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Efficient Portfolios of Market Advisory Services: An Application of Shrinkage Estimators

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Abstract

A Bayesian hierarchical model was employed to estimate individual expected pricing performance for market advisory programs in corn and soybeans. Performance is defined as the difference between the price/revenue obtained by following the program's marketing recommendations and the average price/revenue offered by the market along the marketing window. The estimates obtained from this model are weighted averages of traditional separate and pooled estimates. Based on the sample employed, the most reasonable individual estimates for expected pricing performance imply a substantial shrinkage towards pooled values. The Bayesian estimates for expected pricing performance range from ¢–9/bu to ¢9/bu for corn, from ¢11/bu to ¢17/bu for soybeans and $–0.4/acre to $11/acre for revenue. Bayesian estimates are employed in the construction of efficient portfolios of advisory programs. Results suggest that farmers can benefit from following the marketing recommendations of advisory programs portfolios.

Key Words: Bayesian hierarchical models, corn, market advisory service, portfolio, soybeans

Efficient Portfolios of Market Advisory Services:
An Application of Shrinkage Estimators

Agricultural market advisory services are popular with U.S. farmers (Patrick et al., 1998; Norvell and Lattz, 1999). For a subscription fee, these firms provide market analysis and pricing advice to farmers. In particular, they make recommendations on how to market crops using various instruments, including cash sales, forward, futures and options contracts. Advisory services deliver reports with market information and marketing recommendations via email or web pages at least daily, with some offering multiple updates each day. Marketing recommendations are specific, indicating the portion of a crop that should be marketed, the marketing tool, and the timing of transactions. For example a service can recommend, "buy May soybean puts today with a strike price of $5.00/bu. for 50% of expected production." Market advisory services indicate on their websites that they do market research and employ fundamental and/or technical analysis to identify profitable marketing alternatives.

In 1994, the Agricultural Market Advisory Services (AgMAS) Project was initiated at the University of Illinois to conduct evaluation on the performance of agricultural market advisory services. The AgMAS Project has evaluated about 25 advisory services each crop year since it was initiated. AgMAS subscribes to the services that are followed and records their marketing recommendations on a real-time basis. The crop price that a farmer in central Illinois would receive by following the recommendations of each advisory service for each crop year is computed and compared to external benchmarks. Empirical findings have been disseminated through various

AgMAS research reports, providing valuable information for farmers considering contracting with market advisors. The most recent report presents the pricing performance in corn and soybeans for 1995 to 2003 crop years (Irwin et al., 2005). On average the price obtained by following exactly the recommendations of market advisors is higher than the average price offered by the market for both crops. This price difference is small and statistically insignificant for corn and larger and significant for soybeans. When comparing advisory prices to the price obtained by farmers, results show that, on average, advisory prices exceed this benchmark by a significant amount in corn but not in soybeans. The authors conclude that there is only weak evidence supporting the success of advisory services as a group in outperforming external benchmarks.

A farmer can select an advisory program and sell crop production following the program's marketing recommendations[1]. Moreover, farmers can consider price risk reduction from diversification by following more than one advisory program. The problem of selecting a portfolio of programs is relevant since, according to survey results, farmers that subscribe to advisory programs often subscribe to several (Isengildina et al., 2004). Also, the importance of portfolio construction has risen in recent years due to the development of new marketing contracts by several grain companies. In these "new generation contracts," grain is priced according to the recommendations of market advisors, making it relatively simple to diversify across advisory programs (e.g., Hagedorn et al., 2003).

Two recent studies evaluated portfolios of advisory services for corn and soybean farmers. In one of these studies, Cabrini et al. (2005) evaluated risk reduction benefits from naive diversification among market advisory services for corn and soybeans. Naïve diversification refers to portfolios that are constructed by randomly selecting the components and assigning equal weight to the components. The authors found that possible gains from naïve diversification are low, mainly because advisory prices are on average highly correlated. Moreover, since there is a subscription cost associated with including advisory programs in the portfolio, it is optimal to limit portfolio size to one to three programs. In the second study, Cabrini et al. (2004) applied the Markowitz mean-variance portfolio selection model. A nonlinear integer optimization model was solved to construct the efficient frontier for portfolios of advisory services. The portfolios that belong to the frontier are those that minimize the variance for each level of expected price. The composition of these efficient portfolios is reported, along with average prices and risk levels. Results indicated that there are portfolios in the efficient frontier that provide significantly greater risk/return benefits compared to external benchmarks.

The two aforementioned studies are based on quite different approaches to evaluating the performance of portfolios of market advisory services. On one hand, naïve diversification results are based mainly on the *average* expected price, variance and covariance across services. On the other hand, mean-variance optimization based on traditional sample estimates of individual parameters employs these estimates as if they were the true values, without considering estimation error. The measured portfolio performances are different between the two approaches, being greater when measured by the mean-variance model compared to naïve diversification. For example, a farmer that follows the recommendations of a portfolio of 5 randomly selected advisory programs has standard deviation of $28/acre and expected revenue of $316/acre, while a mean-variance efficient portfolio with the same risk level for 5 programs has expected revenue of $327/acre (Cabrini et al. 2004, 2005).

Several advisory programs are available to farmers and choosing between them requires estimation of individual expected pricing performance based on a relatively small number of past observations. For instance, advisory prices are reported by the AgMAS Project for nine or fewer crop years. In problems like this, traditional estimates, such as simple sample averages, tend to over-fit the data and extremely high and low performance values are likely to appear due to estimation error. Since mean-variance optimization models tend to assign high portfolio weights to those programs with large positive estimation errors in expected performance, the gains from holding portfolios of advisory programs are likely overestimated when traditional estimates are employed. An alternative estimation procedure is to combine the pricing information for all advisory services and compute pooled estimates for pricing performance (as in Cabrini et al, 2005). A pooled estimator is more reliable, since it is based on a larger number of past observations, however, this estimator fully describes the performance for the group of advisory services under the highly restrictive assumption that all services have identical expected pricing performance.

Neither traditional sample averages nor pooled estimates provide the most appropriate information for farmers considering contracting with advisory services.

Instead, a model that combines the information for the group of advisory programs without assuming that they all have equal expected performance is a more reasonable estimation procedure. Bayesian hierarchical models have this characteristic. A hierarchical model based on the normal distribution produces estimators that are weighted averages of separate and pooled estimates. This type of estimator is called a *shrinkage* estimator, since it *shrinks* individual estimates to common values. Shrinkage estimators have been applied to different estimation problems. For example, Gelman (2004) employs a Bayesian hierarchical model to estimate the effect of several coaching programs on SAT test scores. Efron and Morris (1975) discuss the application of shrinkage estimators to predict the batting averages for baseball players and the incidence of toxoplasmosis for cities in El Salvador. In the finance literature, several studies have employed shrinkage estimators to compute expected stock returns, and results indicate that these estimators outperform traditional sample estimates, in particular when the sample size is small (Jorion, 1986; Grauer, 2002).

In this study, a Bayesian hierarchical model is employed to estimate individual expected performance for a group of 8 advisory programs in corn and soybeans. Data is available from the AgMAS Project for the 1995 to 2003 crop years (Irwin et al., 2005). Traditional and Bayesian estimates are employed as inputs in optimization models to select portfolios of advisory programs. Results obtained based on the two estimation approaches are compared. The focus of the analysis is the estimation of expected pricing performance for portfolios of market advisory programs. Variances and covariance are also subject to estimation error. However, previous research in portfolio selection has documented that errors in the estimation of the means result in greater utility loss compared to errors in the estimation of variances and covariances (Chopra and Ziemba, 1993). Then, it is likely than a superior estimator for expected advisory price performance, rather than for variance and covariances, is of particular interest for farmers that are considering contracting portfolios of advisory services. By employing shrinkage estimators in the portfolio selection model more reliable results in terms of the benefits from following the recommendations of a portfolio of advisory programs and portfolio composition can be obtained.

A Bayesian Hierarchical Model for Advisory Program Expected Performance

The problem considered in this study is the estimation of individual expected performance for a group of advisory programs. Performance is defined as the difference between the net price obtained by following the recommendations of the advisory program and the average price offered by the market (benchmark price) along the marketing window:

(1) $$y_{jt} = advisory\ \ price_{jt} - benchmark\ \ price_t ,$$

where y_{jt} is program *j*'s performance in crop year *t*. Traditional estimators for each advisory program's performance are simply individual sample averages:

(2) $$\hat{y}_j = \bar{y}_{j.} = \frac{1}{T}\sum_{t=1}^{T} y_{jt} ,$$

where $\hat{y}_j$ is the traditional estimator for program *j*'s expected performance and *T* is the number of past performance observations available. Traditional estimators are commonly used because they are straightforward to compute and understand. However, they have the drawback that extremely high and low values are likely to appear due to estimation error, in particular when the number of time series observations is low and the number of advisory programs is large. An alternative procedure is to assume that there is not enough data to estimate individual performance, and therefore, information is pooled to obtain one estimator for expected performance for the group of advisory programs:

(3) $$\hat{y}^{pool} = \frac{\sum_{j=1}^{N} \frac{1}{\sigma^2_{\bar{y}_{j.}}} \bar{y}_{j.}}{\sum_{j=1}^{N} \frac{1}{\sigma^2_{\bar{y}_{j.}}}}$$

where $\hat{y}^{pool}$ is the precision weighted pooled estimate, *N* is the number of advisory programs considered and $\sigma^2_{\bar{y}_{j.}}$ is the variance of $\bar{y}_{j.}$. Note that this estimator is different from the simple average of individual expected performance across programs. This pooled estimator is a weighted average, where the weights are the inverse of the squared standard error of each estimate. A simple average would be reasonable under the assumption that individual estimates have the same error, or in other words that the standard deviation of performance is the same for all programs. However, as presented below, the data employed in this study suggest that standard deviation of the performance is different across programs, and hence a weighted pooled estimate seems more appropriate.

Separate and pooled estimates imply extreme assumptions about the estimation model for individual expected performance of advisory programs. On one hand, separate estimates imply that expected performance is completely independent across programs. On the other hand, pooled estimates imply that all programs have the same expected performance. A situation in between seems more reasonable and can be implemented by Bayesian hierarchical models. A hierarchical model based on the normal distribution produces *shrinkage* estimators that are weighted averages of individual and pooled estimates. For example, the estimator for the expected performance for advisory program j ($\hat{y}_j^{shrink}$) is the weighted average of the individual sample mean ($\overline{y}_{j.}$) and a pooled estimate ($\hat{\mu}^{pool}$)[2]:

$$(4) \qquad \hat{y}_j^{shrink} = (1-w)\overline{y}_{j.} + w\ \hat{\mu}^{pool}\ .$$

The coefficient w is defined as the *shrinkage intensity* since it indicates how much individual estimates are shrunk towards pooled values.

A simplified diagram of the structure of the normal hierarchical model for market advisory program performance is presented in Figure 1. There are basically two levels of parameters in this model, the expected performances for each advisory program $\theta=(\theta_1,\dots,\theta_N)$ are in the lower level and the hyperparameters (μ,τ), that combine the information for all programs in the sample are in the higher level,. The general structure of a Bayesian hierarchical model includes a prior distribution for the parameters, $p(\theta)$, that can be decomposed into a conditional prior given the hyperparameters $p(\theta/\mu,\tau)$ and the prior for the hyperparameters $p(\mu,\tau)$, sometimes called the hyper-prior:

(5) $$p(\theta) = p(\mu,\tau)\ \ p(\theta / \mu,\tau).$$

Then the related joint posterior distribution can be expressed as:

(6) $$p(\mu,\tau,\theta / y) \propto p(\mu,\tau,\theta)\ \ p(y / \mu,\tau,\theta) = p(\mu,\tau,\theta)\ \ p(y / \theta),$$

where y is the sample information. The last equality holds because the hyperparameters affect y only through the parameters θ. The key characteristic of this model is that individual performance parameters share a common prior. This prior distribution is not subjective or based on information that precedes the data collection; instead it is constructed from the whole sample. In this context, not only data on price performance of a particular program is helpful in estimating the expected performance for that program, but also information from the rest of the programs contributes to the estimation. A detailed derivation of the probabilistic model for hierarchical models under normality is presented in Gelman (2004). A description of the main points of the model employed in this study follows.

Performance for program j is assumed to be normally distributed with mean θj and variance v_j^2. The simplifying assumption that variances are known is made such that[3]

(7) $$y_{jt} / \theta_j \sim N(\theta_j, v_j^2) \qquad \textit{distribution of } y_{jt}$$

As mentioned before, individual expected performance estimates share the same prior. Specifically this prior is a normal distribution with mean μ and variance τ

(8) $\theta_j / \mu, \tau \sim N(\mu, \tau)$, *prior distribution of θj*

where the parameter τ defines the prior uncertainty and, as explained below, determines the shrinkage intensity. Combining the sample likelihood derived from equation (7) with the prior distribution (equation 8), the posterior distribution of θj conditional on μ and τ is obtained,

(9) $\theta_j / \mu, \tau, y \sim N(\hat{\theta}_j, V_j)$ where $\hat{\theta}_j = \dfrac{\frac{1}{\sigma^2_{\bar{y}_{j.}}}\bar{y}_{.j} + \frac{1}{\tau^2}\mu}{\frac{1}{\sigma^2_{\bar{y}_{j.}}} + \frac{1}{\tau^2}}$, $V_j = \dfrac{1}{\frac{1}{\sigma^2_{\bar{y}_{j.}}} + \frac{1}{\tau^2}}$ and $\sigma^2_{\bar{y}_{j\cdot}} = \dfrac{v_j^2}{T}$

conditional posterior distribution of θj

The above equation shows that the posterior distribution for each program's expected performance is also normal with a mean equal to the weighted average of the sample mean for that program and the mean of the prior distribution. Note that the point estimate for θ_j is the shrinkage estimator, $\hat{y}_j^{shrink}$, presented in equation (4). Note also that the greater the variance of the sample mean $\sigma^2_{\bar{y}_{j.}}$ the more the individual estimate is shrunk towards μ. Finally, the greater the prior uncertainty, measured by τ^2, the lower the shrinkage intensity.

Up to this point, the posterior distribution of expected performance is defined in terms of the hyperpameters μ and τ. A full Bayesian treatment of hierarchical models includes the definition of a prior distribution for the hyperparameters. In this case, the same as in Gelman's example (2004), an uninformative prior is employed for $\hat{\mu}$. The use of this uninformative prior in hierarchical models is reasonable since the whole sample is employed to estimate μ and the total number of observations is large enough to justify relying only on the sample for the estimation of this parameter. The posterior distribution of μ conditional on τ is also normal with a mean equal to the precision pooled estimate ($\hat{\mu}$):

$$(10) \qquad \mu / \tau, y \sim N(\hat{\mu}, V_\mu) \qquad \text{where} \quad \hat{\mu} = \frac{\sum_{j=1}^{N} \frac{1}{\sigma_{\bar{y}_{j.}}^2 + \tau^2} \bar{y}_{j.}}{\sum_{j=1}^{N} \frac{1}{\sigma_{\bar{y}_{j.}}^2 + \tau^2}} \qquad \text{and} \qquad V_\mu^{-1} = \sum_{j=1}^{N} \frac{1}{\sigma_{\bar{y}_{j.}}^2 + \tau^2}$$

conditional posterior distribution of μ

Finally, the posterior distribution of τ is proportional to:

$$(11) \qquad p(\tau / y) \propto p(\tau) \; V_\mu^{1/2} \prod_{j=1}^{N} (\sigma_{\bar{y}_{j.}}^2 + \tau^2)^{-1/2} \; \exp\left(- \frac{(\bar{y}_{j.} - \hat{\mu})^2}{2(\sigma_{\bar{y}_{j.}}^2 + \tau^2)} \right)$$

posterior distribution of τ

An uninformative uniform prior distribution for τ is assumed. According to Gelman (2004b) this type of distribution performs well when the number of groups (advisory programs), is greater than 2 or 3, as is the case in this study. Note that the distribution of τ depends on the dispersion of y_{jt} within programs and the dispersion of $\bar{y}_{j.}$ across programs. For high variability of y_{jt} within programs and low the dispersion of $\bar{y}_{j.}$ across programs, small values for τ will be more likely and the optimal shrinking intensity will be higher.

The computation of the posterior distribution of expected performance is done via simulation in three steps. The first step is to simulate τ from its posterior distribution τ/y (equation 11) using the inverse cumulative density function method. The second step is to simulate μ by drawing from its conditional posterior normal distribution $\mu/\tau,y$ (equation 10), given the simulated values for τ. Finally, the simulation of θ_j is accomplished by sampling from its conditional posterior normal distribution $\theta_j/\mu,\tau,y$ (equation 9) given the simulated values for τ and μ.

Data

Data on corn and soybean net advisory prices are drawn from Irwin et al. (2005). The programs selected for this study were followed by the AgMAS Project for 9 crop years, from 1995 to 2003, so 9 performance observations for each program are available *(T=9)*. The number of programs considered *(N)* is chosen to be *T-1=8*, so that it is possible to employ the traditional variance covariance estimator in the portfolio optimization model.[4] The selected programs are the 8 most popular programs with Midwestern farmers as indicated by survey results (Isengildina et al., 2004). The list of programs along with the subscription costs for each of them is presented in Table 1.

It is common for advisory services to offer two alternative programs, one program where recommendations are restricted to cash transactions and another that includes recommendation in futures and options markets. The first kind is designed for farmers that are not willing to participate in derivatives markets. Some of the services included in this study offer multiple programs, but only one program per service, the one without restrictions on derivative transactions, is considered here. *AgLine by Doane* is an exception, as it is a *cash only* program . It is considered because the other program offered by this firm was not evaluated by the AgMAS Project for the 9 crop years.

Advisory prices can be interpreted as the harvest-equivalent net price received by a farmer who follows the marketing recommendations of a given program. The price is stated on a harvest-equivalent basis because post-harvest sales are adjusted for physical storage and interest opportunity costs. Details on the computations can be found in Irwin et al. (2005). The Bayesian hierarchical model is estimated for corn and soybean pricing performance and also for corn/soybeans revenue performance. Combined revenue is considered because Midwest farmers typically grow corn on half of the farm area and soybeans on the other half, and therefore it is relevant to examine a combined measure of corn and soybean pricing performance. The per-acre revenue for a given advisory program in a given crop year is found by multiplying the net advisory price by the corn or soybean yield for each year. A simple average of the two per-acre revenues is then taken to determine the total revenue obtained from this practice, which is called 'corn/soybean revenue' here.

The market benchmark employed in this study is obtained from the same AgMAS publication (Irwin et al., 2005). It corresponds to the average price offered by the market along a 20-month marketing window spanning from January of the harvest year to one year after harvest. This benchmark reflects the returns to a 'no-information' strategy of marketing equal amounts of grain each day during the crop year.

Expected Performance Estimation Results

In this section, the results from the estimation of the expected price/revenue performance of individual advisory programs are considered. Traditional, pooled and Bayesian hierarchical estimates are presented and compared.[5] Figure 2 shows the traditional point estimates and 95% confidence intervals for the expected performance of the 8 advisory programs. The values in Figure 2 are obtained by estimating separately expected performance for each advisory program. The point estimates are the sample averages (equation 2) and the confidence intervals are computed using the standard errors for these averages.

Panel A in Figure 2 shows the results from separate expected performance estimation for corn. Point estimates range from 30¢/bu above the market benchmark to 9.5¢/bu below the benchmark. Only one program, *AgLine by Doane-cash only* (no.1) has an expected price significantly greater than the benchmark price. Three other programs, *AgResource* (no.2), *AgriVisor-basic hedge* (no.3) and *Brock-hedge* (no.5), have positive expected performance, but not significantly different from zero at the 95% confidence level. The rest of the programs have negative expected performance, with *Stewart-Peterson Advisory Reports* (no.8) being the only program with significantly negative performance.

Panel B shows the estimation results for soybeans. Point estimates for expected performance range from 59¢/bu above the benchmark to 1¢/bu below the benchmark. For all programs, except *Freese-Notis* (no.6) the point estimates indicate positive expected performance, and three of them, *Ag Line by Doane-cash only* (no.1), *AgResource* (no.2) and *AgriVisor-basic hedge* (no.3) have positive significant performance at the 95% confidence level. None of the programs has significantly negative performance for soybeans.

By comparing Panels A and B it appears that advisory programs are more successful in the soybean market compared to the corn market. Note also that there seems to be similarities in the ordering of programs for both markets. For instance, the program that has positive significant performance for corn, *AgLine by Doane-cash only* (no.1), also has significantly positive performance for soybeans, and the program with highest point estimate for expected performance, *Ag Resource* (no.2), is the same for both crops.

The results for corn/soybeans combined revenue are presented in Figure 2, Panel C. The point estimates for expected revenue performance range from \$37/acre above the revenue benchmark to \$3.5/acre below the benchmark. Six of the eight programs have positive point estimates for expected performance. The programs with positive statistically significant performance are *AgLine by Doane-cash only* (no.1), *AgResource* (no.2) and *AgriVisor-basic hedge* (no.3). None of the programs has significantly negative performance for revenue.

The three panels in Figure 2 show substantial overlapping in the confidence intervals. This supports the notion that expected performance is not independent across advisory programs, and that an estimation model that considers this relationship is more appropriate. Figure 2 also shows large differences in the size of the confidence intervals, indicating that performance is quite stable for some programs and highly variable for others. For example, in corn, the confidence interval for *AgResource* (no.2) is five times larger than the confidence interval for *AgLine by Doane-cash only* (no.1). This implies that there are quite different degrees of uncertainty across programs in the estimation of expected performance. This heterogeneity is taken into account for the computation of pooled and shrinkage estimates, as explained next.

A weighted average pooled estimated (equation 3) was computed for corn, soybeans and revenue. Expected performance is 0.32¢/bu, 14.36¢/bu and $5.43/acre for corn, soybeans and revenue, respectively. In the three cases expected performance is positive, and it is statistically significant for soybeans and revenue, but not for corn.[6] Pooled estimates are a measure of performance for the eight most popular advisory programs as a group. Under the assumption that these eight advisory programs have the same performance, pooled estimates fully describe expected performance for the group of advisory programs considered. The assumption that all programs have the same price performance implies that farmers should be indifferent in selecting any program. For corn, given that positive performance is quite small in magnitude and statistically insignificant, farmers should be indifferent between following an advisory program and applying a naïve strategy of spreading sales along the marketing window. For soybeans and revenue, given the magnitude and significance of pooled expected pricing performance, farmers should prefer to apply recommendations from an advisory program rather than a naïve strategy of spreading crop sales.

As mentioned before, a Bayesian hierarchical model combines the information from all programs without imposing the restrictive assumption that all programs have the same expected performance. The first step in the hierarchical model estimation is the computation of the marginal posterior density of τ from equation (11). Recall that τ is the measure of uncertainty of the common prior distribution (equation 8). The greater τ is, the more the individual shrinkage estimators will be close to separate estimates. On the other hand, for low values of τ shrinkage estimates are more similar to pooled estimates. Figure 3 shows the marginal posterior density of τ for corn. Given the sample data, 0.07 is the most likely value for τ, with values around 0.07 being highly likely as well. Figure 4 shows the relationship between the values for τ and the shrinkage intensity ($\hat{w}$ from equation 4). At the left extreme of the figure τ equals zero and the shrinkage coefficient is 1, which means that all individual estimates equal the pooled estimate. When τ is zero there is no uncertainty about the prior, which is equivalent to assuming that all programs have exactly the same performance. Moving to the right in the figure, the degree of uncertainty in the prior distribution increases and less weight is given to the pooled estimate and more weight to separate estimates. The figure shows that for a given level of τ the shrinkage intensity is quite different across programs. Programs with high uncertainty in the separate estimates (large confidence intervals in Figure 2) have higher shrinkage intensity. For instance, note that programs 2, 4 and 5, which have the largest confidence intervals in Figure 2, also have the largest shrinkage intensity. Figure 5 plots the conditional posterior means for individual expected performance $(E(\theta_j / \tau, y))$ for each value of τ. At the left extreme of the figure, τ equals zero and all individual estimates are equal to the pooled estimated. At the right extreme of the figure, with a value for τ of 0.3, individual expected performance is quite different across programs, with the estimates close to the traditional separate estimates. It is also possible to see in this figure how shrinkage intensity varies across programs. For example, note that the lines for *AgLine by Doane-cash only* (no.1) and *AgResource* (no.2) cross each other. This occurs because the first program has a lower separate estimate and lower shrinkage intensity compared to the second.

By considering the information in Figures 3 to 5 it is possible to say that, based on the sample information, the most reasonable estimates for corn price performance imply a substantial shrinkage towards the pooled value. For instance, since values for τ greater than 0.2 are very unlikely (Figure 3), it is very unlikely that the expected performance of any program is greater than ¢25/bu (Figure 5). Compare this result with the traditional point estimate for *AgResource* (no.2) of ¢30/bu (Figure 2).

The marginal posterior density for τ (Figure 3), along with equations (9) and (10) are employed to simulate the posterior distribution of individual performance, as was explained in the previous section. Summary results from the simulation of the posterior distribution of the expected performance for corn are presented in Figure 6, Panel A. The point estimates correspond to the median of the simulated values and the lower and upper bounds for the intervals correspond to the 2.5 and 97.5 percentiles, respectively. The Bayesian confidence intervals can be compared with the traditional confidence intervals in Figure 2, Panel A. Note that both figures suggest the same ordering of programs according to expected performance. For instance, in both cases the program with the highest point estimate is *AgResource* (no.2) and the one with the lowest point estimate is *Stewart-Peterson Advisory Reports* (no.8). Bayesian confidence intervals are smaller and closer to the pooled estimate than to traditional ones. According to this figure it is highly unlikely that the expected performance for an advisory program in corn is higher than ¢35/bu above the benchmark or lower than ¢16/bu below the benchmark. Also, it appears highly likely that following the marketing recommendation from an advisory program for corn will result in an outcome close in the average market price.

Figure 7, Panel A compares the point estimates under the two estimation procedures for corn. The values of the two estimates are similar except for *AgResource* (no.2). The separate estimate for this program is shrunk strongly towards the pooled estimate, since this estimate is the most extreme value in the sample and has the greatest standard error. Recall that the lower the precision of the individual estimate, the greater the shrinkage intensity towards the pooled values. Table 2, Panel A summarizes the performance estimation results for corn. Optimal shrinkage intensity corresponds to the median of the simulated values for shrinkage intensity. Shrinkage coefficients range from 0.11 (for *AgLine by Doane-cash only*) to 0.72 (for *AgResource*). Programs with larger standard errors in the separate estimates (larger confidence intervals in Figure 2) are those with greater optimal shrinkage intensities.

Results for soybeans are similar to those for corn. The Bayesian confidence intervals are presented in Figure 6, Panel B. In this case the optimal shrinkage intensity is higher, since the most likely values for τ are around 0. This is the case for soybean price because the ratio of between program deviations to within program deviations is smaller for this crop compared to corn. Recall that the more similar to each other are the average performances (lower between program deviations), the greater is the optimal shrinkage intensity. Also, the lower the precision of separate estimates (higher within program deviations), the higher is the optimal shrinkage intensity. According to this figure, it is very unlikely that expected performance in soybeans for any given program is greater than 50¢/bu and lower than 7¢/bu. In other word it is highly likely to obtain positive performance when following the recommendation of an advisory program for soybeans.

Figure 7, panel B shows traditional vs. shrinkage point estimates for soybeans. The ordering of program is almost the same according to both estimations, but while separate estimates suggest some differences in performance across programs, Bayesian estimates indicate that expected performance is very similar across programs for soybeans. Panel B in Table 2 summarizes the estimation results for soybeans. Note that the values for the shrinkage coefficients are larger compared to the ones for corn, ranging from 0.34 (for *AgLine by Doane-cash only*) to 0.96 (for *AgResource and Brock-hedge*).

Finally, Panel C in Figures 6 and 7 and Table 2 present the estimation results for combined corn/soybeans revenue. Based on Panel C in Figure 5 is it highly unlikely that expected advisory revenue for any program is more than \$30/acre above the benchmark or more than \$9.6/acre below the benchmark. As expected, the results in terms of shrinkage intensity are in between the ones obtained for corn and soybeans. The optimal shrinkage intensity for revenue ranges from 0.10 (for *AgLine by Doane-cash only*) to 0.79 (for *AgResource*).

The Selection of Portfolios of Market Advisory Programs

As mentioned before, the farmer's decision of selecting one or several advisory programs is modeled as a Markowitz portfolio optimization model. The model for selecting portfolios based on corn/soybeans revenue performance is a quadratic mixed integer program and is presented below:

$$
\begin{aligned}
&\text{Min} \quad \sum_i \sum_j x_i x_j \sigma_{ij} \\
&\text{such that:} \\
&\qquad \sum_j p_j x_j - \frac{c_j z_j}{S} \geq \overline{p} \\
(12) \qquad &\qquad \sum_j x_j = 1 \\
&\qquad x_j \leq z_j \quad \text{for all } j \\
&\qquad x_j \geq 0, \quad z_j = 0,1 \quad \text{for all } j
\end{aligned}
$$

where *i* and *j* represent individual advisory programs, σ_{ij} is the covariance between revenue for program *i* and revenue for program *j* (and revenue variance when *i=j*), p_j is the expected revenue for program j (in \$/acre), $\bar{p}$ is the exogenously specified minimum expected revenue of the portfolio, z_j is a binary variable which indicates whether program j is selected (z_j=1) or not (z_j=0), c_j is the subscription cost associated with program j and S is the farm size (in acres). Farm size must be defined in this model since subscription costs are paid on a per-farm basis. A farm size of 2,000 acres is considered in the present analysis, as this size is typical in the Midwestern US.

The objective function represents the portfolio variance, which is to be minimized. The first constraint restricts the expected revenue (adjusted for the sign-up costs of advisory programs) to be greater than $\bar{p}$. The second constraint establishes that weights add up to 1. The last constraint implies that if an advisory program is to have a positive share in the portfolio, then the farmer must subscribe for that program (i.e., if x_j >0, then z_j =1), in which case the associated fixed cost (per acre) is subtracted from the expected revenue. The above model is used to obtain the efficiency frontier by varying the value of $\bar{p}$ systematically between the maximum expected revenue and the expected revenue of the minimum-variance portfolio.

The portfolio selection model is also solved for corn and soybeans advisory prices individually. In this case, the revenue parameter p_j is replaced by the expected price of program j and the minimum required expected revenue parameter $\bar{p}$ is replaced by the minimum required expected advisory price. In order to avoid making assumption about yield levels and farm size in the models for corn and soybeans advisory price subscription costs are ignored.

Two versions of the model are solved for each of the three cases, corn price, soybean price and revenue. One version is based on traditional and the other on Bayesian point estimates for expected price/revenue. The traditional and Bayesian estimates for expected price/revenue and the standard deviations estimates employed in the portfolios selection models are listed in Table 3. Traditional point estimates for expected advisory price (2nd column in the three panels the Table) are equal to the average benchmark price across years plus the separate estimates for expected pricing performance presented in Table 2. In the same way, Bayesian point estimates for expected advisory price (3rd column in the three panels of Table 3) are equal to the average benchmark price plus the Bayesian estimates for expected performance presented in Table 2. Variance and covariance values correspond to traditional sample estimates in both versions. The standard deviation and average correlation for each program are listed in the last two columns in the three panels of Table 3.

Tables 4, 5 and 6 show the expected price/revenue, risk level and composition for the portfolios in the efficient frontier for corn price, soybean price and revenue, respectively. Portfolios are listed from the minimum variance portfolio (P1) to the maximum expected price/revenue portfolio (P10). Since the composition of the minimum risk portfolio depends only on variance and covariances, the program weights of P1 are identical under the traditional and Bayesian models. Programs in the minimum risk portfolios are *Allendale-futures only* (no.4), *Brock-hedge* (no.5) and *Stewart-Peterson Advisory Reports* (no.8) for corn; *AgResource* (no.2), *Brock-hedge* (no.5) and *Freese-Notis* (no.6) for soybeans and *AgResource* (no.2), *AgriVisor-basic hedge* (no.3), *Allendale* (no.4) and *Stewart-Peterson Advisory Reports* (no.8) for revenue. For portfolios with higher risk and higher expected price/revenue the proportion of *AgResource* (no.2) increases and it reaches 100% for the maximum expected price/revenue portfolios (P10) in all models.

The main difference in portfolio composition based on Bayesian vs. traditional estimates is that for the first case the weights for *AgResource* (no.2) in the efficient portfolios are smaller and decrease more rapidly when going from high expected price/revenue portfolios to low risk portfolios. This effect is stronger for corn and revenue. Recall that *AgResource* is the program with highest expected pricing performance and also highest optimal shrinking intensity for corn, soybeans and revenue. Another difference in portfolio composition under the two estimation procedures is that *AgLine by Doane-cash only* (no.1), which was not included in the efficient portfolios for corn price and revenue under traditional estimates, has quite large weights in the efficient portfolios based on Bayesian estimates. For soybeans, this program is part of the portfolios under both estimation procedures but has larger weights when Bayesian estimates are employed. This effect occurs because *AgLine by Doane-cash only* has relatively high performance and low standard deviation, and it becomes more attractive after *AgResource* expected performance estimate is shrunk towards pooled performance values.

Figure 8 shows the efficient frontiers for corn price, soybean price and revenue. For comparison, the points for the 20-month market benchmark are also included in the three panels. Note that when Bayesian estimates are employed, the frontier is closer to the benchmark implying lower gains from contracting a portfolio of advisory programs. This effect is mainly determined by the high shrinkage intensity for the estimate of expected performance for *AgResource* in the hierarchical model.

For corn price (Panel A), the figure shows that the efficient frontiers are relatively close to the market benchmark. Based on the traditional estimation model, five of the portfolios in the efficient frontier, P3 to P6, dominate the market benchmark in the mean-variance sense. Based on the Bayesian hierarchical model, six portfolios, P3 to P7, dominate this benchmark. These portfolios are located in the Northwest quadrant, so they have higher expected price and lower risk than the market benchmark. Panel B shows the efficient frontiers for soybeans. In this case the frontiers are placed more northwest from the market benchmark, compared to the corn figure. This indicates that possible benefits from holding a portfolio of advisory programs are larger for soybeans. The whole efficient frontier dominates the market benchmark under both estimation models. Panel C presents the results for revenue. In this case, portfolios P1 to P6 dominate the market benchmark based on the traditional model, and portfolios P1 to P7 dominate this benchmark based on the Bayesian hierarchical model. Statistical tests were conducted to evaluate whether the differences in expected price/revenue between the efficient portfolios and the benchmark are significant (at 95% confidence level). Under the traditional estimation approach, a simple *t*-test for portfolio expected performance equal to zero is conducted. For the Bayesian estimation model, the confidence intervals of expected performance for each portfolio are obtained based on posterior distribution for individual expected performance generated by simulation. These tests indicate that the portfolios with expected price significantly higher than the benchmark price are P6 to P9 for corn, P4 to P10 for soybeans and P5 to P10 for revenue based on the traditional estimation model. Based on the Bayesian hierarchical model portfolios P7 and P8 for corn, all portfolios for soybeans and P5 to P10 for revenue have significantly positive expected performance.

Conclusions and Final Remarks

A Bayesian hierarchical model under normality was employed to estimate individual expected pricing performance for eight popular advisory programs for corn and soybeans. Performance is defined as the difference between the price/revenue obtained by following the program's marketing recommendation and the average price/revenue offered by the market along the marketing window. The estimates obtained from this model are shrinkage estimators, since they are weighted averages of traditional separate and pooled estimates. Based on the sample employed, the most reasonable individual estimates for expected performance imply a substantial shrinkage towards pooled values. The optimal shrinkage intensity (weight for the pooled estimate) is on average 0.35, 0.81 and 0.43 for corn price, soybean price and corn/soybeans revenue, respectively. Optimal shrinkage intensity varies substantially across programs, being greater for those programs with high performance variability across years. The median values for the posterior distribution of expected performance range from ¢–9/bu to ¢9/bu for corn, from ¢11/bu to ¢17/bu for soybeans and $–0.4/acre to $11/acre for revenue.

The farmer's decision of selecting one or several advisory programs was modeled as a Markowitz portfolio optimization model. Both Bayesian and traditional estimates for expected pricing performance were employed to compute the inputs in the portfolio selecting model. The main difference in portfolios composition based on Bayesian vs. traditional estimates is that for the first case, the weight for the program with highest expected pricing performance (and also highest shrinking intensity) in the efficient portfolios is smaller, and decreases more rapidly when going from high expected price/revenue portfolios to low risk portfolios. When Bayesian estimates are employed, the efficient frontier is closer to the benchmark implying lower gains from contracting a portfolio of advisory programs. However, even based on the Bayesian model, there are portfolios with expected price/revenue significantly higher than the market benchmark price/revenue. Some of these portfolios also have lower standard deviations (based on point estimates) than the market benchmark price, implying that not only risk neutral but also risk averse farmers may be interesting in contracting these portfolios of advisory programs instead of simple spreading sales along a the marketing window.

The results from the simulation of the Bayesian posterior distributions of expected pricing performance provide information to answer additional interesting questions. For instance, it is possible to evaluate the probability that a certain program has higher expected performance than another. This probability is computed as the proportion of iterations in the simulation where expected performance for the first program is higher than expected performance for the second one. Another relevant question is the probability that certain program has the highest expected performance among the programs considered. This probability is computed as the proportion of iterations in the simulation where expected performance for that program was higher than the simulated expected performances for all other programs. For example, the probability that expected performance is greater for *Brock-hedge* (no.5) than for *Pro Farmer-hedge* (no.7) is 0.81 for corn and 0.34 for soybeans and 0.80 for revenue. The probability of *AgResource* (no.2) being the program with the highest expected performance is 0.49 for corn, 0.34 for soybeans and 0.57 for revenue.

There are some extensions for this research to be considered in the future. For this study the number of programs evaluated was restricted to eight, in order to be able to use traditional variance/covariance estimates in the portfolio optimization models. However, there are other programs that have been evaluated by AgMAS for nine or less crop years that could be considering for expected performance estimation. The Bayesian hierarchical model allows combining programs with different numbers of observations. When this is the case, the number of observations will have an effect on the shrinkage intensity. Separate estimates for programs with less time-series observations, which are less reliable, will be shrunk more towards pooled estimates. In the case of considering a number of programs equal or greater than the number of time-series performance observations, it would be necessary to impose some structure to compute variances and covariances estimates for the portfolio selection models.

Another extension for the hierarchical model is to incorporate characteristics of the programs that could explain differences in performance. For example, evidence suggests that the there is a positive relationship between the degree of activeness of a marketing program and pricing performance (Cabrini et al., 2005). While information on the activeness degree is not available for the entire period included in this study at the current time, incorporating activeness information to a Bayesian hierarchical model is an interesting future extension of this work.

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Endnotes

[1] The term "advisory program" is used because several advisory services have more than one distinct marketing program for farmers

[2] This pooled estimate is very similar to $\hat{y}^{pool}$ (equation 3), the formula is presented below in equation (10).

[3] Although this assumption is not true in most real applications, it is commonly used as a good approximation in this type of estimation procedures. Traditional sample estimates for the variances are employed.

[4] For N > T-1 the traditional estimate for the variance-covariance matrix is singular and cannot be inverted to solve the portfolio optimization model

[5] The Jarque-Bera normality test was conducted to test whether the normality assumption is supported by the data. The test is conducted for the distribution of performance in corn, soybeans and revenue for each of the eight programs, and also for the distribution of expected performance across programs. In none of the cases normality was rejected at 95% confidence level. Although this result should not be interpreted as a strong proof that data is normally distributed, especially given the low number of observations, it is possible to say that there is no evidence of large departures from normality.

[6] The standard error for the pooled estimates is $\hat{\sigma}_{\hat{y}^{pool}} = \sqrt{\left[\sum_{j=1}^{N} \frac{1}{\sigma^2_{\bar{y}_{j.}}}\right]^{-1}}$. The 95% confidence intervals for pooled performance estimates are [¢-2.7/bu , ¢3.3/bu] for corn, [¢10/bu, ¢19/bu] for soybeans and [$3.1/acre, $7.8/acre] for revenue

Table 1. List of Market Advisory Programs

ID number	Program	Subscription Costs ($/year)
1	AgLine by Doane-cash only	300
2	AgResource	600
3	AgriVisor-basic hedge	299
4	Allendale-futures only	300
5	Brock-hedge	240
6	Freese-Notis	360
7	Pro Farmer-hedge	420
8	Stewart-Peterson Advisory Reports	150

Table 2. Expected Performance for Market Advisory Programs, Estimation Results from Traditional and Bayesian Hierarchical Models

Panel A. Corn Price

ID	Market Advisory Program	Separate Estimates	Optimal Shrinkage Intensity	Bayesian Estimates
		($/bu)		($/bu)
1	AgLine by Doane-cash only	0.073	0.11	0.066
2	AgResource	0.305	0.72	0.089
3	AgriVisor-basic hedge	0.030	0.19	0.024
4	Allendale-futures only	-0.037	0.62	-0.012
5	Brock-hedge	0.022	0.63	0.009
6	Freese-Notis	-0.003	0.18	-0.001
7	Pro Farmer-hedge	-0.083	0.20	-0.065
8	Stewart-Peterson Advisory Reports	-0.096	0.18	-0.078
	Precision Weighted Pooled Average ($/bu)		0.003	
	Mean of the Prior Distribution (μ) ($/bu)		0.004	

Panel B. Soybeans Price

ID	Market Advisory Program	Separate Estimates	Optimal Shrinkage Intensity	Bayesian Estimates
		($/bu)		($/bu)
1	AgLine by Doane-cash only	0.145	0.34	0.145
2	AgResource	0.594	0.96	0.167
3	AgriVisor-basic hedge	0.170	0.75	0.151
4	Allendale-futures only	0.078	0.94	0.138
5	Brock-hedge	0.176	0.96	0.146
6	Freese-Notis	-0.014	0.82	0.110
7	Pro Farmer-hedge	0.167	0.79	0.149
8	Stewart-Peterson Advisory Reports	0.130	0.92	0.143
	Precision Weighted Pooled Average ($/bu)		0.144	
	Mean of the Prior Distribution (μ) ($/bu)		0.144	

Panel C. Corn/Soybeans Revenue

ID	Market Advisory Program	Separate Estimates	Optimal Shrinkage Intensity	Bayesian Estimates
		($/acre)		($/acre)
1	AgLine by Doane-cash only	9.16	0.10	8.66
2	AgResource	37.06	0.79	11.01
3	AgriVisor-basic hedge	6.37	0.17	5.97
4	Allendale-futures only	0.48	0.65	3.01
5	Brock-hedge	7.67	0.77	5.04
6	Freese-Notis	0.19	0.24	1.29
7	Pro Farmer-hedge	-2.87	0.30	-0.74
8	Stewart-Peterson Advisory Reports	-3.48	0.38	-0.49
	Precision Weighted Pooled Average ($/acre)		5.43	
	Mean of the Prior Distribution (μ) ($/acre)		4.36	

Note: Performance is defined as the difference between the price/revenue obtained by the advisory program and the benchmark price/revenue (advisory price/revenue - benchmark price/revenue). The estimation was done based on 1995 to 2003 performance data. Average benchmark prices/revenue during these years are $2.26/bu, $5.87/bu and $305/acre, for corn, soybeans and revenue, respectively.

Table 3. Advisory Programs' Expected Price/Revenue, Standard Deviations and Average Correlation with the Rest of the Programs

Panel A. Corn Price

ID	Market Advisory Program	Expected Advisory Price: Traditional Estimates ($/bu)	Expected Advisory Price: Bayesian Estimates ($/bu)	Standard Deviation ($/bu)	Average Correlation
1	AgLine by Doane-cash only	2.34	2.33	0.37	0.76
2	AgResource	2.57	2.35	0.66	0.64
3	AgriVisor-basic hedge	2.29	2.29	0.31	0.75
4	Allendale-futures only	2.23	2.25	0.19	0.39
5	Brock-hedge	2.29	2.27	0.23	0.34
6	Freese-Notis	2.26	2.26	0.41	0.75
7	Pro Farmer-hedge	2.18	2.20	0.44	0.75
8	Stewart-Peterson Advisory Reports	2.17	2.19	0.33	0.69

Panel B. Soybeans Price

ID	Market Advisory Program	Expected Advisory Price: Traditional Estimates ($/bu)	Expected Advisory Price: Bayesian Estimates ($/bu)	Standard Deviation ($/bu)	Average Correlation
1	AgLine by Doane-cash only	6.01	6.01	0.71	0.79
2	AgResource	6.46	6.03	0.68	0.60
3	AgriVisor-basic hedge	6.04	6.02	0.80	0.75
4	Allendale-futures only	5.95	6.01	0.69	0.79
5	Brock-hedge	6.04	6.01	0.70	0.66
6	Freese-Notis	5.85	5.98	0.61	0.82
7	Pro Farmer-hedge	6.03	6.02	0.83	0.85
8	Stewart-Peterson Advisory Reports	6.00	6.01	0.68	0.81

Panel C. Corn/Soybeans Revenue

ID	Market Advisory Program	Expected Advisory Revenue: Traditional Estimates ($/acre)	Expected Advisory Revenue: Bayesian Estimates ($/acre)	Standard Deviation ($/acre)	Average Correlation
1	AgLine by Doane-cash only	314.35	313.85	28.64	0.71
2	AgResource	342.25	316.20	48.82	0.43
3	AgriVisor-basic hedge	311.56	311.16	27.64	0.69
4	Allendale-futures only	305.67	308.20	20.22	0.39
5	Brock-hedge	312.86	310.23	30.10	0.36
6	Freese-Notis	305.38	306.48	33.81	0.71
7	Pro Farmer-hedge	302.32	304.45	35.22	0.69
8	Stewart-Peterson Advisory Reports	301.71	304.70	24.40	0.65

Note: The average correlation for each program is computed as the average of the 7 correlations values between a given program and each of the other programs.

Table 4. Composition of Efficient Portfolios of Advisory Programs for Corn

Panel A. Based on Traditional Estimates

Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #) 2	3	4	5	8
	--- $/bushel ---				--- percent ---		
P1	2.24	0.17			54.61	30.51	14.88
P2	2.27	0.19	5.14	6.06	47.12	41.68	
P3	2.31	0.21	14.67		29.57	55.77	
P4	2.35	0.25	23.18		7.96	68.86	
P5	2.38	0.29	34.58			65.42	
P6	2.42	0.36	47.67			52.33	
P7	2.46	0.43	60.75			39.25	
P8	2.49	0.50	73.83			26.17	
P9	2.53	0.58	86.92			13.08	
P10	2.57	0.66	100				

Panel B. Based on Bayesian Hierarchical Estimates

Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #) 1	2	3	4	5	8
	--- $/bushel ---				--- percent ---			
P1	2.25	0.17				54.61	30.51	14.88
P2	2.26	0.18			10.95	56.83	29.37	2.85
P3	2.27	0.19	12.02		5.77	42.52	39.7	
P4	2.28	0.20	27.01			24.12	48.87	
P5	2.29	0.23	39.75			3.64	56.61	
P6	2.31	0.26	58.82				41.18	
P7	2.32	0.31	79.25				20.75	
P8	2.33	0.37	99.67				0.33	
P9	2.34	0.50	50.4	49.6				
P10	2.35	0.66		100				

Table 5. Composition of Efficient Portfolios of Advisory Programs for Soybeans

Panel A. Based on Traditional Estimates

Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #)			
			1	2	5	6
	--- $/bushel ---			--- percent ---		
P1	6.09	0.56		31.7	20.75	47.55
P2	6.13	0.56		38.65	20.49	40.86
P3	6.17	0.56		45.6	20.22	34.18
P4	6.21	0.57		52.56	19.95	27.49
P5	6.25	0.58		59.51	19.69	20.81
P6	6.29	0.59	1.51	66.01	19.58	12.9
P7	6.34	0.61	8.26	70.97	20.03	0.74
P8	6.38	0.63	3.54	80.28	16.18	
P9	6.42	0.65		90.01	9.99	
P10	6.46	0.68		100		

Panel B. Based on Bayesian Hierarchical Estimates

Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #)				
			1	2	3	5	6
	--- $/bushel ---				--- percent ---		
P1	6.00	0.56		31.7		20.75	47.55
P2	6.01	0.56		36.51		22.82	40.67
P3	6.01	0.56		41.31		24.9	33.79
P4	6.01	0.57	4.43	43.72		26.46	25.4
P5	6.02	0.57	10.8	45.07		27.79	16.34
P6	6.02	0.58	17.18	46.42		29.12	7.27
P7	6.02	0.59	20.49	50.73		28.78	
P8	6.03	0.60		63.03	13.18	23.79	
P9	6.03	0.63		80.94	8.87	10.19	
P10	6.03	0.68		100			

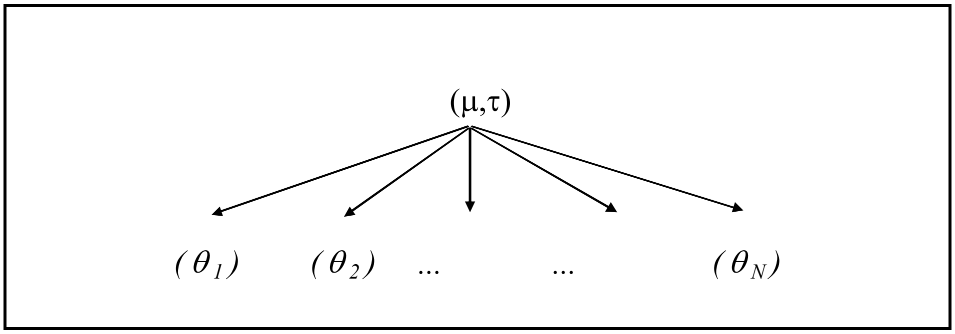
Table 6. Composition of Efficient Portfolios of Advisory Programs for Corn/Soybeans Revenue

Panel A. Based on Traditional Estimates

Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #) 2	3	4	5	8
	--- $/bushel ---		--- percent ---				
P1	306	18.1	0.71	17.19	65.28		16.82
P2	310	18.6	8.91	22.27	68.83		
P3	314	20.1	21.75	11.06	67.19		
P4	318	22.4	31.66		53.95	14.39	
P5	322	25.0	39.36		29.22	31.42	
P6	326	28.0	45.44			54.56	
P7	330	31.8	59.18			40.82	
P8	334	36.8	72.92			27.08	
P9	338	42.6	86.67			13.33	
P10	342	48.8	100				

Panel B. Based on Bayesian Hierarchical Estimates

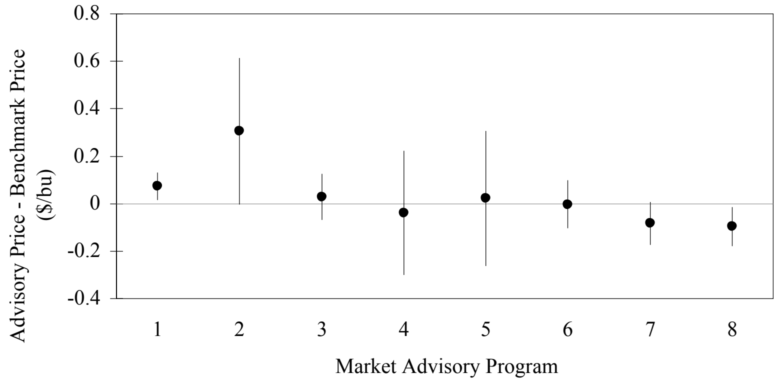
Portfolio Number	Expected Price	Standard Deviation	Portfolio Proportions for Market Advisory Programs (by ID #) 1	2	3	4	5	8
	--- $/bushel ---		--- percent ---					
P1	308	18.1		0.71	17.19	65.28		16.82
P2	308	18.1			27.13	67.35		5.52
P3	309	18.7	20.1		16.29	63.61		
P4	310	19.5	42.5			57.5		
P5	311	21.2	59.02			40.98		
P6	312	23.7	69.53			7.85	22.61	
P7	313	26.2	86.76				13.24	
P8	314	31.5	73.03	26.97				
P9	315	39.8	33.32	66.68				
P10	316	48.8		100				



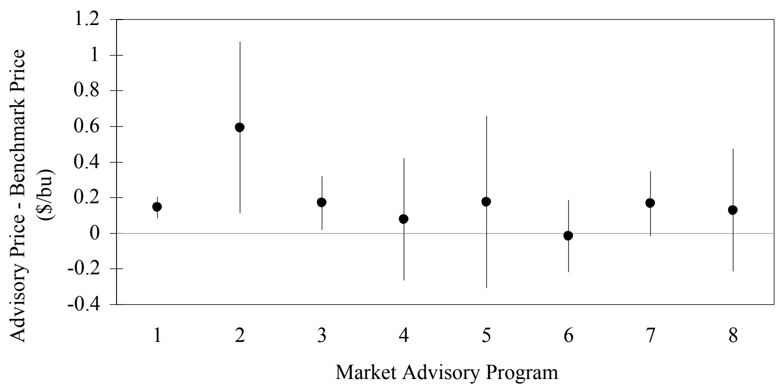
Note: θj is the expected performance for program j; (μ,τ) are the parameters of the common prior distribution.

Figure 1. Diagram for the structure of the hierarchical model for advisory services' expected performance

Panel A. Corn price



Panel B. Soybean price



Panel C. Corn/soybean revenue

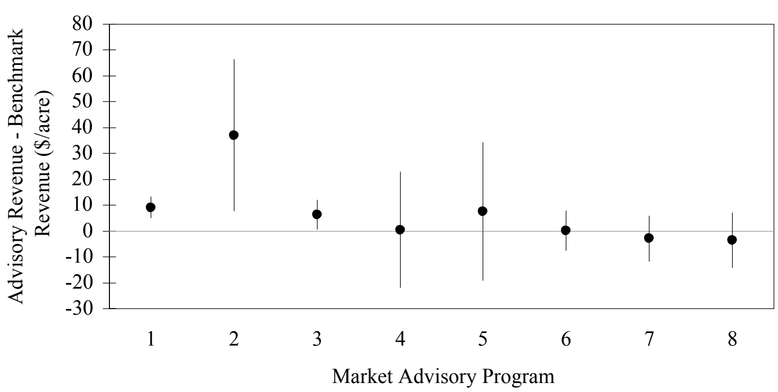


Figure 2. Expected performance of market advisory programs, traditional separate point estimates and 95% confidence intervals

Note: The names of the advisory programs are listed in Table 1. The dots in the figures represent the point estimates and the lines the 95% confidence intervals for expected performance.

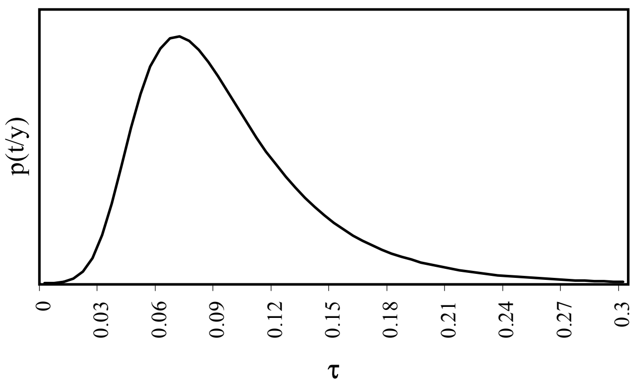
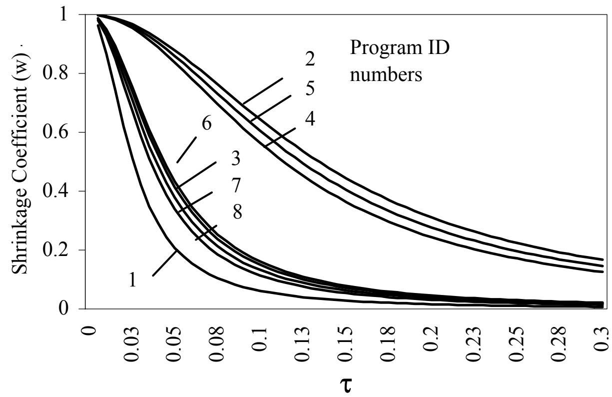


Figure 3. Marginal posterior density of τ for corn pricing performance



Note: The shrinkage coefficient is the weight for the pooled estimate in the shrinkage estimators.

Figure 4. Shrinakge intensity vs. τ for corn performance estimation

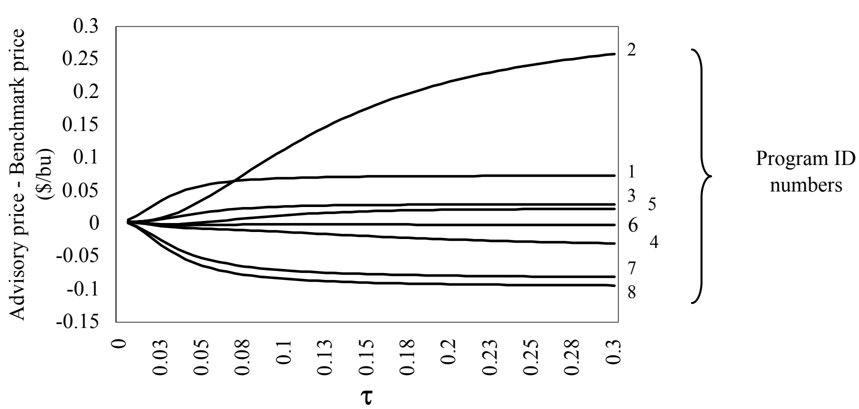
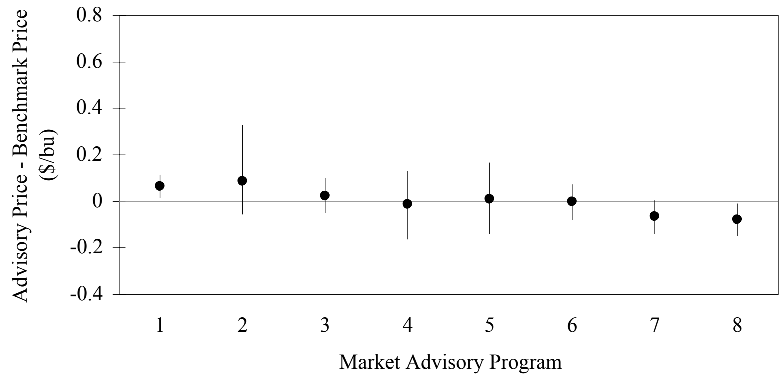
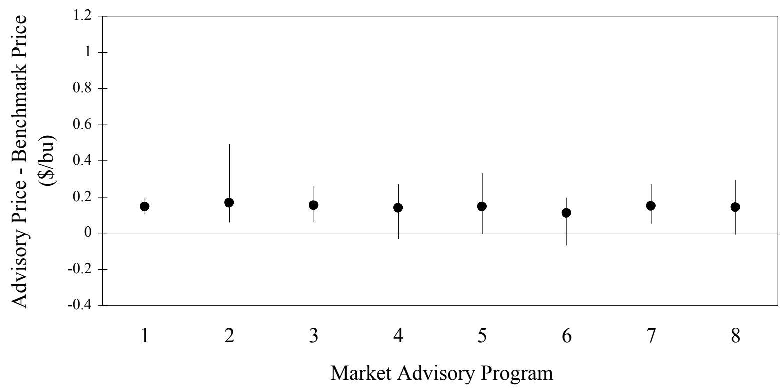


Figure 5. Posterior point estimates for expected corn pricing performance for different levels of shrinkage intensity

Panel A. Corn price



Panel B. Soybeans price



Panel C. Corn/soybeans revenue

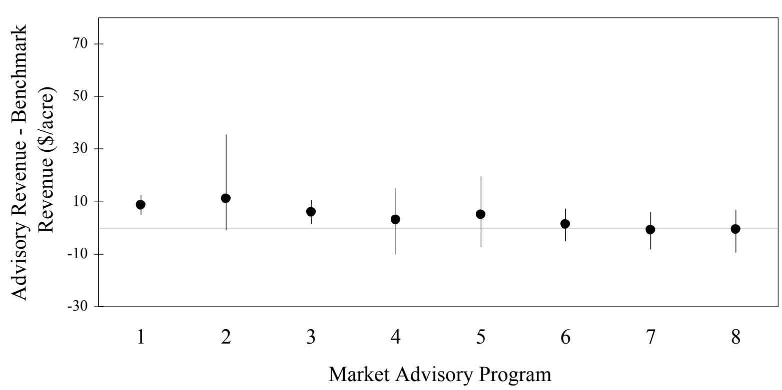
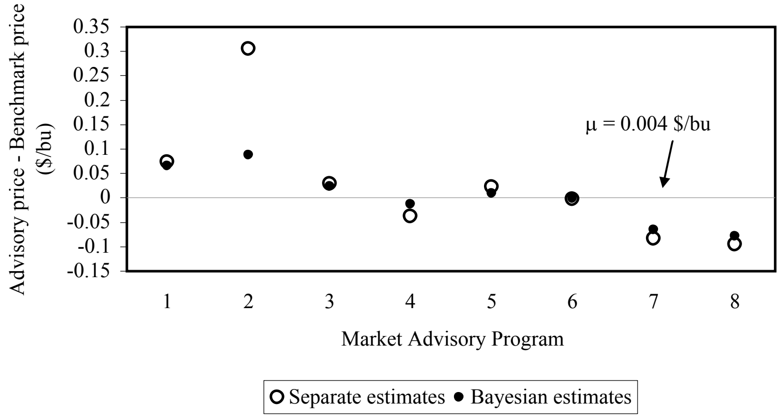


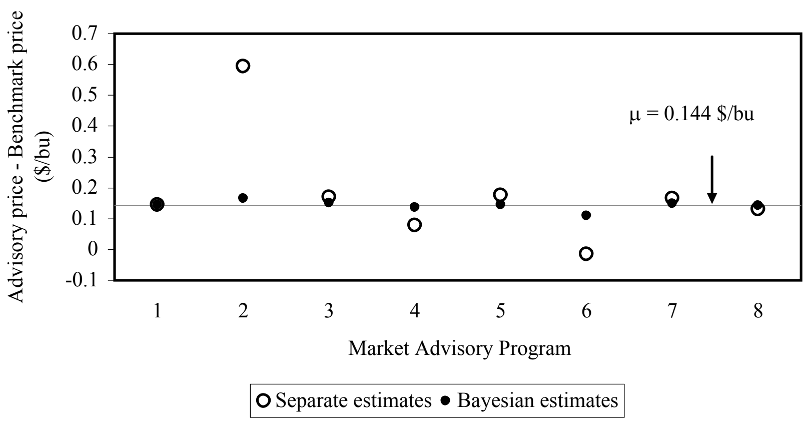
Figure 6. Expected performance of market advisory programs, Bayesian hierarchical point estimates and 95% confidence intervals

Note:The names of the advisory programs are listed in Table . The dots in the figures represent the point estimates and the lines the 95 % confidence intervals for expected performance.

Panel A. Corn price



Panel B. Soybean price



Panel C. Corn/soybean revenue

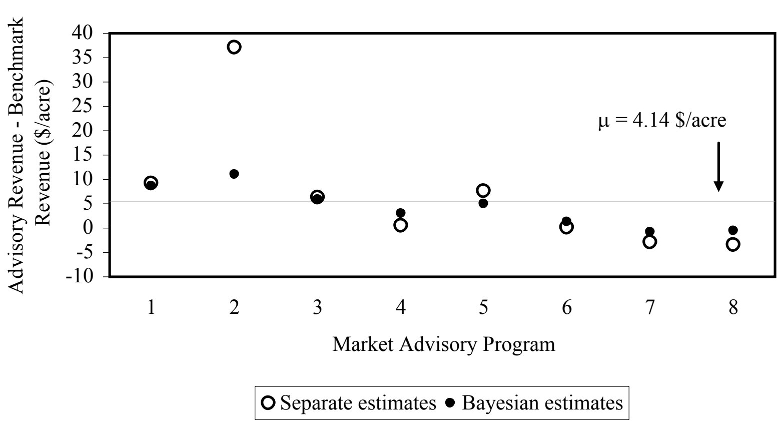
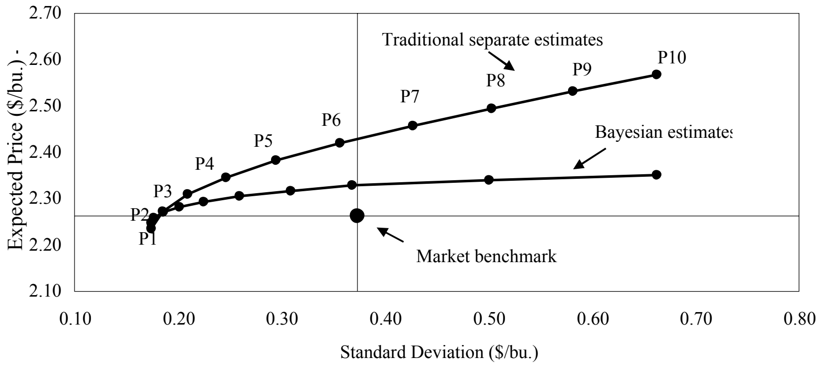
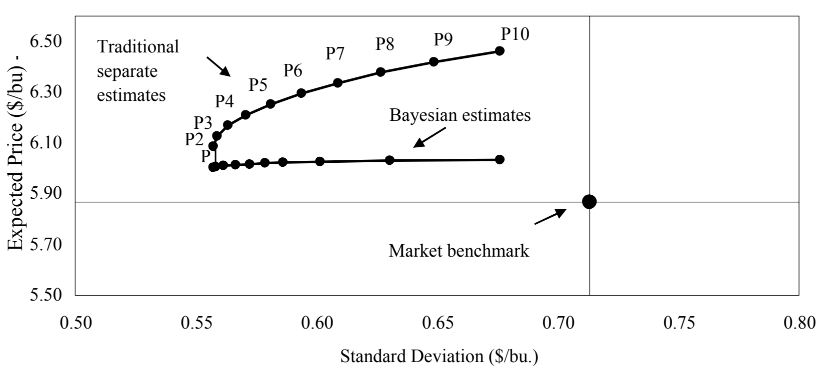


Figure 7. Traditional and Bayesian point estimates for advisory programs expected pricing performance

Panel A. Corn price



Panel B. Soybean price



Panel C. Corn/soybean revenue

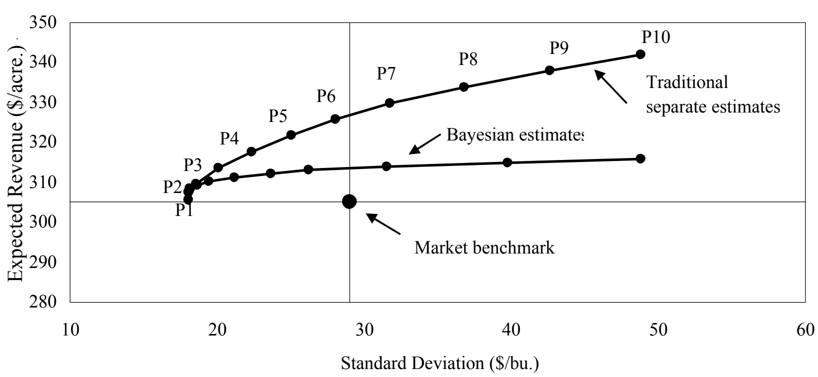


Figure 8. Efficient frontier for portfolios of market advisory programs based on traditional and Bayesian estimates