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Estimating the Costs of Revenue Deficiency Programs

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Abstract

This paper develops an approach to empirically demonstrate how the within-season distribution of U.S. domestic commodity support for corn differs between current-style approaches of support and revenue-based support. From a purely economic standpoint, the results show the revenue-based payment scenarios to be preferable at the national level to the uncoordinated forms of support currently in use, even in a situation where the annual mean payments are set equal across the support scenarios. For revenue-based support, the variability around the total expected annual payment is lower, and perhaps more importantly, the probability of high payments is lower. These results suggest advantages to this type of support, both in terms of lower budgetary uncertainty – for producers and the Federal government – and in meeting multilateral commitments for limiting spending on domestic commodity support.

Key words

Domestic support, marketing loan benefits, counter-cyclical payments, disaster assistance, revenue support, corn, nonparametric, semi-nonparametric, bootstrap

Estimating the Costs of Revenue Deficiency Programs

Introduction

Current U.S. direct commodity support in the form of counter-cyclical payments (CCPs) and marketing loan benefits (MLBs) makes payments to producers in response to price shortfalls. Commodity support programs that only target price variability can over- or under-compensate farmers in some situations. For example, large yields nationally can reduce market prices, generating CCPs. However, the higher yields offset to some extent the effect of lower prices on revenue. CPPs do not take this effect into account, which means that they can over-compensate producers when yields are high. Conversely, price tends to rise with large yield decreases, thereby reducing the counter-cyclical payment, which can under-compensates producer for a revenue decline. Furthermore, yield decreases in some regions may be small enough to have little effect on prices, leading to under-compensation by CCPs and MLBs in those regions. While CCPs and MLBs target low prices, *ad hoc* disaster assistance generally targets low yields. Hence, U.S. direct commodity support for program crops such as corn does address both price and yield, it does not do so in a coordinated fashion.

On the other hand, a direct commodity support program based on revenue deficiencies could make use of the natural hedge inherent in revenue, or price times quantity. Since price and yield tend to be negatively correlated, revenue exhibits less variability than it would otherwise. As such, a revenue deficiency program could provide producers protection against an unexpected decline in revenues, whether due to low yields, low prices, or some combination thereof, while reducing the probability of over-

compensation. A revenue deficiency program could in principle be an efficient substitute for the existing suite of formally uncoordinated direct commodity support programs and *ad hoc* disaster assistance.

This paper develops a stochastic model for estimating potential revenue deficiency payments to U.S. corn producers in a discrete-dynamic context. The analysis uses county-level historic production data for all U.S. counties for which the National Agricultural Statistics Service (NASS) reports corn production, thereby ensuring almost complete coverage of the estimated distribution of corn payments. The market price-yield relationship is treated as stochastic, and the yield relationship itself as spatially stochastic. We minimize the potential for misspecification bias by using nonparametric and semi-nonparametric approaches in the model. With this model, the empirical distribution of payments for a crop year is estimated under two alternative revenue deficiency program scenarios. Comparisons are made to the distribution of payments under generic versions of current production-coupled support programs. Based on the estimated payment distributions, implications for U.S. commodity policy of alternative forms of domestic commodity supports programs are drawn.

Commodity support program scenarios

The core idea of a revenue deficiency program is to pay producers some portion of the difference between expected, or a target revenue, and realized revenue, when the latter is lower than the former. In essence, revenue deficiency programs are forms of revenue insurance (as in the case of Federal crop revenue insurance) for which the farmer does not pay an insurance premium. Hence, they may provide direct income-augmenting

support in addition to risk-reduction benefits. While the concept of a revenue deficiency program is not a new idea (e.g., Miranda and Glauber, 1991; U.S. Congress, 1999), it has only recently begun to receive significant attention from a variety of sources, the most prominent in the academic literature being those of Babcock and Hart (2005) and Zulauf (2006). While noting that the stated positions of interest groups regarding farm policy changes over time, National Corn Growers Association (2007) supported a variation on the Babcock and Hart proposal and American Farmland Trust (2007) supported the Zulauf approach. To gain some insights into the policy implication of revenue support programs, this paper develops an approach for comparing the distribution of payments from hypothetical revenue-based programs to those from a program similar to the current set of programs.

As actual program payments are sensitive to a mind-numbing array of program provisions, seemingly small changes in which can cause large changes in payment levels. Hence, to make the support programs comparable, our program scenarios are designed to differ only in the fundamental program provisions. Our goal is to investigate how payments change with explicit coordination of prices and yields, and not for example, how calculating payments using daily prices rather than monthly prices affects the results. We next lay out our current program scenario as well as two revenue-based program scenarios, with one based (in part) on revenue shortfalls with respect to a target revenue, and one based on revenue shortfalls with respect to an expected, or market, revenue.

Current domestic program scenario

Our scenario for a generic version of the current domestic support has three components: counter-cyclical payments, marketing loan benefits, and disaster payments. The counter-cyclical payments (CCP) are based on a payment rate determined by shortfalls in and "effective" price with respect to a statutory target price, multiplied times a fixed base acreage and yield. The CCP for a producer *i* of crop *j* in year *t* is calculated as:

(1) $\text{CCP}_{ijt} = 0.85 \cdot \max\{ 0, (TP_j - (\text{Max}\ (NP_{jt}, LR_{ijt})) - Dj) \} \cdot (A_{ij}^B \cdot Y_{ij}^B)$,

where *TP*, *LR*, and *D* are the statutory target prices, loan rates, and direct payment rates, respectively, specified in farm legislation, *NP* is a national market price (season average price for actual CCPs), A^B is base acreage, and Y^B is base yield. This acreage and yield are based on a historic period(s) and are fixed. FSA (2006a) provides specifics of how the real CCP program determines the base acreage and yield.

The marketing loan benefits rate is based on shortfalls in market price with respect to a statutory loan rate. For farmer *i* of crop *j* in time *t*, the marketing loan benefit, or equivalently, the loan deficiency payment, is calculated as:

(2) $\text{MLB}_{ijt} = \max\{ 0, (LR_{jt} - AL_{jt}) \} \cdot A_{ijt}^H \cdot Y_{ijt}^H$,

where *LR* is is the national loan rate *LR* adjusted by various county-specific and quality factors. The alternative loan repayment rate is the market price at the time of harvest. The payments are applied to current production on each farm, i.e. harvested area, A^H, times yield, Y^H. Equation (2) is simplified over actual *MLBs*, in which the *LR* is adjusted locally for various county-specific and quality factors and where the A*LR* is essentially a USDA-determined market price that varies daily or weekly (depending on the crop) according to market conditions, and is adjusted to reflect quality of the product. We do

not distinguish between the *MLB* taken by the farmer as a loan deficiency payments or as repayment on a loan (i.e., the "marketing loan gain") as the marketing loan benefit is the same in either case.

The linkage here between the *CCP* and the *MLB* is perhaps higher here than in the actual versions of these programs given that the actual *MLB* is a function of daily prices while the actual *CCP* is a function of the season average price, meaning that *MLB* may even be paid out in some cases even when the season average price is greater than the target price. However, proposals have been made (e.g., USDA, 2007) to lower the possibilities for payment recipients to game the timing of taking *MLBs* by making these a function of monthly average prices. In such a case, assuming that the monthly average price is calculated over the calendar month, the expectation would most likely be that producers will take their *MLB* payments in November, the month when prices tend to be at their lowest due to the bulk of the harvest coming in at that time.

Disaster assistance payments are usually based on shortfall in yield with respect to expected yield, where the lost production is valued at an "established", or expected price. We assume that our disaster assistance operates in this manner, but on a permanent rather than an *ad hoc* basis:

$$(3)\ DA_{ijt} = \max\{\ 0,\ (0.65 \cdot E(Y_{ijt}^{P}) - Y_{ijt}^{P})\ \} \cdot E(P_{ijt}) \cdot A_{ijt}^{P}\ ,$$

where Y_{ijt}^{P} is actual realized yield per planted acre, $E(Y_{ijt}^{P})$ is the expected yield per planted acre, A_{ijt}^{P} is the planted acreage, and $E(P_{ijt})$ is the expected price. As is frequently the case in actual practice (e.g., the 2001 and 2002 *ad hoc* disaster programs (FSA, 2003b), we assume that payments are made when the producer's yield is reduced by more

than 35 percent from expected yield. Note that unlike the *MLB*, *DA* can be nonzero even if harvested yield is 0, hence the moniker "disaster payment".

Target revenue program scenario

We model the three components to this county area revenue program closely to that of Babcock and Hart and NCGA, but with some minor differences (e.g., we use future prices rather than cash prices). The "basic" component is a payment per planted acre to cover county revenue per acre shortfalls with respect to expected county revenue per acre in the county corresponding to farm *i*, or

(4) $\text{Basic}_{ijt} = \max\{ 0, [g \cdot E(R^P_{ijt}) - R^P_{ijt}] \} \cdot A^P_{ijt}$,

where $R^P_{ijt} = P^1_{jt} \cdot Y^P_{ijt}$ is the county average revenue per planted acre at harvest in farmer *i*'s county, P^1_{jt} is the price at harvest, $E(R^P_{ijt})$ is the expected average revenue per planted acre at planting time, A^P_{ijt} is the farmer's planted acreage, and *g* is the coverage rate ($0 < g < 1$). Note that P^1_{jt} could be the season average cash price (*ibid*.) or the futures price at harvest.

The "extended coverage" payment per harvested acre is based on the shortfall in revenue with respect to a target revenue based on a statutory price, and provides supplemental coverage over the basic payment, or:

(5) $\text{EC}_{ijt} = \min\{\max(0, \alpha \cdot ETP \cdot E[Y^H_{ijt}] - P^1_{jt} \cdot Y^H_{ijt}), (\alpha - g) \cdot ETP) \cdot E[Y^H_{ijt}] \} \cdot A^P_{ijt}$

where Y^H_{ijt} is the average actual harvested yield for farmer *i*'s county, $E[Y^H_{ijt}]$ the expected value, α ($g < \alpha < 1$) is the extended coverage box coverage level, *ETP* is the

statutory target price, P_{jt}^{1} is price at harvest, and A_{ijt}^{P} is the farmer's planted acreage. Note that Y_{ijt}^{H} is used here rather than Y_{ijt}^{P}, as per NCGA (2006).

The "production-limited" payment is similar to the extended coverage payment but applied to a fixed base acreage for the farmer, and provides supplemental coverage over the extended coverage payment:

(6) $\mathrm{PL}_{ijt} = \min\{ \max(0, \beta \cdot ETP \cdot E[Y_{ijt}^{H}] - P_{jt}^{1} \cdot Y_{ijt}^{H}), (\beta - \alpha) \cdot ETP \cdot E[Y_{ijt}^{H}] \} \cdot A_{ij}^{B}$

where β ($\alpha < \beta < 1$) is the production-limited box coverage level and A_{ij}^{B} is the farmer's fixed planted acreage base.[1]

Market revenue program scenario

The market revenue program proposal has two components: a national revenue payment (e.g., Zulauf; AFT) and a supplemental county area revenue payment. The national revenue payment is calculated as percentage decrease in national expected total revenue with respect to national average realized total revenue, times the farmer's expected revenue per planted acre times the farmer's planted acres:

(7) $NRP_{ijt} = \max\{ 0, \ (E(TR_{jt}^{P}) - TR_{jt}^{P}) / E(TR_{jt}^{P})\} \cdot E(R_{ijt}^{P}) \cdot A_{ijt}^{P}$

where TR_{jt}^{P} is total national revenue for the commodity.

With the *NRP* only being triggered by national level shortfalls in revenue, Zulauf assumes that a Federal crop insurance program payment is used to ensure that the farmer

[1] The terms "basic", "production limited", and "extended coverage" substitute for the terms Babcock and Hart (2005) use, which are "green", "blue", and "amber", respectively. These colors ("boxes") are references to categorizations by the World Trade Organization's Agreement on Agriculture (AoA) of domestic subsidies according to their impacts on production. Given the political controversy in multilateral negotiations over which support programs should be associated with each of these WTO "boxes", for the sake of avoiding the potential for confusion, we avoid using the WTO terminology in our scenarios.

is covered up to a guaranteed level. However, again for the sake of comparability across scenarios, we instead use a supplemental county area revenue payment to ensure that the farmer is covered up to a guaranteed level:

(8) $SUP_{ijt} = \max\{ 0, (\gamma \cdot E(R^P_{ijt}) - R^P_{ijt}) \cdot A^P_{ijt} - NRP_{ijt} \}$

where γ ($0 < \gamma < 1$) is the desired coverage level.

Calibration and comparability of the payment scenarios

The target revenue program operates at the county level. Hence, to put each of the program scenarios on an equal footing for the simulation, all three of our program scenarios are constructed to operate at the county level as well. For the market revenue approach, total national expected revenue is summed up from the county level estimates of expected yield to ensure that differences between the market revenue approach and the target revenue approach are due to differences in the basic program structures, and not due to aggregation bias in calculating expected national average yield with a national-level Olympic average calculation rather than an Olympic average calculation for each county.

For the expected and harvest time prices, we utilize futures prices, as discussed in more detail below. We use the same year, 2004, in the CCP and the target revenue model for determining base acreage and yield. For the purposes of calculating benefits in time *t*, we use the Olympic average of the prior five year's worth of National Agricultural Statistics Service (NASS) yield data, which is consistent with the approach used in various insurance products administered by the Risk Management Agency (RMA) and various disaster payments administered by the Farm Services Administration. This

Olympic approach may not be as refined as the approach to estimating yield in our econometric model and to simulate realized yield in our bootstrap analysis, but is a likely approach to be applied in an actual policy setting for determining expected yield.

Programs can be compared against each other in a myriad of ways. For the sake of brevity, we calibrate the models by setting the program parameters so that the mean of total annual payments evaluated at historic price-yield points is equal across the program scenarios. Further, it seems reasonable from a policy standpoint to assume that payment recipients would be reluctant to support a revised direct support program unless it provided on average the same support levels as the program it replaces. Given this calibration of the mean payments across the scenarios, higher moments of the distribution of payments can be compared, as can the program provisions necessary to achieve equality of mean total payments across programs.

Methodology for estimating payments

We estimate the distribution of payments for each county given the yield history for that county and the historic relationship between national price and national average yield. Payments to county *j* in crop year *t* are assumed to be a function of planted acres in *j* at the beginning of *t*, the parameters of the commodity programs, and the stochastic price and yield relationships.

Modeling the within-season price-yield relationship

Production is local, while market price is national (excluding arbitrage costs in moving the commodity between markets). Hence, price is a function of, among other things, total

national production, which is the sum of production across all producing regions, or equivalently when scaled by total acres, national average yield Y_t, which is the weighted sum of Y_{jt} , $j = 1,\ldots, J$ counties, $t = 1,\ldots,T$ years.

Our focus is on estimating the distribution of payments for a given reference crop year, in our case 2005, given the difference in realized yield and price over the levels expected at the beginning of the crop year. Hence, for the purposes of estimating the relationship between price and yield, we re-express the historic price and yield data as proportional changes between expected and realized price and expected and realized yield within each period, respectively. We can then apply this history of proportional changes in yield and price to 2005 data to develop the distribution of payments. Specifically, the realized national average yield, Y_t , is transformed to $\Delta Y_t = \left(Y_t - E(Y_t)\right) \Big/ E(Y_t)$. The expected value of Y_t, or $E(Y_t)$, is calculated from an estimated trend equation (as described in detail below). Similarly, the realized price at harvest, P_t , is transformed to $\Delta P_t = \left(P_t - E(P_t)\right) \Big/ E(P_t)$, where E(Pt) is derived from futures prices as discussed in the Data section below.

The historic yield data needs to be detrended before it can be used for our analysis. Namely, the upward trend in corn yields since the mid-1940s has been quite remarkable, and even mean corn yields from the 1970s are significantly lower than that which would be expected today. To generate a distribution for Y_{2005} based on historic yield shocks, the historic yields must be rescaled to reflect the proportional change in the state of technology between that in 2005 and that in time t, i.e., Y_{it} is rescaled to 2005 terms as

(9) $Y_{it}^{d} = E(Y_{i2005})(\Delta Y_{it} + 1), \forall\, i$ counties, t periods, $t \neq$ 2005.

A specific detrending approach used in the literature is to assume that expected yield evolves according to a time trend, or $E(Y_t) = f(t)$, e.g., Paulson and Babcock (2007), who fit a linear model to the time trend.

To separate the stochastic component of yield from the upward trend in yields over time due to technological and managerial innovations, we detrend the yield data using county-specific nonparametric LOESS (Cleveland, 1979; Cleveland and Devlin, 1988) predictions of county yield trends instead of the simple parametric approaches used in the literature. As the LOESS procedure is available as a canned procedure in several common statistical and econometric packages, it is not described in detail here. In short, LOESS specifically denotes a method that is (somewhat) more descriptively known as locally weighted polynomial regression. At each point in the data set a low-degree polynomial is fit to a subset of the data. The polynomial is fit using weighted least squares, giving more weight to points near the point whose response is being estimated and less weight to points further away. A smoothing parameter denotes the degree of the local polynomial, and controls the flexibility of the model.

Our goal in fitting the trend regression was to model yield as a function of technological change and other factors that are correlated with time. Any deviations from the trend are assumed to be due to stochastic shocks. A model that is linear with respect to the time trend for a county i, e.g., $E(Y_{it}) = \alpha_i + \beta_i t + \varepsilon_{it}$, may in certain cases be too restrictive in its assumption with regards to technical change. The parametric specification of the trend function seen in the literature tends to work well for the core grain producing States and for modeling the trend in national average yield as the trend in

this cases has been quite linear since 1946, but not necessarily in various peripheral production regions. For example, a simple linear or log-linear specification of the trend equation leads to negative predicted slope of the estimated trend equation in some counties with crop failures in more recent time periods can more offset the yield trend in the parametric model (also, the log-linear model cannot be used where the crop failure is total, i.e., 0 yields). The nonparametric specification of the trend equation permits us to estimate a trend equation for each corn producing county in the U.S. – close to 2,800 – without having to select different specifications for each county. At the same time, a highly flexible model will chase the standard errors, or stochastic shocks, and not help in identifying the trend. As such, even if the equality of a restricted model to a fully flexible model is not accepted from a statistical standpoint, this result does not imply that the fully flexible model should be used for detrending the data – doing so will be at odds with the goal of separating the yield shocks from trend effects. The Loess yield trend provides some flexibility to $f(t)$ over the linear model while minimizing the chasing of the stochastic yield shocks.

Given the estimated trend yields as the predictions of $E(Y_t)$, we can construct ΔY_t^d and estimate the relationship between it and ΔP_t. In particular, we assume that ΔP_t can only be partially explained by ΔY_t^d, and that the uncertainty in this relationship can be incorporated into the empirical distribution. We do so by specifying ΔP_t as

$$(10)\quad \Delta P_t = g\left(\Delta Y_t^d, z_t\right) + \varepsilon_t,$$

where ε_t is *i.i.d.* with mean 0 and variance σ_ε^2 given $\{\Delta Y_t^d, z_t\}$, and where z_t is a vector of other variables that may explain within season price deviation.[2] We expect that $d\Delta P_t / d\Delta Y_t^d < 0$, that is, the greater the realization of national average yield over expected national average yield, the more likely harvest time price will be lower than expected price.

Based on the econometric estimate of the function for ΔP_t, we can then generate a distribution of estimates of ΔP_t, or $\Delta \hat{P}_{gt}\left(g\left[\Delta Y_t^d, z_t\right]\right)$, for each ΔY_t^d, and consequently we create our empirical distribution of $\{\Delta \hat{P}_t, \Delta Y_t^d, \mathbf{\Delta Y}_t^d\}$, where $\mathbf{\Delta Y}_t^d$ is the vector of county level yield deviations. As will be explained in the next section, to reduce the potential for bias due to the misspecification of equation (9), we utilize a semi-nonparametric (SNP), or flexible, econometric approach as a specification check on a parametric estimate of $g(.)$.

Semi-nonparametric estimation of the price-yield relationship

While the parametric model will be a more efficient specification than the SNP model, a potential drawback of a parametric model for the estimation of equation (9) is that it could potentially be subject to biases associated with incorrect specifications of functional form of $g(.)$. As a specification check on a parametric model, we use the Fourier flexible functional form (e.g., Fenton and Gallant, 1996) to model equation (9). The Fourier functional form is one of the few functional forms known to have Sobolev flexibility, which means that the

[2] For the purposes of the regression itself, either ΔY_t^d or ΔY_t can be used as the difference between the two is simply that the former is expressed with respect to a particular base year.

difference between a function g($\boldsymbol{x}$,$\boldsymbol{\theta}$) and the true function $f(\boldsymbol{x})$ can be made arbitrarily small for any value of $\boldsymbol{x}$ as the sample size becomes large (Gallant, 1987). Letting $\boldsymbol{x}_t$ represent the vector of explanatory variables in equation (9) with 3 or more unique values each, our SNP specification of g(x,θ) is:

$$(11)\quad Y_t = g(\boldsymbol{x}_t, \boldsymbol{\theta}_t) \;=\; \boldsymbol{x}_t'\boldsymbol{\beta} \;+\sum_{m=1}^{M}\sum_{l=1}^{L}\left(v_{lmj}\cos\left[l\boldsymbol{r}_{mj}'s(\boldsymbol{x}_t)\right] - w_{lmj}\sin\left[l\boldsymbol{r}_{mjt}'s(\boldsymbol{x}_t)\right]\right),$$

where the $p\times 1$ vector $\boldsymbol{x}_t$ contains all arguments of the utility difference model, k is the number of coefficients in $\boldsymbol{\theta}$, which consists of the $\boldsymbol{\beta}$, v_{lm}, and w_{lm} coefficients to be estimated, M and L are positive integers, and $\boldsymbol{r}_{\mathrm{m}}$ is a $p\times 1$ vector of positive and negative integers that forms indices in the conditioning variables and that determines which combinations of variables in $\boldsymbol{x}_t$ from each of the transformed variables.[3] The integer m is the sum of the absolute value of the elements in the multi-indexes in vector $\boldsymbol{r}_{\mathrm{m}}$ and L is the order of the transformation, and is basically the number of inner-loop transformations of $\boldsymbol{x}_t$. For example, if $\boldsymbol{x}_t$ contains 3 variables and $M = L = 1$, then the $\boldsymbol{r}_{\mathrm{m}}$ vectors are (1,0,0), (0,1,0), and (0,0,1), resulting in $k = 9$ (not counting the constant). The $p\times 1$ function s($\boldsymbol{x}_i$) prevents periodicity in the model by rescaling $\boldsymbol{x}_t$ so that it falls in the range [0, 2π−0.000001] (Gallant, 1987). This rescaling of each element in $\boldsymbol{x}_t$ is achieved by subtracting from each element in $\boldsymbol{x}_i$ its minimum value (from across the sample), then dividing this difference by the maximum value (from across the sample), and then multiplying the resulting value by [2π−0.000001]. For example, if bid is the only explanatory variable, then $\boldsymbol{r}_{\mathrm{m}}$ is a (1x1) unit vector and max(M) equals 1. If a variable

[3] In addition to appending $x\beta$ to the Fourier series in Equation (11), Gallant suggests appending quadratic terms when modeling nonperiodic functions. Our experiments suggest that inclusion of the quadratic terms as well in the regressions had little impact on the slope estimates. Hence, we leave them out for the sake of efficiency.

has only three unique values, then only the v or *w* transformation may be performed. A dummy variable is not transformed. In practice, the level of transformation embodied in $M = L = 1$ generally adds sufficient flexibility to the model, and the parametric model is nested in the SNP model.

A formal criterion for choosing M and L is not well established. Chalfant and Gallant (1985) suggest a rule of thumb that the dimension of $\theta = N^{2/3}$. Asymptotic theory calls for $\theta = N^{1/4}$ (Andrews, 1991), but Fenton and Gallant (1996) note that $\theta = N^{1/2}$ is likely to be more representative of actual practice. Hong and Pagan (1988) found that the Fourier approximation had low bias in the estimators even for sample sizes as low as n = 30.

Taken individually, Fourier coefficients do not have an economic interpretation. To give those regression coefficients an economic interpretation, they must be re-expressed in terms of the base variables. One way to do this is to evaluate $\partial g(\boldsymbol{x},\boldsymbol{\theta}) / \partial \boldsymbol{x}$, noting that

$$(12)\quad \partial g(\boldsymbol{x},\theta)\big/\partial x \;=\; \boldsymbol{b} + 2\sum_{\alpha=1}^{A}\left\{ \sum_{j=1}^{J} j\left(v_{j\alpha}\cos\left[j\boldsymbol{r}_{\alpha}' s(\boldsymbol{x})\right]+w_{j\alpha}\sin\left[j\boldsymbol{r}_{\alpha}' s(\boldsymbol{x})\right]\right)\boldsymbol{r}_{\alpha}\right\}.$$

Generating the empirical distribution of payments

While national average yields are necessary for modeling the price-yield relationship, county-level yield values are necessary to estimate the commodity payments. The Y_{jt}'s, or in vector notation, $\mathbf{Y}_t$, are not only stochastic, they are spatially stochastic. That is, yield shocks tend to have systemic component to them. Similar weather variations can cover large geographic regions. For instance, a drought can similarly affect yields across

counties in a wide region. Furthermore, if a climatic event affects many counties across a major production region, as it can in the Heartland Region (the USDA's typology for the Corn Belt [Heimlich, 2000]), an area which accounts for the bulk of U.S. corn production, it can affect national price. However, a weather shock across another region that accounts for a small portion of U.S. corn production will have little effect on price to the extent that the correlation of weather in this region with that in the Heartland is low.

Given the spatial component to yield shocks, to achieve a realistic estimate of commodity payments under yield uncertainty, we must simulate county-level yield shocks under the assumption that the between-county standard error of yields, σ_{ij}, are not equal to 0, $\forall\, i, j$ counties, $i \neq j$. Namely, we assume that Y_j, or realized yield for county j, is drawn from a distribution $\mathrm{F}\left(\mu^1, \mu^2, \mu^3, \ldots, \mu^J; \Sigma\right)$, where Σ is the (J x J) spatial correlation matrix between the county yields. We assume that the σ_{ij}'s are identically and independently distributed across time.

Paulson and Babcock (2007), in their study of a county area revenue insurance program for Iowa, Illinois, and Indiana counties, generate a distribution of insurance costs by drawing price and yield deviates from an empirical distribution, where the historical year-to-year relationships between the deviations in price, national average yield, and county yields are maintained. Specifically, as applied to our context and notation, this approach requires the generation of an empirical distribution for $\{\Delta P_t$, ΔY_t^d, $\mathbf{\Delta Y}_t^d\}$. To generate this distribution, Paulson and Babcock (2007) use a rank-based re-sorting process outlined by Iman and Conover (1982). However, this method is impractical in our case with multiple explanatory variables in the specification of equation (9).

We instead use a more general bootstrap method that can allow for flexible right-hand-side regression modeling and allow for modeling interactions between variables. In particular, we use a bootstrap approach in a joint resampling methodology that involves drawing *i.i.d.* observations with replacement from the original data set (Efron, 1979; Yatchew, 1998). The bootstrap data-generating mechanism is to create replications by treating the existing data set of size T as a population from which samples of size T are extracted. Variation in estimates results from the fact that upon selection, each data point is replaced within the population. We use this standard bootstrap to generate a distribution of ΔP_t given ΔY_t^d.

Given the spatial distribution of yield, using a standard bootstrap and drawing each Y_{jt} randomly and with replacement from the yield histories over $j = 1,\ldots,J$ counties and $t = 1,\ldots,T$ will generate incorrect estimates of payments as doing so assumes the between-county standard error of yields, σ_{ij}, equals 0. The resampling method must be carried out in such a way that spatial dependence is preserved, thus it is not possible to use the conventional bootstrap methods based on simple random sampling with replacement. We generate this spatial yield distributions in a nonparametric fashion by appealing to a spatial version of the block-bootstrap (e.g., Lahiri, 1999) applied to the county yield histories over $t = 1,\ldots,T$. In this approach, instead of simply making random draws of Y_{jt} from the yield histories to construct an empirical distribution of yields, we make random draws of the entire (J x 1) vector $\mathbf{Y}_t$, thereby maintaining the spatial relationship between the yields. Hence, the standard bootstrap creates the linkage between ΔP_t and ΔY_t^d and the block bootstrap creates the linkage between ΔP_t, ΔY_t^d, and county level yield shocks $\mathbf{\Delta Y}_t^d$.

Our bootstrap approach to generating the yield distribution and price-yield relationship may not be as smooth as one would obtain with parametric methods or with methods that bridge nonparametric and parameter approaches, such as the rank resorting method, given that no yield draws are made from between observed yield points. However, our bootstrap approach imposes no assumption about the shape of the yield distribution between observed yield points. On the other hand, our estimates of the distribution of price deviates for any given yield deviate can be made arbitrarily smooth and a function of multiple variables.

Data

Data on county yields, planted acres, and harvested acres for all U.S. counties producing corn is supplied by the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. As payments can be collected for corn for silage as well as corn for grain, and because silage can be a significant portion of corn production in some regions outside the Heartland, we merge data on corn for grain and for silage. We convert tons of silage to bushels using a conversion rate of 7.94 bushels per ton, as per FSA (2006b).

County-level production data is not reported by NASS in cases where either the county has no acreage planted to the commodity or the sample size of farmers is deemed too low to report the county data. While the Heartland region is missing few Y_{it} data points for counties that have reported corn production over the period of our analysis, NASS data does contain unreported Y_{it} data points for some counties in peripheral production areas that have a history of corn production. For estimating the county-level

detrended yields, missing yield data points are substituted by crop district estimates.[4] As these substitutions can lead to aggregation biases, we want to minimize them. A trade-off exists between increasing the number of years from which the empirical yield distribution is created and this potential aggregation bias. Counties with continuous year-to-year NASS planting histories over 1975 through 2005 accounted for over 98 percent of total U.S. corn production in 2005. However, NASS county level coverage for earlier periods is less comprehensive. For instance, counties with continuous NASS planting histories over 1969 through 2005 accounted for only 53 percent of total U.S. corn production in 2005. As our estimates of the yield shocks ΔY_t^d over 1948 to 2005 show that the period 1975 to 2005 accounted for the some of largest estimated yield shocks since 1948 and that the average deviation in ΔY_t for 1975 to 2005 is within 2 percent of the average deviation over 1948 to 2005, 1975 to 2005 appears to be a representative sample of yield shocks, and we settle on it for our analysis. Given this time span, 2,784 counties are included in our analysis.

For the expected value of price P_t, or $E(P_t)$, we utilize a non-naive expectation, namely the average of the daily February prices of the December Chicago Board of Trade corn future (CBOT abbreviation CZ) in period t, $t = 1975,\ldots,2005$. The harvest time price P_t is the average of the daily November prices of the December CBOT corn future in period t. These choices of the expected and realized corn price is consistent with those

[4] Note that data substitutions are used only where necessary for the purpose of estimating the trend equation for each county; the program scenarios examined here are for coupled support, and no payments are calculated in t for counties for which NASS has not reported planted corn acreage in t.

the Risk Management Agency of the USDA uses to price certain crop revenue insurance products for corn.[5]

Analytical results

Table 1 provides the econometric results for the parametric and the SNP models over 1975 to 2005. The dummy variable *FarmAct* takes the value of "1" for years 1996 and above (and 0 otherwise), reflecting the Federal government being out of the commodity storage business under recent Farm Acts. We would expect the market to be more efficient in predicting harvest time price without the government build-up of stocks, suggesting a negative sign for *FarmAct*. Regression results show its coefficient to be negative and significant at the 10 percent level in both regressions. Of course, being a dummy variable, FarmAct is treated as fully parametric in the regressions.

In addition to the *t*-statistics for the actual data, the table presents confidence intervals for the regression results that were produced with the bootstrap approach using 1,000 simulated data sets. The confidence intervals presented in Table 1 are constructed from the regression results on each simulated data set and are of the bias corrected accelerated (BCa) type (Efron, 1987), which gives the bootstrap results an interpretation analogous to *t*-statistics by making the estimated confidence interval symmetric around the mean.

The coefficient on ΔY_t is significant at the 1 percent level in both regressions. The higher order transformation terms in the SNP regression are not significant, and the

[5] We depart a bit from RMA practice by calculating average price over a whole month instead of a portion of the month.

value for $d\Delta P_t / d\Delta Y_t$ is nearly the same for both regressions.[6] In fact, a likelihood ratio test cannot reject the hypothesis of the equivalence of the parametric and SNP results.

While the expectation is that the within season yield change would be the most significant explanation of within season change in corn prices – and the R^2 values show that over 50 percent of the variation in the within season change in corn prices is explained by the within season change in corn yields – other potential nonendogenous explanatory variables were examined as well. These included ΔY_t for corn produced in the rest of the world, which was not significant in explaining ΔP_t for U.S. corn. The ΔY_t for soybeans was not included in the regression as the correlation coefficient between ΔY_t for soybeans and ΔY_t for corn is quite high, as one would expect, at 0.74. A proxy for the ΔY_t for corn in the regression is the ΔY_t for all U.S. feed grains. However, substituting this latter value for the former produced almost identical regression results, suggesting that corn yield is the driving force in producing within season changes in corn prices.[7] Also examined was the change in the corn trade-weighted U.S. exchange rate (Economic Research Service, 2007) between the beginning of the crop year and the end of the crop year, and the change in GDP between the first quarter and the fourth quarter of the calendar year. Neither variable was significant in the regression. Another factor that could explain within season change in corn prices is the stocks-to-use ratio, but variables such as this were not included in the analysis as our goal was to model corn price change in a reduced form purely as a function of exogenous

[6] These results also hold for the analysis of the data over 1969 to 2005, which is available upon request.
[7] The correlation coefficient between ΔY_t for U.S. feed grains and ΔY_t for U.S. corn is 0.96.

shocks, and in particular, yield uncertainty. We treat all other variables as exogenous shocks via the error term in the regression.

Before running the bootstrap analysis of the distribution of payments given the regression results, we calibrate the payment scenarios by setting the program parameters so that the mean of total annual payments evaluated at historic price-yield points – the deterministic mean in this context – is equal across the program scenarios. We set the coverage rate γ in the market revenue program to 0.95 to match the upper coverage rate β proposed by Babcock and Hart (2005). Similarly, the basic (g) and extended coverage (α) rates are set to 0.70 and 0.85, respectively (*ibid.*). As the only parameter to set in the market revenue approach is γ, we choose the rest of the parameters in the other program scenarios to achieve the same level of annual mean payments that the market revenue scenario produces, or 2.47 billion dollars. Using a grid search, the required target price *TP* for target revenue to produce the same mean payment is $2.42 per bushel. We choose the parameters of *MLB* and *CCP* so that the ratio of the *CCP* to total payments under the current scenario is similar to the ratio of the production-limited payments to total target revenue scenario payments. The required loan rate *LR* is $2.04 per bushel and with a CCP target price *TP* of $2.35, direct payment rate *D* of $0.09 is necessary for the calibration (note that for CCPs, decreasing *D* is one-for-one the same as increasing *TP*).

The simulated (1 x G) vector $\Delta\hat{\mathbf{P}}_t = \{\Delta\hat{P}_{1t}, \Delta\hat{P}_{2t}, \ldots, \Delta\hat{P}_{Gt}\}$ corresponding to each ΔY_t^d are generated from the $G = 1{,}000$ bootstrapped data sets, with *FarmAct* set equal to 1 in the equation to adjust the predictions of ΔP_t to reflect the post-1996 Farm Act regime:

(13) $\Delta\hat{P}_{gt} = \hat{\beta}_{1g} + \hat{\beta}_{2g}\Delta Y_{gt}^{d} + \hat{v}_{gv}\cos s(\Delta Y_{gt}^{d}) + \hat{w}_{wg}\sin s(\Delta Y_{gt}^{d}) + \hat{\delta}_{g} FarmAct_{gt}$, $t = 1,\ldots,T$ and $g = 1,\ldots,G$

The $\Delta\hat{P}_{gt}$ based on the parametric regressions are similarly derived but exclude the Fourier transformed variables. Figure 1a provides the mean of the estimated function $\Delta\hat{P}_{t} = f(\Delta Y_{t}^{d})$ evaluated over the range $\Delta Y_{t}^{d} = \{\min(\Delta Y_{t}^{d})\ldots\max(\Delta Y_{t}^{d})\}$ for the 1,000 bootstrap data sets, and Figure 1b provides the 99 percent confidence bands for empirical distribution for both the parametric and the SNP approaches. Both approaches capture most of the extreme yield shocks in the 99 percent confidence bands, and in conjunction with the two approaches not being statistically different, one would expect that the payment distribution derived from either approach would lead to similar results.

Discussion of results

Table 2 summarizes the bootstrap results for distribution of payments, applying the price and yield deviations from the bootstrap to equations (1) through (8), using 2005 data as the baseline for planted acres, and the expected yield and price data against which the deviations are applied.[8] The first row under each scenario shows the deterministic means derived from the calibration exercise ("mean – evaluated at actual data points" in the table), and the second the mean of the bootstrap results. The overall coefficient of variation for the two revenue approaches (second column) are roughly equal. However, the coefficient of variation for the current program scenario is twice as high as for the two

[8] For the analysis of the payments, memory limitations of the computer program used the analysis (Windows GAUSS) prevented use of all 1,000 bootstrap outputs. 185 of the boostrapped output sequences from the regression analysis were randomly selected, yielding 5,735 total payment calculations (the 31 x 1 vector of simulated price changes bootstrapped 185 times) for each of the 2,874 counties. In principle, at the expense of slowing down the calculations, additional bootstraps could be added. However, it seems unlikely that doing so would change the results in any essential manner.

revenue programs, with most of the contribution to this value coming from the fully production-coupled MLBs. These results suggest that the revenue-based programs would provide lower Federal budgetary uncertainty than current approach.

Below the coefficient of variation calculated for the bootstrap output are the 99 percent empirical confidence intervals calculated from the same output. A Jarque-Bera test (Greene, 2000) was calculated for each payment type to examine the departure of the distribution of payments from a normal. This statistic has an asymptotic chi-square distribution with two degrees of freedom and can be used to test the null hypothesis that the data are from a normal distribution, or more precisely, that the distribution is symmetric and mesokurtic. With lowest test value for the payment distributions in the table being 123, the null hypothesis of the normality of payments cannot be accepted under any reasonable level of significance. Hence, while one could calculate the BCa confidence intervals for payments, the concept of symmetrical confidence intervals is inappropriate here given that a symmetrical confidence bound would include negative payments. The lower bound of the 90 percent confidence band includes $0 or near zero payment levels in all cases, but also several billion dollars at the upper end. Actual production- coupled corn payments also varies greatly from year to year.[9] The current program scenario has a 90 percent lower bound that is over $1 billion dollars lower than for either of the two revenue programs as well as an upper 90 percent bound that is over $2 billion higher than for the two revenue-based scenarios. This result emphasizes the point that both farmers and the government would face less uncertainty in budgeting for expected payments under a revenue-based alternative.

[9] For instance, over the period 1996 to 2006, actual LDPs for the crop year were $0 in four years, but as high as $4.3 billion in the 2005 crop year (payment variation is a bit less extreme when examined on a fiscal year basis).

Of relevance from the U.S.'s standpoint with respect to multilateral agreements on domestic support are the higher moments of the payment distribution. While the higher moments of the corn programs payment distribution could be summarized by simply presenting the skewness and kurtosis measures for each scenario, such measures are not nearly as intuitive as the graphical representations of the payment distributions, as shown in Figures 2a to 2c. For each program scenario, the figures show both the distribution of total payments and the subset of payments most likely to face payment ceilings in future multilateral agreements on agricultural support. For example, in Figure 2a, we show payments net of disaster payments given that disaster payments can under certain conditions be exempt from support ceilings. Likewise, for Figure 2b, the basic portion of payments could in principle be exempt from support ceilings, and hence the figure shows payments net of basic payments as well as total payments. Figure 2c shows the market revenue payment net of the supplemental payment as well as the total payment, although this breakdown is not intended to be suggestive of any portion of the market revenue payment being exempt from payment ceilings

Given the likelihood that future multilateral agreements on agriculture will continue to have support ceilings for member countries, a critical question then becomes what is the probability that the ceilings could be exceeded in any given year. Given the premise of achieving the same mean annual payment level across the program scenarios, comparison of Figures 2a to 2c clearly shows the current style support scenario to have a distinctly fatter right hand tail than the two revenue-based programs. This fatter tail suggests that payments under revenue-based programs would have a lower probability of exceeding a support ceiling. For example, excluding the portion of payments that may

possibly not be subject to limits, the two revenue based programs would exceed $6.5 billion less than 1 percent of the time, while the current style program payment would exceed $6.5 billion 12 percent of the time.

Figures 2a to 2c can also confirm various priors. For example, the results in Figure 2a show that disaster payments are a lower portion of total payments as total payments level increase. This result suggests that disaster assistance is important in providing payments to regions with low correlation of yields with the Heartland, but higher payments levels are suggestive of high yield levels especially in the Heartland, and the associated lower prices. In Figure 2c, the supplemental payments work as intended and shifts the distribution of total payments to the right.

Conclusions

This paper develops an approach to empirically demonstrating how the within-season distribution of U.S. domestic commodity support for corn differs between current-style approaches to support and revenue-based support. From a purely economic standpoint, the results show the revenue-based payment scenarios to be preferable at the national level to the uncoordinated forms of support currently in use. For revenue-based support, the variability around the total expected annual payment is lower, perhaps more importantly, the probability of high payments is lower. These results suggest advantages to this type of support, both in terms of lower budgetary uncertainty – for producers and the Federal government – and in meeting commitments for limiting spending on domestic commodity support.

As the focus of this paper is on national level impacts, for the sake of brevity this paper summarizes the distribution of payments across counties into total values. Of course, inter-regional comparisons of the performance of the program scenarios are also of policy relevance, and extensions to this analysis could be based on the county-level results that are the basis for our summarized results.

The research results summarized here are dependent on minimal parametric assumptions. On the down side, the results assume that farmers react the same way to all support program scenarios. Namely, our payment scenarios assume that the planted acreage in our reference year of 2005 is the same as that under the provisions of the 2002 Farm Act. As the mean of actual Title I support payments for corn (excluding production-decoupled support) over the 2002 through 2006 crop years is roughly the same as the average yearly payments in our analysis, this assumption is not likely to be overly strong. However, the level of producers' aversion to risk may affect how they respond to differences in higher moments of the distribution of support payments. An extension to the model in this paper could incorporate a structural model for field crops with explicit formulation of supply and demand functions incorporating price and yield risk. While results from such a model would likely be sensitive to parametric assumptions, and would be quit burdensome to construct, it could be used to model how producers would react in the long run to different forms of support, both in terms of planting decisions within and between crops.

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Table 1. Parametric and Semi-Nonparametric (SNP) Regression Results for the Function Explaining ΔP_t

Variable	Parametric	SNP
Constant	-0.043 (-1.878){-0.088, -0.001}	-0.042 (-1.721){-0.086, 0.001}
ΔY_t	-1.368 (-5.763){-1.771, -0.978}	-1.305 (-5.076){-1.797, -0.955}
$\sin s(\Delta Y_t)$	–	0.0095 (0.637){-1.717, -0.907}
$\cos s(\Delta Y_t)$	–	0.0082 (0.551){-0.0198, 0.037}
FarmAct	-0.086 (-2.113){-0.144, -0.029 }	-0.079 (-1.763){-0.152, -0.009}
Ln-L	27.420	27.830
R^2	0.586	0.596
$d\Delta P_t / d\Delta Y_t$	-1.368 {-1.771, -0.978}	-1.369 {-1.797, -0.955}

Notes: *T*-values are shown in parentheses.
The BCa 90% confidence intervals apply the bias corrected accelerated approach (Efron) to 1000 bootstrap runs, and are shown in brackets.
For the parametric case, the parameter value for $d\Delta P_t / d\Delta Y_t$ is the same the coefficient on ΔY_t.

Figure 1a. **Within Season Price Differential Explained by Yield Shock – Corn**
Fitted curve evaluated at the means of the bootstraps

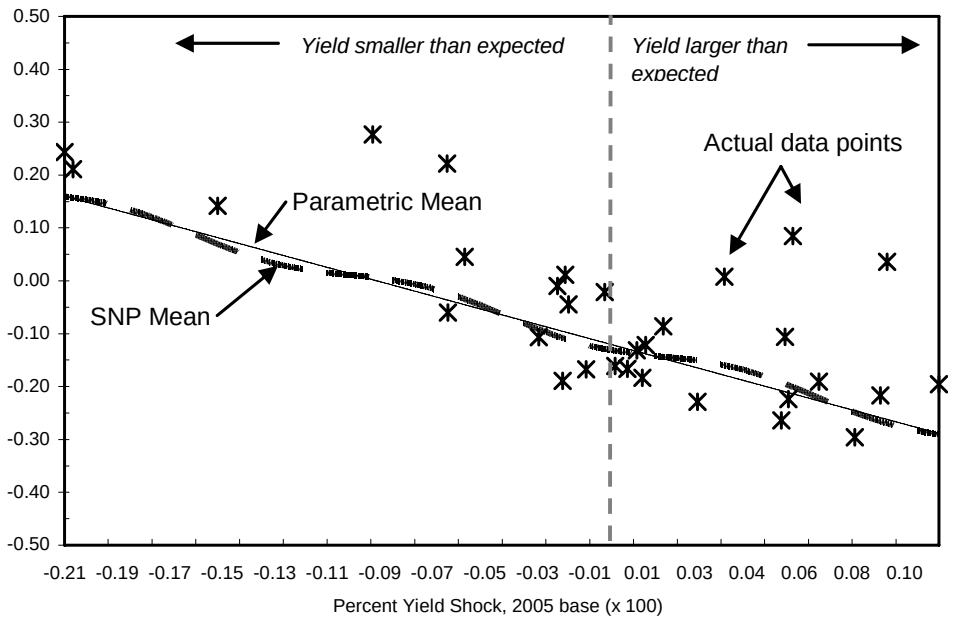
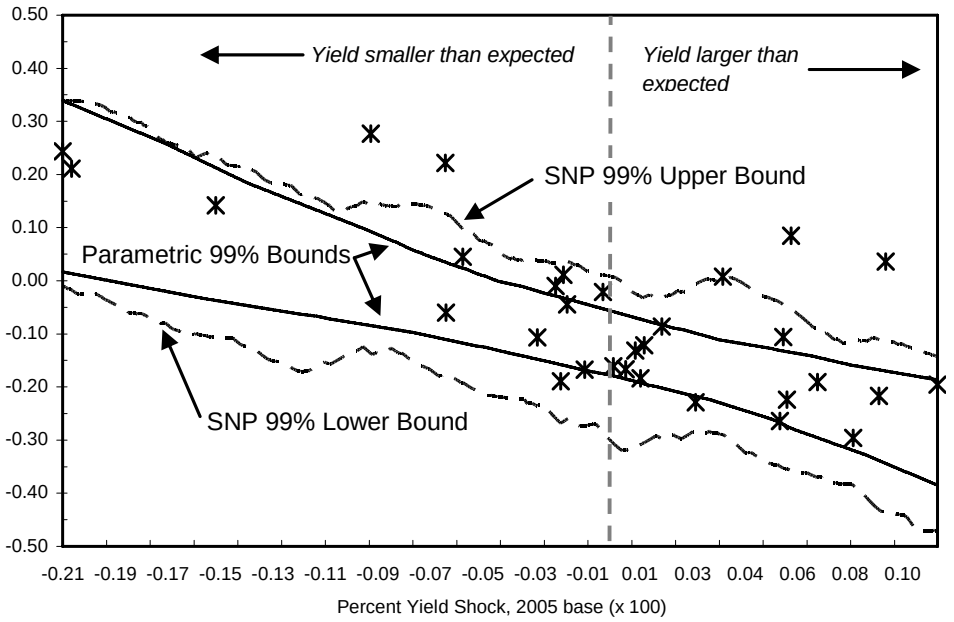


Figure 1b. **Within Season Price Differential Explained by Yield Shock – Corn**
Confidence bounds for the price shocks as derived from the boostrap analysis



Note: Percent price difference is defined as being between the February and November prices of the December CBOT futures contract for corn.

Table 2. Results of the Stochastic Analysis of the Distribution of Corn Program Payments Using 2005 as the Base Year for Evaluation

Target Revenue	Payments (Billion $)			
	Total	Extended Coverage	Production Limited	Basic
Mean - evaluated at actual data points	2.47	0.99	1.28	0.19
Mean - bootstrap	3.03	1.16	1.64	0.22
Standard Error - bootstrap	0.97	0.60	0.40	0.24
Coefficient of Variation	0.321	0.521	0.242	1.062
90% Confidence Interval - lower	1.62	0.39	1.06	0.02
90% Confidence Interval - upper	4.80	2.28	2.37	0.73

Market Revenue w/ Supplemental	Payments (Billion $)		
	Total	National	Supplemental
Mean - evaluated at actual data points	2.47	1.70	0.77
Mean - bootstrap	3.17	2.33	0.85
Standard Error - bootstrap	1.07	1.00	0.50
Coefficient of Variation	0.338	0.430	0.591
90% Confidence Interval - lower	1.55	0.76	0.37
90% Confidence Interval - upper	5.09	4.06	1.97

Pseudo-Current Program	Payments (Billion $)			
	Total	MLB	CCP	Disaster
Mean - evaluated at actual data points	2.47	1.02	1.26	0.19
Mean - bootstrap	3.11	1.26	1.67	0.19
Standard Error - bootstrap	2.13	1.69	0.88	0.28
Coefficient of Variation	0.684	1.346	0.529	1.459
90% Confidence Interval - lower	0.38	0.00	0.00	0.02
90% Confidence Interval - upper	7.10	4.78	2.28	0.83

Figure 2a. **Distribution of Commodity Payments for Corn – Current Style Programs**

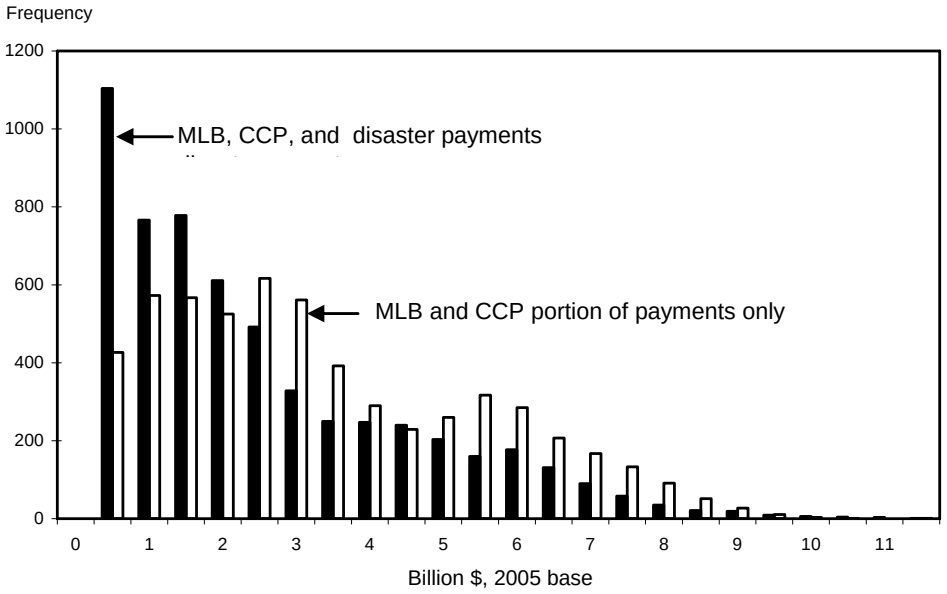


Figure 2b. **Distribution of Commodity Payments for Corn – Target Revenue Program**

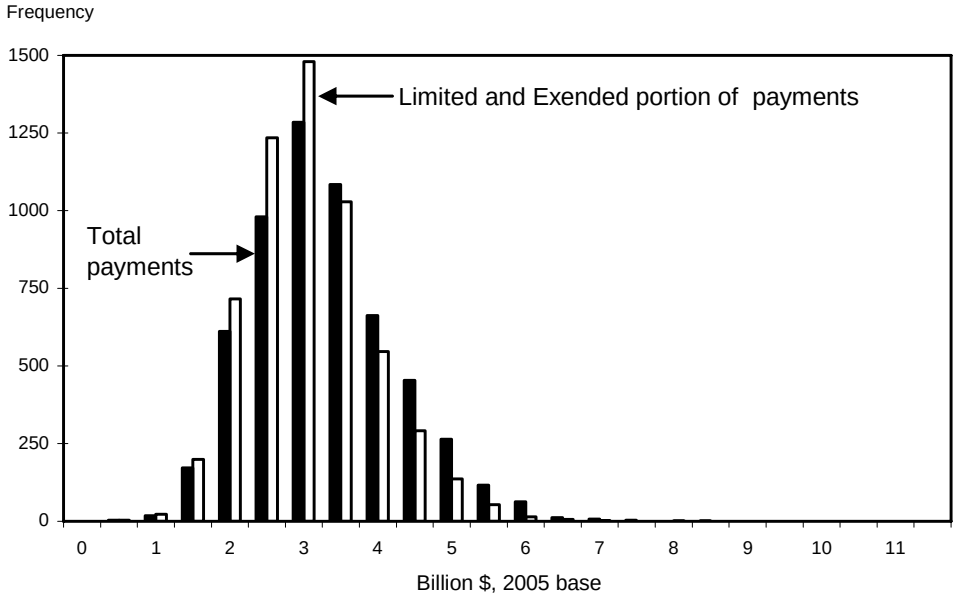
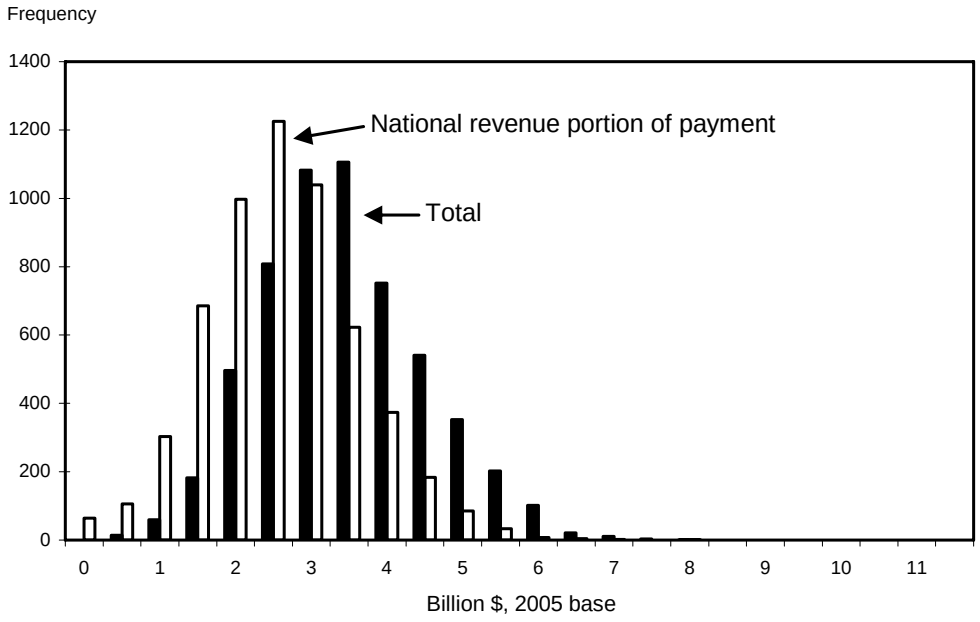



Figure 2c. **Distribution of Commodity Payments for Corn – Market Revenue Program**