Off-Farm Work and Economic Performance on Corn Farms

by

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Abstract

This paper examines the effect of off-farm work on the economic performance of corn farms. It estimates returns to scale and technical efficiency following an input distance function approach and compares the relative performance of corn farm operator households with and without off-farm work. We use farm-level data from the USDA's ARMS survey for 2002-2011. The impact of off-farm work on scale and technical efficiency is examined at the household level. We find that off-farm income boosts scale efficiency on corn farms. We also find that operator hours worked off farm negatively affects technical efficiency, while we find no impact on technical efficiency for spouse hours worked off farm. Finally, we find that corn farms relying on off farm income have comparable returns on farm assets across all size classes, but significantly higher household returns (with off-farm income and assets accounted for) across all size classes.

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Made possible by alternative employment opportunities and facilitated by labor-saving technological progress, such as mechanization, off-farm work by farm operators and their spouses' has risen steadily (until very recently)[1] over the past decades, becoming the most important component of farm household income. Based on USDA data, total net income earned by farm households from farming grew from about $15 billion in 1969 to nearly $50 billion in 1999 and is estimated at $118 billion in 2012. However, off-farm earned income, which began at a roughly comparable figure in 1969 ($15 billion), soared to about $120 billion in 1999 and is estimated at more than $150 billion in 2012. In addition, as women's wages have risen, married women have become more likely to work in the paid labor market and household tasks are now shared between spouses. Moreover, as U.S. farms continue to grow markedly in size, issues related to the interaction of off-farm income, farm size, and economic performance in general are among the leading concerns affecting U.S. agriculture. Because of the controversies surrounding these issues, agricultural economists have been looked to for objective information on these issues. Therefore, the purpose of this study is to analyze how off-farm work affects economic performance of corn farms.

Off-farm income also appears to smooth out income flows because off-farm wages are generally less variable than farm sources of income as described in Mishra and Sandretto (2002). Do off-farm sources of income also increase the overall efficiency of farm operator households and reduce costs as suggested in a report by the USDA, USDA (2001b).[2]

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[1]Using 2011 ARMS data, off-farm work and other sources of off-farm income remain the most important component of farm household income for all farms, with off-farm sources of income now about 20 percent larger than net farm income ($71,000 versus $36,000); however such off-farm sources of income were nearly 5 times larger than net farm income in 2002 ($61,000 versus $13,000).

[2] For purposes of our analysis farm operator household income includes income from farm activities and wages and salaries that the operator and all other household members received from off-farm sources. For our base farm

Gardner (2005) argues that integration of farm and nonfarm labor markets means that many small farms are surviving and even flourishing to an extent not thought possible 20 or 30 years ago. Other authors such as Boisvert (years) have stressed not only the growing links between farming activities and off-farm labor markets but also the links between farm household activities and conservation payments and agricultural pollution. Despite its considerable importance, and perhaps due to modeling and data challenges, issues related to the impact of off-farm income have been largely neglected (with a few notable exceptions) in studies of farm structure and economic performance in U.S. agriculture.

As on-farm and off-farm activities compete for scarce managerial time in U.S. farm operator households, economic decisions (including technology adoption and other production decisions) are likely to shape and be shaped by time allocation within the farm household (Fernandez-Cornejo, 2007). While the importance of off-farm income to all U.S. farmers is widely acknowledged, it is less clear if off-farm work is actually helping farm households to improve their economic performance across farm sizes and types of enterprises. In particular, because of the higher managerial labor required in livestock production (e.g., dairy) compared to crop production, off-farm work is likely to have a larger impact on farm-level efficiency of livestock farms than of crop farms. However, the effect of off-farm work on household-level efficiency is less clear because it depends on the relative weight on on-farm and off-farm activities on the farms under study (Fernandez-Cornejo, 2007).

In a study of U.S. farms, Nehring, Fernandez-Cornejo, and Banker (2005) found that larger farms are generally more efficient than smaller farms in transforming farm

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operator household model we constrain all such off-farm income to zero.

inputs into outputs given the technology at their disposal. But focusing on farm inputs and outputs alone is misleading because off-farm income-generating activities can be important in determining economic performance of the farm household. When off-farm activities are included, farm household-level efficiencies are higher than farm-level efficiencies, across all farm sizes. Further, efficiency gains from integrating off-farm work into the output portfolio are relatively greatest for smaller farms (Fernandez-Cornejo, 2007). As a result, household-level efficiencies of smaller farms are comparable to farm-level efficiencies of larger farms. This suggests that households operating small farms have partially adapted to shortfalls in farm-level performance by increasing their off-farm income. We show these changes by typology—recently update by ERS to reflect commodity price inflation and the shift of production to larger farms---as defined in Table 1 (USDA 2013).

In this study we include the Corn Belt, Lake States, the Northern Plains and Southern Plains. Using farm-level data from Agricultural Resource Management Survey (ARMS) and an input distance function approach we estimate returns to scale and technical efficiency--and compare the relative performance of farm operator households with and without off-farm wages and salaries. The study proceeds as follows. In the first section we provide the background followed by the methodology. We then describe the ARMS data used in this study. Results are discussed in the next section followed by summary and conclusions section.

Background

Off-farm income received by U.S. operators and their spouses' has risen steadily over recent decades as job opportunities grew and technological progress such as mechanization has lessened on-farm labor needs. The off-farm income share of total household income of

U.S. farmers rose from about 50 percent in 1960 to more than 80 percent by the early 2000s, becoming the most important component of farm household income (Mishra et al., 2002).

However, robust growth in farm incomes and soft macroeconomic employment trends in the last five years have dramatically altered the off-farm/farm playing field. Even though off-farm employment by farm families may have decreased in intensity in recent years, as pointed out by Mishra et al., (2002), off-farm employment still varies by farm type. The ARMs data from 2002-2011 indicate a sharp decrease in off-farm participation for specialized corn farms and all farms. For example, off-farm participation by operators decreased from 20 percent in 2002 to 8 percent in 2011 for corn farms and from 53 to 29 percent for all farms. Similarly, spouses off-farm participation decreased from 53 to 20 percent and 45 to 27 percent for specialized and all farms, respectively

Also, data reveal that the average hours worked off-farm by farm operators for all farms decreased from 999 hours per year in 2002 to 509 in 2011, while the hours devoted to farm work increased significantly, from 1,310 hours in 2002 to 1,621 in 2011. Similarly, the number of hours worked off the farm by spouses decreased from 761 in 2002 to 435 in 2011, while the hours devoted to farm work on farm nearly tripled from 301 hours in 2002 to 823 in 2011.

Off-farm employment remains important as a component of total income. But ARMS data indicates that earned income for all farms averaged 15 percent of total income in 2011, down from 21 percent in 2002. Recent increases in farm income and accelerating specialization in corn production have reduced the share of off-farm income in total household income. A farm household earned about $71,000 in 2011, up from about

$10,000 in nominal terms in 2002, but income from farming activities more than doubled to about $36,000.

Another trend that emerges is in cropping patterns. Cropping patterns have changed significantly over the time period analyzed, partly due to the ethanol support policy favoring corn production over alternative crops, particularly soybeans, and new corn seed technology allowing corn production in new growing areas (Malcolm et al.). ARMS data for 2002-2011 show that the proportion of harvested acres in corn on specialized corn farms increased from 47.1 percent in 2002 to 50.3 percent in 2011, while the percent of harvested acres in soybeans decreased from 39.0 percent to 35.5 percent. For example, corn acres in three states (Kansas, North Dakota, and South Dakota) increased from 10.6 million acres in 2002 to 14.5 in 2011.

Cropping pattern shifts favoring corn because of the ethanol program and new seed technology significantly changed pesticide and fertilizer use and altered the composition and level of pesticides and fertilizer used. In general, fertilizer use per acre increased per acre increased as shown in (SWCS 2011). Fertilizer application rates for the Corn Belt increased from 136 pounds per acre for all crops in 2000 to 140 pounds per acre in 2010, with dramatic increases in North and South Dakota, and large increases in Iowa and Minnesota offsetting small declines in Illinois and Nebraska. Concomitantly, increased demand for corn due to the ethanol program and higher disposable incomes (NYT 2013) boosted corn acres at the expense of soybean acres in key states such as Iowa, where corn acres increased from 12.2 million acres in 2002 to 14.1 million acres in 2011 with most of the additional corn acres coming out of soybean acres. SWCS 2011 gives an overview of the changes in fertilizer used in the states analyzed.

Additionally the use of GMOs in corn and soybean production boosted the use of glyphosate relative to other herbicides (Nehring et al. AAEA 2011). This study gives an overview of the changes in herbicides used in the states analyzed. They show that cropping pattern shifts and GMO use led to 1) large increases in herbicide use in the western Corn Belt states, and in general to a substitution of glyphosate for alternative herbicides. Eastern corn belt corn growers encountered weed resistance to heavy glyphosate use in recent years. Hence, alternative herbicide use in these states is now increasing (Nehring. et al. AAEA 2011)

Methodology

We use an input distance function approach to represent the farms' technological structure in terms of minimum input use required to produce given output levels, because farmers typically have more short-term control over their input than output decisions. The resulting theoretical framework characterizes input contributions per acre, which is consistent with analysis of yields in traditional agricultural studies but stems theoretically from the homogeneity properties of the distance function.

Many econometric studies that have modeled a multiple-output technology have used a dual cost function (e.g., Ferrier and Lovell, 1990). The cost function approach requires that output and input prices be observable and requires the assumption of cost-minimizing behavior. The input distance function, on the other hand, permits a multi-input, multi-output technology without requiring observations on output and input prices as described by Coelli and Perelman (1996, 2000). The input distance vector considers how much the inputs may be proportionally contracted with outputs held fixed. In this sense it implies cost minimization. The appropriate functional form is ideally flexible, easy to calculate, and permits the imposition of homogeneity.

This primal representation allows us to measure production structure indicators such as marginal input/output contributions and scale economies, and has advantages over dual measures representing economic optimizing behavior not only because we do not have data on prices across observations, but also because one might not wish to assume full price responsiveness, due to input fixities and time lags in farmers' observation of output prices.

Input endogeneity has been a concern in the estimation of input distance functions; if found, biased estimates result. Some studies have used instrumental variables to correct the problem, while others have argued either that (1) it was not problematic in their studies because random disturbances in production processes resulted in proportional changes in the use of all inputs (Coelli and Perelman 2000, Rodriguez-Alvarez 2007) or (2) no good instrumental variables existed, thus endogeneity was not accounted for (Fleming and Lien 2010). We did not test for endogeneity in the variable inputs in this analysis. The Hausman test was used to test for endogeneity in the Coelli inefficiency effects. Since endogeneity was found, the predicted values are used as instruments in the stochastic production frontier (SPF). We correct for endogeneity of the hours worked off farm by the operator and spouse as they are modeled in the Coelli inefficiency effects; after testing for endogenity and finding it in the inefficiency effects we replace ophours and sphours with predicted values using available instruments in ARMS.

Based on previous related research we expect the distance function analysis to reveal that the economic impact of off-farm activities and income is likely to vary considerably across the subset of corn farms considered over the 2002-2011 period, and, in general, boosting the efficiency of smaller-scale operations. We find that spousal off-farm labor tends to dominate the off-farm labor supply and in contrast to operator labor is consistent with higher overall farm efficiency. When off-farm activities are included, farm **household-level** efficiencies are higher than farm-level efficiencies across all farm sizes, and efficiency gains from integrating off-farm work into the output portfolio are relatively greatest for smaller farms (Fernandez-Cornejo, 2007). As a result, household-level efficiencies of smaller farms are comparable to farm-level efficiencies of larger farms. This suggests that households operating small farms have partially adapted to shortfalls in farm-level performance by increasing their off-farm income.

We also expect climatic variables to impact technical efficiency quite differently across the sub-regions of the corn producing states because of differential changes in weather patterns over time as shown by, among others, Babcock 2012.

The Model

Empirical analysis of economic performance requires representing the underlying multi-dimensional (-input and -output) production technology. A general form for such a technology may be characterized by an input set, $L(\boldsymbol{Y}, \boldsymbol{X}, \boldsymbol{R})$, summarizing the production frontier in terms of the set of all input vectors $\boldsymbol{X}$ that can produce the output vector $\boldsymbol{Y}$, given the vector of shift and environmental variables $\boldsymbol{R}$ (the nonfarm assets, animal units, age, education, soil quality, CRP indicators, and time dummies). From this production set we can specify an input distance function (denoted by superscript I) that identifies the minimum possible input levels for producing a given output vector:

(1) $$D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R}) = \max\{\rho: (\boldsymbol{X}/\rho) \in L(\boldsymbol{Y},\boldsymbol{R})\} .$$

$D^I(\boldsymbol{X,Y,R})$ is therefore essentially a multi-input input-requirement function, representing the production technology while allowing deviations from the frontier.

We estimate this function using stochastic production frontier (SPF) techniques. Technical efficiency is characterized assuming a radial contraction of inputs to the frontier (constant input composition). The econometric model includes two error terms, a random (white noise) error term, v_{it}, assumed to be normally distributed, and a one-sided error term, u_{it}, assumed to be distributed as a half normal, to represent the distance from the frontier. We test for and correct for inputs that are endogenous to the production process.

Estimating $D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})$ requires imposing linear homogeneity in input levels (Färe and Primont), which is accomplished through normalization (Lovell, Richardson, Travers, and Wood); $D^I(\boldsymbol{X},\boldsymbol{Y}, \boldsymbol{R})/X_1 = D^I(\boldsymbol{X}/X_1,\boldsymbol{Y}, \boldsymbol{R}) = D^I(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R})$.[3] Approximating this function by a translog functional form to limit *a priori* restrictions on the relationships among its arguments results in:

(2a) $\ln D^I_{it}/X_{1,it} = \alpha_0 + \Sigma_m\, \alpha_m \ln X^*_{mit} + .5\, \Sigma_m \Sigma_n\, \alpha_{mn} \ln X^*_{mit} \ln X^*_{nit} + \Sigma_k\, \beta_k \ln Y_{kit}$

$+ .5\, \Sigma_k \Sigma_l\, \beta_{kl} \ln Y_{kit} \ln Y_{lit} + \Sigma_q\, \phi_q\, R_{qit} + .5\, \Sigma_q \Sigma_r\, \phi_{qr}\, R_{qit} R_{rit} + \Sigma_k \Sigma_m\, \gamma_{km} \ln Y_{kit} \ln X^*_{mit}$

$+ \Sigma_q \Sigma_m\, \gamma_{qm} \ln R_{qit} \ln X^*_{mit} + \Sigma_k \Sigma_q\, \gamma_{kq} \ln Y_{kit} \ln R_{qit} + v_{it} = TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it}$, or

(2b) $-\ln X_{1,it} = TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it} - \ln D^I_{it} = TL(\boldsymbol{X^*},\boldsymbol{Y}, \boldsymbol{R}) + v_{it} - u_{it}$,

where i denotes farm, t the time period, k,l, the outputs, m,n, the inputs, and q, r the $\boldsymbol{R}$ variables. We specify X_1 as land (acres operated), so the function is specified on a per-acre basis, consistent with much of the literature on farm production in terms of yields.

3. By definition, linear homogeneity implies that $D^I(\omega\boldsymbol{X,Y,R}) = \omega D^I(\boldsymbol{X,Y, R})$ for any $\omega>0$; so if ω is set arbitrarily at $1/X_1$, $D^I(\boldsymbol{X,Y, R})/X_1 = D^I(\boldsymbol{X}/X_1,\boldsymbol{Y, R})$.

In addition, the distance from the frontier, -ln D^I_{it} is explicitly characterized as the technical inefficiency error $-u_{it}$. As in Battese and Coelli,[4] we use maximum likelihood (ML) methods to estimate (2b) as an error components model. The one-sided error term u_{it} is a nonnegative random variable independently distributed as a truncation at zero of the $N(m_{it},\sigma_u^2)$ distribution, where $m_{it}=\boldsymbol{R}_{it}\delta$, $\boldsymbol{R}_{it}$ is a vector of farm efficiency determinants (assumed here to be the factors in the $\boldsymbol{R}$ vector), and δ is a vector of estimable parameters. The random error component v_{it} is assumed to be independently and identically distributed, $N(0,\sigma_v^2)$. We estimate both a household model and a farm model (which omits the off-farm income output and the farm efficiency determinants $\boldsymbol{R}$).

The productivity impacts (marginal productive contributions, MPC) of outputs or inputs can be estimated from this model by the first order elasticities $MPC_m = -\varepsilon_{DI,Ym} = -\partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln Y_m = \varepsilon_{X1,Ym}$ and $MPC_k = -\varepsilon_{DI,X^*m} = -\partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln X^*_k = \varepsilon_{X1,X^*k}$. MPC_m indicates the increase in overall input use when output expands (and so should be positive, like a marginal cost or output elasticity measure), and MPC_k indicates the shadow value (Färe and Primont) of the k^{th} input relative to X_1 (and so should be negative, like the slope of an isoquant). Similarly, the marginal productive contributions of structural factors (TEXTURE, WATER, POPACC, and the time, and farm size shifters) can be measured through the elasticities $MPC_{Rq} = -\varepsilon_{DI,Rq} = -\partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial R_q = \varepsilon_{X1,Rq}$ (if $\varepsilon_{X1,Rq} <0$, increased R_q implies that less input is required to produce a given output, which implies enhanced productivity, and vice versa).[5]

4.We used STATA Version 12 commands for the SPF estimation.

5 Note that a standard “productivity” or “technical change” measure, usually defined as the elasticity with respect to time, or the time trend of the input-output relationship, is not targeted here. Elasticities with respect to the time

Scale economies (SE) are calculated as the combined contribution of the M outputs Y_m, or the scale elasticity SE = $-\varepsilon_{DI,Y} = -\Sigma_m \partial \ln D^I(\boldsymbol{X},\boldsymbol{Y},\boldsymbol{R})/\partial \ln Y_m = \varepsilon_{X1,Y}$. That is, the sum of the input elasticities, $\Sigma_m\, \partial \ln X_1/\partial \ln Y_m$, indicates the overall input-output relationship and thus returns to scale. The extent of scale economies is thus implied by the short-fall of SE from 1; if SE<1 inputs do not increase proportionately with output levels, implying increasing returns to scale.

In addition to the more common estimation of the productive effects of outputs and inputs, we measure the direct marginal productive impacts or contributions of structural/policy factors (such as population accessibility, farm typology, off-farm work hours, and weather trends) on overall scale economies and technical efficiency. To identify the impact of off-farm income on household economic performance we sort on U.S. farm household typologies partitioning small and large farms by whether they reported earned income or not.

Finally, technical efficiency (TE) "scores" are estimated as TE = $\exp(-u_{it.})$. The impact of changes in R_q on technical efficiency can also be measured by the corresponding δ coefficient in the inefficiency specification for $-u_{it}$.

The Data

We use U.S. farm-level data from the 2002 through 2011 ARMS surveys and ARMS surveys in 2001, 2005 and 2010 specifically collecting economic and technical information

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dummies provide indications of production frontier shifts for each time period, but for short time series other external factors such as weather often confound estimation of a real technical change trend.

on corn production. Data from these USDA surveys related to the value of output and cost of production make our analysis possible. ARMS is an annual survey covering farms in the 48 contiguous States, conducted each year by USDA, and designed to incorporate information from both a list and area frame. The list and area frame components are incorporated using a system of weights. Inferences for the states and regions must account for the survey design by using weighted observations. The farm-level data is used in an innovative way. We link ten annual ARMS surveys to form a pooled time-series cross-section, assuming that the survey design for each year is comparable. We define three outputs: corn, livestock/other crops, and off-farm income, and three inputs: labor, miscellaneous (including fertilizer and fuel) , capital, and a quality adjusted land input (including climate information).

The summary statistics for the 2002-2011 data, presented in Table 4, document the sharp variation across farm size in the value/level of revenues, expenses and selected farm characteristics.

Our data cover thirteen primary corn producing states in the Corn Belt, Lake States, Northern Plains and Southern Plains : Illinois, Indiana, Iowa, Kansas, Missouri, Ohio, Nebraska, Michigan, Minnesota, North Dakota, South Dakota, Texas, and Wisconsin. We define corn farms as those grain only corn farms reporting corn acres and corn\livestock farms (less than 30 cows, 250 hogs, 50 beef units, and 1000 chickens) reporting corn acres. Using these criteria our sample averages more than 47 percent of total value of farm production from corn.   Many corn farmers in these states have opportunities to work off farm. Our sample contained 17,992 observations on such specialized corn farms. Summary statistics are presented in table 2. We see that off-farm income (including earned income and other off-farm income such as social security payments and dividends on stocks) represents close to 12 percent of total household income on corn farms, ranging from about 40 percent on retirement farms to about 20 percent on small farms to 8 percent on midsized farms to only 3 percent on large farms.

These data include information on the value of earned income (EARNED), the soil texture by county, (TEXTURE), water holding capacity, (WATER), and population accessibility (POPACC). Additional outputs and inputs distinguished for our analysis include three specific outputs for dairy farms: Y_{CRP}= all crops, Y_{LIV}=livestock (primarily dairy cows) and Y_{OFF}=off-farm earned income; and three specific outputs for corn farms Y_{CRN}= corn, Y_{NCRN}= non corn production, and Y_{OFF}=off-farm earned income; and six inputs for both dairy and corn farms , X_{LD}=land, X_{L}=labor, X_{K}=capital, and X_{MIS}=miscellaneous inputs (primarily feed, fuel and fertilizer on corn/small livestock farms). Time dummies, t_{2005}-t_{2011}, are also included as fixed effects. In the household model, labor is augmented by adding a wage bill for operator and spouse earned income off-farm.

Agricultural outputs are computed as the sum of the value of sales for each type of farm product, in dollars per farm. The variable inputs, capital and machinery, are measured as annual per-farm expenditures on each input category. Land is measured as an annualized flow of services from land (the quality adjusted price by state using data from ERS productivity accounts multiplied times acres operated, annualized over 20 years at a discount rate of 5 percent). All these variables are deflated by the estimated increase or decrease in agricultural production prices in 2002-2011 compared to 2002.[6]

We include county-level monthly climate data (min-temperature and max-temperature, 1982-2011, computing 20 year growth rates for 2002-2011). Our analysis is based on the impact of seasonally adjusted growth rates in maxtemp, mintemp, and precipitation.

The Empirical Results

The parameter estimates for corn household model are reported in Table 3. Although most of the parameter estimates are not directly interpretable due to the flexible functional form (the elasticity measures are combinations of various parameters and data), some estimates are directly interpretable. For example, we find that increased urbanization (POPACC) decreases the productive contribution of (increases the inputs required for) corn but increases the productive contribution of noncorn. Also, the variables in the technical inefficiency effects are directly interpretable. Notably we find that higher number of operator hours in off-farm work decrease technical efficiency suggesting that this activity reduces the time spent on making effective management decisions in the farm operation. In contrast we find no significant impact on technical efficiency as spouse hours worked off-farm increase. Among the weather variables we find that growth rates in precipitation have no significant impact on technical efficiency[7] while most interesting of the results is a

6**.** These deflators are computed using the indexes of prices received and paid (1990-92=100), Ag Statistics.

7 We calculated growth rates by county (20 year seasonally adjusted trends beginning in 1982) for precipitation, tmin, and tmax for all Corn Belt states used in the analysis. Notably, we generally found fewer than 10 percent of counties exhibiting significant declines or increases in precipitation (Indiana, Minnesota, Ohio and Texas Counties

positive impact on technical efficiency due to increases in tmin centered in Minnesota providing an expanded growing season for corn production. Weather data information is documented in PRISM.

Table 4 presents the average MPCs across all observations for each output and input to further evaluate the estimated production patterns. The MPCs for the outputs represent the proportional "marginal cost" or input-use share of the output. On corn farms corn and non corn outputs represent roughly equal shares.

The MPCs for the inputs indicate the contribution of that input to overall input use (substitutability). The largest (in absolute value) MPC is capital and labor on corn farms.

Table 5 reports by typology the levels of our overall performance indicators (scale economy, SE, and technical efficiency, TE), and the productive contributions (MPCs) for the whole sample, and for different size farms.

As shown in table 5 the measures show strong scale economies, which are greatest for smaller farms, indicating scale inefficiency for these farms (lower unit costs associated with growth, due to increasing returns to scale). Technical efficiency is basically constant as farm size increases. We see no major difference in TE across size classes in corn farms induced by adding off-farm income to the model.

However we find that off-farm income significantly boosts scale efficiency on corn farms. As shown in table 5 household model calculations indicate that scale efficiency on small, midsize, and large corn farms with earned income is significantly higher than on small, midsize, and large corn farms with no earned income.

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are exceptions), and in tmin (Minnesota, Texas, and Wisconsin are exceptions) and in tmax trends (Ohio and Texas are exceptions) using PRISM data.

Finally, we find that corn farms relying on off farm income have significantly higher returns on household assets, with comparable returns on farm assets.

Summary and Concluding Remarks

This study examines the economic impact of off farm income and environmental factors on economic performance in key corn-producing states. It uses an input distance function approach to evaluate the scale and technical efficiency of small independent as compared to large farming operations, and the additional productive and thus competitive contributions of off-farm income (both operator and spousal). We correct for endogeneity of the hours worked off farm by the operator and spouse as they are modeled in the Coelli inefficiency effects[8].

As U.S. farms continue to grow markedly in size, issues related to the interaction of off-farm income, farm size, and economic performance in general are among the leading concerns affecting U.S. agriculture. Because of the controversies surrounding these issues, agricultural economists have been looked to for objective information on these issues. Despite its considerable importance, and perhaps due to modeling and data challenges, issues related to the impact of off-farm income have been largely neglected (with a few notable exceptions) in studies of farm structure and economic performance in U.S. agriculture.

8 The Durbin-Wu-Hausman test concluded that spousal and operator hours worked were both endogenous in the inefficiency term of the input distance function. The chi-square test statistic of 114.23 with 2 degrees of freedom is highly significant.

We find the economic impact of off-farm work varies considerably across types of farms. For our sample of corn farms, off-farm work by spousal labor has no impact on household-level technical efficiency while operator labor off farm decreases the household technical efficiency. Most importantly, we find that off-farm income significantly boosts scale efficiency on corn farms. Finally, we find that corn farms relying on off farm income have significantly higher household returns on small and midsize farms.

Recent work by Babcock on corn yields and drought emphasizes the importance of including salient climatic information in any thorough specification examining performance measures related to corn production. For our sample of corn farms we find that 20 year growth rates of minimum and maximum temperatures have a significant impact on the efficiency of corn production. We find that 20 year growth rates in precipitation (basically flat in most corn belt Counties, particularly in Illinois and Iowa) have no impact on corn production efficiency[9].

We did not test for endogeneity in the variable inputs used in the primal in this analysis and leave this task for future research. We also will include off-farm trends in the dairy industry as they influence economic performance as a useful counterpoint to the corn analysis (See Fernandez et al. 2007).

9 Removing the weather trend variables from the inefficiency effects in Table 2 does not materially affect the results for the off-farm variables.

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Table 1. Farm Typology Groupings

Small Family Farms (sales less than $350,000)

1. Retirement farms. Small farms whose operators report they are retired (excludes limited-resource farms operated by retired farmers).

2. Off-farm occupation* farms. Small farms whose operators report a major occupation other than farming.

3. Farming occupation/low-sales. Small farms with sales less than $150,000 whose operators report farming as their major occupation.

4. Farming occupation/moderate-sales. Small farms with sales between $100,000 and $349,999 whose operators report farming as their major occupation.

Midsize family Farms (sales of $350,000 to $999,999)**

5. Family farms with sales between $350,000 and $999,999 whose operators report farming as their major occupation.

Large-scale family Farms (sales $1,000,000 or more)

6. Large family farms. Sales between $1,000,000 and $4,999,999.

7. Very large family farms. Sales of $5,000,000 or more

Nonfamily Farms (no occupation or farm size criterion)

8. Nonfamily farms. Farms for which principal operator and those related to the principal operator own 50% of the farm business.

Source: U.S. Department of Agriculture, Economic Research Service
***** Operator spend 50 percent or more of work time
** majority of business owned by family

Table 2. Summary Statistics for Corn Farms by Group: Size, Earned and No Earned Income, 13 States, 2002-2011: New ERS Farm typologies

	GROUP								
Item	Retire Off-farm occup	Small Farms: No Earned Income	Small Farms: Earned Income	Midsize Farms: No Earned Income	Midsize Farms: Earned Income	Large Farms: No Earned Income	Large Farms: Earned Income	Non Family Corp	All Farms
Number of obs.	1,571	492	6,811	508	5,507	284	2,199	620	17,992
Number of farms	144,712	31,592	469,522	14,842	184,719	3,857	34.183	27,392	910,821
Percent of farms	15.88	3.47	51.55	1.63	20.28	0.42	3.75	3.00	100.0
Percent of production	6.29	2.11	31.21	2.81	32.94	2.24	18.47	3.93	100.0
Revenues	(Dollars/farm)								
Corn production	63,568	90,003	90,209	249,840	290,402	746,651	663,361	182,206	146,087
Soybean production	53,921	79,392	78,453	193,695	210,938	498,327	495,109	163,652	123,314
Other crop production	8,650	23,825	22,635	101,755	65,384	427,459	429,808	76,139	49,016
Animal production	4,487	10,187	8,119	34,166	19,902	135,939	123,728	22,645	15,745
Earned income	74,229	0	36,926	0	43,219	0	47,147	0	41,435
Expenditures	(Dollars/farm)								
Labor	44,970	39,362	41,621	51,197	54,507	128,526	118,948	46,120	48,351
Pesticides	8,313	12,250	12,069	35,585	31,987	108,870	90,210	25,982	19,666
Fertilizer	22,792	33,875	32,081	95,992	86,608	294,533	257,238	70,589	53,893
Miscellaneous	110,673	165,043	157,934	506,198	457,702	1,823,640	1,644,081	363,863	286,163
Capital	18,775	24,945	27,789	82,393	80,524	224,693	207,013	46,711	45,972
Land	176,061	254,392	236,193	563,504	582,079	1,656,816	1,510,590	505,650	364,700
Other variables	(Item/farm)								
Average acres operated (acres)	470	781	731	1,909	1,579	4,207	3,802	1,263	1,024
Off-farm earned/totalin	0.347	0	0.145	0	0.065	0	0.023	0.0	0.098
Age	52.5	56.4	53.6	52.6	52.2	51.5	51.7	53.8	53.3
Education	2.877	2.462	2.614	2.707	2.855	2.831	2.968	2.804	2.720

Earned income=wages/salaries plus off farm interest income. Off-farm all includes earned income only. totalin= total farm income plus earned income.

Table 3 Parameter Estimates for input distance function for corn farmers.

Variable	Parameter (t-value)	Variable	Parameter (t-value)
α_{0}	164.98 (26.62)***	$\alpha_{XL,XM}$	0.008 (1.16)
α_{XL}	-0.202 (-13.47)***	$\alpha_{XL,XK}$	0.014 (4.14)***
α_{XMISC}	-0.232 (-10.22)***	$\alpha_{XM,XK}$	-0.014 (6.35)***
α_{XK}	-0.008 (-0.95)	$\phi_{2005\text{-}2011}$	-0.102 (-5.09)***
β_{YCRN}	-1.384 (-11.24)***	ϕ_{year}	-0.075 (-24.13)***
β_{YNCRN}	-0.018 (-0.40)	$\phi_{MEDLARGE}$	0.120 (7.37)***
$\beta_{YOff,}$	-0.014 (-0.40)	ϕ_{lARGE}	0.127 (6.35)***
$\beta_{YCRN,YCRN}$	0.087 (15.65)***	δ_{0}	203.94 (3.62)***
$\beta_{YNCRN,YNCRN}$	0.032 (35.08)***	$\delta_{POPDUME}$	-44.38 (-43.21)***
$\beta_{YOFF,YOFF}$	0.005 (6.15)***	$\delta_{POPDUMW}$	-0.162 (-0.72)
$\beta_{YCRN,YNCRN}$	-0.027 (-7.95)***	$\delta_{Spousehrs}$	-0.021 (-0.10)
$\beta_{YCRN,YOFF}$	-0.001 (-0.22)	$\delta_{Operhrs}$	1.201 (2.16)***
$\beta_{YNCRN,YOFF}$	-0.003 (-2.87)***	δ_{Precip}	72.81 (1.05)
$\gamma_{YCRN,Text}$	0.011 (6.68)***	$\delta_{PrcipCenter}$	-111.7 (-0.61)
$\gamma_{YCRN,Water}$	-0.003 (-5.00)***	δ_{Tmin}	216.6 (4.00)***
$\gamma_{YCRN,POP}$	0.005 (1.59)	$\delta_{TminCent}$	-455.3 (-5.58)***
$\gamma_{YNCRN,POP}$	-0.006 (-1.99)*	δ_{Tmax}	-131.3 (-4.11)***
$\alpha_{XL,XL}$	-0.022 (-15.07)***	δ_{YEAR}	-0.104 (-3.70)
$\alpha_{XM,XM}$	-0.008 (-1.46)	Sigma	0.317 (63.40)
$\alpha_{XK,X}$	-0.006 (4.33)***		

Log likelihood = -377239.20

Notes: *** Significance at the 1% level (t=2.576). ** Significance at the 5% level (t=1.96). * Significance at the 10% level (t=1.645) based on a robust estimators in STATA. The t-statistics are based on 22,261 observations using robust estimators in STATA.

Table 4. Marginal Productive Contributions (MPC) for Outputs, Inputs, and Time Shifts, Full Sample for Corn Farms for the Household Model, 2002 to 2011

Output	**MCP**	**t-value**	**Input**	**MCP**	**t-value**
Corn	**0.339**	9.11	Labor	**-0.183**	-2.11
Non Corn	**0.352**	10.71	Miscellaneous	**-0.314**	-4.39
Off-farm earned income	**0.033**	1.65	Capital	**-0.132**	0.16

Table 5. Performance Measures for Corn Farms by Group: Size, Earned and No Earned Income, 13 States, 2002-2011: ERS Farm typologies									
	GROUP								
Item	Retirement Off-farm occupation	Small Farms: No Earned Income	Small Farms: Earned Income	Midsize Farms: No Earned Income	Midsize Farms: Earned Income	Large Farms: No Earned Income	Large Farms: Earned Income	Non Family Corporations	All farms
Corn Household Model									
Efficiency score	0.94	0.94	0.93	0.94	0.94	0.94	0.93	0.93	0.94
Returns to scale	0.62	0.62	0.67*	0.81	0.85*	0.97	1.00*	0.70	0.71
Net return on assets	3.90	4.10	4.36	7.14	7.34	9.76	11.82	5.50	6.36
Household assets return	10.33	3.94	7.40*	7.81	9.59*	14.57	16.04	n.a.	9.37
Ophours on-farm	1738	2142	2075	2318	2160	2585	2419	1789	2060
Sphours on-farm	602	472	564	532	787	765	983	690	615
Ophours off-farm	1140	0	308	0	204	0	136	0	394
Sphours off-farm	706	0	634	0	608	0	518	0	596
Ophours off-farm 2002	1647	0	405	0	205	0	113	0	421
Sphours off-farm	1496	0	1274	0	1202	0	1244	0	929
Ophours off-farm 2011	610	0	232	0	189	0	89	0	169
Sphours off-farm	475	0	571	0	669	0	632	0	395
* Significantly differently from farms in the same size category at the 1% level of significance									