FARMS' TECHNICAL INEFFICIENCIES IN THE PRESENCE OF GOVERNMENT PROGRAMS

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, OR, July 29-August 1, 2007

Abstract

We focus on determining the impacts of government programs on farms' technical inefficiency levels. We use Kumbhakar's (2002) stochastic frontier model that accounts for both production risks and risk preferences. Our theoretical framework shows that decoupled government transfers are likely to increase (decrease) DARA (IARA) farmers' production inefficiencies if variable inputs are risk decreasing. However, the impacts of decoupled payments cannot be anticipated if variable inputs are risk increasing. We use farm-level data collected in Kansas to illustrate the model.

1. Introduction

The analysis of technical efficiency involves the assessment of the degree to which production technologies are being utilized. Traditionally, technical efficiency has been measured as the ratio of observed output to maximum feasible output. Stochastic frontier models have been widely used to assess this issue. When studying producers' technical inefficiencies, one needs to carefully integrate the stochastic component of production into the stochastic frontier models, in order to derive reliable information on input allocation decisions, agricultural production, production risks, and farmers' attitudes towards these risks. However, with some exceptions, stochastic frontier frameworks have not adequately modeled production risks (Battese *et al.* 1997; O'Donnell *et al.* 2006).

As explained by Just and Pope (1978), the usual stochastic specification used in the economic literature to estimate production functions can be too restrictive. Specifically, traditional approximations do not allow the effects of inputs on the deterministic component of production to differ from their effects on the stochastic element of output. Since agricultural inputs can either increase or decrease output variability, Just and Pope (1978) propose a stochastic specification of input-output response to correctly capture this matter. Battese *et al.* (1997) incorporate the structure of the stochastic frontier model into the Just and Pope (1978) flexible risk model. This yields a stochastic frontier with additive errors, as opposed to the conventional multiplicative framework. The additive stochastic frontier model has a heteroskedastic error structure and yields a measure of technical inefficiencies that does not only depend on the stochastic technical inefficiency effect, but that is also a function of input allocation since it depends on both the mean and standard deviation of production. Specifically, technical inefficiencies are found to have a positive relationship with the output risk and a negative association to the production mean. This implies that any change in input use will also have an impact on technical inefficiency. Battese *et al.* (1997) argue that the additive model is likely to better represent production behavior of modern agricultural enterprises. An objective of our article is to test the multiplicative model versus the additive one for a sample of U.S. farms specialized in the production of cereals. As predicted by Battese *et al.* (1997), we find the additive model to outperform the multiplicative framework. We then study the impacts of government farm programs on a farm's technical inefficiency.

Analyses of the effects of decoupling of agricultural policies have shown that apparently decoupled payments can affect farmers' risk attitudes, which can have implications for input allocation (see Sandmo 1971; or Hennessy 1998). It is thus interesting to study whether these changes in input allocation will have any impact on farms' technical inefficiencies. Previous literature on the effects of decoupling has mainly focused the attention towards determining the impacts of lump-sum transfers on input use and output levels (see, for example, Hennessy 1998; Oude Lansink and Peerlings 1996; Sckokai and Moro 2006; Serra *et al*. 2006). By assuming decreasingly absolute risk-averse (DARA) producers, Hennessy (1998) has shown that decoupled government transfers will have the effect of stimulating input use and production. Serra *et al.* (2006) have refined this conclusion by showing that, if input use has an impact on output variability, then these payments will only lead to an increase in production if inputs are risk increasing. If they are risk decreasing, the impacts of decoupled transfers are inconclusive. Nevertheless both analyses find decoupled payment effects to be of a rather small magnitude.

To our knowledge previous studies on decoupling have not accounted for production inefficiencies, nor assessed the impacts of policy instruments on technical inefficiencies. We present a theoretical model to analyze this issue. Our theoretical framework is based on the model developed by Kumbhakar (2002), which essentially includes risk preferences in the efficiency model by Battese *et al.* (1997). We use this framework, include policy instruments, and develop a comparative statics analysis to study the impacts of decoupling on technical inefficiencies. Within the framework of the stochastic frontier with flexible risk properties, we show that the effects of decoupled government payments on technical inefficiencies can only be anticipated in a single-output and single risk-decreasing input model. This makes the investigation of this issue essentially an empirical question. Our empirical analysis uses farm-level data collected in Kansas. Results show that an increase in decoupled transfers is likely to increase our sample farms' technical inefficiencies albeit with a very small magnitude.

It is important to note here that our paper focuses on "inside-farm" technical inefficiencies and that we do not assess the impacts of decoupled programs on the entry-exit decision and on the consequent changes in the distribution of the technical inefficiency parameter. We face important data limitations to assess the impacts of decoupling on the extensive margin, as we do not observe the entry-exit decision. While, with regards to the extensive margin, it may be reasonable to anticipate that a policy reform reducing government support to farmers would trigger the abandonment of the less efficient farms, anticipating the impacts of decoupled payments on "inside-farm" technical inefficiencies becomes more complicated. As noted above, in the additive stochastic frontier specification, technical inefficiencies are found to be positively related to the output risk and negatively associated to production mean. From MacMinn and Holtmann (1983) and Serra *et al*. (2006), it can be inferred that decoupled payments are likely to increase the use of risk-increasing inputs. However, the question of whether marginal increases in output variability will be bigger or smaller than marginal increases in output mean remains unanswered. This makes this issue essentially an empirical one. It is also true that decoupled payments are government transfers not linked to production or yields. If income supports are based on these transfers, production is not receiving any premium, which may reduce incentives to produce the maximum attainable output and thus may increase inefficiencies.

Our article is organized as follows. In the next section we present the conceptual framework. The theoretical model is specified for econometric estimation in the following section. The empirical implementation offers a discussion of the data used and the results derived. Concluding remarks are presented in the last section.

2. Conceptual Framework

A standard feature of conventional stochastic frontier models (Aigner *et al.* 1977) is that they do not allow the impacts of input use on output mean to differ from their effects on the output risk, yielding measures of technical inefficiency that are stochastic and that do not depend on input allocation decisions. In such a framework, a government program altering input use will not have a direct effect on a farm's technical inefficiency.[1] Battese *et al.* (1997) criticize conventional models on the grounds that they do not correctly capture production risks and propose an alternative formulation to properly predict producers' technical inefficiencies. As opposed to conventional models, the formulation by Battese *et al.* (1997) has additive rather than multiplicative errors. The additive model is more flexible than the multiplicative one in that the marginal production risk of an input does not depend on its mean output elasticity. In the additive formulation, input use impacts on technical efficiency measures through its different effects on the mean and the variance of output.

To briefly explain the differences between the additive and the multiplicative models, consider a single-output firm that produces output y. A single input is also used in this theoretical model for

[1] As an anonymous referee has pointed out, conventional stochastic frontier models can yield technical inefficiency measures that depend inversely on the output mean if production is measured in its original units instead of logarithms.

the sake of simplicity. However, in the empirical application the model is generalized. Under the additive hypothesis, the single-output production function can be represented by $y = f(x) + g(x)(\varepsilon - u)$, where x is a variable input, $f(x)$ is the production frontier describing the maximum output that can be attained with a given input level, and $g(x)$ is a function that captures the relationship between inputs and output variability. Variable ε, representing production uncertainty, is assumed to be an independent and identically distributed standard normal random variable, with variance equal to 1 and mean equal to 0. The non-negative variable u is assumed to be an independent and identically distributed truncation of the $N(0, \sigma_u^2)$ that is related to firms' technical inefficiencies. Hence, $E(u) = a = \sqrt{\frac{2}{\pi}}\sigma_u$ and $Var(u) = b = \frac{\pi - 2}{\pi}\sigma_u^2$. If $u = 0$, the producer is said to be fully efficient or to operate at the production frontier. Following Battese *et al.* (1997) and Kumbhakar (2002), the output mean and variability functions are defined at the frontier ($u = 0$), hence $E(y|_{u=0}) = f(x)$ and $Var(y|_{u=0}) = g(x)^2$. An input will cause production risk to increase (stay constant) [decrease] if $\frac{\partial Var(y|_{u=0})}{\partial x} > (=)[<]0$. If technical efficiency is defined as the ratio of observed output to maximum feasible output, the following measure of technical inefficiency can be derived under the additive hypothesis: $TI = 1 - \frac{E\left(y|_{x,u}\right)}{E\left(y|_{x,u=0}\right)} = u\frac{g(x)}{f(x)} \leq 1$. This measure depends on two factors: (1) the non-negative random variable u and (2) the ratio $\frac{g(x)}{f(x)}$, which the firm can control through input use. Any increase in the standard deviation of output will increase inefficiency, while improving the output mean will reduce it. Essentially, the ratio $\frac{g(x)}{f(x)}$ weights the technical inefficiency random parameter according to the firm's ability to manage both the stochastic and the deterministic components of production. In this regard, if a change in input use increases both $g(x)$ and $f(x)$ in the same proportion, technical efficiency estimates will be left unaltered. However, a firm will be considered less efficient, for example, if it follows a production strategy that increases output variability at a quicker path than output mean.

Under the more restrictive multiplicative model, production can be represented as (Kumbhakar 2002): $y = f(x)(1-u) + g(x)\varepsilon$.[2] Under such model, technical inefficiency can be expressed as: $TI = 1 - \frac{E\left(y|_{x,u}\right)}{E\left(y|_{x,u=0}\right)} = u\frac{f(x)}{f(x)} = u \leq 1$, i.e., the impact of inputs on the output variability is not allowed to differ from their impact on the deterministic component of production, which involves that technical inefficiencies do not depend on input use. Battese *et al.* (1997), argue that the additive model is likely to better represent production behavior of developed agricultural industries rather than traditional farming in developing countries. Since the measure of *TI* depends on the specification of the stochastic production frontier, it is very relevant to test the assumption of a linear model versus a multiplicative specification. As it will be discussed in the empirical application and according to Battese *et al.'s* (1997) expectations, the additive model is found to outperform the multiplicative alternative. The superiority of the additive model involves that technical efficiencies can, to a certain extent, be controlled by producers through input use.

It is thus clear that under the multiplicative framework any government program altering input use will not have a direct impact on farms' technical efficiencies. However, government programs will be relevant under the additive specification. We now focus on studying these impacts. Kumbhakar (2002) extends Battese *et al.'s* (1997) model to accommodate producers' attitudes towards risk. We extend Kumbhakar's (2002) additive framework to allow for policy instruments and develop a

[2] In here we follow Kumbhakar (2002) and use $(1-u)$ as an approximation of e^{-u}.

comparative statics analysis to assess the effects of decoupling on technical inefficiency measures. In order to formulate the optimization problem, it is assumed that producers take their decisions with the aim of maximizing the expected utility of wealth $\max_x E\left[U(W)\right] = \max_x E\left[U(W_0 + y - wx + C)\right]$, where W represents a farm's total wealth, W_0 stands for a farm's initial wealth, w is the input price normalized by the output price, and C represents decoupled government payments.[3] In following the framework developed by Kumbhakar (2002), we assume that risk comes only from production, but not from market conditions. Omission of price risk can be relevant if analyzing the impacts of policy setups that influence price variability. This is certainly a very relevant topic that merits further research. The first-order condition of the expected utility maximization problem can be expressed as follows:

$$E\left[U'(W)\left(f_x(x)+g_x(x)(\varepsilon - u) - w\right)\right] = 0, \qquad (1)$$

where subscripts denote partial derivatives, $f_x(x)$ represents the expected value of input x's marginal output, and $g_x(x)$ measures the marginal contribution of variable input x to the output standard deviation. If we take expectations and divide throughout by $E\left[U'(W)\right]$, expression (1) changes to:

$$f_x(x)+g_x(x)(\theta - \lambda) - w + \eta = 0 \qquad (2)$$

[3] As an anonymous referee has noted, initial wealth could be omitted from the model.

where η is a normally distributed error term that measures the departure from the optimality condition (allocative inefficiency), expression $RP_x = g_x(x)(\theta - \lambda)$ represents the marginal risk premium, which will be positive (zero) [negative] if variable input x is risk decreasing (neutral) [increasing] and if producers are averse to risk, and $\theta = \frac{E[U'(W)\varepsilon]}{E[U'(W)]}$ and $\lambda = \frac{E[U'(W)u]}{E[U'(W)]}$ capture producers' risk attitudes. In case producers are averse to risk, $\theta < 0$ and $\lambda > 0$ (see Kumbhakar 2002, for further detail). Risk-aversion functions have opposite signs because of the opposite effects on production of ε and u.

If we approximate the utility of wealth using a second-order Taylor-series expansion at $\varepsilon = u = 0$, the following forms of the risk preference functions can be derived: $\theta = -\frac{Rg(x)}{1+Rg(x)a}$ and $\lambda = \frac{a + Rg(x)\left(a^2 + b^2\right)}{1+Rg(x)a}$, where R represents the Arrow-Pratt coefficient of absolute risk aversion. Following Kumbhakar (2002), we assume R to be a function of a farm's expected wealth which can be represented by the following expression: $R = -\frac{U_{WW}(\mu)}{U_W(\mu)} = \gamma_0 + \gamma_1\mu$, where γ_0 and γ_1 are parameters, and $\mu = W_0 + f(x) - wx + C$. If farmers are risk averse (risk neutral) [risk lovers], then $R > (=)[<]0$. We assume farmers to be risk averse. If parameter $\gamma_1 < (=)[>]0$ then producers are characterized by decreasing (constant) [increasing] absolute risk aversion (DARA (CARA) [IARA]). A substantial number of previous analyses that have tested for risk preferences have provided evidence in favor of DARA (Isik and Khanna 2003; Saha 1997; Bar-Shira *et al.* 1997).

To assess the impacts of decoupled programs on farms' technical inefficiencies, we carry out a comparative statics analysis. Agricultural policies in developed economies have traditionally involved the use of coupled measures of income support such as price supports that have kept market prices at artificially high levels. Agricultural policy decoupling processes have usually involved a decline in output price supports in favor of more decoupled transfers. It is thus interesting to compare the effects of decoupled transfers with the impacts of market prices that have a coupled element of support. As a result, we extend our comparative statics analysis to a consideration of the impacts of a change in w, representing the input price normalized by the output price, on farms' technical inefficiencies. The comparative statics results can be summarized in the following propositions (proofs are presented in the appendix).

PROPOSITION 1. *Within the framework of a stochastic frontier model with additive heteroskedastic error structure, under the assumption of positive expected marginal productivity and for a risk-averse producer and a risk-increasing input:*

a. $$\begin{cases} \dfrac{\partial TI}{\partial C} > (<) 0 \text{ under DARA preferences and } \dfrac{f(x)}{g(x)} > (<) \dfrac{f_x(x)}{g_x(x)}, \text{ as well as under IARA} \\ \text{risk attitudes and } \dfrac{f(x)}{g(x)} < (>) \dfrac{f_x(x)}{g_x(x)} \\ \dfrac{\partial TI}{\partial C} = 0 \text{ under CARA preferences or if } \dfrac{f(x)}{g(x)} = \dfrac{f_x(x)}{g_x(x)} \end{cases}$$ *b.*

$\dfrac{\partial TI}{\partial w}$ *is of indeterminate sign.*

PROPOSITION 2. *Within the framework of a stochastic frontier model with additive heteroskedastic error structure, under the assumption of positive expected marginal productivity and for a risk-averse producer and a risk-decreasing input:*

a. $\dfrac{\partial TI}{\partial C} > (=)[<] 0$ *under DARA (CARA) [IARA] preferences.*

b. $\frac{\partial TI}{\partial w}$ *is of indeterminate sign.*

The comparative statics developed above provide evidence of the relevance of accounting for the influence of output risk, risk preferences, and technical inefficiencies when studying the effects of decoupling. We show that, within the framework of a stochastic frontier model with additive heteroskedastic error structure, an increase in decoupled government transfers will motivate an increase (decrease) in DARA (IARA) farmers' technical inefficiencies if the input x is risk decreasing. However, if the input is risk increasing, inefficiencies could both increase or decrease. Under DARA preferences, for example, they will decrease if $\frac{f(x)}{g(x)} < \frac{f_x(x)}{g_x(x)}$, i.e., when an increase in input use causes an increase in the output mean relatively bigger than the increase in production risk, and will increase otherwise. This result is relevant and contrasts with the popular belief that decoupled government transfers are most likely to increase "inside-farm" inefficiencies. The comparative statics analysis also proves that the effects of a change in price supports on farms' technical efficiencies cannot be predicted by theory, making it necessary to resolve the question empirically. In the next sections we carry out an empirical analysis. A parametric representation of the model is specified and estimated using farm-level data for a sample of Kansas farms. The results section presents the outcomes of this estimation.

Before concluding this section, it is relevant to note that, according to Chambers and Quiggin (2000), conventional stochastic frontier models do not correctly capture the stochastic decision environment in which firms take their decisions. Following these authors, the stochastic random variable (ε) in stochastic frontier models is primarily employed to capture measurement errors or missing variables, not representing the uncertain conditions under which production takes place. To overcome this limitation, they propose an alternative model based on the state-contingent approach. O'Donnell *et al.* (2006) use simulation methods based on this approach to show that not accounting properly for the stochastic elements in production can yield biased measures of inefficiency and productivity. Specifically, they show that conventional estimators of efficiency will be biased, except when all producers choose to select riskless production plans. Unfortunately, data requirements to apply a state-contingent approach are usually unavailable[4] (O'Donnell *et al.* 2006; Quiggin and Chambers 2006). We would also like to note, however, that according to Chambers and Quiggin (2002) and Quiggin and Chambers (2006), any estimated Just and Pope technology could be interpreted as arising from a state-contingent model with two states of nature.

3. Model specification

We generalize the model developed in the previous section to allow for two variable inputs, x_1 and x_2, and a quasi-fixed input z_1, where x_1 represents the quantity used of pesticides and insecticides, x_2 measures the fertilizer applied, and z_1 stands for a farm's labor. Though our analysis focuses on the short run, scale effects are accounted for by expressing the variables used in the analysis on a per acre basis (see the next section for further detail). It is assumed that the deterministic component of production follows a quadratic specification and is defined as:

[4] As an anonymous referee points out, input allocations across crops, which we do not observe, would be needed to estimate flexible state-contingent models. O'Donnell and Griffiths (2006) propose an estimation approach based on a finite mixtures framework that, in the words of O'Donnell *et al.* (2006) offers "some promise of being able to identify flexible stochastic technologies."

$f(x_1, x_2, z_1) = \alpha_0 + \sum_{i=1}^{2} \alpha_i x_i + \alpha_3 z_1 + \sum_{j=1}^{2} \sum_{i=1}^{2} \alpha_{ji} x_{ji} + \alpha_{33} z_1^2 + \sum_{i=1}^{2} \alpha_{i3} x_i z_1$ where the alphas are parameters. The stochastic component of production is defined as a linear function: $g(x_1, x_2) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$, being β_0, β_1, and β_2 parameters. The conclusions derived from our theoretical model are robust to any specification of the production function.

We estimate both the multiplicative and the additive models using maximum likelihood (ML) techniques (see next paragraph for more detail). Using Pollak and Wales (1991) likelihood dominance criterion for testing non-nested hypotheses and Akaike's information criterion, we find the multiplicative model to clearly dominate the additive one (see table 1).[5] This shows the importance of using flexible specifications when testing for farms' technical inefficiencies.

With the additive model, the system of first-order conditions can be expressed as follows:

$$\begin{cases} f_{x_1}(x_1, x_2, z_1) + g_{x_1}(x_1, x_2)(\theta - \lambda) - w_1 + \eta_1 = 0 \\ f_{x_2}(x_1, x_2, z_1) + g_{x_2}(x_1, x_2)(\theta - \lambda) - w_2 + \eta_2 = 0 \end{cases}. \qquad (3)$$

The model is estimated using the two-stage ML procedure proposed by Kumbhakar (2002).[6] In the first stage, ML methods are applied to estimate the stochastic frontier model. After estimating production parameters, we derive estimates for u and *TI* following Kumbhakar and Lovell (2000, chapter 3). In the second step, risk preference parameters are derived by estimating the system of

[5] As Pollack and Wales (1991) explain, if the two models contain the same number of parameters, both the dominance ordering and the likelihood dominance criteria will always prefer the hypothesis with the higher likelihood.

[6] As Kumbhakar (2002) notes, the single-step ML approach is computationally demanding relative to the two-step method that he uses in his empirical implementation. Though we tried to estimate all parameters in a single step, the optimization process failed to converge. This is why we decided to estimate the model using the two-stage process.

first-order conditions in (3), conditional on the parameters obtained in the first step, by full information ML. In order to be able to determine the impacts of decoupling on farmers' technical inefficiencies, we compute the elasticities of *TI* with respect to government payments and prices. The price elasticity is computed assuming that it is the output price (not the input price) that changes, thus yielding a single elasticity. To compute *TI* elasticities, we use formulas (4) and (5) in the appendix and generalize them to a two-variable and a semi-fixed input model.

4. Empirical implementation

In recent years, the world has witnessed important agricultural policy reforms that have been characterized by a certain degree of decoupling. Not being an exception to this reform trend, the United States' overall farm policy underwent substantial alterations with the 1996 Federal Agriculture Improvement and Reform (FAIR) Act. These reforms involved a reduction in price support payments in favor of decoupled transfers, the Production Flexibility Contract (PFC) payments, and a deficiency payment program aimed at guaranteeing a minimum support price for program crops. According to USDA baseline policy variables (see USDA 2000), marketing assistance loan rates for the crops considered in our analysis were reduced around a 6.3 per cent over the period of analysis. PFC payments were continued with the 2002 Farm Bill under the name of Fixed Direct Payments, and crop loan rates were rebalanced with soybean rates falling while other commodity rates were increased slightly.

Eligibility for the seven-year PFC payments required a farm operator to have a planting history of a contract commodity for at least one of the previous five years, or otherwise have land enrolled in the Conservation Reserve Program (CRP) with planting history of a contract commodity.

New entrants could become program participants on the basis that they purchased or share rented land already under PFC. The effects of government cash transfers on land values has been widely considered by the literature (see, for example, Barnard *et al.* 1997; Goodwin and Ortalo-Magné 1992; Weersink *et al*. 1999; Just and Miranowski 1993; Schertz and Johnston 1998) and there seems to be a general agreement that economic rents from policy are likely to influence land prices which in turn is likely to cause changes in relative input prices. In that we consider PFC payments as fully decoupled, our model does not capture these changes, which certainly constitute an interesting avenue for future research.

The aim of our empirical implementation is to assess the influence of government payments on production inefficiencies of a sample of Kansas farmers. Serra *et al*. (2006) examined the effects of decoupling on both the output mean and variability using the same dataset. Our article extends their work in several ways. While Serra *et al*. (2006) estimate a stochastic production function, we use a stochastic production frontier that is more consistent with economic theory (Aigner *et al.* 1977). As noted above, the literature on decoupling has not yet accounted for production inefficiencies, nor assessed the impacts of policy instruments on technical inefficiencies. In this regard, our model extends the work by Serra *et al*. (1996) along the lines suggested by Kumbhakar (2002), which essentially includes risk preferences in the efficiency model developed by Battese *et al.* (1997). In doing so, and contrary to the paper by Serra *et al*. (2006), our article allows assessing the impacts of decoupling on farms' technical inefficiencies. Also, our paper better represents farmers' behavior under risk, since it allows for the opposite effects on production of the purely stochastic random shocks and the stochastic technical inefficiencies.

Farm-level data are taken from farm account records from the Kansas Farm Management Association dataset for the period comprised from 1998 to 2001. Retrospective data for these farms are used to approximate farm-level PFC as described later in this section.[7] The FAIR Act PFC payments correspond to our definition of fixed payments per farm. Means and standard deviations for the data used are offered in table 2. Other sources that contain aggregate data are also employed to define some variables unavailable from the Kansas dataset. These sources are the National Agricultural Statistics Service (NASS), the United States Department of Agriculture (USDA), and the BRIDGE database. From NASS, we derive country-level price indices and state-level output prices and quantities; state-level marketing assistance loan rates and PFC payment rates are obtained from USDA, while BRIDGE provided futures prices.

Table 1 Model selection

	Additive model	Multiplicative model
Log likelihood	11,524.44	11,072.86
Akaike information criteria	0.20	1.54

Our database does not provide information on the allocation of variable inputs across crops. Hence, we define a single output category (y) that aggregates the production of wheat, corn, grain sorghum, and soybeans—the predominant crops in Kansas. Davis *et al.* (2000), by extending the generalized composite commodity theorem, provide support for consistent aggregation of U.S. agricultural production into as few as two categories: crops and livestock. Variable y is defined as an implicit quantity index and computed as the ratio of production in currency units to the output price index. Because our database does not contain information on market prices, we use price indices as a proxy. Specifically, we build an expected Paasche price index by defining expected unit prices for each crop and using state-level production data. Expected prices are approximated as the maximum

[7] To be able to do so, a balanced panel of 523 farms was built out of our sample.

between the expected cash price and the assistance loan rate, thus explicitly taking into account price supports. The expected cash price is defined as the futures price adjusted by the basis, the latter being the five previous years' average of the wedge between the cash price (state-level output price) and the futures price. The futures price is approximated as the daily average price registered during the planting season for the harvest month contract. As noted above, in order to account for scale effects, we express the variables in the model on a per acre basis, by dividing them by the acres planted to the crops considered.

Table 2 Summary statistics for the variables of interest

Variable	Mean (Standard deviation) n= 2,094
y	113,45 (64,52)
x_1	16.95 (14.18)
w_1	1.08 (0.06)
x_2	24.51 (25.92)
w_2	1.10 (0.12)
z_1	0.53 (1.24)
C	14.37 (11.43)
W_0	1,052.46 (1,456.32)

Note: all monetary values are expressed in constant 1998 currency units.

Input x_1 includes the use of pesticides and insecticides, while x_2 represents fertilizer. Input prices are measured using national input price indices. Variables x_1 and x_2 are defined as implicit quantity indices. Variable z_1, representing farms' labor, is expressed in "productive work units" as a fraction of a 10-hour per day. The Kansas database does not register PFC government payments. In its place, a single measure including all government payments received by each farm is available. We estimate farm-level PFC payments by approximating the acreage of the program crops (base acreage) and the base yield for each crop using farm-level data. The approximation uses the 1986-1988 average acreage and yield for each program crop and farm. PFC payments per crop are computed by multiplying 0.85 by the base acreage, yield, and the PFC payment rate. PFC payments per crop are then added to get total direct payments per farm. This estimate is compared to actual government payments received by each farm. If estimated PFC payments exceed actual payments, the first measure is replaced by the second. This happens to 7per cent of our observations. A farm's initial wealth is defined as the farm's net worth.

Production function parameter estimates are presented in table 3. Parameter estimates for the stochastic element of production provide evidence that variable inputs exert a positive and statistically significant influence on output variability. Hence, both variable inputs are risk increasing, i.e., $g_{x_i}(x_1, x_2) > 0$ for $i = 1, 2$, which is compatible with Serra *et al*. (2006). While fertilizers have traditionally been considered as risk-increasing inputs, pesticides have often been regarded as risk-decreasing factors. Contrary to common belief, Horowitz and Lichtenberg (1994) show that pesticides can increase output variability in a number of situations. More specifically, they prove that pesticides will increase output risk whenever pest populations increase with favorable crop growth conditions. As explained above, first-stage parameter estimates allow deriving estimates for the technical inefficiency stochastic term, as well as for the technical inefficiency measure. The mean and standard deviation of the estimator of u are, respectively, 0.50 and 0.11, yielding a mean *TI* equal to 0.21 with a standard deviation equal to 0.06. The frequency distribution of *TI* is presented in table 5. Our technical inefficiency estimates are above Villano *et al.* (2005) who, using the Kumbhakar (2002) framework, derived mean *TI* levels of 0.12 for lowland rice farms in the Philippines, but are closer to other estimates by Giannakas *et al*. (2003) for a sample of Greek olive farms, Karagiannis and Tzouvelekas (2005) for a sample of Greek sheep holdings, or Kumbhakar *et al.* (1991) for a sample of U.S. dairy farms.

Table 3 Parameter estimates and summary statistics for the production function

Parameter (standard error)	Deterministic component of production	Stochastic component of production
α_0	81.7414* (3.0470)	
α_1	2.8492* (0.2687)	
α_2	1.4560* (0.1197)	
α_3	-34.5777* (4.2466)	
α_{11}	0.1035E-01 (0.7306E-02)	
α_{22}	-0.1932E-02 (0.1119E-02)	
α_{33}	4.5840* (0.4440)	
α_{12}	0.2724E-02* (0.5137E-02)	
α_{13}	-0.9445* (0.1063)	
α_{23}	-0.7380E-01 (0.7373E-01)	
β_0		26.1909* (0.6312)
β_1		1.6770* (0.6641E-01)
β_2		0.1957* (0.2885E-01)
σ_u^2		0.4141* (0.9598E-01)
Wald Test		23,080.1400*

Note: An asterisk (*) denotes statistical significance at the α = 0.05 level.

Parameter estimates for the system of first-order conditions (3), which are presented in table 4, are all statistically significant and provide evidence that farms in our sample exhibit DARA preferences. These parameters allow predicting the coefficient of absolute risk aversion whose mean is 0.008 (see table 4). The coefficient of relative risk aversion, which does not depend on the units of measure, takes the value of 7.4 at the data means, which is compatible with the findings of Saha *et al.* (1994) or Chavas and Holt (1990). Such coefficients yield mean values for θ and λ on the order of -0.37 and 0.57, which are compatible with Villano *et al.* (2005).

Table 4 Parameter estimates and summary statistics for the coefficients of risk aversion

Parameter	Mean predicted value (Standard deviation)
γ_0	0.0092* (0.0002)
γ_1	-9.6000-7* (1.5990E-8)
θ	-0.3748 (0.1036)*
λ	0.5698 (0.0156)*
R Absolute risk aversion	8.2240E-03 (1.1510E-3)*
Relative risk aversion	7.4619 (8.8375)
Wald test	249,932.000*

Note: An asterisk (*) denotes statistical significance at the α = 0.05 level.

Frequency distributions of technical inefficiency elasticities with respect to decoupled payments and output prices are offered in tables 6 and 7. The effects of both decoupled and coupled payments cannot be predicted by our theoretical model and need to be empirically determined. The generalization of the model to a consideration of more than one input and the fact that all variable inputs are found to be risk increasing preclude this prediction. Table 6 shows that a majority of farms (almost 90 per cent) will increase their production inefficiencies as a response to an increase in PFC payments. As explained in the theoretical section, this situation will occur whenever a change in input allocation causes an increase in the output mean smaller than the increase in output risk. The increase in *TI* is compatible with decoupled payments being government transfers not linked to production or yields. Because production is not receiving any reward, incentives to produce the maximum attainable output may be reduced. It is important to note however that elasticity values are very small, indicating that large changes in payments are required to generate substantial impacts. This result is consistent with previous research (Hennessy 1998). For an overwhelming majority of farmers, a decline in output price supports will result in an increase in *TI* (see table 7). It is important to recall here that our analysis does not assess the impacts of decoupled programs on the entry/exit decision and the consequent changes in the distribution of the technical inefficiency parameter. In a scenario where the number of farms is assumed to remain constant, our model shows that farmers may respond to a decline in price supports by reducing the efficiency with which they operate. This is compatible with reduced motivation to produce efficiently in light of the lower rents derived from producing. Further, this result reinforces the positive value of the payment elasticity for most of the farms in the sample. In light of the previous results, we can conclude that a policy-reform process consisting of a reduction in output price supports and an increase in decoupled government transfers may involve an increase in *TI* levels.

Table 5 Frequency distribution of technical efficiency ratings for Kansas farms, 1998-2001

Inefficiency (%)	1998	1999	2000	2001
<10	12	11	9	4
10-20	306	265	231	221
20-30	179	213	241	247
30-40	15	25	28	33
>40	5	8	9	4
N	517	522	518	509
mean	0.19	0.20	0.21	0.21

Table 6 Frequency distribution of payment elasticities for Kansas farms, 1998-2001

Payment elasticity	1998	1999	2000	2001
$E_{TI\_C} < -0.001$	2	5	2	4
$-0.001 < E_{TI\_C} < 0$	61	52	37	54
$0 < E_{TI\_C} < 0.0004$	297	309	320	354
$0.0004 < E_{TI\_C} < 0.0008$	115	102	113	69
$0.0008 < E_{TI\_C} < 0.003$	39	48	42	24
$E_{TI\_C} > 0.003$	3	5	4	4
N	517	521	518	509
mean	0.0003	0.0003	0.0003	0.0003

Table 7 Frequency distribution of price elasticities for Kansas farms, 1998-2001

Payment elasticity	1998	1999	2000	2001
$E_{TI\_p} < -5$	0	2	0	0
$-5 < E_{TI\_p} < -2$	8	34	26	74
$-2 < E_{TI\_p} < -1$	270	318	296	341
$-1 < E_{TI\_p} < 0$	231	144	180	80
$0 < E_{TI\_p} < 5$	8	23	16	14
$E_{TI\_p} > 5$	0	0	0	0
N	517	521	518	509
mean	-1.0382	-1.1955	-1.1239	-1.4398

5. Concluding remarks

Previous literature on the effects of decoupling has focused the attention towards determining the impact of decoupled government transfers on input use and output levels. However, to our knowledge, no analysis has attempted to assess the effects of decoupling on farms' technical inefficiency levels. Late studies on technical efficiencies have combined the conventional stochastic frontier models and Just and Pope (1978) specification of production, yielding stochastic frontier models with additive heteroskedastic error structures (Battese *et al.* 1997). We find the additive model to better represent production behavior of our sample of Kansas farms than the more restrictive and widely used multiplicative framework. Additive models yield a measure of technical inefficiencies that does not only depend on the stochastic technical inefficiency effect, but that also depends on input use. Specifically, technical inefficiencies are found to have a positive relationship with the variance of output and a negative relationship with production mean. Hence, a decoupling process that alters a farm's input use will also impact on its technical inefficiency levels.

We present a theoretical model to assess the impacts of decoupling on production inefficiencies. Our paper focuses on "inside-farm" technical inefficiencies and does not enter into the question of the impacts of decoupled programs on the entry-exit decision and on the consequent changes in the distribution of the technical inefficiency parameter. Our model is based on the model developed by Kumbhakar (2002) who extends Battese *et al.'s* (1997) framework to a consideration of economic agents' risk preferences. We extend this framework to include policy instruments and develop a comparative statics analysis to study the impacts of decoupling on *TI*. This analysis shows the relevance of accounting for the influence of output risk, risk preferences, and technical inefficiencies when studying the effects of decoupling. We show that an increase in decoupled transfers will motivate an increase (decrease) in DARA (IARA) farmers' technical inefficiencies if input x is risk decreasing. However, if the input is risk increasing, inefficiencies could both increase or decrease. This result is relevant and contrasts with the widespread belief that decoupled government transfers will increase "inside-farm" inefficiencies. Compatible with the findings of Just and Zilberman (1986), the effects of decoupled payments on *TI* cannot be predicted by theory. We use farm-level data collected in Kansas to illustrate the model. Our results show that, for an overwhelming majority of farms, an increase in decoupled payments will increase farms' technical inefficiencies. This result is compatible with decoupled payments being government transfers not linked to production or yields. Because production is not receiving any premiums, incentives to produce the maximum attainable output may be reduced. Previous research has shown that decoupled government transfers may have only minor or no impact on input use. Consistently with this research, PFC payment elasticities are very small requiring relevant changes to these payments to generate substantial impacts. Our results also show that farmers may respond to a decline in price supports by reducing the efficiency with which they operate. This result thus reinforces the positive value of payment elasticities, in that lower rents derived from producing are found to reduce the motivation to produce efficiently.

Appendix

Proof of propositions 1 and 2. The effects of decoupled payments can be determined as follows:

$$\frac{\partial TI}{\partial C}=\frac{\partial TI}{\partial x}\frac{\partial x}{\partial C}, \tag{4}$$

where $\frac{\partial x}{\partial C}=-\frac{g_x(x)(\theta_C-\lambda_C)}{E[U(W)]_{xx}}$ is the marginal input use effect of government payments and can be determined by totally differentiating the first-order condition in (2), and $\theta_C=-\frac{\gamma_1 g(x)}{(1+ag(x)R)^2}$ is the marginal payment effect on θ and is $\theta_C>(=)[<]0$ under DARA (CARA) [IARA] preferences. The marginal payment effect on λ is captured by $\lambda_C=\frac{\gamma_1 g(x)b^2}{(1+Rg(x)a)^2}$, which is $\lambda_C<(=)[>]0$ under DARA (CARA) [IARA] risk attitudes. The expression in the denominator of $\frac{\partial x}{\partial C}$, $E[U(W)]_{xx}=f_{xx}(x)+g_{xx}(x)(\theta-\lambda)+g_x(x)(\theta_x-\lambda_x)<0$, represents the second- order condition of the optimization problem. Expression $\frac{\partial TI}{\partial x}=\frac{g_x(x)f(x)-g(x)f_x(x)}{f(x)^2}u$ captures the marginal impact of a change in input use on the technical inefficiency measure. Formula (4) shows that a change in decoupled government transfers will induce a change in input consumption, which will in turn alter a farm's measure of technical inefficiency. An increase in government transfers will increase (leave constant) [decrease] DARA (CARA) [IARA] farmers' willingness to assume more risk, thus reducing (leaving constant) [increasing] the Arrow-Pratt coefficient of absolute risk aversion. This change in risk attitudes will cause θ to increase (remain constant) [decrease] and λ to decrease (remain constant) [increase] under DARA (CARA) [IARA], involving a marginal risk premium of a smaller (equal) [bigger] magnitude in absolute terms. The sign of $\frac{\partial x}{\partial C}$ also depends on the sign of $g_x(x)$. If $g_x(x) > (=)[<]0$, then $\frac{\partial x}{\partial C} > (=)[<]0$ under DARA, $\frac{\partial x}{\partial C} = 0$ under CARA, and $\frac{\partial x}{\partial C} < (=)[>]0$ under IARA. Hence, our results show that under DARA preferences for example, an increase in decoupled government payments will increase the demand for risk-increasing inputs, while reducing the application of the risk-reducing ones. This result is compatible with the findings of MacMinn and Holtmann (1983) and represents an extension of their work. While the sign of $\frac{\partial x}{\partial C}$ can be predicted by theory, one cannot forecast the sign of $\frac{\partial TI}{\partial x}$. Under the assumption that the expected marginal productivity is positive, this expression will be negative if x is a risk-decreasing input. However, if the input is risk increasing, $\frac{\partial TI}{\partial x}$ could be either positive or negative.

The impacts of coupled policies can be computed as follows:

$$\frac{\partial TI}{\partial w} = \frac{\partial TI}{\partial x}\frac{\partial x}{\partial w}, \qquad (5)$$

where $\frac{\partial x}{\partial w} = -\frac{g_x(x)(\theta_w - \lambda_w) - 1}{E[U(W)]_{xx}}$ is the marginal input use effect of price and can be determined by totally differentiating the first-order condition in (2), $\theta_w = \frac{\gamma_1 x g(x)}{\left(1 + a g(x) R\right)^2} < (=)[>]0$ under DARA

(CARA) [IARA] risk attitudes is the marginal price effect on θ, and $\lambda_w = \frac{-\gamma_1 x g(x) b^2}{\left(1+Rg(x)a\right)^2} > (=)[<]0$

under DARA (CARA) [IARA] preferences is the marginal price effect on λ.

Expression (5) shows that a change in price supports will induce a change in input allocation, which will in turn alter a farm's technical inefficiency. A reduction in market output price supports will decrease (leave constant) [increase] DARA (CARA) [IARA] farmers' willingness to assume more risk, which will cause an increase (no change) [a decrease] in the Arrow-Pratt coefficient of absolute risk aversion. This in turn will cause θ to decrease (stay constant) [increase] and λ to increase (stay constant) [decrease]. The absolute value of the marginal risk premium will increase (stay constant) [decrease]. The sign of $\frac{\partial x}{\partial w}$ also depends on the sign of $\left[g_x(x)\left(\theta_w - \lambda_w\right) - 1\right]$, thus not being possible to anticipate whether input use and technical efficiencies will increase or decrease with a decline in output price supports.

Just and Zilberman (1986), by introducing risk and risk preferences into production decision models, challenge the widely held conjecture of the law of supply. As the authors note, the law of supply is mainly based on the assumption of full certainty of production relationships and risk neutrality. They show that the law of supply may fail whenever an increase in output price causes an increase in profit risk above the increase in its mean (Leathers and Quiggin, 1991, as well as Serra *et al*., 2006 find results compatible with Just and Zilberman, 1986). The results in our comparative statics analysis are also compatible with Just and Zilberman (1986) and thus do not allow to unambiguously sign equation: $\frac{\partial TI}{\partial w}$.

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