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Farms' technical inefficiencies in the presence of government programs*

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We focus on determining the impacts of government programs on farms' technical inefficiency levels. We use Kumbhakar's 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.

Key words: Just and Pope production function, risk preferences, stochastic frontier models.

1. Introduction

The analysis of technical efficiency involves the assessment of the degree to which production technologies are being utilised. 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 modelled production risks (Battese *et al.* 1997; O'Donnell *et al.* 2006).

As explained by Just and Pope (1978), the common 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

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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 behaviour of modern agricultural enterprises. An objective of our article is to test the multiplicative model vs. the additive one for a sample of US farms that specialise in cereal production. 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 on the impacts of lump-sum transfers on input use and output levels (see, e.g. Oude Lansink and Peerlings 1996; Hennessy 1998; 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 analyse 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. The aim of our empirical implementation is to assess the influence of government payments on production inefficiencies of a sample of Kansas farmers. Results show that an increase in decoupled

transfers is likely to increase our sample farms' technical inefficiencies albeit with a very small magnitude.

Our article extends Serra *et al.* (2006), who examined the effects of decoupling on both the output mean and variability using the same dataset, 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.* (2006) along the lines suggested by Kumbhakar (2002). In doing so, and contrary to the paper by Serra *et al.* (2006), our article allows for an assessment of the impacts of decoupling on farms' technical inefficiencies. Also, our paper better represents farmers' behaviour under risk, since it allows for the opposite effects on production of the purely stochastic random shocks and the stochastic technical inefficiencies.

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 and needs to be empirically resolved. It is also true that decoupled payments are government transfers not linked to production or yields. If income supports are based on these transfers, higher production levels are not receiving any premium, which may reduce incentives to produce the maximum attainable output and thus may increase inefficiencies.

Our article is organised 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 section 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) criticise 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 conventional 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 the sake of simplicity. However, in the empirical application the model is generalised. 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 $N(0,1)$. 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, $E(u) = a = \sqrt{(2/\pi)}\sigma_u$ and $\text{Var}(u) = b = (\pi - 2/\pi)\sigma_u^2$. 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 $\text{Var}(y|_{u=0}) = g(x)^2$. An input will cause production risk to increase (stay constant) [decrease] if $(\partial \text{Var}(y|_{u=0})/\partial x) > (=)[<] 0$. 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: $TI = 1 - (E(y|_{x,u})/E(y|_{x,u=0})) = u(g(x)/f(x)) \leq 1$. This measure depends on two factors: (i) the non-negative random variable u ; and (ii) the ratio $g(x)/f(x)$, 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 $g(x)/f(x)$ 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

¹ Conventional stochastic frontier models, however, can yield technical inefficiency measures that depend inversely on the output mean if production is measured in its original units instead of logarithms.

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. The additive theoretical framework has the desirable property that marginal expected products are not constrained to have the same signs as marginal risks. However, this framework can also have restrictive implications for measures of technical inefficiency. If technical inefficiency remains unaltered with varying input levels, the signs of the marginal expected product and risk are forced to be the same, which is precisely the desirable property that the Battese *et al.* (1997) and Kumbhakar (2002) models were designed to avoid.

The multiplicative version of the previous model can be represented as (Kumbhakar 2002): $y = f(x)(1 - u) + g(x) \varepsilon$.² Under such model, technical inefficiency can be expressed as: $TI = 1 - (E(y|_{x,u})/E(y|_{x,u=0})) = u(f(x)/g(x)) = u \leq 1$ and does not depend on input use. Battese *et al.* (1997), argue that the additive model is likely to better represent production behaviour 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 vs. 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 technical efficiencies, to a certain extent, being 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 comparative statics analysis to assess the effects of decoupling on technical inefficiency measures. In order to formulate the optimisation problem, it is assumed that producers take their decisions with the aim of maximising the expected utility of wealth $\max_x E[U(W)] = \max_x E[U(W_0 + y - wx + C)]$, where W represents a farm's total wealth normalised by output price (p), W_0 stands for a farm's initial wealth, w is the input price relative to 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 analysing the impacts of policies that influence price variability. Though the effects of decoupled transfers on price variability are not likely to be very relevant, this is certainly an

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

³ Initial wealth could be omitted from the model.

interesting topic that merits further research. The first-order condition of the expected utility maximisation problem can be expressed as follows:

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

where subscripts denote partial derivatives, $f_x(x)$ represents 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 $E[U'(W)]$, expression (1) changes to:

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

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 (0) [negative] if variable input x is risk decreasing (neutral) [increasing] and if producers are averse to risk, and $\theta = E[U'(W)\varepsilon]/E[U'(W)]$ and $\lambda = E[U'(W)u]/E[U'(W)]$ 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: $\theta = -Rg(x)/1 + Rg(x)a$ and $\lambda = a + Rg(x)(a^2 + b^2)/1 + Rg(x)a$, 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: $R = -(U_{ww}(\mu)/U_w(\mu)) = \gamma_0 + \gamma_1\mu$, 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 characterised 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 favour of DARA (Bar-Shira *et al.* 1997; Saha 1997; Isik and Khanna 2003).

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 artificial levels. Agricultural policy decoupling processes have usually involved a decline in output price supports in favour 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 normalised by the output price, on farms' technical inefficiencies. The comparative statics results can

be summarised 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:*

$$(a) \left\{ \begin{array}{l} \frac{\partial TI}{\partial C} > (<) 0 \text{ under DARA preferences and } \frac{f(x)}{g(x)} > (<) \frac{f_x(x)}{g_x(x)}, \\ \text{as well as under IARA} \\ \text{risk attitudes and } \frac{f(x)}{g(x)} < (>) \frac{f_x(x)}{g_x(x)} \\ \frac{\partial TI}{\partial C} = 0 \text{ under CARA preferences of if } \frac{f(x)}{g(x)} = \frac{f_x(x)}{g_x(x)} \end{array} \right.$$

$$(b) \frac{\partial TI}{\partial w} \text{ is of indeterminate sign.}$$

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:*

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

$$(b) \frac{\partial TI}{\partial w} \text{ is of indeterminate sign.}$$

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 $(f(x)/g(x)) < (f_x(x)/g_x(x))$, that is, 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 normalised input prices (w) on farms' technical efficiencies cannot be predicted by theory. It can also be shown that a change in output price supports cannot be predicted by theory either, making

it necessary to resolve the question empirically, which will be done in the next sections.

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 the state-contingent approach and show that failure to account properly for the stochastic elements of production can give rise to spurious measures of efficiency. Consequently, results presented in this paper should be interpreted with care. While we acknowledge the potential limitations of our approach, we would like to note that, unfortunately, data requirements to apply a state-allocable approach are usually unavailable⁴ (O'Donnell *et al.* 2006; Quiggin and Chambers 2006).

3. Model specification

We generalise the model developed in the previous section to allow for two variable inputs, x_1 and x_2 , and two quasi-fixed inputs x_3 and x_4 , where x_1 represents the quantity used of pesticides and insecticides, x_2 is a composite input including both fertiliser and seeds used in the production process, x_3 stands for a farm's labour and x_4 represents capital inputs. Since production for the farms in the sample is characterised by constant returns to scale,⁵ the variables used in the analysis are expressed 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: $f(x_1, x_2, x_3, x_4) = \alpha_0 + \sum_{i=1}^4 \alpha_i x_i + \sum_{i=1}^4 \sum_{j=1}^4 \alpha_{ji} x_j x_i$ 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

⁴ Input allocations across crops, which we do not observe, would be needed to estimate flexible state-allocable 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.'

⁵ The hypothesis of constant returns to scale was tested using both a Cobb–Douglas and a quadratic specification for the production function. At the data means, returns to scale are close to 1.02 under both specifications. A Wald test for constant returns to scale generated values of 1.3 under the Cobb–Douglas specification, and 1.35 for the quadratic model. In both cases, the null hypothesis is comfortably accepted.

Table 1 Model selection

	Additive model	Multiplicative model
Log likelihood	12145.29	11538.63
Akaike information criteria	0.74	4.04

and Wales (1991) likelihood dominance criterion for testing non-nested hypotheses and Akaike's information criterion, we find the additive model to clearly dominate the multiplicative one (see Table 1).⁶ 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:

$$\begin{cases} f_{x_1}(x_1, x_2, x_3, x_4) + g_{x_1}(x_1, x_2)(\theta - \lambda) - w_1 + \eta_1 = 0 \\ f_{x_2}(x_1, x_2, x_3, x_4) + g_{x_2}(x_1, x_2)(\theta - \lambda) - w_2 + \eta_2 = 0 \end{cases} \quad (3)$$

The model is estimated using the two-stage ML procedure proposed by Kumbhakar (2002).⁷ 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 first-order conditions in Equation (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 prices) that changes, thus yielding a single elasticity. To compute TI elasticities, we use formulas (4) and (5) in the Appendix, and adapt them to our two-variable and two semi-fixed input model.

4. Empirical implementation

In recent years, the world has witnessed important agricultural policy reforms that have been characterised by a certain degree of decoupling. Not being an

⁶ As Pollak 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.

⁷ 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 optimisation process failed to converge. That is why we decided to estimate the model using the two-stage process.

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 favour 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 by 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 to have land enrolled in the Conservation Reserve Program (CRP) with a 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 have been widely considered by the literature (see, e.g. Goodwin and Ortalo-Magné 1992; Just and Miranowski 1993; Barnard *et al.* 1997; Schertz and Johnston 1998; Weersink *et al.* 1999) 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 analysis is to assess the influence of government payments on production inefficiencies of a sample of Kansas farmers. Farm-level data are taken from farm account records from the Kansas Farm Management Association dataset for the years 1998–2001. Retrospective data for these farms are used to approximate farm-level PFC as described later in this section.⁸ The FAIR Act PFC payments correspond to our definition of fixed payments per farm. Means and standard deviations for the data used are listed 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.

The Kansas Farm Management Association dataset collects financial and production information for full-time commercial holdings in Kansas. The

⁸ To be able to do so, a balanced panel of 549 farms was built out of our sample.

Table 2 Summary statistics for the variables of interest

Variable	Mean (Standard deviation) $n = 2\ 196$
y	112.09 (64.16)
x_1	16.27 (14.28)
w_1	1.08 (0.06)
x_2	39.96 (33.17)
w_2	1.12 (0.09)
x_3	0.53 (1.24)
x_4	237.51 (226.50)
C	14.40 (11.45)
W_0	1073.92 (1505.53)

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

average value of farm production in 2001 was \$214 664 for the farms in the dataset and remained more or less constant during the period of analysis. Net farm income, averaging \$27 995 in 2001 is subject to considerable fluctuations. Crop production and government payments represent around 80 per cent of the value of the farm production, with corn, wheat, soybeans and sorghum being the predominant crops in the state (Albright 2002). During the period of analysis, each farm in our sample had, on average, 1081 acres of cropland, of which 82 per cent was planted to these commodities that were mainly produced on dryland. Fertiliser and lime, seeds and crop protection products represent the most relevant crop-specific costs which are more than a fourth of total farm operating expenses. Machinery and equipment-related expenses, excluding financial expenses, represent around 17 per cent of operating expenses. Conversely, hired labour is only 6 per cent of operating expenses, though it is relevant to note that unpaid family and operator labour are the predominant form of labour in this farming system.

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 generalised 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 is 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 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, since production for the farms in our sample is characterised by constant returns to scale, we express the variables in the model on a per acre basis, by dividing them by the acres planted to the crops considered.

Input x_1 includes the use of pesticides and insecticides, while x_2 is a composite input that represents fertiliser and seeds. Input prices are measured using national input price indices. Variables x_1 and x_2 are defined as implicit quantity indices. Variable x_3 , representing farms' labour, is expressed in 'productive work units' as a fraction of a 10-h per day. Variable x_4 , representing capital inputs, includes the value of machinery and other equipment used in the production process. 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. Approximating base acreage and yields requires using data corresponding to the period shortly after 1985. Base acres were originally determined in the early 1980s. With the 1985 Food Security Act, a farm's crop base acreage was set equal to the arithmetic average of the acreage planted to that crop during the five previous years. If a producer overplanted the base acreage, she would be ineligible for the payments that year. The 1985 Act also froze program yields at 1985 levels. Therefore, and as Smith and Glauber (1997) note, most links at the farm-level between current production decisions and deficiency payments had been severed by 1986. Following this argument, we use the 1986–1988 average acreage and yield for each program crop and farm.

Following the 1996 FAIR Act provisions (see Young and Shields 1996), PFC payments per crop are computed by multiplying 0.85 by the base acreage, yield and the PFC payment rate which, as noted above, is taken from USDA. 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 7 per 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, that is,

Table 3 Parameter estimates and summary statistics for the production function

Parameter value (standard error)	Deterministic component of production	Stochastic component of production
α_0	83.1112* (3.3205)	
α_1	2.1017* (0.2543)	
α_2	1.0480* (0.0773)	
α_3	-51.7559* (3.8940)	
α_4	0.1178* (0.0179)	
α_{11}	0.0123* (0.5241E-02)	
α_{22}	-0.7333E-03 (0.5057E-03)	
α_{33}	4.8137* (0.7999)	
α_{44}	-0.5416E-04* (0.1094E-04)	
α_{12}	0.0214* (0.3284E-02)	
α_{13}	-1.0500* (0.1201)	
α_{14}	-1.3480E-02* (0.5158E-03)	
α_{23}	-0.2013* (0.0378)	
α_{24}	0.1829E-03 (0.1245E-03)	
α_{34}	0.0185* (0.6873E-02)	
β_0		25.4861* (0.6207)
β_1		1.4737* (0.0586)
β_2		0.0564* (0.0135)
σ_u^2		1.6133* (0.1641)
Wald Test		24 290.57*

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

$g_{x_i}(x_1, x_2) > 0$ for $i = 1, 2$, which is compatible with Serra *et al.* (2006). While fertilisers 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 favourable crop growth conditions. As explained above, first-stage

Table 4 Frequency distribution of technical efficiency ratings for Kansas farms, 1998–2001

Inefficiency (%)	1998	1999	2000	2001
< 10	11	14	11	2
10–20	115	91	77	68
20–30	237	206	167	166
30–40	122	148	166	164
40–50	39	55	84	89
> 50	23	35	36	50
<i>N</i>	547	549	541	539
Mean	0.29	0.30	0.32	0.32

Table 5 Parameter estimates and summary statistics for the coefficients of risk aversion

Parameter	Mean predicted value (standard deviation)
γ	0.0213* (0.0002)
γ	–2.8200E-06* (8.9330E-09)
θ	–0.4603 (0.3258)
λ	1.2833* (0.1910)
R	0.0179* (0.0042)
Absolute risk aversion	14.9953 (33.6683)
Relative risk aversion	
Wald test	653 596.00*

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

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, 0.96 and 0.35, yielding a mean TI equal to 0.30 with a standard deviation of 0.12. The frequency distribution of TI is presented in Table 4. 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. Parameter estimates for the system of first-order conditions (3), which are presented in Table 5, 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 0.018 (see Table 5). The coefficient of relative risk aversion is compatible with the findings of Love and Buccola (1991). Our results yield mean values for θ and

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

Payment elasticity	1998	1999	2000	2001
$E_{TLC} < -0.001$	2	2	1	0
$-0.001 < E_{TLC} < 0$	3	8	5	7
$0 < E_{TLC} < 0.0004$	400	399	410	472
$0.0004 < E_{TLC} < 0.0008$	119	103	109	52
$0.0008 < E_{TLC} < 0.003$	22	35	15	8
$E_{TLC} > 0.003$	1	2	2	1
N	547	549	542	540
Mean	0.0003	0.0004	0.0003	0.0002

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

Payment elasticity	1998	1999	2000	2001
$E_{TLC} < -5$	0	0	0	0
$-5 < E_{TLC} < -2$	5	16	10	40
$-2 < E_{TLC} < -1$	86	119	135	158
$-1 < E_{TLC} < 0$	453	412	396	341
$E_{TLC} > 0$	3	2	0	0
N	547	549	541	539
Mean	-0.5963	-0.7339	-0.7920	-0.9337

λ on the order of -0.46 and 1.28 , which are compatible with Villano *et al.* (2005).

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 generalisation 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 virtually all farms 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 a change in the output mean smaller than the change in output risk. The increase in TI is compatible with decoupled payments being government transfers not linked to production or yields. Because these payments are constant and do not increase with higher production levels or different land allocations, they provide planting flexibility to farmers and we would expect that they may involve a reduction in input use and production levels relative to a scenario with price-supports. Farmers receiving a fixed government transfer every year may have fewer incentives to efficiently work the land relative to farmers relying on (supported) market prices as their single income source. Our results seem to confirm this hypothesis. 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 practically all farmers, a decline in output price supports will result in an increase in *TI* (see Table 7). This is again consistent with changes in input use having stronger impacts on the output mean than on the output standard deviation. 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 as a response to the lower rents derived from producing. Further, this result reinforces the positive value of the payment elasticity. 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.

5. Concluding remarks

Previous literature on the effects of decoupling has focused on 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. Some studies on technical efficiencies have combined the conventional stochastic frontier models and Just and Pope's (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 behaviour of our sample of Kansas farms than the more restrictive multiplicative framework. Additive models yield a measure of technical inefficiencies that does not only depend on the stochastic technical inefficiency effect, but which 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 Leathers and Quiggin (1991), the effects of coupled 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 higher production yields are 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.

Our analysis is necessarily constrained by data availability. As noted above, failure to account properly for the stochastic elements of production can give rise to spurious measures of efficiency. Collecting data on input allocations across crops, which we do not observe, would allow estimating flexible state-allocable models to then determine to what extent our results may be biased.

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Appendix

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

$$\frac{\partial TI}{\partial C} = \frac{\partial TI}{\partial x} \frac{\partial x}{\partial C}, \quad (4)$$

where $(\partial x / \partial C) = -(g_x(x)(\theta_c - \lambda_c) / E[U(W)]_{xx})$, is the marginal input use effect of government payments and can be determined by totally differentiating the first-order condition in Equation (2), and $\theta_c = -(\gamma_1 g(x) / (1 + ag(x)R)^2)$ 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 $\lambda_c = \gamma_1 g(x)b^2 / (1 + Rg(x)a)^2$, which is $\lambda_c < (=)[>]0$ under DARA (CARA) [IARA] risk attitudes. The expression in the denominator of $\partial x / \partial C$, $E[U(W)]_{xx} = f_{xx}(x) + g_{xx}(x)(\theta - \lambda) + g_x(x)(\theta_x - \lambda_x) < 0$, represents the second-order condition of the optimisation problem. Expression $(\partial TI / \partial x) = (g_x(x)f(x) - g(x)f_x(x) / f(x)^2)u$ 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 $\partial x / \partial C$ also depends on the sign of $g_x(x)$. If $g_x(x) > (=)[<]0$, then $(\partial x / \partial C) > (=)[<]0$ under DARA, $(\partial x / \partial C) = 0$

under CARA, and $(\partial x/\partial C) < (=)[>]0$ 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 $\partial x/\partial C$ can be predicted by theory, one cannot forecast the sign of $\partial TI/\partial x$. 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, $\partial TI/\partial x$ could be either positive or negative.

The impacts of a change in normalised input prices can be computed as follows:

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

where $(\partial x/\partial w) = -(g_x(x)(\theta_w - \lambda_w) - 1/E[U(W)]_{xx})$ is the marginal input use effect of price and can be determined by totally differentiating the first-order condition in Equation (2), $\theta_w = (\gamma_1 x g(x)/(1 + ag(x)R)^2) < (=)[>]0$ under DARA (CARA) [IARA] risk attitudes is the marginal price effect on θ , and $\lambda_w = (-\gamma_1 x g(x)b^2(1 + Rg(x)a)^2) > (=)[<]0$ under DARA (CARA) [IARA] preferences is the marginal price effect on λ .

Expression (5) shows that a change in normalised input prices will induce a change in input allocation, which will in turn alter a farm's technical inefficiency. An increase in w 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 $\partial x/\partial w$ also depends on the sign of $[g_x(x)(\theta_w - \lambda_w) - 1]$, thus not being possible to anticipate whether input use and technical efficiencies will increase or decrease with a change in normalised input prices.

The results in our comparative statics analysis are compatible with Leathers and Quiggin (1991) who claim that the sign of $\partial x/\partial w$ is ambiguous for risk-reducing inputs if farmers are characterised by DARA preferences. Leathers and Quiggin (1991), however, state that the Just and Pope production function yields a representation of risk that is specially restrictive for risk-reducing inputs, thus making models of this type unsatisfactory for this sort of inputs. Finally, we should note that, as an anonymous referee points out, more recent work by Chambers and Quiggin (2000) confirms that increases in input prices will lead to non-negative changes in input demands irrespective of risk attitudes and input types.