries. The forecasts are produced by an interagency process that includes the Agricultural Marketing Service (AMS), the Agricultural stabilization and Conservation Service (ASCS), the Economic Research Service (ERS), the Foreign Agricultural Service (FAS), National Agricultural Statistics Service (NASS), and the World Agricultural outlook Board (WAOB). Annual U.S. average farm prices are also forecast for key commodities each month. These are forecasts of annual totals on crop marketing years or calendar years, and they are published in the <u>World Agricultural Supply and Demand Estimates</u>.

Every 3 months USDA publishes forecasts of U.S. fiscal year exports for a smaller group of commodities in the <u>Outlook for U.S. Agricultural Exports</u>. Forecasts for most of these commodities are also published monthly, but some forecasts are published only quarterly. Total agricultural export value and volume forecasts for the United States are available only quarterly. The same is true of all the other forecasts of annual export value. These include forecasts of the total value of U.S. agricultural exports to selected countries and regions during the current fiscal year and forecasts of commodity export values. The forecasts analyzed included 15 different commodities by value, 10 commodities by volume, and 21 regional aggregations. Forecasts published during 1977-89 were studied.

Quarterly forecasts are produced through an interagency process, but with only ERS, FAS, and the WAOB participating. As much as possible, these quarterly forecasts are intended to be consistent with the most recent monthly forecasts, which precede the quarterly forecasts by a few weeks. Quarterly forecasts are consistent with the monthly forecasts even when more current information indicates that conditions determining the monthly forecasts have changed. This is unusual and is acknowledged in the outlook for U.S. Agricultural Exports when necessary. Updates are published between quarters if circumstances warrant. These updates were not included in this analysis.

Table 1--Timing of USDA's quarterly export forecasts

Order of publication	Month published	Export data available
First quarter	November or December	None
Second quarter	February	October-December
Third quarter	May	October-March
Fourth quarter	August	October-June

The first forecast of the fiscal year is published in late November or early December when no official trade data are available {table 1). A revised forecast is published 3 months later in late February with actual export data available for the first 3 months of the fiscal year. When the next revised forecast is published, 6 months of actual data are available, and when the final forecast is published, 9 months of actual data are available. In other words, the final forecast of total fiscal year exports is actually made with only 3 months of exports unknown. These later forecasts are therefore very accurate.

An important point is that each quarter's forecasts are conditional on different information sets. Throughout this report, four sets of quarterly forecasts are compared. These are not necessarily forecasts made through different processes (for example, using different models), but forecasts made with increasing amounts of information. The question of what sort of models produce the forecasts is a good one. In general terms, the process is best described as using a "delphic" method, averaging the judgment of a large number of experts.

Forecast Analysis

In this report, USDA's quarterly forecasts of fiscal year exports were tested by regressing actual exports (A_i) on export forecasts (F_i). These regressions yielded measures of correlation that are used to measure efficiency. The regressions also provided estimated coefficient values that were tested to determine bias and consistency. Regression analysis was used rather than decomposition of mean squared error {MSE} because of regression's superior ability to separate the effects of bias and consistency (see Appendix). Regression analysis also lends itself to statistical testing to determine the significance of the results.

"Efficiency's" general econometric meaning refers to an estimator's "spread" around its expected value. In this report, the term efficiency is used in a somewhat similar sense and is measured by the correlation between a forecast (F) and its actual variable (A). Correlation is used rather than a measure of variance between F and A (σ_{F-A}) in order to allow comparison between different forecasts because correlation is always between 0 and 1 regardless of the magnitude of the variables. Correlation is also affected by the randomness of the spread. A forecast with low σ_{F-A} might be less accurate than one with a high σ_{F-A}. To completely understand forecast error, knowledge of the pattern of error is as critical as that of its size.

Bias refers to whether we can expect the forecast to exceed the actual variable or perhaps vice versa. The expected value of the difference between the forecast and the actual variable must be zero for the forecast to be unbiased:

$$E(F - A) = 0.$$

Consistency generally refers to the asymptotic property of an estimator: the increasing accuracy of an estimator's ability to approximate the parameter as sample size increases. In this report, consistency also refers to a parameter value. Consistency is perhaps best understood here as the forecast's ability to predict the magnitude of change in a variable. Consistency refers to a parameter value because when a series of annual forecasts are compared with the respective actual values of the variable through a regression equation,

$$dA_i = \alpha + \beta dF_i + e_i,$$

then a consistent forecast is one where the estimated $\beta = 1$. Inconsistency and bias may be indistinguishable in some cases. If an otherwise perfect forecast were decreased by 10 percent every year, there would be a downward bias equal to 10 percent of the average value of the actual data over the sample period, and β could equal 1.11.

Consistency and bias also determine if a forecast is rational. Forecasts have been used to measure expectations and tested to see if these expectations conform to the rational expectations hypothesis. If a test of α and β estimated in the above Regression $\alpha = 0$ and $\beta = 1$ cannot be rejected, then the forecast is described as rational. This is a weak-form test for rationality (7).[1] This report does not explicitly explore whether USDA's export forecasts are rational, but most of the forecasts described in this report as either biased or inconsistent also fail the above weak-form test for rationality.

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[1] Underscored numbers in parentheses refer to citations in the References section.

Whether or not bias and inconsistency are separable depends on the behavior of the actual variable. In the example above, if the actual variable always fell or always rose, then β = 1.11. If the variable rose half the time and fell half the time in roughly the same magnitude, then β =1.00, and the bias would be obvious. Figure 1 presents an example of the first case, with actual U.S. exports to Eastern Europe largely declining during 1977-89. The forecast is inconsistent and almost significantly biased, and evidence for both can be seen in the graph. Figure 2 is an example of an inconsistent forecast with no bias. U.S. exports to Sub-Saharan Africa rose and fell in an offsetting manner during 1977-89, but the USDA forecast underestimated the magnitude of change in 10 out of 13 years.

In this report, most of USDA's forecasts examined were determined to be efficient. The exceptions were largely confined to commodities or regions where exports were so small that rounding played a significant role in determining the forecast. In the first quarter (the forecasts published in November or December), only two forecasts had average errors above 22 percent, and by the last quarter (published in August) the forecast for total U.S. exports was wrong by less than 2 percent on average. Few commodity 'forecasts appear biased, but both upward and downward bias were more common in the regional forecasts.

Some key forecasts showed signs of inconsistency. The magnitude of change in total U.S. export value was typically underestimated. The same was true of grain exports, particularly when exports were falling. Underestimating the magnitude of change was more common than overestimating it.

Methodology

Mean squared error (MSE) is perhaps the most frequently used measure of forecast accuracy. It is particularly appealing when comparing various models predicting a common dependent variable. If the various models' equations are estimated using ordinary least squares (OLS), then each model's parameters will be estimated so as to minimize the sum of squared errors (SSE). Taking a mean of the squared errors simply normalizes SSE by sample size:

$$MSE(F_i) = \frac{1}{N} \sum_{i=1}^{N} (F_i - A_i)^2$$

where F is the series of forecasts and A the actual data.

The goal in this report is to measure the reliability of forecasts of many different variables rather than one variable with different models; MSE is not an appropriate statistic

Figure 1--U.S. exports to Eastern Europe: Actual and third quarter forecasts

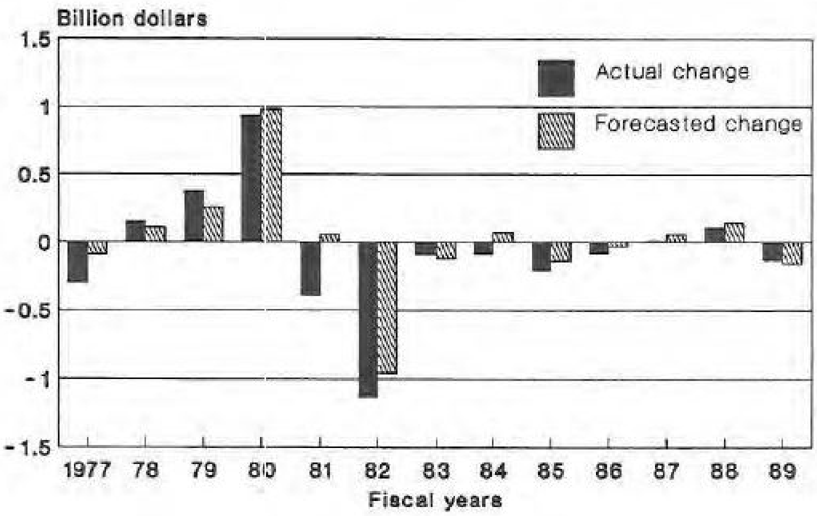
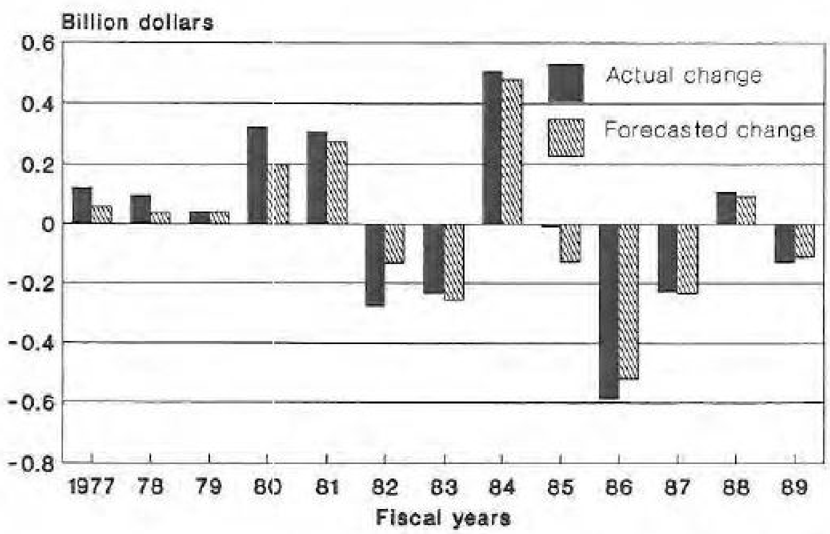


Figure 2--U.S. exports to Sub-Saharan Africa: Actual and fourth quarter forecasts



because the MSE of a variable averaging $30 billion would not be comparable to the MSE ,of a variable averaging $300 million. However, MSE can be "decomposed" into components that provide more specific characterizations of forecast reliability. The simplest decomposition,

$$MSE(F) = \left(\overline{F} - \overline{A}\right)^2 - \sigma^2_{(F-A)}$$

separates MSE into a statistic measuring bias and another measuring the variance of the forecast errors. The effect of bias on forecast accuracy is clear, but the inevitable variation of the errors can take many forms. Therefore, a simple measure of forecast error variance is inadequate in characterizing reliability. Also, the variance of forecast errors (as with MSE) is not independent of the magnitude of the variables in question.

Correlation, however, is independent of magnitude. Granger and Newbold (1) demonstrate through a further decomposition of MSE that correlation between a series of forecasts and a series of matching actual data is a good measure for analyzing these further errors in variation.

$$MSE(F) = \left(\overline{F} - \overline{A}\right)^2 + \sigma_F^2 + \sigma_A^2 - 2\rho_{FA}\sigma_F\sigma_A$$

$$\sigma_j = standard\ deviation\ of\ j$$

$$\rho_{FA} = correlation\ of\ A\ and\ F.$$

This equation shows that MSE(F) is minimized by a smaller bias and a larger correlation. Equivalence between the two series' variances would not minimize MSE(F), except when bias is zero and correlation is perfect:

$$\frac{\partial MSE(F)}{\partial \sigma_F} = 2\left(\sigma_F - \rho_{FA}\sigma_F\sigma_A\right), \text{ and}$$

$$\sigma_F = \rho\sigma_A.$$

Kost (6), Maddala (8), and others point out that correlation is a poor measure of forecast reliability because it does not account for bias or some other systematic linear error. Correlation, however, is not the sole measure of reliability in this report, but it is combined with further measures of bias and consistency.

The accuracy of USDA's quarterly forecasts of U.S. agricultural exports by commodity and region were analyzed by regressing series of actual data on their respective forecasts:

$$dA_i = \alpha + \beta dF_i + \varepsilon_i .$$

These regressions yielded coefficients of determination (R^2) that were used to measure the efficiency of the forecasts and coefficient values that were tested to determine bias and consistency[2]. As the "d" preceding A_i and F_i implies, forecasts were examined as forecasts of the amount of change.

This is not the form in which they were published. USDA publishes its forecasts as rounded actual values. The previous year's level of the variable was subtracted from the published forecast for the current year. Thus, $dA_i = A_i - A_{i-1}$ and $dF_i = F_i - A_{i-1}$. Regardless of whether the forecast is measured as dF_i or as F_i, if a forecast is perfect throughout the sample, then $A_i = F_i$, $dA_i = dF_i$, and, therefore $\alpha = 0$ and $\beta = 1$. Similarly, the level of bias will be the same regardless of how the forecast is stated.

Expressing the forecast as a difference removes the effect of a trend that is irrelevant to understanding the pattern of errors in these particular forecasts. Long-term trends will always be embodied in the F_i forecasts. However, the forecasts studied here are always for one period ahead. Therefore, any trends of the preceding years will spuriously appear to be correctly forecasted. That is, including long-term trends will raise measured forecast accuracy to no useful end.

In addition to inflating R^2, when one uses A_i and F_i rather than dA_i and dF_i, one also introduces a multiyear effect into the estimated β. The only difference between the two series, A_i and F_i, will be the errors in F_i's single-year forecast. The value of β in the regression will reflect the apparent errors in forecasting the trend introduced by incorrectly forecasting one year's change. It would be difficult to meaningfully interpret β in such circumstances.

The use of A_i and F_i rather than dA_i and dF_i can be described as imposing a strong restriction on the model below:

$$\begin{aligned}
&Given, F_i = dF_i + A_{i-1}, then \\
&\quad A_i = \alpha + \beta_1 F_i \\
&\quad A_i = \alpha + \beta_1(\beta_2 dF_i + \beta_3 A_{i-1}) \\
&with\ \beta_2 = 1, \\
&and\ \beta_3 = 1.
\end{aligned}$$

Using dA_i and dF_i imposes only one restriction, $\beta_3\beta_1 = 1$.

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[2] In a regression with one independent variable, the square root of the R^2 equals the simple correlation between the dependent and independent variables.

In some studies, the term efficiency has a broader meaning that combines both consistency and efficiency. For example, both Thomson (9) and Dietrich and Gutierrez (1) use the above regression to test reliability. In both articles, $\beta = 1$ is described as a test of efficiency. In fact, β can be affected by bias (see Appendix), and a forecast with $\beta \neq 1$ and $\beta \neq 0$ can be quite different from one with β = 0. Kost (6) describes efficiency more broadly, saying both $\alpha = 0$ and $\beta = 1$ are necessary for a forecast to be efficient, but he also notes that these conditions are necessary to ensure an absence of bias. Granger and Newbold demonstrate that some forecasts meeting these two conditions are far from efficient, "according to any acceptable interpretation of that word" (p. 40, 3).

Efficiency has a more restrictive meaning in this report. Efficiency is measured with little reference to the regression coefficients, using correlation. Consistency refers to the ability to correctly forecast the magnitude of change and is determined by testing $\beta = 1$.

Suppose a hypothetical forecast for grain exports published during each of the four quarters is examined. The first quarter's forecast may not be correct in forecasting even the direction of change. In that case, the regression will probably yield an estimated value for p that is not significantly different from zero. This is because there is too much random error in the forecast to yield a statistically significant relationship between dA_i and dF_i. Correlation will naturally be low. In this study, the highest R^2 of a regression with an estimated $\beta = 0$ was 0.43, with results below 0.20 more common.

The next earliest forecast will probably be more efficient. Correlation would be higher and regression would probably yield a value of f3 significantly different from zero. The weakest definition of efficiency would describe any forecast with a regression value of significantly different from zero as efficient. In other words, the amount of random error is small enough to reveal some relationship between dA_i and dF_i. Because most of the forecasts examined surpass this criterion, the additional condition that the R^{21} s of their respective regressions must be at least 0.80 was arbitrarily imposed. With an R^2 of at least 0.80, correlation between actual and forecasted change reaches at least: 0.89. The forecast is usually correct with respect to direction of change and has limited variation in errors in predicting the magnitude of change.

If a forecast is efficient, then $\beta \neq 0$, and if there is no bias, then testing the difference of the estimated β from 1 reveals consistency. If the forecast's estimated value of β is not significantly different from 1, then there is no tendency to over- or underestimate the magnitude of annual change. If β is less than 1, change is typically overestimated: if β is more than

1, change is underestimated. This is distinct from bias, which would depend on the average level of forecasted change. For example, inconsistency would be likely if USDA forecasted a $250 million decline one year and then a $600 million increase the next, while the actual changes in those years were $200 million down, then $500 million up. First, USDA would have made a 25-percent overestimate of a decline, and then a 20-percent overestimate of an increase. The forecasts differ in that one is too high and one is too low, but the average level of the estimates is close to zero. Bias would be likely if the second forecast had been a $400 million increase rather than $500 million. Then the forecasts are too low in both years, with an average further from zero.

Bias and consistency are not always so obviously separated. The above examples involve a variable that both increases and decreases. Over a longer period, the variable would possibly average to zero, showing neither an increasing nor a decreasing trend. If the actual data are always changing in one direction, then bias in the same direction implies that change is typically overestimated, and bias in the opposite direction implies that change is underestimated. If change in the actual data averages to zero (no trend) and a forecast is biased, then 1) there are offsetting errors in estimating the magnitude of change, 2) there are errors in predicting the magnitude of change in one particular direction, or 3) the pattern is unclear. The relationship between bias and consistency is discussed in the section on consistency.

Another summary statistic presented for each forecast series is mean absolute percent error (MAPE) (tables 2-4). MAPE provides comparison between forecasts of series with different average values. The errors are put into absolute values to ensure that over- and underestimates do not offset into a mean of zero. Squaring errors for a MSE serves the same purpose, and a square root of a mean squared percent error (RMSPE) would provide a statistic similar to MAPE. The difference between RMSPE and MAPE is that RMSPE gives larger weight to larger errors.

Results

Examination of 48 series of U.S. agricultural exports forecast by USDA found that forecasts made during the first quarter have MAPE generally ranging from 6 to 22 percent (tables 2-4). Two forecasts exceeded this range, the forecasts of U.S. exports to China and the former USSR, with MAPE of 66 and 37 percent, respectively. China and the former USSR were generally the world's largest grain importers during 1977-89. They were also the world's largest grain producers, and their imports fluctuated widely with shortfalls in production. The first quarter's forecasts are published well in advance of the period when grain supplies in these countries are determined for the year and, therefore, well in advance of events determining their highly variable demand for gratin. A relative lack of reliable information concerning events within these countries also hampered forecast accuracy during the period studied.

Much of the 37-percent average error in the forecasts for the former USSR stems from a partial U.S. embargo on grain sales to the Soviets following the Soviet invasion of Afghanistan. If that year were excluded, the average first quarter error would be 27 percent, much closer to the normal range. This illustrates an important point about forecast accuracy. A forecast can be inaccurate because either the forecaster does not understand how circumstances can affect trade, or because these circumstances change. The former error should be avoided, while the latter is often unavoidable.

The first-quarter forecast of total export value tended to be off by 10 percent, and volume by 8 percent. By the last quarter, the forecast for total export value had a 1.4-percent MAPE, and the forecasts' MAPE for most major commodities were below 5 percent. The regional forecasts were only slightly less accurate. Most of the forecasts for individual commodities and regions were only slightly less accurate than the forecasts for total value and volume. Better accuracy in the total forecasts is not surprising because they are aggregations of the individual commodity forecasts. Offsetting errors among the commodity and regional forecasts probably improve the accuracy of the totals.

The accuracy of the forecasts in most cases improved with each subsequent quarter, in other words,

$$MAPE_1 > MAPE_2 > MAPE_3 > MAPE_4$$

and,

$$R^2_1 < R^2_2 < R^2_3 < R^2_4 .$$

The only exceptions were the value forecasts for rice, dairy products, Oceania, and Canada, and the volume forecasts for animal fats, tobacco, and rice. The exceptions number less than 10 percent of all forecasts examined.

Most of these exceptions are probably the result of random rounding errors. Forecasts are published in rounded numbers: to the nearest $100 million and 100,000 tons. If a commodity's exports never vary by more than these amounts, forecast errors are inevitable. Tobacco volume forecasts were particularly vulnerable: exports were always between 200,000 tons and 300,000 tons during 1977-89, often closer to 250,000 tons than to any publishable forecast. Similarly, exports to Oceania have slowly fluctuated between $200 million and $300 million.

Canada is a special case due to chronic reporting errors. During 1977-89, U.S. agricultural exports to Canada were underreported by as much as $1 billion each year. Canadian import data showed about SO percent more U.S. agricultural products entering Canada than did the U.S. export data reported by USDA and the U.S. Department of Commerce. For the forecasts to correctly align with the underreported export data, it would have been necessary to both estimate what Canada imported and what went uncounted.

There is no such simp1le explanation for rice. The rice forecasts are examined more carefully in the discussion of consistency.

Correlation

Efficiency was naturally weakest for the first-quarter forecasts. Less than half the R^2 values for the first-quarter commodity forecasts were above 0.50 (tables 5-7). Total export value had an R^2 of 0.38, while volume reached only 0.20. A total of 14 first-quarter forecasts were so explicitly inefficient that β was not significantly different from zero, including total export volume.[3] The regional forecasts generally have slightly better R^2 values than the commodity value forecasts, and the commodity value forecast R^2 values were better than those for volume. This was true in every quarter.

By the fourth quarter, it was unusual to find R^2 values below 0.90, and common to observe values above 0.95. Out of 20 regional forecasts analyzed, 13 showed R^2 of at least 0.95. The same was true with most of the other forecasts.

The regional forecasts were more efficient in all quarters, and value was also more efficient than volume. (These are very general statements based on the frequency that any forecast's R^2 in one group significantly exceeded any forecast's R^2 in another group.[4]) When accuracy is measured by MAPE, the regional

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[3]The other forecasts were: Western Europe, North Africa, the Middle East, Other Latin America, developed countries, oilseeds and products, soybean value, soybean meal value, livestock products, co2trse grains volume, tobacco volume, animal fats volume, and other volume.

[4]The further the population correlation is from zero, the more skewed is the sample distribution of its estimator. We assume all correlations; between these forecasts and their respective variables are substantially different from zero. However, it is possible to transform such a sample correlation into a variable that is normally distributed, assuming that the

forecasts are less accurate than the commodity forecasts. One implication is that there is more systematic error in the regional forecasts and more random error in the commodity forecasts. Bias is found more frequently among the regional forecasts, as noted earlier. This may be the source of the higher MAPE, since inconsistency does not seem particularly more common among the regional forecasts.

The higher R^2 values for the regional forecasts may also reflect differences in the characteristics of global versus regional trade. An individual country's demand for imports varies more than global demand; therefore, there is somewhat more variation in U.S. exports by region than by commodity. Given two forecasts--one commodity and one region, for example--equally accurate in terms of MAPE, but with more variation in exports to the region, then the regional forecast will show higher correlation with actual exports.

The commodity value forecasts were more accurate than the volume forecasts both in terms of MAPE and R^2. USDA generally bas enough information about global supply and demand to correctly forecast the direction of change. This makes the value forecasts more accurate because they embody the correct direction in prices as well as volume.

The greater ease of forecasting export value is also demonstrated by differences in how accuracy increased from one quarter to the next. The R^2, as noted above, rises almost invariably. However, some of these changes were too small to be statistically significant. Statistically significant improvements in R^2 are more common for the regional and volume forecasts than for the commodity value forecasts in any quarter-to-quarter comparison.

No forecast's R^2 showed a significant deterioration, but some forecasts never improved from one quarter to another.[5] The forecasts failing to improve their correlation were generally the same forecasts that showed anomalous quarter-to-quarter changes *in* MAPE. These forecasts also failed to reach the R^2 threshold of 0.80, along with the forecasts for other volume and Oceania.

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sample size is larger than 10 (4):

$$z_r = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right), with$$

$$\sigma_{z_r} = \frac{1}{\sqrt{n-3}}.$$

The transformed variable lends itself to statistical testing.

[5]Tobacco value and volume, dairy, and animal fats.

Most forecasts by the third quarter had R^2 exceeding 0.80. Exceptions included the forecasts for high-value products (HVP). The third-quarter forecasts for livestock, poultry, dairy, and horticultural products all had an R^2 below 0.80. The below-average accuracy of these forecasts may reflect the effect of the data problems with Canadian trade. Canada is one of the largest buyers of HVP's from the United States. Horticultural products, however, performed the best of this group, with a third-quarter R^2=0.76, and horticultural exports were the most underreported of any commodity group.

Relatively poor efficiency for the HVP forecasts may have stemmed from a concentration of USDA's resources on program commodities. The differentiated nature of these goods multiplies the number of markets that would have to be monitored to anticipate events. Furthermore, USDA's intelligence gathering and analysis are geared toward low-value crops because of several priorities. One priority is that durin9 much of the past 20 years, low-value products have dominated U.S. agricultural exports, Also, a substantially larger proportion of U.S. production is exported for low-value crops than for most high-value products. Perhaps most important, domestic commodity programs involving substantial Government expenditure exist for most low-value crops, necessitating increased vigilance by and for policymakers.

Another third-quarter forecast with an R^2 below 0.80 was soybean value. Soybean value was not particularly inconsistent with an R^2=78, but this R^2 was significantly below the R^2 for wheat, cotton, and coarse grain value. In all quarters, the oilseed product forecasts seemed less consistent than grain forecasts. For example, the direction of change in wheat volume and coarse grain value were always correctly forecast. But, the direction of change for oilseeds and products was incorrectly forecast 54 percent of the time. The first quarter R^2 values of grains and feeds and oilseeds and products were significantly different at 0.60 and 0.05, respectively. Finally, among the very few forecasts whose R^2 surpassed 0.80 during the second quarter are grains and feeds, coarse grains value, and cotton value and volume.

The United States accounts for a substantially larger share of world trade in soybeans than for grains or cotton. During 1977-89, the U.S. share of world trade in soybeans was as high as 92 percent, while wheat, coarse grains, and cotton peaked at 47, 72, and 39 percent. Both the number of significant competitors and the number of significant customers are smaller for soybeans than for other products, and competitors are largely confined to the Southern Hemisphere. This concentration increases the effect of unforeseen events in key countries. Finally, the reliability of the cotton export forecasts is probably improved by cotton importers' extensive use of forward contracting.

This uncertainty in soybean trade probably accounts for the poor consistency of USDA's forecasts for Western Europe. Grain exports to Western Europe declined significantly during 1977-89, as the European Community's price supports drove grain production steadily higher. As a result, U.S. agricultural exports to Western Europe are almost exclusively composed of oilseeds and products and high-value products, all products with inconsistent forecasts in the early quarters.

Bias

As forecast efficiency improves in the later quarters, one can measure bias and consistency. The ability to measure bias does not necessarily depend on strong correlation, but the weaker the bias, the greater the correlation must be to prove it is not a random occurrence.

In the regression equations shown earlier, the average difference between the forecasts and actual exports (or bias) can be found and tested by estimating with β restricted to 1. If the forecast is biased, then the estimated value of α will be significantly different from zero. This is essentially a "matched pair" test where the differences between the forecasts and actual trade are averaged across the sample (4). For example, the first-quarter forecasts for exports to North Africa averaged $124 million higher than actual exports during 1977-89 (table 8). This is the estimated bias resulting either from a restricted regression or from the matched-pair test.[6]

Bias occurred more frequently in the regional forecasts than in the commodity forecasts, and upward bias was more often found to be statistically significant than downward bias. Upward bias was generally found among the forecasts for the less developed countries and downward bias in the forecasts for developed countries.

The forecasts for North Africa and South Asia were upwardly biased in every quarter, although by smaller amounts in later quarters (table 8). During the first quarter, these forecasts were the only two that demonstrated statistically significant bias, with North Africa $124 million too high and South Asia $186 million too high. In the last two quarters, Eastern Europe, the Middle East, and East and Southeast Asia were biased upward.

[6]The standard deviation of this average bias is calculated differently in the matched pair test than is the deviation for α in the restricted estimations. Usually both tests give the same results. The t-statistic for α in the restricted equation is used in this report.

Downward bias was more frequent among the commodities. However, cotton value forecasts were upwardly biased during the third and fourth quarters (by $77 and $61 million, respectively) and coarse grain value was upwardly biased by $353 million in the third quarter. Rice volume forecasts were downwardly biased during the last three quarters, and livestock products during the second quarter. The downward bias for tobacco volume and animal fats is less significant because these forecasts show such poor efficiency.

Coarse grain value's upward bias was large, but the size of the sample examined was below 10 observations. The smaller the sample, the less likely is one to find a normally distributed mean if the population is not normally distributed, and the less likely these tests are appropriate. Most of the forecasts analyzed here had been published for 13 years, every year since the U.S. Government switched its fiscal year to October-September. But some forecasts were published for fewer years. The first forecast in the Outlook for U.S. Agricultural Exports for the value of U.S. coarse grain exports was published in May 1981. Note that the coarse grain volume forecast, with a sample size of 13, does not demonstrate bias. If only forecasts since May 1981 are used, then the volume forecasts are also biased upward (see section on Consistency).

Although USDA does not publish explicit export price forecasts, an average price is implied when forecasts of value and volume are published for a commodity. Rounding in the published forecasts often deprived these implied prices of precision, but they are strongly correlated with actual average export prices.

No bias was apparent in the coarse grain implied price forecasts, but cotton and rice prices were biased upward (table 9). Upward bias in the cotton price probably accounted for the bias in cotton value, but upward bias in rice prices offset downward bias in rice volume. The rice value forecasts were unbiased as the opposing biases of volume and price offset each other. Possibly, biased price expectations were an input in a biased export forecast, or vice-versa.

Effect of Partial Year Export Data on the Forecasts

Examining how USDA's forecasts might be formed offers some evidence useful in discerning the source of bias. When the three forecast updates are published, actual data for part of the year being forecast are available (see table 1). This partial year data can be compared with exports during the same portion of the previous year. The comparison is inevitable, and, given the strongly seasonal nature of U.S. agricultural exports, it is also a useful forecasting tool (5). In a few isolated cases, the following naive model

$$dF'_i = \frac{(PA_i - PA_{i-1})}{PA_{i-1}} A_{i-1}$$

(PA referring to partial year actual data) gave better forecasts than USDA's interagency process. This naive model extrapolates the percentage change in the partial year data to cover the entire year. In two cases, dF'_i from the above model was more correlated with actual exports than were the published forecasts.[7] But, more frequently the published forecasts were significantly more efficient than the above model.

Two cases stand out. The naive former USSR forecast achieved an R^2 of 0.21 in the third quarter versus an R^2 of 0.92 for USDA's published forecast. For North Africa, the naive model's R^2 was 0.23 versus an R^2 of 0.76 for USDA's forecast. Because USDA's forecast performance far exceeded that of the naive model, it is obvious that USDA used more information than year-to-date trade performance to forecast U.S. trade with the former USSR and North Africa.

These naive forecasts provide a benchmark for comparison with USDA's forecasts. In several reports on USDA's forecast accuracy the General Accounting Office (11) suggested that USDA find benchmarks to gauge forecast accuracy. The above results indicate that in some important respects, USDA's forecasts compare favorably with the benchmark.

In addition to comparing the benchmark's ability to correlate with actual exports to the USDA's ability, it is useful to see if USDA was biased with respect to the benchmark. Were USDA's forecasts consistently higher or lower than the benchmark derived solely from the partial year data? If so, the question then becomes whether the decision to disregard this information improved USDA's accuracy. Generally, it did not, and, in this respect, USDA's forecasts do not compare favorably with the benchmark.

Following the methodology used earlier, one first hypothesizes,

$$dF_i = \alpha + \beta dF'_i$$

and estimates the coefficients with ordinary least squares with β restricted to 1. This is equivalent to a matched-pair test to determine bias. In this case, the goal is to determine if the forecasts are biased with respect to one particular set of

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[7]For livestock products in the second quarter, $R^2 = 0.44$ for dF'_i, versus $R^2 = 0.08$ for dF_i, and for horticultural products in the third quarter, $R^2 = 0.93$ for dF'_i, versus $R^2 = 0.76$ for dF_i.

evidence. Table 10 lists forecasts that demonstrate this sort of bias, most of which also demonstrated overall bias in table 8. Japan is significantly biased in table 10 and is almost significantly biased in table 8 in the same quarters. In other words, although USDA's forecasts did not demonstrate significant overall bias, the forecasts were regularly based on a belief that the rate of growth in exports to Japan would slow later in the year. If published forecasts for Japan are converted into annual percentage changes, the forecasts are significantly biased downward, compared witr1 actual annual percentage changes (table 11).

USDA's forecasting procedures for exports to the Middle East and South Asia appeared upwardly biased in the third quarter, and North Africa (almost significant) and East and Southeast Asia test similarly in the fourth quarter. Forecasts for the Middle East were biased $122 million upward in the third quarter, North Africa $50 million upward in the fourth quarter, South Asia $76 million in the third quarter, and East and Southeast Asia $128 million in the fourth quarter. The only other regional forecast with both forecast bias and an apparently biased forecasting procedure was Oceania in the second quarter (both downward).

Sources of Bias in Regional Forecasts

This report does not attempt to exhaustively explore the causes of bias in the regional forecasts. But, a number of the upwardly biased forecasts share some characteristics that may be relevant to their bias: 1) U.S. Government programs were involved in one-third to three-fourths of the total exports to these regions, substantially more than average, 2) wheat and rice accounted for a substantially higher than average proportion of U.S. exports to these regions, and 3) exports tended to rise to some of these regions during the period studied.

U.S. Government programs are involved in a large share of exports to most of the upwardly biased regions. This is the characteristic common to the largest number of these regions. Exports are included in the Government share if they are shipped through Public Law (P.L.) 480, the Export Enhancement Program (EEP), Section 416, or USDA credit guarantees. The highest share of exports under U.S. Government programs for any region was held by an unbiased forecast, Sub-Saharan Africa. Excluding Sub-Saharan Africa, the highest Government share of exports of any region was found in five of the upwardly biased regions. In 1985, the last year with no EEP shipments, U.S. Government programs accounted for 15 percent of all U.S. agricultural exports, the highest in 13 years. Shares were substantially higher, however, for Middle East, North Africa, South Asia, and Eastern Europe with 30 percent, 52 percent, 74 percent, and 33 percent, respectively.

Sub-Saharan Africa is a special case because of multilateral cooperation among food aid donors. Because concessional, humanitarian food aid consistently accounts for a substantial portion of the region's imports, donors regularly consult and cooperate to ensure that food flows to the region are sufficient and orderly. Therefore, many of the decisions regarding the levels and sources of food imports are made by donors rather than by importers or governments in Sub-Saharan Africa. The donors jointly make their decisions. This multilateral element is largely missing from the other regions where the U.S. Government share of U.S. agricultural exports is high.

The upward bias in forecasted exports to these regions may have reflected optimism within USDA concerning the efficacy of Government programs to promote exports. At the time U S. program details are determined, USDA may have every reason to expect that each allocation will be consummated by sales. The resources available to these programs are not unlimited, and, if USDA plans to assist sales in one case, then it must exclude assistance in another case. Correctly anticipating which customers will respond to offers under U.S. programs reduces the effort and costs required to later reallocate unconsummated offers. However, circumstances can change very quickly. As a 1986 ERS report noted for North Africa,

> [C)ompetition...usually takes the form of credit terms for financing wheat sales. Because the terms of the credit packages of the major suppliers vary considerably, the actual unit cost of wheat...often varies considerably within a given marketing year. The annual market shares of the supplier nations are determined accordingly. (p. 26, 2)

In other words, USDA may formulate plans to assist exports based on what it believes is likely to be actually purchased. USDA then bases its published export forecasts on this information. Competing exporters, however, pursue pricing strategies of undercutting U.S. prices. The United States has been more willing to accumulate stocks than other exporters. Some countries carry virtually no stocks from one year to the next, and the European Community subsidizes exports to prevent stock accumulation. These competitors, therefore, frequently have been willing to sell below the U.S. price.

Another characteristic: shared by many of the regions with upwardly biased forecasts is that they are important markets for wheat or rice. The regions that were large markets for U.S. wheat and rice generally had forecasts with poor efficiency. Wheat and rice are the least seasonal of all major U.S. agricultural export products. Coarse grains, soybeans, soybean meal, and cotton are e:ignificantly seasonal, with larger exports at the beginning of the fiscal year. Thus, when half the year has passed, more than half the year's total exports have been shipped. However, because the timing of wheat and rice harvests *in* competing and consuming countries is substantially less concentrated than for other crops, customers' import needs and U.S. export availability are far less seasonal for wheat and rice. The United States harvests both spring and winter wheat crops, and competing nations harvest in both the Northern and Southern Hemispheres. Many important rice producers harvest multiple crops during the year.

Uncertainty may have created conditions that permitted the exercise of bias, but bias clearly did not occur in every such case. Bias also occurred in other regions where uncertainty seemed much less of a problem. Exports to Eastern Europe were among the most consistent regional forecasts, with the third highest R^2 *in* the second quarter, but the forecasts were biased upward in the third and fourth quarters and showed nearly significant bias in the second. Export forecasts for East and Southeast Asia were consistent and, like Eastern Europe, had wheat and rice account for a smaller than average share of U.S. agricultural exports to the region. The forecasts for south and Southeast Asia were upwardly biased in the third and fourth quarters.

The coincidence between biased regional forecasts and food grain customers may simply stem from the fact that the customers mostly purchasing wheat and rice are the same customers purchasing crops under some form of U.S. Government assistance. Low-income, food-grain-importing countries are often under foreign exchange constraints, and often rely on exporter assistance in their purchases. Another reason may be the greater competitive challenges the United States faces marketing wheat and rice overseas compared with other major agricultural products. The United States faces heavily subsidized competition from EC wheat and low-cost rice from Thailand, the world's largest exporter. The U.S. share of world trade is smaller for wheat and rice than for corn and soybeans. 1rhe result is greater U.S. government participation intended to ensure a level playing field.

One more factor worth noting is an upward trend in exports to some of the regions with upwardly biased forecasts. Exports to North Africa, the Middle East, and Other Asia (which includes both East and Southeast Asia and South Asia) all rose more often than they fell during 197'7-89. These regions contain many middle-income countries with relatively strong population growth, characteristics generally acknowledged to provide the best source of growth for world agricultural trade in future years. It is possible that too much emphasis was placed on this potential when forming the export forecasts.

Similarly, overall economic growth for much of the developing world was relatively sluggish during the 1980's, particularly when compared with the 1970's. As prices for petroleum and other commodities weakened and commercial bank lending contracted, the economies of many developing countries were frequently weaker than expected. The over-optimistic scenarios that were widely accepted for general economic performance by these countries would be consistent with over-optimistic expectations of their willingness and ability to import goods, including farm products. However, although Latin America was a region suffering from such a reversal in growth prospects, downward rather than upward bias was found in the U.S. export forecasts for the region.

Downward bias is relatively rare among the regional forecasts. The former USSR in the second quarter and Latin America in the fourth quarter are the only regions with large, statistically significant downward bias. Yet, if some regions are biased upward, and the forecast of total exports is unbiased, then one would expect offsetting downward bias in other regions. The apparent absence of regions with offsetting downward bias might lead one to question either the apparent lack of upward bias in total exports or the upward bias estimated for some regions.

Downward bias could vary randomly among the regions from one year to the next, while the upward bias was regularly focused on particular regions. This could be possible if the downward bias were in some sense "caused" by the upward bias noted above. The upward bias was specific to regions with certain characteristics, but if the downward bias in other regions resulted from efforts to prevent bias from affecting the forecast for total exports, then there is no reason for any region to be regularly affected.

Putting the forecasts in a percentage change format results in a slight increase in the number of regional forecasts exhibiting downward bias (table 11). As noted earlier, Japan's downward bias is statistically significant in the percentage change format. Japan is biased downward by 5 percent in the second quarter and 3 percent in the third quarter. Latin America in the third quarter is another forecast that is biased downward as a percentage change but not otherwise. Finally, the fourth quarter forecast for centrally planned economies loses its upward bias in the switch to percentage change format.

With more downwardly biased regions and one less upwardly biased region, the percentage change forecasts demonstrate a better balance between the two groups. Stating the forecasts in percentage change format in effect changes the weight given to errors in various years. In most cases, the differences are slight between analysis of forecasts as percentage changes and the sort of analysis used elsewhere in this report. One exception is U.S. exports to China, which were less than $50 million in 1978 and about 37,000 percent higher the following year. USDA forecast a 1,000-percent increase during the first quarter that year, but the correlation between forecasts and actual changes in the first quarter was 100 percent. This compares with an R^2 of 0.46 in table 7. Forecasts were not examined in percentage change format in this report in anticipation of such distortions.

Sources of Bias in the Commodity Forecasts

The largest case of bias among the commodity forecasts during 1977-89 was livestock's downward bias. Because Japan is the largest market for U.S. livestock products, and both are biased downward in the second quarter, a link between the two seems worth considering. There is evidence that both the Japan forecast and the livestock forecast were downwardly biased because USDA regularly underestimated their steady growth, but there is also evidence that the errors are independent. Note that the Japan forecast is biased in the third quarter while livestock is not (see table 11}. The volume forecast for animal fats is downwardly biased, but Japan accounts for only 4 percent of U.S. exports of animal fats. The livestock export forecasts may have been based on incorrect data concerning the U.S. cattle industry (8).

As noted earlier, the least efficient forecasts among the commodities were those for high-value products, such as livestock products. The inefficiency may reflect less attention toward events in these markets, which would increase the likelihood that rapid growth could be unanticipated, resulting in downward bias. Although horticultural and dairy products had inefficient forecasts and an upward trend in exports, several characteristics may mitigate governmen1 inattention. For dairy, one such mitigating characteristic is that the U.S. Government accounts for most of the exports, shipping nonfat dried milk under food aid and other programs (although unbiased, dairy export forecasts demonstrate poor efficiency and large MAPE). u.S. horticultural production was more heavily weighted toward exports than are livestock products and, through marketing orders, have more domestic government programs.

Consistency

Consistency means to correctly forecast the magnitude of change. Export forecasts were examined for inconsistency by testing the ordinary least squares estimates of

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[8]Livestock product exports during 1977-89 were equivalent to 4-8 percent of domestic producers' cash receipts. Nut, fresh fruit, and fresh vegetable exports were equivalent to 12-19 percent of growers' cash receipts. Additional exports of processed horticultural products ensure that the actual share was higher, and the undercounting of exports to Canada also increases the actual share.

$$dA_i = \alpha + \beta dF_i + \varepsilon_i$$

For $\beta = 1$. If a forecast fails the test, and there is no bias present, it is usually considered inconsistent. How to interpret the test when bias is present is discussed below.[9]

The earlier discussion of A_i and F_i versus dA_i and dF_i noted that using A_i and F_i amounted to most ng a severe restr1ct on on the model. One can further argue that the dA_i and dF_i model also is restricted and that loosening the restriction permits an intuitive interpretation of the resulting β's. If one postulates that the relationship between dA_i and dF_i differs depending on whether exports are rising or falling, then $dA_i = \alpha + \beta dF_i$ is a restricted model, and the estimated β is affected by aggregation:

$$dA_i = \alpha_r + \beta_r dF_i \text{ if } dA_i > 0$$
$$dA_i = \alpha_f + \beta_f dF_i \text{ if } dA_i < 0$$

In presenting the results of testing for consistency, I first present results based on the restricted model: $\alpha_r = \alpha_f$, $\beta_r = \beta_f$.

Another important factor affecting the estimated value of β is autocorrelation. Autocorrelated residuals are important in their own right in tests of weak-form rationality (1), and in the tests here for consistency they are important because they introduce bias into the OLS estimates of β. A handful of the OLS equations had Durbin-Watson statistics that indicated autocorrelated residuals.[10] Before testing for $\beta = 1$, the data for these forecasts were transformed using the Prais-Winsten method. Prais-Winsten was chosen to preserve degrees of freedom.

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[9]seemingly Unrelated Regression (SUR) is appropriate for the sets of equations used in this report since the error terms are highly correlated across equations. Our ability to use SUR was constrained by possible linear relationships among the error terms and lagged correlations across equations. Evidence that at least one of these conditions holds was found in the instability of some coefficient estimates from one SUR system to the next. The instability is never such that an equation determined to be inconsistent with OLS tests for consistency under SUR, but some equations consistent under OLS test either way under SUR, depending on what other equations are included in the system.

[10]In the first quarter: total export value, Asia, horticultural products, and grains and feeds. In the second quarter: sugar and tropical products. In the third quarter: China, livestock, Oceania, and coarse grains volume.

Consistency Estimates for the Restricted Model

Underestimates seem more common among the forecasts than overestimates. That is, $\beta > 1$ is observed more frequently than $\beta < 1$. The magnitude of change in total U.S. agricultural exports was typically underestimated about 25 percent by the third-quarter forecast (table 12). About a 7-percent underestimate was typical during the fourth quarter. As with bias, significant inconsistency is more common during the third and fourth quarters. This does not necessarily mean that the forecasts published *in* the first half of the year were more accurate: quite the opposite according to R^2 and MAPE. Instead, the early quarter forecasts have a greater degree of random error, which could conceal a systematic error like inconsistency.

A lack of consistency 1nay lead to forecast bias or vice-versa. If actual exports are ending to increase or decrease, then bias and inefficiency are likely to coincide (if actual exports rise every year and the forecasts are biased upward, then clearly the magnitude of change is overestimated). If actual exports show no trend, and if the change in actual exports during the period studied averages to zero, then bias and inefficiency are more likely to be distinct.

Cotton value was significantly overestimated in the fourth quarter, while cotton volume was insignificantly overestimated. The cotton estimates leaned toward overestimation in all quarters, but reached significance in only one case. In addition, cotton value forecasts were biased upward in the last two quarters. Similarly, forecast changes for South Asia were consistently overestimated, and the forecasts were biased upward.

The only other biased forecast to demonstrate inefficiency (excluding Oceania} was Eastern Europe. Eastern Europe's bias was in the same direction as South Asia, upward, but its inefficiency was in the opposite direction.

With cotton and Eastern Europe, the direction of trend, bias, and inefficiency agree in a manner that makes it impossible to use the restricted equation to tell which came first, bias or inefficiency. With cotton, overestimated growth possibly led to upward bias; with Eastern Europe, underestimated declines possibly led to upward bias. South Asia strikes a discordant note--it does not seem logical that an overestimated decline would led to upward bias. This would imply a bias distinct from inefficiency. Relax ng the constraint that $\alpha_r = \alpha_f$ and $\beta_r = \beta_f$ leads to the conclus1on that the forecasts for Eastern Europe are definitely biased, and the forecasts for cotton are likely biased as well.

Inconsistency and bias, in some cases, are quite clearly distinct. Sub-Saharan Africa was an efficient forecast without a hint of bias, but with substantial inconsistency. It had the second highest R^2 of any forecast in the first quarter and a higher than average second quarter R^2, just below 0.80. Sub-Saharan Africa was the sole first-quarter example of pure inefficiency. Table 1shows five forecasts testing for a significant lack of consistency in the first quarter. One, South Asia, was influenced by bias, and two others suffered from extreme rounding errors. Sub-Saharan Africa's forecasted change is underestimated by about 59, 61, and 34 percent in the first three quarters. Because there is absolutely no trend in exports to Sub-Saharan Africa during the period studied, inefficiency does not result in bias.

Western Europe was another region with no trend in exports, and the third quarter forecasts are inconsistent and underestimated. Interestingly, China showed a strong upward trend, was inefficient, but showed no bias. USDA avoided downward bias despite a tendency to underestimate change in a growing market. This growth tendency was probably caused by the fact that the United States exported virtually no agricultural products to China in fiscal years 1976 and 1977. Had the study period begun in a year during which the United States was already achieving significant export sales to China, China's average change would probably not be the most positive.

If dA_i and dF_i are largely unrelated, then $\beta = 0$. If there is a weak relationship between the two, then it is possible to have $\beta \neq 0, \neq 1$, particularly if β is about midway between 0 and 1. For example, in the fourth quarter, the forecast for Oceania has $\beta = 0.41$ that meets these criteria. However, $R^2 = 0.70$ was very low for the fourth quarter and the direction of change was incorrectly forecast in 5 years. These problems are largely attributable to rounding errors, but illustrate that the value of should be clearly attributed to under- or overestimating change only for fairly accurate forecasts. Other examples include dairy in most quarters and South Asia in the first quarter.

Consistency Estimates for the Unrestricted Model

Dividing the forecasts into two groups corresponding to years of rising and falling exports incorporates additional information into the equations. The results provide evidence that upward bias is more frequently the cause of overestimated change than vice-versa. The results also provide evidence that USDA's forecasts are less accurate in years when exports decline than in years they increase.

When exports trend upward, then upward bias would inevitably lead to an apparent overestimate of change (β<1), and an overestimate of change would inevitably lead to an apparent bias. With the restricted equation used above, it is impossible to determine which is the cause and which is the result. A tendency to overestimate change seems counterintuitive, while a tendency to underestimate change seems plausible (β>1). The difficulty economists have in predicting turning points in the economy has been widely documented. It is not too surprising that models, which must be estimated with historical data, fail to anticipate changing circumstances. Also, since time series are by nature strongly correlated with past values, a similar tendency for forecasts of time series data is rational. One would be suspicious of evidence that implies that USDA overanticipates events. However, some of the estimates for β in table 12 suggest USDA overestimates the amount of annual change by 100 percent.[11] This can be reconciled by more closely examining how β can vary from 1.

A forecast's bias could easily be proportional to amount of change. An upwardly biased forecast might be produced by increasing forecast change by 10 percent when exports are forecast to rise, and decreasing it by 10 percent when exports are forecast to decline. What is important here is that the first case is consistent with β = 0.91 and that the second case is consistent with β = 1.11. If export increases and declines occur with similar frequency and magnitude, then the estimated β of $dA_i = \alpha + \beta\, dF_i$ will be 1. If exports trend upward, however, this bias will lead to β <1.

To discern such cases, the following equation was estimated:

$$dA_i = \alpha_r + \alpha_f + \beta_r dF_{ri} + \beta_f dF_{rf} + \varepsilon_i$$
$$dF_{ri} = dF_i \text{ when } dA_i < 0$$
$$dF_{fi} = dF_i \text{ when } dA_i > 0$$

This equation has no constant term, with α_r and α_f being dummy variables corresponding to rising and falling exports. The proportional bias described above would imply $\beta_r = 2 - \beta_f$.

There are several issues associated with estimating such a model. One is that if one can reject the pair of restrictions, $\alpha_r = \alpha_f$ and $\beta_r = \beta_f$ then it may be necessary to estimate separately rising and falling exports. The difference in the parameters may mean differences between the two sets of residuals and the associated variances. Unfortunately, given an overall sample

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[11] Intuitively, β = 0.5 means that 50 percent of the forecast is excess. Restating β so that the excess of the forecast is stated as a percentage of the actual: $(1/\beta) - 1$. Thus, when β = 0.5, half the forecast is excess, and the forecast is 100 percent greater than the actual value. Most of the estimated β's are closer to 1, and the difference between β and $1/\beta$ is substantially smaller.

size of 13 observations, dividing the samples into two sets makes for extremely small samples.[12]

In some cases, this model results in values of a and ß that imply a "complex" relationship between dAi and dFi. "Complex" is used as a description to contrast with a simple case of bias or inconsistency. A simple case of bias or inconsistency *is* one where α_j and β_j (where $j = r$ or f) both imply the same relationship be dAi and dF_i : for example, $\alpha_r<0$ and $\beta_r<1$, or $\alpha_f<0$ and $\beta_f>1$. Each member of each pair above implies upward bias. The closest to this simplest case of bias is the forecast for Eastern Europe in the fourth quarter (t-statistics for the difference from zero in parentheses):

$$\alpha_r = 0.024 \ (0.632) \qquad \beta_r = 0.78 \ (11.262)$$
$$\alpha_f = -0.011 \ (0.364) \qquad \beta_f = 1.19 \ (14.137).$$

This bias is not ideal because α_r has the wrong sign. However, this bias is of little concern because each α_j is so clearly insignificant and each β_j is so clearly different from 1. The relationship between dAi and dFi is a simple one of the forecast being biased upward 20 percent.

An example of a "complex" relationship is the forecast for Western Europe in the fourth quarter:

$$\alpha_r = 0.130 \ (1.273) \qquad \beta_r = 0.98 \ (11.672)$$
$$\alpha_f = -0.312 \ (2.394) \qquad \beta_f = 0.73 \ (8.133).$$

Note that $\alpha_f<0$ implies an upward bias, but $\beta_f<1$ implies that the declines are overestimated causing a downward bias. In each case, the difference is significant. The estimated values of α_r and β_r imply bias in different directions, but in neither case are the tendencies significant. Reestimating the equation after restricting either $\alpha_r = \alpha_f = 0$ or $\beta_r = \beta_f = 1$ reveals which of the opposing tendencies predominates: downward bias for both the rising and falling years, but the bias is not significant.

Upwardly Biased Forecasts. The fourth-quarter forecast for Eastern Europe is an example in which relaxing the restrictions $\alpha_r = \alpha_f$ and $\beta_r = \beta_f$ provides some insight into the appearance of bias. The first section on inconsistency highlighted this forecast's underestimated change and declining trend as a possible cause of upward bias. However, because the tendency to underestimate change did not extend to periods when exports rose

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[12]The pair of restrictions is rejected quite frequently: all but three of the first-quarter forecasts studied rejected it with 10-percent significance. The restrictions were rejected less frequently in subsequent quarters; the restrictions could not be rejected for a majority of the fourth-quarter forecasts.

and was replaced by a tendency to overestimate change, bias seems to be a factor.

Cotton value was an example of an apparent overestimate possibly causing bias according to the restricted coefficient estimates. Relaxing the restrictions gives results that imply that upward bias was confined to years when exports rose. Earlier, when $\alpha_r = \alpha_f$ and $\beta_r = \beta_f$ were imposed, the estimated β was less than **1** because of the effect of aggregating $\beta_r<1$ and $\beta_f = 1$ with exports rising in more years than falling. Therefore, the presence of $\beta<1$ seems to be a result of upward bias rather than representing its cause. This also seems to describe the forecasts for South Asia in all four quarters.

North Africa and the Middle East are also upwardly biased, and, although the restricted estimates for β did not imply significant inconsistency, dividing the forecasts into rising and falling years provides useful insights. The results imply that USDA has more problems with these forecasts during years exports fall than when they rise.

For North Africa, estimating the unrestricted fourth quarter equation gives $\beta_f = 0$. This is also true in the third quarter and when estimating with $\alpha_r = \alpha_f = 0$. In the second quarter, when estimating with $\alpha_r = \alpha_f = 0, \beta_f \neq 0$ significantly, but with the wrong sign! The negative sign implies that the forecast is in the wrong direction. The same estimated β_f for the Middle East also has the same sign,but is not significantly different from zero.For North Africa, an estimate with the wrong sign is also significant in the first quarter. This is not the only forecast where β_f has the wrong sign in the first quarter.When estimated with $\alpha_r = \alpha_f = 0$, horticultural and poultry products forecasts also have significant β_f estimates with inappropriate signs (table 13). No forecast's estimated β_r in any quarter has a negative sign. Estimated values for β_f are far more frequently insignificant than those for β_f tables 14-16). This indicates that USDA has more trouble correctly forecasting exports in years when exports decline.

This asymmetric tendency is also relevant to the forecast for coarse grains volume. It was noted earlier that the forecasts for coarse grain exports appeared upwardly biased in both value and volume when the period of analysis is restricted to 1981-89. During this period, U.S. coarse grain exports generally declined.

When coarse grains volume data for 1977-89 are examined with rising and falling years separated, the estimates imply forecasts during declining years are more biased and less accurate than forecasts during rising years. Because exports rose more years than they fell during 1977-89, USDA's forecasts avoided bias on average during this period. This is fortunate because coarse grains are the United States' highest volume export and sometimes its highest value export as well.

Other Forecasts. Unlike the upwardly biased forecasts, most of the downwardly biased forecasts stem from problems during years that exports rose. Both rice and sugar and tropical products (second quarter) are characterized by an upward trend, underestimated change (β>1), and downward bias. Sugar and tropical products' bias seems to result from the underestimated change, since both rising- and falling-year forecasts display underestimated change. Rice seems more likely to be directly biased. The second quarter was the only quarter where the rice forecasts were both inconsistent and biased. Both the bias and the inconsistency seem confined to rising year exports.

The less restricted equations are also useful for exploring forecasts that are inconsistent but without any average bias. By definition, if a forecast is equally inconsistent during rising and falling years, then it will also be biased during rising and falling years. The biases will be in opposite directions and can average to zero bias over all years. Restricted OLS estimates found inconsistency in the forecasts for Sub-Saharan Africa (first three quarters), Western Europe, and China (both in the third quarter). Less restricted estimates found that the inconsistency was essentially the same during rising and falling years. Each β_j was greater than one, usually equally greater than one during rising and falling years for each region.

Conclusions

USDA's quarterly export forecasts were largely efficient and unbiased, although they showed signs of being consistently cautious. The forecasts for grain exports were the most accurate of the group. They generally had the smallest percentage error and the best correlation, but the magnitude of change was conservatively forecast. Given the importance of grain to total exports, this led to conservative forecasts of change for total U.S. agricultural exports. Cotton exports were also accurate, matching grains in correlation, but showing bias and larger average errors. Cotton exports also varied from grain exports in that the forecasts were not conservative: the magnitude of change was overestimated on average. Since the 9verestimation was confined to the years exports rose, bias probably caused the overestimated change. Oilseed and product forecasts were less accurate than grain and cotton forecasts, probably due to the concentration of trade among a small number of countries.

Upward bias occurred in the forecasts of exports to a number of less developed countries that chiefly imported food grains and also received U.S. Government assistance in their purchases. Conclusions regarding the causes of upward bias in the regional forecasts can come only after further research. In some cases, the bias seemed concentrated in years when exports to a given region rose; in other cases the bias seemed concentrated in years when exports to the region fell.

The upward bias found for a number of regional forecasts does not necessarily reflect a bias by analysts responsible for concentrating on any of these regions. The regional forecasts published in the *Outlook for U.S. Agricultural Exports* are based on unpublished commodity forecasts that receive interagency review. Each month USDA publishes forecasts of expected marketing year U.S. e ort volume for a number of crops produced through a process of interagency review. To reach a consensus regarding the total for U.S. exports, unpublished forecasts of U.S. exports to each U.S. customer are formulated. These unpublished forecasts are then combined with ERS price forecasts to form the foundation of the published forecasts for the total value of U.S. agricultural exports to various regions. The regional forecast bias found in this report may stem from errors in either the interagency or the ERS component of these published forecasts.

Downward bias occurred in forecasts to some developed regions and the largest high-value commodity group, livestock products. Japan was the only developed-country forecast that was close to being biased and also important and otherwise accurate. But, its possible bias was less than 2 percent of the value of fiscal 1989 exports to that market. Livestock's bias was of equivalent absolute magnitude and totaled little more than 3 percent of fiscal 1989 exports. In both cases, underestimates of rapid export growth probably led to downward bias.

While it is of course desirable to eliminate such systematic errors, increasing forecast reliability is likely to entail costs. Any desire to improve forecast accuracy must be balanced by considerations of how costs compare with benefits. USDA is unlikely to reorient its intelligence-gathering efforts toward high-value products simply to increase the accuracy of its export forecasts for these products.

The first step *is* discovering systematic errors. Unforeseeable events will always result in some forecast error, but when errors fall into discernible patterns they represent behavior that can be altered to improve forecast accuracy.

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Appendix

The following decomposition of MSE is commonly used to analyze forecast accuracy:

$$MSE(F) = \left(\overline{F} - \overline{A}\right)^2 + (1-\beta)^2\sigma_F^2 + \left(1-\rho_{FA}^2\right)\sigma_A^2$$
$$MSE(F) = \quad U^B \quad + \quad U^R \quad + \quad U^D$$

The three components are referred to as the "bias" component (U^B), the "regression" component (U^R), and the "disturbance" component (U^D). A forecast with no bias or regression component is considered generally preferable, given comparable levels of MSE(F.). U^R is more typically shown in a slightly different formulation (2,3,4) but this equivalent, a clearer formulation, is occasionally used (1,5).

U^R and U^D bear a relationship to the coefficients of a regression of A_i on F_i. Given,

$$A = \alpha + \beta F + \varepsilon \text{, then}$$

$U^R = 0$ if $\beta = 1$, and U^D approaches zero as the regression's R^2 approaches 100.

The drawback of using this decomposition of MSE is demonstrated by the fact that, despite the conventions in naming each MSE component, bias could cause both $U^R \neq 0$ and $U^B \neq 0$ simultaneously.

Imagine a forecasting process under a condition of perfect foresight: the actual data are anticipated exactly. Forecasts could then be generated by multiplying the anticipated actual data by some number, $z \neq 1$. If the number were consistently greater than 1, then the forecasts would be biased upward. A regression of A_1 on F_i, would yield a coefficient for F_i significantly smaller than 1, and U^R would not equal zero. The simple MSE(F_i) decomposition would imply the error was divided between the bias component and the regression component when in fact a form of bias was solely responsible. There would be no point in distinguishing between U^B and U^R.

Table 2--Average percentage error in value forecasts, by commodity and quarter, 1977-89[1]

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
	Mean absolute percent error			
Exports:				
Grains and feeds	12	9	5	3
Wheat and flour	15	10	7	4
Rice	11	11	9	5
coarse grains	22	14	8	2
Oilseeds and products	12	9	5	3
Soybeans	15	9	7	3
Soybean cake and meal	14	8	5	4
Soybean oil	21	19	12	10
Livestock products	12	9	5	2
Poultry and products	15	10	10	6
Dairy products	16	16	18	11
Horticultural products	7	6	4	3
Tobacco	6	5	5	6
Cotton and linters	19	13	7	5
Sugar and tropical products	15	10	8	5
Total export value	10	7	4	1
I1nports	6	4	3	2
Trade balance	23	16	11	4

[1] some value forecasts were made only during 1981-89: Wheat and flour, coarse grains, rice, soybeans, soybean meal, and soybean oil.

Table 3--Average percentage error in volume forecasts, by commodity and quarter, 1977-89[1]

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
	Mean absolute percent error			
Wheat and flour	10	7	6	4
Coarse grains	11	9	5	2
Rice	11	9	10	7
Soybeans	8	8	6	2
Oilseed cake and meal	12	9	6	3
Animal fats	12	7	5	5
Tobacco	17	16	16	18
Cotton and linters	17	12	5	3
Other	8	7	5	4
Total	8	7	3	2

[1]Total volume and other volume forecasts were studied only for 1981-89. Earlier data 'Were not directly comparable.

Table 4--Average percentage error in value forecasts, by region and quarter, 1977-89[1]

Region	First quarter	second quarter	Third quarter	Fourth quarter
	Mean absolute percent error			
Western Europe	13	9	5	2
Eastern Europe	23	16	11	8
Former USSR	37	22	13	6
Asia	10	6	4	2
Japan	9	7	5	3
China	66	38	18	11
Other Asia	11	7	5	4
East and Southeast Asia[2]	9	7	4	4
South Asia[2]	31	21	16	10
Middle East	19	14	13	4
Africa	11	8	8	6
North Africa	14	10	8	7
Sub-Saharan Africa	21	17	13	6
Latin America	17	13	9	5
Mexico	23	21	17	10
Other Latin America	9	7	7	5
canada	7	6	6	3
Oceania	20	15	18	17
Developed countries	6	5	3	3
Less developed countries	12	9	6	4
Centrally planned countries	32	20	12	7

[1]Mexico and Other Latin America were forecast only during 1981-89. In the first quarter the earliest forecasts were for 1982.

[2]Data are for 1977-87.

Table 5--correlation of forecast change with actual change in value, by commodity and quarter, 1977-89[1]: Regression coefficient of determination (R^2)

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
		Percent		
Grains and feeds	60	81	95	98
Wheat and flour	60	77	93	96
Rice	67	63	88	97
coarse grains	61	89	95	99
Oilseeds and products	5	45	81	98
soybeans	5	71	78	94
Soybean cake and meal	31	76	85	89
Soybean oil	57	68	89	97
Livestock products	9	8	53	93
Poultry and products	6	45	45	91
Dairy products	45	54	41	67
Horticultural products	50	60	76	90
Tobacco	37	57	56	53
Cotton and linters	60	87	95	98
Sugar and tropical products	50	85	96	98
Total	38	70	92	98

[1]some value forecasts were made only during 1981-89: Wheat and flour, coarse grains, rice, soybeans, soybean meal, and soybean oil.

Table 6--correlation of forecast change with actual change in volume by commodity and quarter, 1977-89[1]: Regression coefficient of determination (R^2)

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
	Percent			
Wheat and flour	55	76	86	97
Coarse grains	16	63	90	97
Rice	50	68	61	91
Soybeans	70	77	87	97
Oilseed cake and meal	50	66	84	98
Animal fats	0	46	68	81
Tobacco	0	11	11	17
Cotton and linters	70	86	97	99
Other[1]	0	3	63	64
Total[1]	20	55	92	97

[1]Both total and other volume during 1977-80 are inconsistent with those published since 1981.

Table 7--correlation of forecast change with actual change, by region and quarter, 1977-89[1]: Regression coefficient of determination (R^2)

Region	First quarter	Second quarter	Third quarter	Fourth quarter
	Percent			
Western Europe	5	49	90	97
Eastern Europe	54	87	81	96
Former USSR	26	88	92	98
Japan	54	73	89	97
China	46	75	94	99
Other Asia	25	60	90	95
East and Southeast Asia[2]	37	63	90	93
South Asia[2]	58	78	83	94
Middle East	1	15	42	94
North Africa	16	47	76	80
Sub-Saharan Africa	67	79	85	95
Latin America	41	67	84	95
Mexico	52	57	75	91
Other Latin America	15	67	89	97
Canada	59	57	58	91
Oceania	32	69	67	70
Developed countries	18	55	88	97
Less developed countries	34	63	99	98
Centrally planned countries	49	90	96	99

[1]Mexico and Other Latin America were forecast only during 1981-89. In the first quarter the earliest forecasts were for 1982.

[2]Data are for 1977-87.

Table a--Forecast bias, by quarter, 1977-89[1]

Commodity and region	First quatrter	Second quarter	Third quarter	Fourth qua.rter
		1,000 metric tons		
Commodity:				
Rice		-155 (2.276)*	-140 (1..955)*	-147 (3.754)--
Tobacco				-22 (1.980)*
Animal fats		-60 (1.851)*		-35 (1.915)1\'
		Million dollars		
Coarse grains[2]			353 (2.050)*	
Livestock products		-187 (1.953)*		
Cotton			77 (1.839)*	61 (2.037>*
Sugar and tropical products		-50 (2.007>*		
Region:				
Eastern Europe		88 (1.611)	80 (2.083)*	57 (2.236)"
Former USSR		-200 (1.915*)		
Japan		-207 <1.679)	-138 (1.698)	
Other Asia			185 (2.992)**	163 (3.755)**
East and Southeast Asia[3]			117 (2.223>*	135 (3.080)1*
South Asia[3]	186 (2.736)**	95 (2.304)**	95 (2.995)**	41 (1.853>*
Middle East			129 (2.117)'1\'	44 (2.226)*
North Africa	124 (2.029)*	85 (1.940)*	70 (2.271)*	47 ci.733>
Latin America				-127 (2.314)*
Oceania		-26 (3.797)*		
Centrally planned countries			115 (1.800)*	115 (2.405)**

[1] T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent.
[2] Data are for 1981-89.
[3] Data are for 1977-87.

Table 9--Bias in implied price forecasts, by quarter, 1981-89[1]

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
		Dollars per metric ton		
Rice		22 (1.959)*		17 (2.002)*
Cotton[2]		70 (3.005)**	53 (2.384>**	30 (2.848)**
Wheat and flour			-3 (3.531)**	-4 (3.813)**
Soybean meal		-6 (2.373)*		

[1] T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent.
[2] Cotton and tobacco are the only commodities with implied price forecasts available during 1977-89. The other implied price forecasts are for 1981-89.

Table 10—USDA forecast bias compared with naive model, by quarter, 1977-89[1]

Commodity and region	First quarter[2]	Second quarter	Third quarter	Fourth quarter
		1,000 metric tons		
Commodity:				
Rice		-241 (2.035)*	-222 (2.241)**	-202 (2.389)**
Tobacco				-23 (2.505)**
Animal fats		-81 (1.732)	-46 (2.410)**	-37 (2.038)*
		Million dollars		
Rice			-58 (1.851)	
Soybean meal	-134 (2.616)**			
Livestock products	11.8 (2.001)*	-217 (2.209)**		
Horticultural	18:0 (5.101)**			
Poultry	312 (4.462)*			
Region:				
Japan		-254 (2.753)**	-191 (1.840)*	
Other Asia	442 (2.732)**		159 (2.077)*	131 (2.372)**
East and south-east Asia	3!8 (2.3:70)**			128 (2.736)**
South Asia			76 (2.051)*	
Middle East	217 (3.384)**		122 (2.203)**	48 (1.729)
North Africa	194 (3.9';11)**			50 (1.629)
Oceania		-32 (2.501)**		

[1]T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent.
[2]There are no partial year data available in the first quarter. Thus, the naive forecast *is* the previous year's unadjusted total.

Table 11--Bias of implied percentage change forecasts, by quarter, 1977-89[1]

Commodity and region	First quarter	Second quarter	Third quarter	Fourth quarter
		Percent of volume		
Commodity:				
Rice	-6.7 (1.925)*	-7.5 (2.421)**	-6.5 (2.032)*	-6.5 (3.594)**
Tobacco				-9.0 (2.141)*
Animal fats	-6.8 (1.821)*	-4.9 (2.018)*		-2.9 (2.161)*
		Percent of value		
Livestock products		-5.8 (2.230)*		
Cotton			7.2 (1.631)	5.5 (1.754)*
Sugar and tropical		9.0 (2.652)**		
Region:				
Eastern Europe		6.1 (1.640)	6.4 (2.488)**	4.7 (2.349)**
Former USSR		-19.5 (2.423)**		
Japan	-5.2 (1.702)	-4.8 (2.007)**	-3.1 (1.982)*	
Other Asia			4.2 (2.893)**	3.7 (3.639)**
Middle East			7.9 (2.117)*	2.9 (2.362)**
North Africa	9.0 (1.918)*	6.4 (1.912)*	5.8 (2.314)**	
Latin America	-10.4 (1.649)		-5.6 (1.834)*	-4.4 (2.583)**
Oceania		-14.9 (3.339)**		

[1]T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent.

Table 12--Forecasts lacking consistency, by quarter, 1977-89[1]

Commodity and region	First quarter	Second quarter	Third quarter	Fourth quarter
		Estimated coefficient value		
Commodity:				
Total value			1.26 (2.385)**	1.07 (1.77)*
Grains and feeds			1.21 (2.464)**	
Dairy	.47 (3.417)**	.46 (4.140)**	.36 (4.740)**	.72 (1.819)*
Cotton value				.95 (1.915)*
Sugar and tropical products	2.21 (2.3.9)**	1.38 (4.780)**		
Total volume			1.31 (1.933)*	
Rice				1.21 (3.196)**
Coarse grains			1.820 (1.942)*	1.24 (1.954)*
Cotton				.94 (1.735)
Region:				
Western Europe			1.24 (2.000)*	
Eastern Europe		1.33 (2.179)*		
China			1.18 (1.972)*	
South Asia	.53 (3.167)**	.73 (2.04)*		.85 (1.998)*
Sub-Saharan Africa	1.59 (1.7 .6)*	1.61 (2.47)**	1.34 (2.010)*	
Canada				.86 (1.774)
Oceania	.31 (5.025)**	.63 (2.846)**	.41 (6.644)**	.41 (7.205)**
Less developed countries			1.23 (1.794)*	1.11 (2.135)*
Centrally planned countries		1.36 (2.590)**	1.23 (2.610)**	

[1]T-statistics for difference from zero in parentheses:
* = significant at 10 percent
** = significant at 5 percent.

Table 13—Forecasts with incorrect signs for β_f when $\alpha_r = \alpha_f = 0$[1,2]

Commodity and region	First quarter	Second quarter	Third quarter	Fourth quarter
	Estimated coefficient value			
Commodity:				
Horticultural	-1.10 (2.424)**			
Poultry	-2.55 (2.0143)*			
Region:				
Middle East	-.51 (1.7'11)	-..60 (1.1'10)	-1.08 (2.0140)*	
North Africa	-.61 (1.1!198)*	-1.26 (2.182)*		

[1]T-statistics .for difference from zero in parentheses:
*significant at 10
**significant at 5 percent.

[2]No estimates for β_r had incorrect signs.

Table 14--Estimated β's for value forecasts not significantly different from zero, by commodity and quarter, 1977-89[1]

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
	Coefficients failing to reach 10-percent significance			
Grains and feeds	β_f	β_f	--	--
Oilseeds and products	β_r, β_f	--	--	--
Livestock products	β_r, β_f	β_r, β_f	β_f	β_f
Poultry and products	β_r, β_f	β_f	β_f	--
Dairy products	β_f	β_f	β_r, β_f	β_f
Horticultural products	β_f	β_f	β_f	β_f
Tobacco	β_r, β_f	β_r	--	--
Cotton and linters	β_r	--	--	--
Sugar and tropical products	--	--	--	--
Total export value	β_r, β_f	β_f	β_f	--

[1]Estimated with α_r, α_f, β_r, and β_f unrestricted.

Table 15--Estimated β's for volume forecasts not significantly different from zero, by commodity and quarter, 1977-89[1]

Commodity	First quarter	Second quarter	Third quarter	Fourth quarter
	Coefficients failing to reach 10-percent significance			
Wheat and flour	β_r, β_f	β_r, β_f	--	--
Coarse grains	--	--	--	--
Rice	β_r, β_f	β_r, β_f	β_r	--
Soybeans	--	--	--	--
Oilseed cake and meal	β_r	β_r	β_r	--
Animal fats	β_r, β_f	β_r, β_f	--	--
Tobacco	β_r, β_f	β_r, β_f	β_r, β_f	β_r, β_f
Cotton and linters	--	--	--	--

[1]Estimated with α_r, α_f, β_r, and β_f unrestricted.

Table 16 -- Estimated β's for value forecasts not significantly different from zero, by region and quarter, 1977-89[1]

Region	First quarter	Second quarter	Third quarter	Fourth quarter
	Coefficients failing to reach 10-percent significance			
Western Europe	β_r, β_f	--	--	--
Eastern Europe	β_f	--	--	--
Former USSR	β_r, β_f	β_f	--	--
Asia	β_r, β_f	β_f	--	--
Japan	β_f	β_f	--	--
China	β_r	β_r	--	--
East and Southeast Asia	β_r, β_f	β_f	β_f	--
South Asia	β_f	β_f	β_f	--
Middle East	β_r, β_f	β_r, β_f	β_r, β_f	--
North Africa	β_r, β_f	β_f	β_f	β_f
Sub-Saharan Africa	β_f	--	--	--
Latin America	β_r, β_f	--	--	--
Canada	β_f	β_f	β_f	β_f
Oceania	--	--	--	--

[1]Estimated with α_r, α_f, β_r, and β_f unrestricted.