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Full Research Article

Positive Mathematical Programming and Risk Analysis

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Abstract. In 1956, Freund introduced the analysis of agricultural price risk in a mathematical programming framework. His discussion admitted only constant absolute risk aversion. This paper generalizes the treatment of risk preference in a mathematical programming approach along the lines suggested by Meyer (1987) who demonstrated the equivalence of expected utility of wealth and a function of mean and standard deviation of wealth for a wide class of probability distributions that differ only by location and scale. This paper extends the definition of calibration under Positive Mathematical Programming (PMP) by considering limiting input prices along with the traditional decision variables. Furthermore, it shows how to formulate an analytical specification for the estimation of the risk preference parameters and calibrates the model to the base data within small deviations. The PMP approach under generalized risk allows also the estimation of output supply elasticities and the response analysis of decoupled farm subsidies that recently has interested policy makers. The approach is applied to a sample of farms that do not produce all the sample commodities.

Keywords. Risk analysis, positive mathematical programming, model calibration, chance constraint, policy analysis.

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1. Introduction

This paper accomplishes several objectives:

1. It presents a procedure to estimate generalized risk preferences in combination with Positive Mathematical Programming (PMP).
2. It obtains a unique calibrating solution of a PMP model even with a sample of farms that produce zero levels of some crops.
3. It estimates a complete cost function that can be used in a calibrating model for policy analysis.
4. It shows that Phase I and Phase II of the classical PMP procedure give identical and unique results.
5. It shows how to incorporate exogenously given supply elasticities.

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6. It extends the meaning of calibration in PMP by minimizing the distance of optimal solutions from observed output levels and limiting input prices. In this way, it dispenses from the necessity of a user-determined parameter that was originally introduced to guarantee a positive shadow price of binding constraints.

The treatment of agricultural price risk in a mathematical programming framework has dealt mainly with either an exponential utility function and constant absolute risk aversion (CARA) or the minimization of total absolute deviation (MOTAD) of income. The first approach, originally proposed by Freund (1956), appealed to the expected utility (EU) hypothesis and assumed that random prices were normally distributed. These assumptions lead to a mean-variance specification of the certainty equivalent (CE) defined as total expected revenue minus a risk premium. Such a premium corresponds to half the variance of revenue multiplied by a constant absolute risk aversion coefficient. The MOTAD approach was proposed by Hazell (1971) who justified its introduction with the difficult access – at that time – to a quadratic programming computer software necessary to solve a mean-variance model. According to Hazell (1971, p. 56), the MOTAD specification "has an important advantage over the mean-variance criterion in that it leads to a linear programming model in deriving the efficient mean-absolute deviation farm plans." The MOTAD model approximates a mean-standard deviation (MS) criterion but it says nothing about the economic agent's risk preference with regard to either decreasing (constant, increasing) absolute or relative risk aversion.

Recently, Cortignani and Severini (2012), Arata *et al.* (2017) and Paris (2018) have combined PMP with a CARA specification of risk preferences. It is difficult, however, to accept the idea that farmers risk behavior does not account for changes in wealth as the CARA approach stipulates. Petsakos and Rozakis (2015) have presented a combination of the traditional PMP specification with a decreasing absolute risk aversion (DARA) parameter. The present paper combines a more encompassing specification of PMP (calibration of output quantities and limiting input prices) with generalized risk preferences where the behavior of the risk-avert farmer can vary over all theoretically possible preferences (CARA, DARA, IARA, constant, decreasing and increasing relative risk aversion). The paper deals with market price risk leaving the treatment of production risk for further research.

The mean-standard deviation approach has a long history [Fisher (1906), Hicks (1933), Tintner (1941), Markowitz (1952), Tobin (1958)]. Meyer (1987) presented a reconciliation between the EU and the MS approaches that may be fruitfully applied in a positive mathematical programming (PMP) analysis of economic behavior under risk. The main objective of Meyer was to find consistency conditions between the EU and the MS approaches in such a way that an agent who ranks the available alternatives according to the value of some function defined over the first two moments of the random payoff would rank those alternatives in the same way by means of the expected value of some utility function defined over the same payoffs. It turns out that the location and scale condition is the crucial link to establish the consistency between the EU and the MS approaches. We reproduce here Meyer's argument (1987, p. 423):

"Assume a choice set in which all random variables Y_i (with finite means and variances) differ from one another only by location and scale parameters. Let X be the random variable obtained from one of the Y_i using the normalizing transformation $X_i =$

$(Y_i\text{-}\mu_i)/\sigma_i$ where μ_i and σ_i are the mean and standard deviation of Y_i. All Y_i, no matter which was selected to define X, are equal *in distribution* to $\mu_i+\sigma_i X$. Hence, the expected utility from Y_i for any agent with utility function $u(\ )$ can be written as

$$EU(Y_i)=\int_a^b u(\mu_i+\sigma_i x)dF(x)\equiv V(\mu_i,\sigma_i) \tag{1}$$

where a and b define the interval containing the support of the normalized random variable X." "… under the location and scale condition, various popular and interesting hypotheses concerning absolute and relative risk-aversion measures in the EU setting can be translated into equivalent properties concerning $V(\mu_i,\sigma_i)$." Given the assumptions made by Meyer about first and second derivatives, $V(\mu,\sigma)$ is a concave function of μ and σ. Concavity is established when second derivatives $V_{\mu\mu}$ and $V_{\sigma\sigma}$ are non-positive and $V_{\mu\mu}V_{\sigma\sigma}\text{-}V^2_{\mu\sigma}\geq 0$.

The structure of absolute risk (AR) is measured by the slope of the indifference curves in the (μ,σ) space that is represented as

$$AR(\mu,\sigma)=\frac{-V_\sigma(\mu,\sigma)}{V_\mu(\mu,\sigma)} \tag{2}$$

where $V_\mu(\mu,\sigma)$ and $V_\sigma(\mu,\sigma)$ are first partial derivatives of the $V(\mu,\sigma)$ function. Some properties of this risk measure are:

1. Risk aversion is associated with $AR(\mu,\sigma)>0$, risk neutrality with $AR(\mu,\sigma)=0$ and risk propensity with $AR(\mu,\sigma)<0$.
2. If $u(\mu+\sigma x)$ displays decreasing (constant, increasing) absolute risk aversion for all $\mu+\sigma x$, then

   $\dfrac{\partial AR(\mu,\sigma)}{\partial \mu}$ <(=,>) 0 for all μ and $\sigma>0$.
3. If $u(\mu+\sigma x)$ displays increasing (constant, decreasing) relative risk aversion for all $\mu+\sigma x$, then

   $\dfrac{\partial AR(t\mu,t\sigma)}{\partial t}$ >(=,<) 0 for $t>0$.

Saha (1997) proposed a two-parameter MS utility function that conforms to Meyer's specification:

$$V(\mu,\sigma)=\mu^\theta\text{-}\sigma^\gamma \tag{3}$$

and assumed that $\theta>0$. According to this MS utility function, the absolute risk measure (AR) is specified as

$$AR(\mu,\sigma)=\frac{-V_\sigma(\mu,\sigma)}{V_\mu(\mu,\sigma)}=\frac{\gamma}{\theta}\mu^{(1-\theta)}\sigma^{(\gamma-1)}. \tag{4}$$

Hence, risk aversion, risk neutrality and risk propensity are specified by $\gamma>0$, $\gamma=0$ and $\gamma<0$, respectively. As economic agents do not, in general, operate directly upon expected wealth and its standard deviation but, rather, upon a string of decision variables such as output and input levels, it is important to analyze the behavior of the absolute risk measure (AR) under risk aversion and risk propensity. The justification for this requirement is due to the fact that knowledge of parameters θ and γ is obtained only by empirical estimation of economic relations involving entrepreneur's decisions. The sign of these parameters, therefore, is an empirical question.

For $\gamma>0$, (risk aversion), decreasing, constant and increasing absolute risk aversion is defined by

$$\frac{\partial AR(\mu,\sigma)}{\partial \mu} = \frac{(1-\theta)\gamma}{\theta}\mu^{-\theta}\sigma^{(\gamma-1)} < (=,>) 0 \tag{5}$$

and, therefore, by $\theta>1$, $\theta=1$, $\theta<1$, respectively. For $\gamma>0$, (risk propensity), decreasing, constant and increasing absolute risk propensity is defined by $\theta<1$, $\theta=1$, $\theta>1$, respectively.

For $\gamma>0$, (risk aversion), decreasing, constant and increasing relative risk aversion is defined by

$$\left.\frac{\partial AR(t\mu,t\sigma)}{\partial t}\right|_{t=1} = (\gamma-\theta)AR < (=,>) 0 \tag{6}$$

and, therefore, by $\theta>\gamma$, $\theta=\gamma$, $\theta<\gamma$ respectively. For $\gamma<0$, (risk propensity), neither decreasing nor constant relative risk propensity are applicable because the combination of parameters' signs produces always a positive derivative. Increasing relative risk propensity is defined by any value of $\theta>0$.

The meaning of decreasing absolute risk aversion relates to an economic agent who experiences a wealth increase and chooses to augment his investment – measured in absolute terms – in the risky asset. Decreasing relative risk aversion relates to an economic agent who experiences a wealth increase and chooses to increase the share of his investment in the risky asset. It is possible, therefore, for an economic agent to behave according to a decreasing absolute risk aversion framework and an increasing relative risk aversion scenario if the absolute amount of increase in the risky asset is not sufficient to increase also the share of that asset. In any given sample of economic agents' performances, therefore, the prevailing combination of risk preference is an empirical question. The risk analysis of Meyer (1987) admits all possible combinations of risk behavior (risk aversion and risk propensity). Saha (1997) listed the risk aversion combinations for the MS utility function specified in relation (3) when $\gamma>0$. Table 1, for example, admits absolute risk aversion behavior that may be decreasing, when $\theta>1$ and $\gamma>0$, in association with either increasing relative risk aversion when $\gamma>\theta>0$ or decreasing relative risk aversion when $\theta>\gamma$. Decreasing, constant and increasing absolute risk aversion are denoted by DARA, CARA and IARA, respectively. Decreasing, constant and increasing relative risk aversion are denoted by DRRA, CRRA and IRRA, respectively.

Table 1. Possible risk preferences under risk aversion (θ>0, γ>0)

	DRRA	CRRA	IRRA
DARA	$\theta>1, \theta>\gamma$	$\theta>1, \theta=\gamma$	$\theta>1, \theta<\gamma$
CARA	$\theta=1, \theta>\gamma$	$\theta=1, \theta=\gamma$	$\theta=1, \theta<\gamma$
IARA	$\theta<1, \theta>\gamma$	$\theta<1, \theta=\gamma$	$\theta<1, \theta<\gamma$

Table 2. Possible risk preferences under risk propensity (θ>0, γ<0)

	DRRP	CRRP	IRRP
DARP	$\theta<1$, *NA*	$\theta<1$, *NA*	$\theta<1$, *YES*
CARP	$\theta=1$, *NA*	$\theta=1$, *NA*	$\theta=1$, *YES*
IARP	$\theta>1$, *NA*	$\theta>1$, *NA*	$\theta>1$, *YES*

"NA" stands for "Not Applicable" because the combination of parameters' signs produces always a positive value of the derivative (6).

When θ>0 and γ<0, risk propensity is active and the behavior of the risk measure *AR*, under the given MS utility, assumes the specification reported in Table 2. Decreasing, constant and increasing absolute risk propensity are denoted by DARP, CARP and IARP, respectively. Decreasing, constant and increasing relative risk propensity are denoted by DRRP, CRRP and IRRP, respectively.

The $V(\mu,\sigma)=\mu^{\theta}\text{-}\sigma^{\gamma}$ function is concave with respect to μ and σ when θ<1 and γ>1. The same function $V[\mu(\mathbf{x}),\sigma(\mathbf{x})]=\mu(\mathbf{x})^{\theta}\text{-}\sigma(\mathbf{x})^{\gamma}$, however, exhibits a flexible behavior with respect to entrepreneur's decisions, $\mathbf{x}$. This behavior depends on the relative values of parameters θ and γ. In other words, the upper contour sets of $V[\mu(\mathbf{x}),\sigma(\mathbf{x})]=\mu(\mathbf{x})^{\theta}\text{-}\sigma(\mathbf{x})^{\gamma}$ are convex for a wide range of values of parameters θ and γ. A few examples illustrate the function's graph and the associated upper contour sets in the appendix.

The rest of the paper is organized as follows. Section 2 discusses a PMP model that combines a generalized risk analysis with an extension of calibration constraints involving observed prices of limiting inputs. This extension integrates the traditional PMP specification of calibration constraints dealing only with observed levels of realized outputs. In particular, the extension provides a unique estimate of the optimal decision variables and avoids the user-determined perturbation parameters introduced by Howitt (1995a, 1995b) to guarantee that the dual variables of binding structural constraints will assume positive values. Section 3 discusses a chance-constrained relation that anchors the θ and γ parameters to the decision quantities and, therefore, provides an independent relation for their estimation. Section 4 assembles a Phase-I estimation model of the novel PMP approach. Section 5 defines and estimates a complete cost function involving output quantities and limiting input prices. The derivatives of the cost function are used in calibrating models that are suitable for policy analysis. Section 6 discusses how to obtain endogenous (to a farm sample) output supply elasticities. This section matches exogenous (to the farm sample) supply elasticities (available through econometric estimation, for example) with the endogenous supply elasticities. Section 7 states that optimal decision variables are identical whether estimated as solution of the Phase I model or solution of Phase I and Phase II models combined. Section 8 defines two alternative calibrating equilibrium models which reproduce calibrating solutions that are identical to those ones obtained in section 4. Section 9 presents the empirical results of the more elaborate PMP and risky model applied to a sample of 14 farms when not all farms produce all commodities. Conclusions follow.

2. Generalized Risk Preference in a PMP Framework

A Positive Mathematical Programming approach has been adopted frequently to analyze agricultural policy scenarios ever since Howitt proposed the methodology (1995a, 1995b). In this section, we extend the PMP methodology to deal with generalized risk preference and risky market output prices. Furthermore, we extend the PMP methodology to deal with calibration constraints involving observed prices of limiting inputs, say land. This extension modifies the traditional specification of calibration constraints and the notion of calibrating solution, as explained further on.

Suppose N farmers produce J crops using I limiting inputs and a linear technology. Let us assume that, for each farmer, the $(J\times1)$ vector of crops' market prices is a random variable $\tilde{\boldsymbol{p}}$ with mean $E(\tilde{\boldsymbol{p}})$ and variance-covariance matrix Σ_p. A $(J\times1)$ vector $\mathbf{c}$ of accounting unit costs is also known. The $(I\times1)$ vector $\mathbf{b}$ indicates farmer's availability of limiting resources. The matrix A of dimensions $(I\times J, I<J)$ specifies a linear technology. The $(J\times1)$ vector $\mathbf{x}$ symbolizes the unknown output levels to be optimized. Furthermore, farmer has knowledge of previously realized levels of outputs that are observed (by the econometrician) as $\mathbf{x}_{obs}$. Random wealth is defined by previously accumulated wealth, $\bar{w}$, augmented by the current random net revenue. Assuming a MS utility function under this scenario, mean wealth is defined as $\mu=[\bar{w}+(E(\tilde{\boldsymbol{p}})-\mathbf{c})'\mathbf{x}]$ with standard deviation equal to $\sigma=(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}$.

Then, a primal PMP-MS model is specified as follows:

$$\max_{\boldsymbol{x},\boldsymbol{h},\theta,\gamma} V(\mu,\sigma)=\mu^\theta-\sigma^\gamma=[\bar{w}+(E(\tilde{\boldsymbol{p}})-\mathbf{c})'\mathbf{x}]^\theta-(\mathbf{x}'\Sigma_p\mathbf{x})^{\gamma/2} \tag{7}$$

$$\begin{array}{lll} \text{subject to} & A\mathbf{x}\leq\mathbf{b} & \text{dual variable } \mathbf{y} \\ & \mathbf{x}=\mathbf{x}_{obs}+\mathbf{h} & \text{dual variable } \boldsymbol{\lambda} \end{array}$$

where $\mathbf{h}$ is a vector of deviations from the realized and observed output levels, $\mathbf{x}_{obs}$. The first set of constraints forms the structural (technological) relations while the second set constitutes the calibration constraints. This specification of the calibration constraints differs from the traditional statement $\mathbf{x}\leq\mathbf{x}_{obs}(1+\varepsilon)$ where ε is a user-determined, small positive number whose purpose is to allow the dual variables of binding structural constraints to take on positive values. In Howitt's words (1995a, p. 151): "The ε perturbation on the calibration constraints decouples the true resource constraints from the calibration constraints and ensures that the dual values on the allocable resources represent the marginal values of the resource constraints." The present paper avoids the user-determined parameter ε of the traditional PMP methodology and allows the empirical data to reveal the components of the vector of deviations **h**. Such deviations can take on either positive or negative values. To justify the specification of the calibration constraints $\mathbf{x}=\mathbf{x}_{obs}+\mathbf{h}$, we note that the vector of realized output levels, $\mathbf{x}_{obs}$, has been "observed", that is measured, by persons other than the economic entrepreneur, say by an econometrician. It is likely, therefore, that the measured $\mathbf{x}_{obs}$ vector may either overstate or understate the true levels of realizable optimal outputs. The deviation vector **h** captures these likely measurement errors.

The dual constraints of problem (7) – derived by Lagrange methods – turn out to be .

$$\gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x}+A'\mathbf{y}+\boldsymbol{\lambda}\geq\theta[\,\overline{w}+(E(\tilde{\boldsymbol{p}})-\mathbf{c})'\mathbf{x}]^{(\theta-1)}[E(\tilde{\boldsymbol{p}})-\mathbf{c}] \tag{8}$$

Parameters θ and γ are unknown as are the output levels, **x**, the deviations, **h**, the dual variables, **y**, and the Lagrange multipliers, $\boldsymbol{\lambda}$. Appropriate initial values of the unknown variables are of great importance to achieve an admissible solution. Furthermore, it is often the case that also the (approximate) market price of some input – say land – is known for the region of the sample farms or even for a single farm. The PMP methodology of this paper, therefore, uses also information $\mathbf{y}_{obs}$ while the unknown dual variable **y** is treated as

$$\mathbf{y}=\mathbf{y}_{obs}+\mathbf{u} \tag{9}$$

with **u** as an $(I\times 1)$ vector of deviations from the observed input prices.

Let W be a nonsingular diagonal matrix of dimensions $(J\times J)$ with positive diagonal terms equal to observed expected price $E(\tilde{\boldsymbol{p}}_j)>0$. And let V be a nonsingular diagonal matrix of dimensions $(I\times I)$ with positive diagonal terms $b_i/y_{obs,i}>0$. The purpose of matrices W and V is twofold. First, to render homogeneous the units of measurement of all terms in the objective function of models defined below. Second, to weigh the deviations **h** and **u** according to the scale of the corresponding expected price and input size, respectively. Using a least-squares approach for the estimation of deviations **h** and **u**, it turns out that, by the self-duality of least squares (LS), $\boldsymbol{\lambda}=W\mathbf{h}$ and $\boldsymbol{\psi}=V\mathbf{u}$, where $\boldsymbol{\psi}$ is the vector of Lagrange multipliers associated with constraints (9): see Paris (2015). To show this result, consider the following weighted LS problem

$$\min LS=\mathbf{h}'W\mathbf{h}/2+\mathbf{u}'V\mathbf{u}/2$$

subject to $\quad \mathbf{x}=\mathbf{x}_{obs}+\mathbf{h} \quad$ dual variable $\boldsymbol{\lambda}$

$\qquad\qquad\quad \mathbf{y}=\mathbf{y}_{obs}+\mathbf{u} \quad$ dual variable $\boldsymbol{\psi}$.

The corresponding Lagrange function and first-order-necessary conditions with respect to **h** and **u** are

$$L=\mathbf{h}'W\mathbf{h}/2+\mathbf{u}'V\mathbf{u}/2+\boldsymbol{\lambda}'(\mathbf{x}-\mathbf{x}_{obs}-\mathbf{h})+\boldsymbol{\psi}'(\mathbf{y}-\mathbf{y}_{obs}-\mathbf{u})$$

$$\frac{\partial L}{\partial \mathbf{h}}=W\mathbf{h}-\boldsymbol{\lambda}=0$$

$$\frac{\partial L}{\partial \mathbf{u}} = V\mathbf{u} - \boldsymbol{\psi} = 0$$

with the result that $\boldsymbol{\lambda}=W\mathbf{h}$ and $\boldsymbol{\psi}=V\mathbf{u}$ as asserted.

A crucial issue concerns parameters θ and γ. On the one hand, an economic entrepreneur wishes to maximize her utility of random wealth while minimizing the disutility of its risk. On the other hand, it is a fact that high levels of current income (a component of wealth) are associated with high risk of losses. Another fact is that this entrepreneur has already made her choice and executed a production plan, $\mathbf{x}_{obs}$, in the face of output price risk. It is also likely that she does not know (or that she is not even aware of) parameters θ and γ. The challenge, therefore, is to infer – from her decisions – the values of parameters θ and γ that could explain the behavior of this entrepreneur in a rational fashion.

3. A Chance-Constrained Relation for θ and γ

Charnes and Cooper (1959) proposed a very interesting approach to deal with risky prospects based upon the notion of chance-constrained programming. This idea is particularly useful within the context of this paper because it establishes an independent link between the θ and γ parameters, on one side, and the entrepreneur's decisions, $\mathbf{x}$, on the other side. Consider the following scenario. With some probability, a farmer may survive unfavorable events such as total revenue being less than total cost. In terms of the chance-constrained methodology this risky scenario is expressed by the following probabilistic proposition:

$$Prob\{\tilde{\mathbf{p}}'\mathbf{x} \leq \mathbf{y}'A\mathbf{x} + (\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}\} \leq 1-\beta \tag{10}$$

where the probability that uncertain (random) total revenue $\tilde{\mathbf{p}}'\mathbf{x}$ be less than or equal to certain total cost $\mathbf{y}'A\mathbf{x}+(\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}$ should be smaller than or equal to 1-β. Intuitively, for how many years could a farmer survive while operating in the red? As an example, say once every ten years. In this case, the estimated probability equals to 1-β=1/10=0.10. The $\mathbf{y}'A\mathbf{x}$ term is total cost associated with fixed limiting inputs ($\mathbf{y}'A\mathbf{x}= \mathbf{y}'\mathbf{x}$). The $(\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}$ term is total variable cost associated directly with output levels.

To derive a deterministic equivalent of relation (10) it is convenient to standardize the random variable $\tilde{\mathbf{p}}'\mathbf{x}$ by subtracting its expected value $E(\tilde{\boldsymbol{p}})'\mathbf{x}$ and dividing it by the corresponding standard deviation $(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}$:

$$\begin{aligned}
&Prob\left(\frac{\tilde{\mathbf{p}}'\mathbf{x}-E(\tilde{\mathbf{p}})'\mathbf{x}}{(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}} \leq \frac{\mathbf{y}'A\mathbf{x}+(\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}-E(\tilde{\mathbf{p}})'\mathbf{x}}{(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}}\right) \leq 1-\beta \\
&Prob\left(\tau \leq \frac{\mathbf{y}'A\mathbf{x}+(\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}-E(\tilde{\mathbf{p}})'\mathbf{x}}{(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}}\right) \leq 1-\beta \\
&Prob[E(\tilde{\mathbf{p}})'\mathbf{x}+\tau(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2} \leq \mathbf{y}'A\mathbf{x}+(\mathbf{c}+\boldsymbol{\lambda})'\mathbf{x}] \leq 1-\beta.
\end{aligned} \tag{11}$$

By assuming that τ is a standard normal random variable and choosing a value, say $\tau = \bar{\tau}$, that corresponds to probability 1-β, the deterministic equivalent of relation (11) assumes the specification

$$E(\tilde{\mathbf{p}})'\mathbf{x} + \bar{\tau}(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2} \leq \mathbf{y}'A\mathbf{x} + \mathbf{c}'\mathbf{x} + \boldsymbol{\lambda}'\mathbf{x} \tag{12}$$

To establish the relation between the $\bar{\tau}$ parameter and the MS coefficients θ and γ the dual complementary slackness condition of constraint (8) is subtracted from the deterministic equivalent (12) (recall that $\boldsymbol{\lambda}=W\mathbf{h}$):

$$\begin{aligned} E(\tilde{\mathbf{p}})'\mathbf{x} + \bar{\tau}(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2} &\leq \mathbf{y}'A\mathbf{x} + \mathbf{c}'\mathbf{x} + \mathbf{h}'W\mathbf{x} \\ -\theta[\bar{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]^{\theta-1}(E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x} &= -\mathbf{y}'A\mathbf{x} - \mathbf{h}'W\mathbf{x} - \gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{\gamma/2}. \end{aligned} \tag{13}$$

With simplification, relation (13) corresponds to

$$E(\tilde{\mathbf{p}})'\mathbf{x} - \mathbf{c}'\mathbf{x} + \bar{\tau}(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2} - \theta[\bar{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]^{\theta-1}(E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x} + \gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{\gamma/2} \leq 0 \tag{14}$$

Relation (14) establishes a simultaneous and independent link between the risk parameters θ, γ and the decision variables $\mathbf{x}$, once the value of $\bar{\tau}$ is selected by the researcher. As an example, if the survival probability is determined to be 1-β=0.10, the one tail value of the standard normal random variable is $\bar{\tau}$ =-1.285.

4. Phase I PMP Model – Estimation of Calibrating Primal and Dual Solutions

The components of Phase I PMP model are ready to be assembled. For estimation purposes, deviations $\mathbf{h}$ and $\mathbf{u}$ will be minimized in a weighted least-squares objective function subject to relevant primal and dual constraints, their associated complementary slackness conditions and relation (14). This task leads to the following Phase I model

$$\min LS = \mathbf{h}'W\mathbf{h}/2 + \mathbf{u}'V\mathbf{u}/2 \tag{15}$$

subject to

$$A\mathbf{x} \leq \mathbf{b} + V\mathbf{u} \tag{16}$$

$$\theta[\bar{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]^{(\theta-1)}[E(\tilde{\mathbf{p}}) - \mathbf{c}] \leq A'\mathbf{y} + W\mathbf{h} + \gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x} \tag{17}$$

$$\mathbf{x} = \mathbf{x}_{obs} + \mathbf{h} \tag{18}$$

$$\mathbf{y} = \mathbf{y}_{obs} + \mathbf{u} \tag{19}$$

$$\mathbf{y}'(\mathbf{b} + V\mathbf{u} - A\mathbf{x}) = 0 \tag{20}$$

$$\mathbf{x}'\{A'\mathbf{y}+W\mathbf{h}+\gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x}-\theta[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(\theta-1)}[E(\tilde{\mathbf{p}})-\mathbf{c}]\}=0 \tag{21}$$

$$E(\tilde{\mathbf{p}})'\mathbf{x}-\mathbf{c}'\mathbf{x}+\overline{\tau}(\mathbf{x}'\Sigma_p\mathbf{x})^{1/2}-\theta[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{\theta-1}(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}+\gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{\gamma/2}=0 \tag{22}$$

with $\mathbf{x}\geq\mathbf{0},\mathbf{y}\geq\mathbf{0},\theta>0,\gamma,\mathbf{h}$ and $\mathbf{u}$ free.

With the specification of the calibration constraints as in relations (18) and (19), the notion of a PMP calibrating solution differs from the traditional concept according to which the optimal calibrating solution is equal to the observed output levels, that is, $\mathbf{x}^*\cong\mathbf{x}_{obs}$, as the perturbation results in a very small (user-determined) positive number. With the methodology proposed in this paper, a calibrating solution $(\hat{\mathbf{x}},\hat{\mathbf{y}})$ will not, in general, be exactly equal to the corresponding vectors of the observed production plan and input prices $(\mathbf{x}_{obs},\mathbf{y}_{obs})$. The objective of model (15)-(22), therefore, is to minimize the deviations $\mathbf{h}$ and $\mathbf{u}$ in the amount allowed by the technological and risky environment facing farmers.

Constraints (16) represent the structural (technological) relations of input demand being less-than-or-equal to the effective input supply. Constraints (17) represent the dual relations with marginal utility of the production plan being less-than-or-equal to its marginal cost. Here marginal cost has two parts: the marginal cost due to limiting and variable inputs, $A'\mathbf{y}+W\mathbf{h}$, and the marginal cost of output price risk, $\gamma(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x}$. Constraints (18) and (19) are the calibration relations. Constraints (20) and (21) are complementary slackness conditions of constraints (16) and (17). Constraint (22) results from the chance-constrained specification (10). Because constraints (16)-(22) represent primal and dual relations and their complementary slackness conditions, any feasible solution of relations (16)-(22) constitutes an admissible economic equilibrium that is consistent with the behavior of decision making under price risk. Furthermore, the calibrating solution $(\hat{\mathbf{x}},\hat{\mathbf{y}})$ is unique because the least-squares solution of $(\hat{\mathbf{h}},\hat{\mathbf{u}})$ is also unique.

5. Phase II PMP Model – Estimation of the Cost Function

Phase II of the PMP methodology deals with the estimation of a cost function that embodies all the technological and behavioral information revealed in Phase I. Typically, a marginal cost function expresses a portion of the dual constraints in a Phase I PMP model. In the absence of risk, PMP marginal cost is defined as $A'\mathbf{y}+W\mathbf{h}+\mathbf{c}$, where $A'\mathbf{y}$ stands for the marginal cost due to limiting inputs and $W\mathbf{h}+\mathbf{c}$ for the effective marginal cost due to variable outputs. In the risky price case, marginal cost is given by the right-hand-side of relation (17) where all the elements are measured in utility units. It is crucial to obtain a dollar expression of marginal cost, as in the familiar relation $MC\geq E(\tilde{\mathbf{p}})$. To achieve this result, the elements of relation (17) will be divided by the term $\theta[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(\theta-1)}$ to write

$$MC\geq E(\tilde{\mathbf{p}}) \tag{23}$$

$$\mathbf{c}+\frac{1}{\theta}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(1-\theta)}[A'\mathbf{y}+W\mathbf{h}]+\frac{\gamma}{\theta}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(1-\theta)}(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x}\geq E(\tilde{\mathbf{p}})$$

In relation (23), all the terms are measured in dollars. The marginal cost due to limiting and variable inputs is given by

$$\left\{\mathbf{c}+\frac{1}{\theta}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(1-\theta)}[A'\mathbf{y}+W\mathbf{h}]\right\}.$$

The marginal cost due to risky output prices is given by

$$\left\{\frac{\gamma}{\theta}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\mathbf{x}]^{(1-\theta)}(\mathbf{x}'\Sigma_p\mathbf{x})^{(\gamma/2-1)}\Sigma_p\mathbf{x}\right\}.$$

The cost function selected to synthesize the technological and behavioral relations of Phase I is expressed as a modified Leontief cost function such as

$$C(\mathbf{x},\mathbf{y})=(\mathbf{f}'\mathbf{x})(\mathbf{g}'\mathbf{y})+(\mathbf{g}'\mathbf{y})(\mathbf{x}'Q\mathbf{x})/2+(\mathbf{f}'\mathbf{x})[(\mathbf{y}^{1/2})'G\mathbf{y}^{1/2}] \tag{24}$$

A cost function is non-decreasing in output quantities and input prices. It is linearly homogeneous and concave in input prices, **y**. The $(I\times I)$ matrix G has elements $G_{i,ii}=G_{ii,i}\geq 0, i\neq ii, i, ii=1,\ldots,I$. The diagonal elements $G_{i,i}$ can take on either positive or negative values. The $(J\times J)$ matrix Q is symmetric positive semidefinite. The components of vectors **f** and **g** are free to take on any value as long as $\mathbf{f}'\mathbf{x}>0$ and $\mathbf{g}'\mathbf{y}>0$. The reason for introducing a term like $(\mathbf{f}'\mathbf{x})(\mathbf{g}'\mathbf{y})$ is to add flexibility to the cost function.

The marginal cost function associated with cost function (24) is given by

$$MC_{\mathbf{x}}=\frac{\partial C}{\partial \mathbf{x}}=\mathbf{f}(\mathbf{g}'\mathbf{y})+(\mathbf{g}'\mathbf{y})Q\mathbf{x}+\mathbf{f}[(\mathbf{y}^{1/2})'G\mathbf{y}^{1/2}] \tag{25}$$

The derivative of the cost function with respect to input prices corresponds to Shephard's lemma that produces the demand function for inputs:

$$\frac{\partial C}{\partial \mathbf{y}}=(\mathbf{f}'\mathbf{x})\mathbf{g}+\mathbf{g}(\mathbf{x}'Q\mathbf{x})/2+(\mathbf{f}'\mathbf{x})[\Delta(\mathbf{y}^{-1/2})'G\mathbf{y}^{1/2}]=A\mathbf{x} \tag{26}$$

where $\Delta(\mathbf{y}^{-1/2})$ represents a diagonal matrix with elements $y_i^{-1/2}$ on the main diagonal.

With knowledge of the solution components resulting from the Phase I model (15)-(22), $\hat{\mathbf{x}},\hat{\mathbf{y}},\hat{\mathbf{h}},\hat{\mathbf{u}},\hat{\theta},\hat{\gamma}$, a Phase II model's goal is to estimate the parameters of the cost function, $\mathbf{f},\mathbf{g},Q,G$. This task is accomplished by means of the following specification

$$\min Aux=\mathbf{d}'\mathbf{d}/2+\mathbf{r}'\mathbf{r}/2 \tag{27}$$

subject to

$$\mathbf{f}(\mathbf{g}'\hat{\mathbf{y}})+(\mathbf{g}'\hat{\mathbf{y}})Q\hat{\mathbf{x}}+\mathbf{f}[(\hat{\mathbf{y}}^{1/2})'G\hat{\mathbf{y}}^{1/2}]= \tag{28}$$

$$\mathbf{c}+\frac{1}{\hat{\theta}}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\hat{\mathbf{x}}]^{(1-\hat{\theta})}[A'\hat{\mathbf{y}}+W\hat{\mathbf{h}}]+\frac{\hat{\gamma}}{\hat{\theta}}[\overline{w}+(E(\tilde{\mathbf{p}})-\mathbf{c})'\hat{\mathbf{x}}]^{(1-\hat{\theta})}(\hat{\mathbf{x}}'\Sigma_p\hat{\mathbf{x}})^{(\hat{\gamma}/2-1)}\Sigma_p\hat{\mathbf{x}}+\mathbf{d}$$

$$(\mathbf{f}'\hat{\mathbf{x}})\mathbf{g}+\mathbf{g}(\hat{\mathbf{x}}'Q\hat{\mathbf{x}})/2+(\mathbf{f}'\hat{\mathbf{x}})[\Delta(\hat{\mathbf{y}}^{-1/2})'G\hat{\mathbf{y}}^{1/2}]=A\hat{\mathbf{x}}+\mathbf{r} \tag{29}$$

$$Q=LDL' \tag{30}$$

$$QQ^{-1}=I \tag{31}$$

with $\mathbf{f}'\hat{\mathbf{x}}>0, \mathbf{g}'\hat{\mathbf{y}}>0, D\geq 0$, **f** and **g** free. The GAMS software requires an objective function. The vector variables **d**,**r** perform the role of slack variables in the estimation of the marginal cost function and Shephard's lemma, respectively.

The objective function (27) is a typical least-squares specification. Relation (28) represents the marginal cost function. Relation (29) is Shephard's lemma. Relation (30) is the Cholesky factorization of the *Q* matrix with *D* as a diagonal matrix with nonnegative elements on the main diagonal and *L* is a unit lower triangular matrix. The Cholesky factorization guarantees symmetry and positive semidefiniteness of the *Q* matrix. Relation (31) defines the inverse of the *Q* matrix and, thus, guarantees the positive definiteness of that matrix. This constraint assumes relevance for computing the supply elasticities of the various outputs. Any feasible solution of model (27)-(31) is an admissible cost function for representing the economic agent's decisions under price risk.

6. PMP and Output-Supply Elasticities

It may be of interest to estimate price supply elasticities for the various commodity outputs involved in a PMP-MS approach. The supply function for outputs is derivable from relation (25) by equating it to the expected market output prices, $E(\tilde{\mathbf{p}})$, and inverting the marginal cost function:

$$\mathbf{x}=-Q^{-1}\mathbf{f}-Q^{-1}\mathbf{f}[(\mathbf{y}^{1/2})G\mathbf{y}^{1/2}]/(\mathbf{g}'\mathbf{y})+[1/(\mathbf{g}'\mathbf{y})]Q^{-1}E(\tilde{\mathbf{p}}) \tag{32}$$

that leads to the supply elasticity matrix

$$\Xi=\Delta[E(\tilde{\mathbf{p}})]\frac{\partial\mathbf{x}}{\partial E(\tilde{\mathbf{p}})}\Delta[(\mathbf{x}^{-1})]=\Delta[E(\tilde{\mathbf{p}})]Q^{-1}\Delta[(\mathbf{x}^{-1})]/(\mathbf{g}'\mathbf{y}) \tag{33}$$

where matrices $\Delta[E(\tilde{\mathbf{p}})]$ and $\Delta[\mathbf{x}^{-1}]$ are diagonal with elements $E(\tilde{p}_j)$ and x_j^{-1} on the main diagonals, respectively. Relation (33) includes all the own- and cross-price elasticities for all the output commodities admitted in the model.

PMP has been applied frequently to analyze farmers' behavior to changes in agricultural policies. A typical empirical setting is to map out several areas in a region (or state) and to assemble a representative farm for each area (or to treat each area as a large farm). When supply elasticities are exogenously available (say the own-price elasticities of crops) at the regional (or state) level (via econometric estimation or other means), a connection of all area models can be specified by establishing a weighted sum of all the areas endogenous own-price elasticities and the given regional elasticities. The weights are the share of each area's expected revenue over the total expected revenue of the region. The advantage of using exogenously supply elasticities has been asserted by Mérel and Bucharam (2010) and Petsakos and Rozakis (2015) in order to account for second-order conditions' information.

Let us suppose that exogenous own-price elasticities of supply are available at the regional level for all the J crops, say $\bar{\eta}_j, j=1,\ldots,J$. Then, the relation among these exogenous own-price elasticities and the corresponding areas' endogenous elasticities can be established as a weighted sum such as

$$\bar{\eta}_j = \sum_{n=1}^{N} w_{nj}\eta_{nj}$$

where the weights are the areas' expected revenue shares in the region (state)

$$w_{nj} = \frac{E(\tilde{p}_{nj})x_{nj}}{\sum_{t=1}^{N} E(\tilde{p}_{tj})x_{tj}} \tag{34}$$

$$\eta_{nj} = E(\tilde{p}_{nj})Q^{jj}x_{nj}^{-1} / (\mathbf{g}'_n\mathbf{y}_n) \tag{35}$$

where Q^{jj} is the jth element on the main diagonal in the inverse of the Q matrix.

The Phase II model that executes the estimation of the cost function parameters and the disaggregated (endogenous) output supply elasticities for a region (state) that is divided into N areas takes on the following specification:

$$\min Aux = \sum_{n=1}^{N} \mathbf{d}'_n\mathbf{d}_n / 2 + \sum_{n=1}^{N} \mathbf{r}'_n\mathbf{r}_n / 2 \tag{36}$$

subject to

$$\begin{aligned} &\mathbf{f}_n(\mathbf{g}'_n\hat{\mathbf{y}}_n) + (\mathbf{g}'_n\hat{\mathbf{y}}_n)Q\hat{\mathbf{x}}_n + \mathbf{f}_n[(\hat{\mathbf{y}}_n{}^{1/2})'G\hat{\mathbf{y}}_n{}^{1/2}] = \\ &\mathbf{c}_n + \frac{1}{\hat{\theta}_n}[\bar{w}_n + (E(\tilde{\mathbf{p}}_n) - \mathbf{c}_n)'\hat{\mathbf{x}}_n]^{(1-\hat{\theta}_n)}[A'_n\hat{\mathbf{y}}_n + W_n\hat{\mathbf{h}}_n] \\ &\qquad + \frac{\hat{\gamma}_n}{\hat{\theta}_n}[\bar{w}_n + (E(\tilde{\mathbf{p}}_n) - \mathbf{c}_n)'\hat{\mathbf{x}}_n]^{(1-\hat{\theta}_n)}(\hat{\mathbf{x}}'_n\Sigma_p\hat{\mathbf{x}}_n)^{(\hat{\gamma}_n/2-1)}\Sigma_p\hat{\mathbf{x}}_n + \mathbf{d}_n \geq E(\tilde{\mathbf{p}}_n) \end{aligned} \tag{37}$$

$$(\mathbf{f}'_n\hat{\mathbf{x}}_n)\mathbf{g}_n + \mathbf{g}_n(\hat{\mathbf{x}}'_nQ\hat{\mathbf{x}}_n)/2 + (\mathbf{f}'_n\hat{\mathbf{x}}_n)[\Delta(\hat{\mathbf{y}}_n{}^{-1/2})'G\hat{\mathbf{y}}_n] = A_n\hat{\mathbf{x}}_n + \mathbf{r}_n \tag{38}$$

$Q=LDL'$ positive semidefiniteness (39)

$QQ^{-1}=I$ positive definiteness (40)

$$\Xi_n = \Delta[E(\tilde{\mathbf{p}}_n)]Q^{-1}\Delta[(\mathbf{x}_n{}^{-1})]/(\mathbf{g}'_n\mathbf{y}_n) \quad \text{endogenous own- and cross-price elasticities} \tag{41}$$

$$w_{nj} = \frac{E(\tilde{p}_{nj})\hat{x}_{nj}}{\sum_{t=1}^{N} E(\tilde{p}_{tj})\hat{x}_{tj}} \quad \text{expected revenue weights} \tag{42}$$

$$\eta_{nj} = E(\tilde{p}_{nj})Q^{jj}\hat{x}_{nj}^{-1}/(\mathbf{g}'_n\hat{\mathbf{y}}_n) \quad \text{own-price elasticities} \tag{43}$$

$$\bar{\eta}_j = \sum_{n=1}^{N} w_{nj}\eta_{nj} \quad \text{disaggregation of exogenous elasticities} \tag{44}$$

with $D_n \geq 0, \mathbf{g}_n$ and $\mathbf{f}_n$ free and $\mathbf{f}'_n\hat{\mathbf{x}}_n > 0$, $\mathbf{g}'_n\hat{\mathbf{y}}_n > 0$.

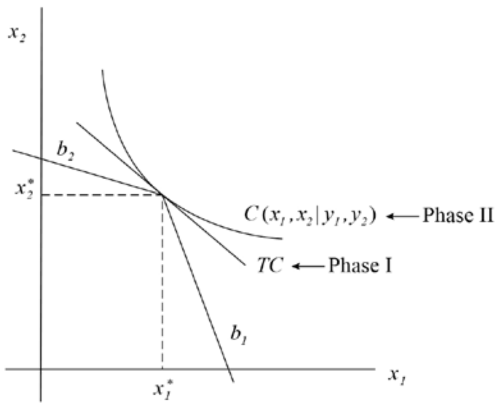
The GAMS software requires an objective function. The objective function *Aux* minimizes the pseudo slack variables, $\mathbf{r}_n$ and $\mathbf{d}_n$, of the primal and dual constraints.

7. Phase I Versus Phase I-II Estimates of the Calibrating Solution

A strand of the PMP literature has discussed the issue of whether the Phase I estimates of decision variables and input shadow prices, $\mathbf{x}$,$\mathbf{y}$, are consistent with the corresponding Phase II estimates where the cost function parameters are estimated simultaneously with them. The short answer is positive because the amount of information is the same in the two Phases. With the limitations of a two-dimensional diagram, Figure 1 illustrates the issue. In Phase I, total cost is a linear function of the decision variables while in Phase II total cost is a nonlinear function of the same variables. Hence, the calibrating optimal solution, $\mathbf{x}^*$, is the same in the two Phases.

In the context of this paper, Phase I model is stated as a LS specification of relations (15) through (22). This model results in a unique Least-Squares solution of deviations $\mathbf{h}$ and $\mathbf{u}$ and, therefore, of the decision variables $\hat{\mathbf{x}}, \hat{\mathbf{y}}$. The Phase II model that estimates

Figure 1. Phase I and Phase II estimates of decision variables **x** and input shadow prices **y**.



simultaneously the cost function parameters and the optimal decision variables is stated as the LS specification in Phase I combined with constraints (28) through (31) (where the "$\hat{}$" symbol is removed from the decision variables). The original information is identical in the two models and, therefore, the LS methodology guarantees the unique and identical solution for the two sets of estimates.

8. Phase III PMP Model – Calibrating Models

With the parameter estimates of the cost function, $\hat{\mathbf{f}}_n, \hat{\mathbf{g}}_n, \hat{Q}, \hat{G}$, derived from either Phase II model (27)-(31) or model (36)-(44), it is possible to set up a calibrating equilibrium model to be used for policy analysis. Such a model takes on the following economic equilibrium specification

$$\min CSC = \mathbf{y}'\mathbf{z}_p + \mathbf{x}'\mathbf{z}_d = 0 \tag{45}$$

subject to

$$(\hat{\mathbf{f}}'\mathbf{x})\hat{\mathbf{g}} + \hat{\mathbf{g}}(\mathbf{x}'\hat{Q}\mathbf{x})/2 + (\hat{\mathbf{f}}'\mathbf{x})[\Delta(\mathbf{y}^{-1/2})'\hat{G}\mathbf{y}^{1/2}] + \mathbf{z}_p = \mathbf{b} + V\hat{\mathbf{u}} \tag{46}$$

$$\hat{\mathbf{f}}(\hat{\mathbf{g}}'\mathbf{y}) + (\hat{\mathbf{g}}'\mathbf{y})\hat{Q}\mathbf{x} + \hat{\mathbf{f}}[(\mathbf{y}^{1/2})'\hat{G}\mathbf{y}^{1/2}] = E(\tilde{\mathbf{p}}) + \hat{\mathbf{z}}_d \tag{47}$$

with $\mathbf{x}\geq\mathbf{0}, \mathbf{y}\geq\mathbf{0}, \mathbf{z}_p\geq\mathbf{0}, \mathbf{z}_d\geq\mathbf{0}$. The objective function represents the complementary slackness conditions (*CSC)* of constraints (46) and (47) with an optimal value of zero. The variables $\mathbf{z}_p$ and $\mathbf{z}_d$ are surplus variables of the primal and the dual constraints, respectively. The solution of model (45)-(47) calibrates precisely the solution obtained from the Phase I model (15)-(22), that is, $\hat{\mathbf{x}}_{LS} = \hat{\mathbf{x}}_{CSC}$ and $\hat{\mathbf{y}}_{LS} = \hat{\mathbf{y}}_{CSC}$. This remarkable result is due simply to the fact that all the information of the Phase I model has been transferred to the cost function. Note that the matrix of fixed technical coefficients A does not appear in either constraint (46) or (47). The calibrating model, then, can be used to trace the production and revenue response to changes in the expected output prices, subsidies and the supply of limiting inputs in a more flexible technical framework.

An alternative calibrating equilibrium model is suitable for dealing with a crucial aspect of a risky policy scenario. Wealth is the anchoring measure of risk preference of an economic agent. As illustrated above, wealth is composed of accumulated income (or exogenous income) and net revenue derived from the current production cycle as in $[\bar{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]$ where $\bar{w}$ measures the amount of exogenous income. Agricultural policies in many countries deal with subsidies to farmers for cultivating (or not cultivating) crops. These subsidies may or may not be coupled to the level of crop production. Subsidies that are decoupled from the crop production decisions of farmers constitute exogenous income and end up in the term of wealth that becomes an important target of policy makers. The $\bar{w}$ term, then, must appear in the calibrating model to allow the representation of decoupled subsidies as in the following specification

$$\min CSC = \mathbf{y}'\mathbf{z}_p + \mathbf{x}'\mathbf{z}_d = 0 \tag{48}$$

subject to

$$(\hat{\mathbf{f}}'\mathbf{x})\hat{\mathbf{g}} + \hat{g}(\mathbf{x}'\hat{Q}\mathbf{x})/2 + (\hat{\mathbf{f}}'\mathbf{x})[\Delta(\mathbf{y}^{-1/2})\hat{G}\mathbf{y}^{1/2}] + \mathbf{z}_p = \mathbf{b} + V\hat{\mathbf{u}} \tag{49}$$

$$\begin{aligned} \mathbf{c} &+ \frac{1}{\hat{\theta}}[\overline{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]^{(1-\hat{\theta})}[A'\mathbf{y} + W\hat{\mathbf{h}}] \\ &+ \frac{\hat{\gamma}}{\hat{\theta}}[\overline{w} + (E(\tilde{\mathbf{p}}) - \mathbf{c})'\mathbf{x}]^{(1-\hat{\theta})}(\mathbf{x}'\Sigma_p\mathbf{x})^{(\hat{\gamma}/2-1)}\Sigma_p\mathbf{x} = E(\tilde{\mathbf{p}}) + \mathbf{z}_d \end{aligned} \tag{50}$$

with $\mathbf{x}\geq\mathbf{0},\mathbf{y}\geq\mathbf{0},\mathbf{z}_p\geq\mathbf{0},\mathbf{z}_d\geq\mathbf{0}$. Also the solution of model (48)-(50) calibrates precisely the solution obtained from the Phase I model (15)-(22), that is, $\hat{\mathbf{x}}_{LS} = \hat{\mathbf{x}}_{CSC}$ and $\hat{\mathbf{y}}_{LS} = \hat{\mathbf{y}}_{CSC}$.

9. Empirical Implementation of PMP-MS With Supply Elasticities

The PMP-MS approach described in previous sections was applied to a sample of N = 14 representative farms of the Emilia-Romagna region of Italy. There are four crops: sugar beets, soft wheat, corn and barley. There is only one limiting input: land. Empirical reality compels a further consideration of the above methodology in order to deal with farm samples where not all farms produce all commodities. It turns out that very little must be changed for obtaining a calibrating solution in the presence of missing commodity levels, their prices and the corresponding technical coefficients. Using the GAMS software, it is sufficient to condition the various constraints of Phase I, Phase II and Phase III models by the nonzero observations of the output levels. To exemplify, the available farm sample displays the following Table 3 of observed crop levels while Table 4 presents the variance-covariance matrix of the market output prices.

Table 3. Observed output levels, $\mathbf{x}_{obs}$, with non produced commodities.

Farm	Sugar Beets	Soft Wheat	Corn	Barley
1	1133.4240	0	341.3693	18.2398
2	3103.7830	841.7445	0	59.8025
3	0	450.7937	881.9748	0
4	3488.3540	821.3934	1493.3320	51.1247
5	959.1102	468.2848	0	28.2406
6	942.2039	801.1288	1283.5910	152.5810
7	1600.7310	0	899.4739	66.9718
8	0	1212.8550	1237.5840	98.0497
9	1050.5370	332.3773	0	63.6696
10	3473.6780	952.5199	774.7402	0
11	0	765.1689	501.9673	59.5366
12	3276.1450	1100.1680	0	177.9740
13	877.0970	380.9171	564.6091	76.2122
14	1430.9460	0	1309.3920	0

Other missing information deals with prices and unit accounting costs associated with the zero-levels of crops. Furthermore, the technical coefficients of farms not producing the observed crops also equal to zero. Hence, we can state that, for n=1,…,N, the number of farms, and j=1,…,J, the number of crops, if $x_{nj}^{obs}=0$, also p_{nj}=0, c_{nj}=0 and A_{nij}=0. Furthermore, suppose that only one input, land, is involved in this farm sample. Let us assume also that the land price is observed for all farms. The procedure to deal with this type of sample data consists in conditioning the relevant constraints on the positive values of the output levels. In GAMS, this procedure requires a conditional statement using the $ sign option.

Table 4. Variance-covariance matrix of the market output prices.

	Sugar Beets	Soft Wheat	Corn	Barley
Sugar Beets	0.0024719	-0.0164391	-0.0117184	-0.0121996
Soft Wheat	-0.0164391	0.2386034	0.1821288	0.2049011
Corn	-0.0117184	0.1821288	0.1530464	0.1610119
Barley	-0.0121996	0.2049011	0.1610119	0.1830829

Tables 5 and 6 present the estimated output levels and input prices ($\hat{\mathbf{x}},\hat{\mathbf{y}}$). They also exhibit the percent deviation of the solution ($\hat{\mathbf{x}},\hat{\mathbf{y}}$) of model (15)-(22) from the corresponding targets ($\mathbf{x}_{obs}$,$\mathbf{y}_{obs}$). It is of interest to report that the same identical solution was obtained in three different ways. All the estimations were performed with the GAMS software. The first round of estimates were obtained by solving model (15)-(22) one farm at a time. The second round of estimates were obtained by solving model (15)-(22) using the entire sample of observations. This means that the objective function was specified as

$$\min LS = \sum_{n=1}^{N} \mathbf{h}_n W_n \mathbf{h}_n + \sum_{n=1}^{N} \mathbf{u}_n V_n \mathbf{u}_n$$

subject to constraints (16)-(22) specified for each single farm observation. The third round of estimates of the optimal decision variables were obtained by solving model (36)-(44) with the “ ˆ ” symbol removed from the variables.

Table 7 presents the estimates of the parameters θ and γ of the MS utility function.

The sample is composed of relatively homogeneous farms. Hence, the limited numerical range of variation of the MS utility parameters is not a surprise. Within that range, however, a wide variety of risk preferences is detected. Seven farmers exhibit decreasing absolute risk aversion accompanied by increasing relative risk aversion. This result matches a statement of Tsiang (1972, p. 357): “…the most commonly observed pattern of behavior toward risk of a risk-averter individual is probably decreasing absolute risk-aversion coupled with increasing relative risk-aversion when his wealth increases…” Two farmers exhibit increasing absolute risk aversion associated with decreasing relative risk aversion. Four farmers exhibit decreasing absolute risk propensity and increasing relative risk propensity. It should be noted that the negative gamma coefficients of these four farmers are

Table 5. Estimated LS solution, $\hat{\mathbf{x}}$, and percent deviation from the observed levels, $\mathbf{x}_{obs}$ with zero levels for some crops and some farms.

Farm	Optimal Decisions $\hat{\mathbf{x}}$				Percent deviation from $\mathbf{x}_{obs}$			
	Sugar Beets	Soft Wheat	Corn	Barley	Sugar Beets	Soft Wheat	Corn	Barley
1	1133.851	0	341.622	18.156	0.0377	0	0.0741	-0.4587
2	3104.392	861.829	0	52.923	0.0196	0.0098	0	0.2021
3	0	450.794	881.975	0	0	-0.0000	0.0000	0
4	3488.400	821.340	1493.477	51.165	0.0013	-0.0065	0.0097	0.0791
5	959.234	468.140	0	28.308	0.0129	-0.0310	0	0.2399
6	942.488	801.394	1283.947	152.923	0.0301	0.0331	0.0278	0.2238
7	1601.381	0	899.724	67.104	0.0406	0	0.0278	0.1975
8	0	1213.157	1237.937	98.080	0	0.0249	0.0285	0.0307
9	1051.373	332.592	0	63.767	0.0796	0.0645	0	0.1528
10	3474.183	952.606	774.966	0	0.0145	0.0085	0.0291	0
11	0	765.267	502.186	59.659	0	0.0128	0.0436	0.2052
12	3276.657	1100.245	0	178.324	0.0156	0.0070	0	0.1964
13	877.324	380.970	564.926	76.467	0.0258	0.0138	0.0561	0.3347
14	1431.231	0	1309.653	0	0.0199	0	0.0199	0

Table 6. Deviation of $\hat{\mathbf{y}}$ from $\mathbf{y}_{obs}$.

Farm	Observed Land Prices $\mathbf{y}_{obs}$	Estimated Land Prices $\hat{\mathbf{y}}$	Percent Deviation
1	4.42	4.4213	0.0287
2	4.38	4.3810	0.0219
3	6.98	6.9800	0.0000
4	5.73	5.7302	0.0036
5	4.40	4.3995	-0.0111
6	1.86	1.8609	0.0458
7	3.65	3.6517	0.0454
8	3.36	3.3609	0.0266
9	2.75	2.7521	0.0780
10	4.28	4.2807	0.0158
11	3.28	3.2810	0.0318
12	1.93	1.9305	0.0281
13	2.32	2.3213	0.0579
14	4.03	4.0308	0.0199

rather small, suggesting that risk neutrality may – probably – be a better risk-preference representation of these farmers. The approach does not allow for a statistical testing of this conjecture. Finally, one farmer exhibits increasing absolute and relative risk aversion. This

Table 7. Estimates of θ and γ.

Farm	Parameter θ	Parameter γ	Risk Preference
1	1.0131215	1.1397862	DARA, IRRA
2	1.0050568	1.0766995	DARA, IRRA
3	1.1313873	1.2841485	DARA, IRRA
4	0.9836798	0.9273945	IARA, DRRA
5	0.9578977	-0.1867746	DARP, IRRP
6	0.9645178	-0.1465580	DARP, IRRP
7	1.0183502	1.1310367	DARA, IRRA
8	1.0562629	1.1969911	DARA, IRRA
9	1.0277583	1.1992494	DARA, IRRA
10	1.0043433	1.0570120	DARA, IRRA
11	0.9503372	-0.1567640	DARP, IRRP
12	0.9986044	1.0263446	IARA, IRRA
13	0.9577406	-0.1663556	DARP, IRRP
14	0.9797649	0.8443536	IARA, DRRA

empirical result is a clear illustration of the flexible structure of risk preferences as stated by the theoretical analysis. The corresponding meaning of the various acronyms is derived from Table 1 and Table 2.

The estimated parameters of the cost function are reported in Tables 8 and 9. In this numerical example, the G matrix contains only one parameter whose value is $G_{i,i}$=-11.39904.

Regional, exogenous own-price supply elasticities were available in the magnitude of 0.6 for sugar beets, 0.5 for soft wheat, 0.7 for corn and 0.4 for barley. The endogenous own-price elasticities of all farms were aggregated to be consistent with the regional exogenous elasticities according to relation (44). Table 10 presents the farms' own-price supply elasticities used in the aggregation relation.

10. Conclusion

This paper accomplished several objectives. First, it extended the treatment of risk in a mathematical programming framework to include any combination of risk preferences represented by absolute risk aversion (or absolute risk propensity) and relative risk aversion (or relative risk propensity). Second, it modified the traditional PMP approach to deal with calibration constraints regarding observed output levels and observed input prices by eliminating the user-determined perturbation parameter. The combination of these two approaches provides suitable models for agricultural policy analysis that take into consideration farmers' risk preferences associated with the randomness of output prices. Third, this paper integrated the use of exogenous supply elasticities observed for, say, an entire region with the endogenous elasticities derived from the supply functions of the sample farms. This objective is achieved by specifying a complete and flexible total cost function that fulfills all the theoretical requirements. Fourth, it resolves in a positive

Table 8. Intercepts $\hat{\mathbf{f}}$ and $\hat{\mathbf{g}}$ of the marginal cost and input demand functions.

Farm	$\hat{\mathbf{f}}$				$\hat{\mathbf{g}}$	$\hat{\mathbf{f}}'\hat{\mathbf{x}}$	$\hat{\mathbf{g}}'\hat{\mathbf{y}}$
	Sugar Beets	Soft Wheat	Corn	Barley			
1	0.00949	0	0.00666	-0.00320	0.00465	12.923	0.02055
2	0.00364	0.03154	0	-0.06940	0.00149	34.378	0.00654
3	0	-0.00290	0.00374	0	0.00129	1.965	0.00901
4	0.00734	-0.00284	0.00902	-0.06489	0.00132	33.448	0.00756
5	-0.00307	0.02349	0	-0.05730	0.00202	6.426	0.00888
6	-0.02082	0.08018	0.08193	0.26459	0.00658	190.289	0.01224
7	0.00473	0	0.02687	0.05681	0.00271	35.568	0.00992
8	0	0.08121	-0.00668	-0.05092	0.00220	85.254	0.00738
9	0.00408	0.04408	0	0.07081	0.00610	23.462	0.01679
10	0.00905	0.03772	-0.02931	0	0.00164	44.673	0.00703
11	0	0.08005	-0.04152	-0.05365	0.00300	37.213	0.00985
12	0.00395	0.11439	0	0.06448	0.00329	150.291	0.00635
13	0.00041	0.05078	0.03585	0.19131	0.00950	54.584	0.02205
14	-0.00159	0	0.03287	0	0.00192	40.770	0.00773

Table 9. Estimated matrices $\hat{Q}$ and $\hat{D}$.

	Matrix $\hat{Q}$			
	Sugar Beets	Soft Wheat	Corn	Barley
Sugar Beets	0.0408842	-0.0269584	-0.0084418	-0.0405819
Soft Wheat	-0.0269584	0.8509183	-0.1850005	-0.5925655
Corn	-0.0084418	-0.1850005	0.3698877	-0.0130721
Barley	-0.0405819	-0.5925655	-0.0130721	7.7008830
	Matrix $\hat{D}$			
	Sugar Beets	Soft Wheat	Corn	Barley
Sugar Beets	0.0408842			
Soft Wheat		0.8331423		
Corn			0.324558	
Barley				7.1182454

way the dispute debated in the PMP literature whether Phase I calibrating estimates are consistent with Phase II estimates. Fifth, a calibrating model resulting from the PMP-MS framework described here allows for the analysis of policy scenarios dealing with farm subsidies that are decoupled from the current crop production. Consider the parameter

Table 10. Disaggregation/aggregation of the regional, exogenous own-supply elasticities with zero observations of some output levels.

Farm	Exogenous Sugar Beets: 0.6	Exogenous Soft Wheat: 0.5	Exogenous Corn: 0.7	Exogenous Barley: 0.4
1	0.4422	0	0.9144	0.7529
2	0.6093	0.6344	0	0.8320
3	0	0.8010	0.7415	0
4	0.3126	0.5757	0.6101	0.8427
5	1.1497	0.6980	0	1.1181
6	0.9824	0.3464	0.4243	0.1741
7	0.5677	0	0.7124	0.4221
8	0	0.3910	0.6719	0.4075
9	0.5837	0.5928	0	0.2624
10	0.3482	0.4793	1.1446	0
11	0	0.4196	1.2469	0.4779
12	0.6557	0.4610	0	0.2876
13	0.5061	0.3453	0.4804	0.1667
14	1.0249	0	0.6590	0

$\bar{w}$ in the measure of wealth that may represent exogenous income subsidy. With a Freund approach to risk based upon a constant absolute risk aversion utility function, the wealth parameter disappears from the programming model. On the contrary, one version of the calibrating equilibrium model presented in this paper allows for the analysis of decoupled farm subsidies that are more frequently the target of policy makers. This general model has been tested on different farm samples with satisfactory results including a data sample where not all farms produce all the commodities.

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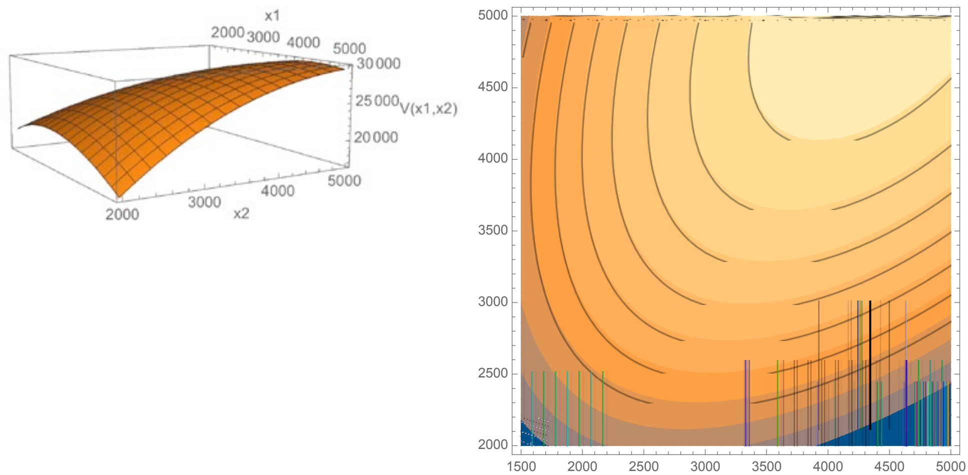
Appendix

The function $V(\mu,\sigma)=\mu^{\theta}-\sigma^{\gamma}$ is concave in μ and σ when the corresponding Hessian matrix is negative definite. This event occurs when $\theta<1$ and $\gamma>1$. When the mean and standard deviation of wealth, μ and σ, are expressed in terms of decision variables, $\mathbf{x}$, $\mu(\mathbf{x})$ and $\sigma(\mathbf{x})$, the resulting function assumes a flexible structure whose concavity depends on different values of parameters θ and γ. This appendix illustrates the possible shapes of the MS utility function (as a function of decision variables) by means of simple graphs and the associated upper contour sets that are conditional upon the magnitude of the θ and γ parameters. The value of θ and γ are chosen to reflect the estimates of Table 7. The MS utility function is simplified to show two decision variables, x_1 and x_2. The expected prices are chosen as $E(\tilde{p}_1)=4$ and $E(\tilde{p}_2)=6$ with standard deviation σ_{p1}=0.5, σ_{p2}=0.7 and σ_{p1p2}=0.1. With these stipulations, all the figures' functional forms and the upper contour sets exhibit the following specification

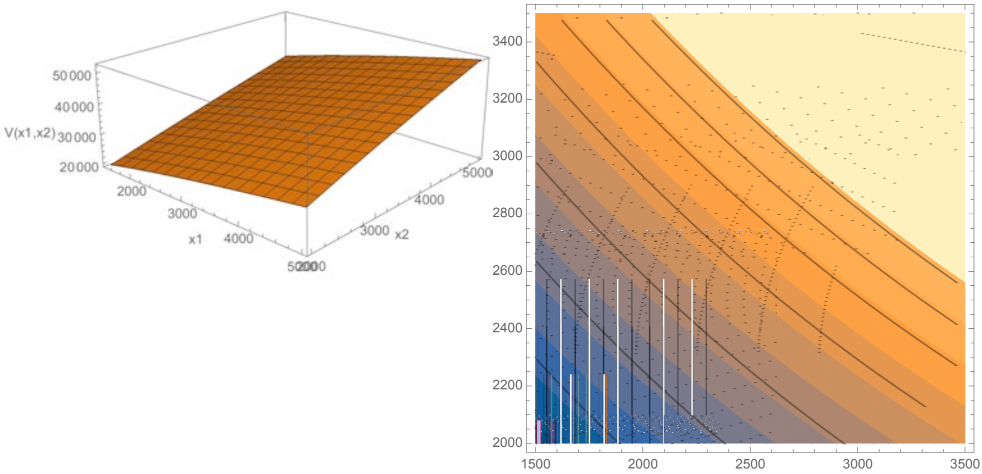
$$V[\mu(\mathbf{x}),\sigma(\mathbf{x})]=\mu(\mathbf{x})^{\theta}-\sigma(\mathbf{x})^{\gamma}=[E(\tilde{p}_1)x_1+E(\tilde{p}_2)x_2]^{\theta}-[\sigma_{p_1}^2x_1^2+\sigma_{p_2}^2x_2^2+2\sigma_{p_1p_2}x_1x_2]^{\gamma/2}$$
$$=[4x_1+6x_2]^{\theta}-[0.5^2x_1^2+0.7^2x_2^2+0.2x_1x_2]^{\gamma/2}$$

In all the figures, the upper contour sets appear to be convex even though the contour levels appear rather flat in some figures. The convexity of the upper contour sets is a crucial reason for obtaining an optimal solution. The flatness of the contour levels may make it more laborious for the algorithm to converge to an optimal solution. The figures were drawn using Mathematica.

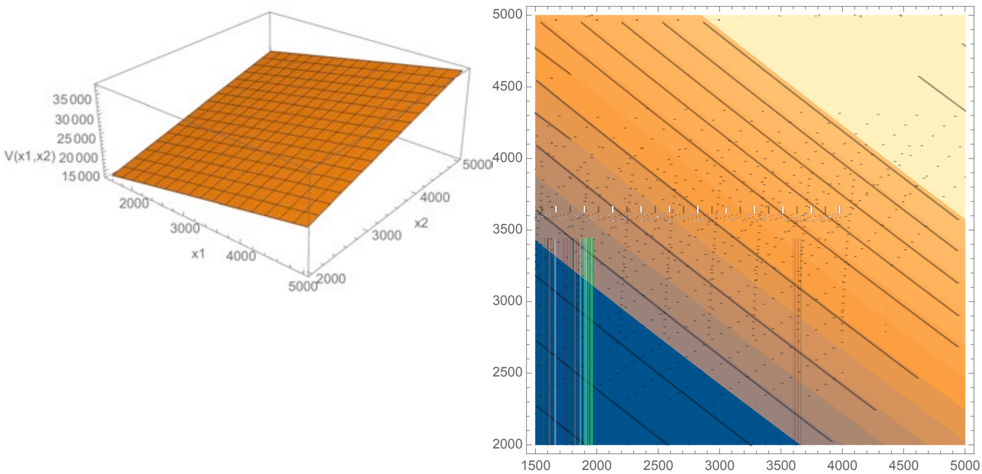
θ=1.1, γ=1.36 DARA, IRRA



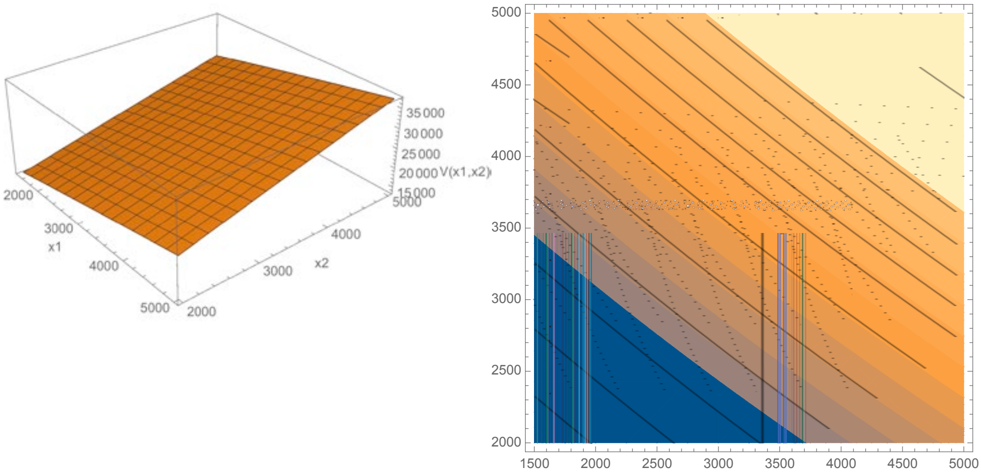
θ=1.05, γ=1.20 DARA, IRRA



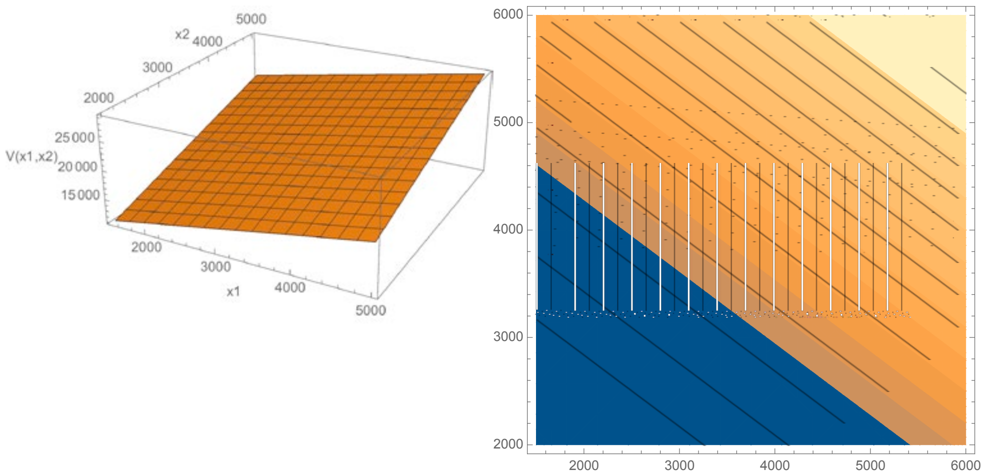
θ=0.98, γ=0.92 IARA, DRRA



θ=0.99, γ=1.03 IARA, IRRA



θ=0.95, γ=-0.15 DARP, IRRP



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Full Research Article

The hedonic contents of italian super premium extra-virgin olive oils

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Abstract. This study focuses on the Italian market for high quality olive oil and seeks at assessing the value of a set of emerging quality clues. To this aim a hedonic price model is proposed where the price is regressed on various product attributes using a quantile regression that allows for deeper insights. The analysis covers about one thousand Italian extra-virgin olive oils reviewed by Slow Food guide. Overall, results indicate that various quality clues (e.g.: variety of the olives, the production area, the certification of origin, the organic certification) are associated with relevant price premiums. Moreover, the quantile regression reveals the values associated to quality changes at different price levels. It is worthwhile to underline that the usual negative price premium against olive oils produced in Southern Italy tends to decrease in higher market segments.

Keywords. Hedonic price, extra-virgin olive oil, quantile regression, quality clues.

JEL. Q11, Q13.

1. Introduction

Olive oil is an important component of the Mediterranean diet, it is used as a seasoning and as such it is basically eaten in association with many different foods. More than half of the world olive oil production and consumption are concentrated in EU and other Mediterranean countries which traditionally are both producers and consumers. However, olive oil is increasingly appreciated worldwide as a healthy and tasty vegetable fat and its use is growing all around the world given the increased popularity of the Mediterranean diet, especially among consumers in North America, Australia and large parts of Asia (Bottcher *et al*., 2017; Romo Muñoz *et al*., 2015).

Over the last years several new quality features started playing an important role for enhancing product differentiation and market segmentation both in traditional and newer

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consumption countries. This process not only leads to a segmentation of consumers based on taste and other personal variables, but also differentiates olive oils on the basis of different consumption occasions and of the kind of foods that olive oil is going to match. Olive oil is becoming a trendy seasoning with a hedonic connotation so that its market started resembling that of wine (Cacchiarelli *et al.*, 2016b; Cabrera *et al.*, 2014). Traditionally, differences in olive oils were mainly related to chemical attributes (i.e. acidity or polyphenols) that are, in turn, related to cultivation and olive-picking techniques as well as to the technology adopted for extracting oil from olives. Besides, in the Italian market olive oil quality is also largely associated to the production area (particularly to soil, climate and olive varieties that are associated to the place of production). The area of production may be defined at different levels such as country level, regional level, or even with reference to smaller areas (Menapace *et al.*, 2011; Van der Lans *et al.*, 2001; Verbeke *et al.*, 2012).

In this changing market the importance of some quality clues is emerging, although these may have different roles in different demand segments. Among the others, it is worth recalling: i) the environmental impact of the production process and the related certifications (Cacchiarelli *et al.*, 2016a; Marette, 2017) including organic that has gained momentum as a relevant quality feature also for olive oil (Schleenbecker and Hamm, 2013; Cabrera *et al.*, 2014; Martinez *et al.*, 2002); ii) the kind of flavor that may match different foods (i.e. intense or mild fruity); iii) the color (i.e. green vs. yellow) and the turbidity; iv) the shape, the size and the color of the bottle or the design of the label.

All these quality features generate a complex system of both vertical and horizontal differentiation, as some attributes (i.e. acidity) can be ranked from the best to the less preferred ones, while for other attributes consumers' preferences are not aligned (i.e. filtered vs non-filtered olive oil, oils from Tuscany vs. Umbria Regions).

In countries where the use of olive oil is traditional and common, the consumers' ability to choose quality attributes is widely based on buying habits. In newer markets consumers need to collect information in different ways and many quality clues have been developed at different stages of the value chain and by different stakeholders (Roselli *et al.*, 2016). Relevant quality clues are mainly experience and credence attributes, implying that the market is affected by a significant degree of asymmetric information (Mastronardi *et al*, 2015). As the sophistication of the product and the complexity of the market increase, additional information is required and the effectiveness and reliability of each quality attribute can be questioned (Hassan and Mornier-Dilhan, 2002). In this context, reviews by experts in journals and guides as well as testing events and prizes, become a relevant source of information. They also provide comparisons between individual preferences and external, more competent and objective judgments, thus contributing to increase product value (Spiller and Belogolova, 2017). These reviews are used not only by the final consumers but also by many different kinds of stakeholders along the chain (Poroissien and Vissier, 2018; Cacchiarelli *et al.*, 2016b; Delgado and Guinard, 2011).

Such a complex market implies that also prices are diversified and span over a large range; as a consequence, price itself further segments the market and contributes to convey information about quality and safety (Haws *et al.*, 2017). In order to fully understand the crucial role of price in this market it is useful to keep in mind that olive oil, besides being itself a differentiated good, has also many cheap substitutes among other vegetable oils. This means that when purchasing olive oil and particularly extra-virgin ones

(EVOO), consumers are already in high segments of the wider vegetable oil market and are seeking for a quality product for which they carefully consider price and attributes (Martinez *et al.*, 2002).

Following these premises, this study aims at assessing the role of different quality clues in the creation of value in higher segments of the Italian olive oil market. On the one side, this focus allows to get insights on one of the oldest and largest EVOO market; on the other side, we argue that looking at the higher and more sophisticated segments of the market contributes to understanding which tendencies will spread in the near future in the wider EVOO market. To meet this goal, a hedonic price model is estimated where price is regressed on different quality clues (Rosen, 1974; Thrane, 2004). Most works employing the hedonic price approach have focused on wine (Benfratello *et al.*, 2009; Schamel, 2006; Cacchiarelli *et al.*, 2016a). However, in recent years, various studies aimed at identifying the more effective variables in creating value in the olive oil markets, both in EU Mediterranean Countries (Italy, Greece and Spain) and in the so called "New Countries" (Chile and US) (Romo Muñoz *et al.*, 2015; Gazquez-Abad and Sanchez-Perez, 2009; Roselli *et al.*, 2016; Carbone *et al.*, 2018).

In literature, the hedonic price models have been usually estimated by using ordinary least squares (OLS) regression. However, over the last few years the quantile regression model (QRM) has also been applied in order to establish whether the relationship between price and other product characteristics and quality clues varies at different price levels (Cacchiarelli *et al.*, 2014; Costanigro *et al.*, 2010). While the former shows how the various quality clues affect, on average, prices, the latter detects additional patterns (location, scale and skewness shifts) related to the effects of the covariates and, thus, allows to investigate consumer behaviour at different price levels.

The paper is organized as follows. Section 2 illustrates the source of data, the model specification and the methods employed in the estimations. Section 3 reports and discusses results, while section 4 concludes.

2. Methodology

2.1 The source of data

Data used for estimating the hedonic price model comes from one of the major Italian olive oil guides: Slow Food guide (2014 edition).This guide has been chosen for three basic reasons: i) the data set is quite large as it includes 1024 EVOOs (of which 1001 have been utilized for the analysis due to missing data for the remaining 23); ii) coverage of Italian production areas is wide; iii) information released about each product is rich and relevant for stakeholders. For each reviewed producer/oil the guide reports a set of information about the product, about the farm/mill and about the production process. Olive oils included in this guide account for about 3% of EVOO national production (in volume) and represent the top segment of the market with an average price that is about 5 times higher than the average unit value of bulk production. This focus on top quality EVOOs allows us to investigate on a quite peculiar market segment where quality and attention to quality clues are very high (Slow Food, 2014). Evidences from such a peculiar market segment cannot be extended *sic et simpliciter* to the whole EVOO market. However, considering that market niches and especially high market segments tend to anticipate upcoming trends that spread out over time, these findings bring interesting insights on what will likely be general future trends (Yeoman and McMahon-Beattie, 2006; Latacz-Lohmann & Foster, 1997).

2.2 Model specification

2.2.1 The Model

In the analysis of differentiated products, several studies have adopted hedonic price models in which the price is described as a function of product characteristics (Deselnicu *et al.*, 2013; Oczkowski, 2001). In this study, with the aim of measuring the price premiums associated to different quality clues in the Italian olive oil market we use a hedonic price model specified as follows:

$$Log\ P_{OILi} = \alpha_0 + \alpha_{1i} Cu_i + \alpha_{2i} Pi_i + \alpha_{3i} Mi_i + \alpha_{4i} Vol_i + \alpha_{5i} Or_i + \alpha_{6i} Sz_i + \alpha_{7i} Gi_i + \alpha_{8i} MR_i + \varepsilon_i \quad (1)$$

where: $Log\ P_{OILi}$, the logarithm base 10 of the EVOO price, is the dependent variable; Cu_i indicates a set of dummy variables accounting for olive variety; Pi_i is a dummy variable that indicates the technique of harvesting; Mi_i is an ordinal variable indicating the degree of vertical integration; Vol_i is an ordinal variable measuring production volumes by class; Or_i is the dummy for organic EVOOs; Sz_i accounts for bottle size (ordinal); Gi_i assesses the presence of the certification of origin; MR_i is a categorical variable for the macro-area of origin.

It is worth to underline that not all the quality cues here considered have the same visibility for consumers. In fact, while some appear in the label of the bottle, other do not. However almost all can be found in the producer/seller website and all of them are released by Slow Food Guide. The model assumes that consumers in this super premium market segment are so interested in quality features that, not only are willing to pay very high prices but also devote time and expertise in collecting and evaluating these less visible pieces of information. Besides, it should also be taken into account that retailers in these premiums market segments are usually willing and committed to release additional information they consider valuable to customers (Clerides *et al.*, 2008).

2.2.2 The variables.

The variables included in the model are described below while Table 1 reports frequencies and descriptive statistics of price distribution for all the selected explanatory variables.

1) Prices are released by producers at the final consumers' price (in Euros, VAT included). Each price is referred to the actual bottle size used for packaging (250/500/750 ml and 1 liter) so that, in order to allow for correct comparisons, the dependent variable was transformed in Euros per liter. The mean and the median values (respectively 16 and 18.7 Euros/Lt. as shown in Table 1) confirm that the market reviewed by the guide is correctly defined as super premium[1].

[1] The maximum price value, as evidenced in table 1, is very high due to an outlier present in the sample, as it is also confirmed by the price value at 90th quantile (30 Euros).

2) *Cu* relates to olive variety (i.e. the cultivar of the tree). Mono-cultivar oils were not so common in Italy until a few years ago though presently their number is increasing as a mean for differentiation and following consumers' interest for variety based also on sensory features and their inclination for (re)discovering old traditional varieties. Slow Food guide devotes much attention to mono-cultivar oils. The model includes three categories of mono-cultivar oils that are distinguished according to the territorial diffusion of the olive variety: i) national olives such as Pendolino, Moraiolo, Leccino, and a few others (14% of the sample); regional varieties such as Itrana, Carolea, Carboncella and many others (13% of the sample); and local varieties that are hundreds each cultivated in a very limited area (altogether these account for 23% of the sample). This distinction is aimed to get information about the value that consumers may attach to diversification and strong territorial roots vs wider diffusion and more general reputation of more common and better-known varieties. The remaining half of the oils reviewed in the guide are blend of different cultivars; this dummy act as benchmark for the other cases.
3) *Pi* indicates the technique of harvesting: where 100% hand picking and machine aided hand picking are both included in the same dummy (that accounts for 77% of the sample) as opposed to complete machine picking (23%), as the latter has a different impact on product quality and on cost level and structure.
4) *Mi* is an ordinal variable reflecting the degree of vertical integration and, thus, measuring the strengths of the relation among stakeholders in charge of olive production and oil processing and packaging. The stricter relation holds when there is an on-farm

Table 1. Frequencies and descriptive statistics of price distribution for the different quality clues.

	Variable	obs	freq	min	10th Quantile	30th Quantile	50th (median)	mean	70th Quantile	90th Quantile	max
Cu	National Cultivar	141	0.14	7.5	10.5	14	16.5	19.88	20	30	52
	Regional Cultivar	134	0.13	8	10.5	14	16.5	19.16	20	30	80
	Local Cultivar	227	0.23	6.5	10.5	14	16.5	19.48	20	30	100
	Olive oil blend	499	0.50	5.5	10.5	14	16.5	18.71	20	30	100
Pi	Hand picked	778	0.77	5.5	10.5	14	17	19	20	30	100
Mi	Cooperative mill	133	0.13	5.5	10.5	13.5	16	18.3	20	30	50
	Mill on farm	394	0.39	6.5	10	13.5	17.25	19.4	21.5	30	100
	Mill off farm	474	0.47	6	10.5	14	16	18.3	20	30	80
Vol	1-50 hl	562	0.56	5.5	10.5	14	17	19.1	20	30	100
	51-100 hl	154	0.15	7	10	13	17	18.6	20	28	52
	101-500 hl	94	0.09	8	10	13	15.75	17.2	20	28	42
	>501 hl	191	0.19	6	9.5	13	16	18.25	20	30	48
Or	Organic	475	0.47	5.5	10.5	14	16.5	18.5	20	30	80
Sz	Bottle of 250 ml	30	0.03	12	19.5	30	32	37	40	54	100
	Bottle of 500 ml	583	0.58	9	13	16	20	21.2	24	30	60
	Bottle of 750 ml	329	0.33	5.5	9.5	10.5	13.5	13.9	15.5	20	48
	Bottle of 1 litre	59	0.06	6	7.5	9	12	11.4	13	16	20
Gi	PDO-PGI	183	0.16	5.5	10	14	17	20.4	20	30	60
MR	North	147	0.15	10	14	20	24	24.7	28	37	100
	Centre	361	0.36	8	12	16	18	20.0	22	30	50
	South	492	0.49	5.5	9.5	12	14	15.8	18	24	80
	Total	1001	1.00	5.5	10.5	14	16	18.71	20	30	100

Source: Our elaborations on Slowfood 2013.

mill (39% of the sample), the second level refers to farms cooperatives that mill olives conferred by members (which are 13%) and the third case is represented by private mills (47% of the sample) that process olives bought from different farms (that are mostly located, nearby). In this case we estimate the price premiums associated to oils from on-farm mills, or from cooperatives in comparison with oils from off-farm mills (the benchmark for the estimation of the PP).

5) *Vol* expresses the production scale as follows: 1-50 hl (56%), 51-100 hl (15%), 101-500 hl (9%) and more than 500 hl (19%). Although the most of the producers in the sample are small or medium-small, the relation between production volumes and price may be complex due to possible diverging reputational effects as it will be discussed later on in the text.
6) Organic oils (*Or)* represent a bit less than half of the Slow Food selection (47%). Organic production is quite established in the Italian olive oil sector thanks to the favorable climatic conditions in many areas and to the emerging consumers' interest for this attribute.
7) Variable *Sz* represents the following bottle size: 250 ml (3%), 500 ml (58%), 750 ml (33%) and 1000ml (6%). The size of the bottle affects the use of the product; smaller bottles are preferred for making presents, for trying new products (Martinez *et al.*, 2002), for special occasions and in case of difficult transport conditions (e.g. in case tourists buy EVOO when travelling). Conversely, larger bottles are preferred for domestic every-day consumption.
8) *Gi* is the European certification of origin which includes PDO (Protected Designation of Origin) and PGI (Protected Geographical Indication); however, since in Italy there is only one PGI olive oil but many PDOs, for the purposes of this analysis they have been all gathered in one dummy that distinguish between GI (PDO and PGI) certified EVOOs (16%) and non-certified ones (84%).
9) *MR* represents the area of origin defined at the following macro-area level: Northern (15%), Central (36%) and Southern Italian regions (49%). In the Italian EVOO market, especially in segments where quality is relevant, the macro-area of production matters for consumers as it is also confirmed by significant and persistent price differences for both bulk and bottled oils. Although the reputation of EVOOs from different regions varies significantly within the country, stricter area definition was not possible due to the small size of some regional sub-samples in the guide.

As it can be seen from Table 1, the mean of the price distribution is higher than the median, for many quality clues, thus suggesting that the dependent variable is positively skewed (the value of the Fischer coefficient is 2.35). Moreover, the range values (max-min) suggest a great heterogeneity of prices in the sample. Figure 1 shows the distribution of prices through a probability density function, which is a powerful tool to describe several properties of a variable of interest (Cowell and Flachair, 2013). Although this function seems basically unimodal (about 18 euros), it also presents a few additional, much less pronounced, modes (see in the highest quantiles) and a stretched shape of the right-side tail of the distribution. Such a distribution suggests exploring the relationship between prices and the selected quality clues as they might change along the different quantiles and particularly at the two extremes (Table 1).

The choice of the functional form of the hedonic model is essential because it determines the way marginal prices will be related to attributes (Rasmussen and Zuehlke, 1990). A RESET test (Regression Equation Specification Error Test) was run in order to explore a series of possible transformations of the dependent variable (e.g. log, inverse square root). The test has revealed that the log-linear specification performs better than other functional forms so that it has been chosen for estimating equation (1). Log-linear specification presents a twofold advantage with respect to other ones: i) it allows obtaining residuals that are approximately normally distributed as required by the selected regression models; ii) the interpretation of regression coefficients is immediate: the dependent variable changes by $100^*(e^{coef}-1)$ percent for a one-unit increase in one of the regressors, holding all other variables fixed. Last, heteroskedasticity proportional to the predicted values was tested via Goldfeld–Quandt statistics (Goldfeld and Quandt, 1965).

2.3 Estimation Methods

Clearly, even in this super premium market segment, the impact of quality attributes on price may differ across price levels. Therefore, following the prices distributions described in Table 1 and shown in Figure 1, a QRM was run to go deeper into the analysis of the market segmentation mechanism. Selected quantiles are: 0.1, 0.30, 0.50, 0.70, 0.90 percent[2]. Quantile regression (Koenker, 2005) is used for estimating the functional relationship between olive oil price and quality attributes at different points in the conditional distribution of y. Moreover, quantile regression is more robust than OLS regression in response to large outliers which may be present in the olive-oil top market segment. Consequently, we estimate model (1) over the various quantiles which are of interest in our research context.

The QRM analyzes the effects of the explanatory variables at different quantiles of the price distribution as opposed to focusing on the mean of the distribution (Cameron and Trivedi, 2005). Although its computation requires linear programming methods, the quantile regression estimator is asymptotically normally distributed.

Moreover, QRM is a semi-parametric approach since it avoids assumptions concerning the parametric distribution of the regression errors. This technique specifies the conditional quantile as a linear function of covariates (Koenker, 2005).

Quantile regression has several advantages over OLS. Indeed, OLS can be inefficient if errors are highly non-normal while QR is more robust to non-normal errors and outliers.

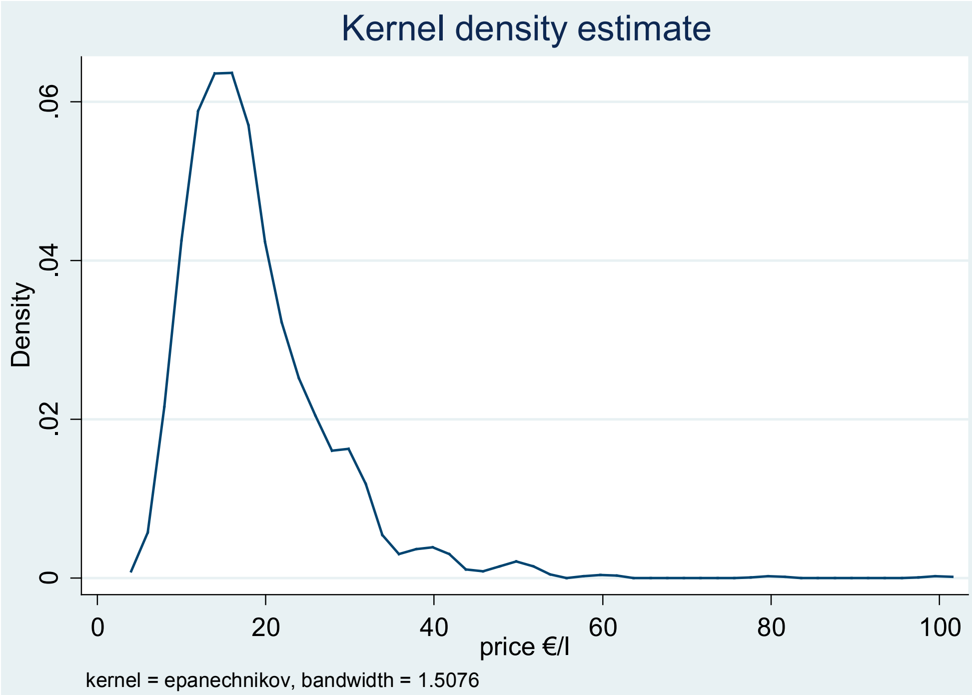
In the present case, the θth quantile regression can be written as:

$$Q_\theta\left(y_i \mid \mathbf{x}_i\right) = \mathbf{x}_i^{'}\beta_\theta + \varepsilon_\theta \tag{2}$$

where y_i (i=1,…,n) is the dependent variable (logarithm of the price), x_i is the sequence of the k-vector of regressors while β_θ is an unknown vector of regression parameters associated with the θ_{th} quantile and $\varepsilon\theta$ is an unknown error term. The quantile regression estimator for quantile $0<\theta<1$ minimizes the sum of absolute deviation residuals:

[2] For quantile estimates, standard errors were calculated by bootstrapping and, specifically, 400 random draws were taken. Moreover, by using Wald test, comparing pairwise at each fifth quantile within the 5th and 95th, we formally verify whether the effect of each variable statistically differs across quantiles (Hao and Naiman, 2007).

Figure 1. Prices distribution.



Source: Our elaborations on Slowfood 2013.

$$\min_{\beta \in R^K} \left\{ \sum_{i:y_i \geq \mathbf{x}^i\beta} \theta | y_i - \mathbf{x}_i^{'}\beta | + \sum_{i:y_i \geq \mathbf{x}^i\beta} (1-\theta) | y_i - \mathbf{x}_i^{'}\beta | \right\} \tag{3}$$

which is solved by linear programming methods. When θ is continuously increased from 0 to 1, we obtain the entire conditional distribution of y conditional on x.

3. Results

Table 2 reports estimation results from quantile models at the selected points of the price distribution. Figure 2 provides a graphical view of the QRM estimates where, for each selected quality clue, the vertical axis shows the PPs associated to the different quantiles[3] (horizontal axes).

The fit of the model, measured by pseudo R^2, is quite good. These values indicate that the model takes into account the effects of important quality clues related to prices

[3] In figure 2, the gray-shaded area illustrates the bootstrap 95% confidence interval while the line shows QRM estimates.

in the Italian market for sophisticated EVOOs. Nevertheless, the model proposed clearly focuses on the value of quality features captured by the market while leaves out of the picture other features that, altogether, may be relevant and able to influence consumers' prices.

Coming to detailed estimation results, we start from those that generate the higher PPs, even if in some cases the effects in the different price quantiles vary and generate an uneven ranking.

First, bottle size confirms to be an important leverage for price. As a matter of fact, smaller sizes get, on average (i.e. 50^{th} quantile), always a positive price premium compared to larger bottles: 750 ml worth +23.7% compared to 1000ml, while they get, respectively, -80.5% compared to 250 ml and -32.9% compared to 500 ml. These results are in line with findings of other studies (Cabrera *et al.*, 2014). Results for different quintiles provide additional insights by showing that the mentioned price differentials are higher and more significant in the highest market segments where packaging matters more; in particular the smallest bottle size is associated with the highest PPs observed in the sample (+89%) (see also the bottom of figure 2). Wald test confirms these results showing that in case of bottles both from 250 ml and 500 ml the 30th, 50^{th} and 70th quantiles are statistically different from 90th (at 5% level of significance).

Second, variables related to the place of origin are all associated with significant and large price premiums. Olive oils from northern and central regions worth more compared to products from southern regions (46.1% and 18.4%, respectively). This result reflects the widely known segmentation of the Italian olive oil market and it is in line with the findings of other studies focused on high quality EVOO markets (Carbone *et al.*, 2014; Di Vita *et al.*, 2013). Moreover, the QRM provides additional non-trivial insights also confirmed by Wald test (see the upper part of figure 2). The price premiums associated to Northern and Central regions decrease in the upper quantiles (70^{th} and 90^{th}), indicating that in the higher market segments consumers are less influenced by the macro-area of origin. This is probably due to the higher consumers' willingness to collect detailed information about producers and their products before buying more expensive bottles instead of using proxies such as those related to the production area. This result suggests that olive oil producers from Southern regions that seek at marketing excellent EVOOs might reduce the negative price gap that affects EVOOs from the South, provided they are able to select appropriate information and quality clues for each market segment.

According to the important role played by the area of origin, our findings show that also the certification of the place of origin (*Gi*) affects prices. In line with findings from other works (Carlucci *et al.*, 2014), PDO/PGI EVOOs get, on average, a price premium of +12.5% compared to non-certified olive oils, showing that this certification is a much-appreciated quality clue. Looking at the different quantiles (at the top right of figure 2) it appears how the certification of origin plays a greater role in the highest market segment (+ 18.9% at the 0.90 quantile). Wald test confirms this result proving that the 70th quantile is statistically different from the 90th at 10% level of significance.

Organic certification affects positively EVOO prices (on average +9.3%) as well. The result holds at any price quantile without relevant differences in the size of the PP. This outcome confirms the positive role played by organic certification in the EVOO market as emerged in other works (Delmas and Lessem, 2017).

Table 2. QRM estimation results for various conditional quantiles.

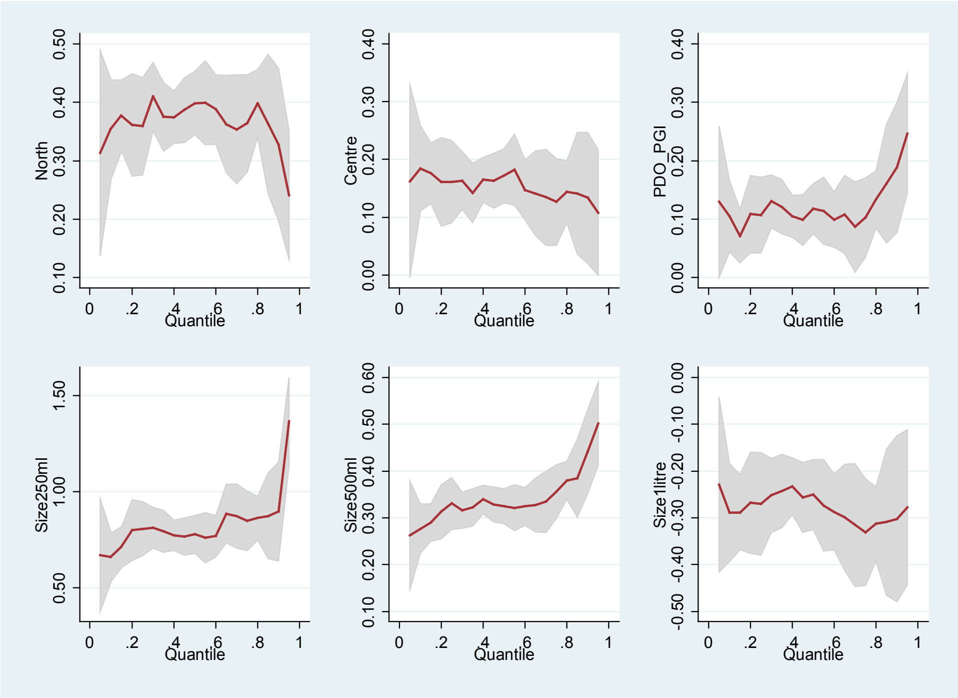
	Variable	10th Quantile	30th Quantile	50th Quantile	70th Quantile	90th Quantile
Cu	National cultivar	0.091*	0.089*	0.098*	0.121*	0.102
		(0.0241)	(0.0283)	(0.0238)	(0.0318)	(0.0682)
	Regional cultivar	0.067**	0.091**	0.110*	0.158*	0.093*
		(0.0284)	(0.0216)	(0.0219)	(0.0272)	(0.0272)
	Local cultivar	0.088*	0.106*	0.085*	0.051*	0.093*
		(0.0263)	(0.0243)	(0.0253)	(0.0342)	(0.0343)
Pi	Hand picked	-0.002	-0.027	-0.032***	-0.051**	-0.082**
		(0.0192)	(0.0259)	(0.0226)	(0.0284)	(0.0282)
Mi	Coop Mill	-0.022	-0.042	-0.024	-0.024	-0.056***
		(0.0425)	(0.0325)	(0.0261)	(0.0263)	(0.0317)
	Mill on farm	-0.016	-0.003	0.032	0.047***	0.103**
		(0.0232)	(0.0243)	(0.0258)	(0.0334)	(0.0321)
Vol	51-100 hl	-0.019	-0.027	0.011	0.095**	0.100*
		(0.0370)	(0.0361)	(0.0341)	(0.0362)	(0.0342)
	101-500 hl	-0.024	0.010	0.003	0.021	-0.005
		(0.0382)	(0.0364)	(0.0352)	(0.0323)	(0.0612)
	>501 hl	0.006	-0.027	-0.032	-0.005	0.027
		(0.0231)	(0.0252)	(0.0325)	(0.0554)	(0.0323)
Or	Organic	0.073*	0.086*	0.093*	0.079*	0.068*
		(0.0172)	(0.0275)	(0.0192)	(0.0248)	(0.0241)
Sz	Bottle of 250 ml	0.677*	0.811*	0.805*	0.867*	0.892**
		(0.1128)	(0.0372)	(0.0613)	(0.1352)	(0.4127)
	Bottle of 500 ml	0.281*	0.317*	0.329*	0.335*	0.452*
		(0.0196)	(0.0218)	(0.0223)	(0.0283)	(0.0291)
	Bottle of 1 litre	-0.285*	-0.249*	-0.237*	-0.316*	-0.313*
		(0.0243)	(0.0623)	(0.0321)	(0.0363)	(0.0372)
Gi	PDO/PGI	0.121*	0.137*	0.125*	0.080*	0.189*
		(0.0182)	(0.0277)	(0.0253)	(0.0318)	(0.0512)
MR	North	0.430*	0.484*	0.461*	0.418*	0.366*
		(0.0413)	(0.0372)	(0.0314)	(0.0451)	(0.0421)
	Centre	0.207*	0.179*	0.184*	0.150*	0.138*
		(0.0312)	(0.0272)	(0.0269)	(0.0334)	(0.0417)
	cons	2.143*	2.332*	2.414*	2.607*	2.733*
		(0.0362)	(0.0382)	(0.0381)	(0.0551)	(0.0524)
	Pseudo R^2	0.325	0.335	0.321	0.305	0.287

Source: Our elaborations on Slowfood 2013.

[1] Table reports coefficients and standard errors (in brackets).

[2] *means significant at 1%; **means significant at 5%; ***means significant at 10%.

Figure 2. QRM estimates of place of origin, PDO and bottle size.



With respect to the role of the cultivar, the model provides interesting findings. First, mono-cultivar oils are always associated with positive PPs ranging between 8% and 11%, regardless to the size of the diffusion area of the cultivar itself and regardless to quantiles. Since usually labels explicitly claim whether the oil is made with one olive variety, regardless to the specific cultivar utilized, mono-cultivar oils are appreciated and valued as such. As this kind of product is almost new in the Italian market and introduces a new factor of differentiation, the result seems to indicate that consumers in this market segment appreciate novelty and variety. This finding is in line with recent literature (Carlucci *et al.*, 2014).

Moving to the next set of variables, results show that the scale of the production process affects prices in a quite complex fashion. In particular, the estimates show that production volumes have limited or non-significant impacts on price in the lower price quantiles, while at 70^{th} and 90^{th} quantiles medium-small producers are favored compared both to very small producers and to larger ones, with a PP of around 10%. This is probably due to a complex reputational effect, according to which very small producers are hardly visible in larger markets where they find difficult to establish their own reputation and to get a PP; at the other extreme, very large companies may give an image of a more standardized less valuable product compared to medium and medium-small producers who can be associated to a sense of rarity, exclusivity and preciousness that pushes price up (Eisend, 2008; Kristofferson *et al.*, 2017).

As for other features of the production process, and, in particular, the way olives are picked, results show that hand picking negatively affects prices (on average, -3.2%). The price premium becomes even more negative in the highest market segments (-8.2% in the 90th quantile). Even considering that most consumers may not be aware of the methods adopted for harvesting, this result is hard to explain and requires further explorations. In fact, so far, hand picking has been considered a superior technique in terms of preserving sensorial qualities and avoiding high acidity rate. However, more recently, technological change has improved the performance of harvesting machinery also in terms of plant health and product quality. Besides, machine harvesting requires shorter time than hand picking; this, in turn, allows for processing fresher olives, thus contributing, other things being equal, to push up oil quality. Summing-up, the role of this feature shall be further explored and/checked also looking at different datasets.

Finally, concerning vertical integration, again, this does not seem to significantly affect price on average. However, in the highest market segments the presence of on-farm mill is statistically associated with a positive price premium between 5% (70^{th} quantile) and 10% (90^{th} quantile); while, on the other hand, a negative PP (-5.6%) is associated to cooperative mills at the 90^{th} quantile. The first of these results can be explained by the deeper interest of consumers in buying an EVOO strictly connected to the farm –and as such, regarded as to more genuine, traditional and so forth - when they are spending more. The negative PP associated to the coop mills may be explained by the negative reputation that surrounds coops in some Italian regions, where, due to different reasons whose analysis is beyond the scope of this paper (Carbone *et al.*, 2010), coops are not regarded as able to provide quality products.

4. Concluding remarks

Trends in consumers' demand as well as marketing strategies in the olive oil sector seem to increasingly push towards product differentiation, following to some extent the wine market. The increasing role of different quality clues creates different and inter-related layers of horizontal and vertical differentiation that frame the market as progressively sophisticated.

In the present study a hedonic price model has been built for exploring the Italian high-quality olive oil market in order to identify the price-quality relation for different quality features. Quantile regression has been used for analyzing the functional relationship between olive oil price and quality attributes at different points in the conditional distribution of price. Data used have been collected from Slow Food olive oil guide that portraits the Italian high quality EVOO market.

In particular, our model specification brings about some interesting insights that in some cases confirm results already discussed in the literature; while in others provide original indications.

The quantile regression estimates indicate that overall the quality clues included in the model have a significant impact on price at the different price quantiles. However, in the lower quantiles there are some clues that do not impact prices while they are effective at higher price levels. Among these there are clues that are not released by the labels such as the kind of olive-picking, the size of the production units and the degree of vertical integration. This can be explained by the deeper interest of consumers in some quality features when they are spending more money. This more demanding attitude towards quality may push them to collect additional information with respect to that released in the label. As for the remaining quality attributes, all have a significant impact on price and this impact significantly increases with price.

While price differentials between Italian macro-regions are well known and represent no novelty at all, the finding that these differences reduce in higher price quantiles is original and valuable. This may suggest that southern producers shall use different communication strategies, with respect to the place of origin, when targeting at different market segments.

Also results about certifications of origin (PDO/PGI), showing a higher PP in the highest price quantile, are not trivial. This is especially true when comparing them to those found for the wine market where the certifications of origin are more rewarding at medium-low price levels. In fact, in the case of wine, they seem to act more as a minimum quality standard than as a clue for excellence. The explanation of this difference between the two sectors is given by the extreme sophistication of the wine market where quality clues are many and diverse and wine producers have reached a greater visibility and reputation in the marketplace, while, on average, olive oil producers are far less reknown (except large industrial firms that do not belong to the kind of market we are looking at). Besides, the certification of origin is relatively less used and more recent in the olive oil market compared, for example, to wine, so that it has not yet become a trivial quality clue as it is in some cases for wines where it also suffers from a lack of trust.

As expected, bottle size is associated with the highest PP evidenced by the model estimates. Specifically, smaller sizes cost more compared to bigger ones. Again the QRM brings additional insights: just as in the case of the place of origin, the quantile estimates show that PP increases in higher quantiles.

One more original result of the study concerns the value associated to olive varieties, with mono-cultivar and the nationally widespread olive cultivars that add values to the oil. These results can be taken by producers in order to adopt relatively easy differentiation strategies based on the separation of olive varieties before milling, hence increasing the value of their oil.

Results on harvesting methods were unexpected and remain unexplained, thus shedding light on an area that requires further explorations for improving our knowledge of this changing market.

Besides, the overall results obtained also indicate that some factors - that were not included in the model due to lack of data- may play an important role in the olive oil market, so that more work is needed for a better understanding of additional relevant and more recent tendencies.

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Full Research Article

Corporate R&D and the performance of food-processing firms: Evidence from Europe, Japan and North America

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Abstract. This paper investigates the impact of corporate research and development (R&D) on firm performance in the food-processing industry. We apply Data Envelopment Analysis (DEA) with two step bootstrapping using a corporate data for 307 food-processing firms from the EU, US, Canada and Japan for the period 1991-2009. The estimates suggest that R&D has a positive effect on the firms' performance, with marginal gains decreasing in the R&D level as well as the performance differences are detected across regions and food sectors. R&D investments in food processing can deliver productivity gains, beyond the high-tech sectors generally favoured by innovation policy.

Keywords. Corporate R&D, DEA, double bootstrapping, food-processing industry.

JEL codes. O30, L66.

1. Introduction

Both the theoretical and empirical literature established that R&D is critical for firm productivity growth. For example, the empirical literature has found that between 1% and 25% of variance in the actual productivity across firms can be explained by differences in R&D investment (Hall *et al.*, 2010). However, there is considerably less agreement on the size of the R&D impact on the firm's productivity (e.g. the size of marginal impact, diminishing vs. increasing returns to R&D).

Existing analysis of the implications of R&D mainly focus on knowledge-intensive businesses; there are less studies covering R&D and innovation in low- medium-tech sectors such as food-processing. The literature is highly scattered in the field of agro-food sector ranging from conceptual analysis, system-oriented approach analysis (e.g. Jongen and Meulenberg, 2005; OECD, 2012, 2013) to public R&D in agro-food sector (Alston,

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2010). Analyses on public R&D and its impact on primary agriculture production are more numerous given that the relevant data is more accessible. Conversely, much less effort has poured into the private R&D even though it probably represents the largest share of the overall sector's R&D (e.g. 59% in Japan, 51% in US according to Alston *et al.* 2010). Furthermore, the firm level studies seldom focus on specific aspects of R&D (e.g. adoption, product variety). Most are case studies with a limited regional or sectorial coverage (e.g. one country, part of the sector). Broader quantitative analyses are limited by data measurement and availability constraints.

The food-industry is usually considered to be a medium to low R&D intensity sector representing around 0.27 % of the total output in the EU agro-food industry (FoodDrinkEurope, 2015) compared to other sectors such as the automobile (5.5%) or pharmaceutical (13.1%) industries (Hernández *et al.* 2015). This is understood, among others, to be related to the fact that the agro-food sector is dominated by SMEs which do little research, many innovations are often derived from other input sectors and thus are incorporated in machinery, packaging and other manufacturing supplies (e.g. Menrad, 2004) as well as many food-products are rather easy to imitate with significant R&D spillovers which reduces firms' incentive to invest in R&D (Gopinath & Vasavada, 1999).

Although this general patterns may hold, the agro-food industry shows a high heterogeneity in the R&D intensity (Avermaete *et al.*, 2003; Winger and Wall, 2006; Feigl and Menrad, 2008; Capitanio *et al.*, 2010). There is a strong geographic heterogeneity in the level of private R&D. Heterogeneity is also present in the type of innovation among firms: process, product, or organisational innovation. Finally, it is important to mention that firms also differ whether they invest in R&D externally or internally.

The objective of this paper is to contribute to this literature by providing empirical evidence on the impact of private (corporate) R&D on productivity of food-processing firms. More specifically, we analyse the size of firm inefficiency and explore the determinants of the inefficiency against the frontier production function using a unique corporate data set of food-processing firms from the EU, US, Canada and Japan for the period 1991-2009. To derive productivity parameters, we apply Data Envelopment Analysis (DEA) with two step bootstrapping which allows us to correct the bias in (in)efficiency and generate unbiased estimates for (in)efficiencies.

2. Methodology

To estimate the impact of private R&D on firm productivity we adopt a two-step approach. First, we use DEA to estimate firm performance (inefficiencies). Second, we run regression to explain the determinants of firm inefficiencies on a set of explanatory variables including private R&D.

Different approaches have been applied in the literature to identify production frontiers using both parametric and non-parametric methods. Here we adopt a non-parametric approach - DEA with two step bootstrapping (Simar and Wilson, 2007). The advantage of DEA is that it does not require imposing assumption on the functional form of the frontier, there are no restrictions regarding the number of parameters required, it is relatively easy to deal with a whole range of inputs and outputs, and inputs and outputs can have very different units. However, in general, some limitations remain in terms of considering time series, sensitiveness to outliers, demanding to incorporate (nonparametric) statistical inference, etc.

Methodologically, however, the assumption of a common frontier across countries and sectors is a sensitive issue potentially leading to biased results (Koop *et al.*, 2000; Limam and Miller, 2004; Orea and Kumbhakar, 2004). This paper avoids assuming a common technology across sectors by estimating at industry-specific technology level.

A frontier production function, in general, defines the maximum output achievable, given the current production technology and available inputs. We estimate DEA model in the formulation of output distance function:

$$\hat{\delta}_i = \delta_i(\mathbf{X}, \mathbf{Y} \mid T) = \max\left\{\delta > 0 \mid \delta \mathbf{y}_\mathbf{i} \le \mathbf{Y}\lambda, \mathbf{x}_\mathbf{i} \le \mathbf{X}\lambda, \mathbf{i}'\lambda = 1\right\} \tag{1}$$

where δ_i is inefficiency parameter of firm i, y_i is output; δy_i is maximum output achievable (frontier), x_i and X are inputs; λ are weights used to construct the virtual producer (frontier). The main idea of DEA is to find virtual firm (combination of other firms) capable of producing more output for the given inputs.

In the second stage, the inefficiency parameters are regressed on a set of explanatory variables, z_i, to estimate the determinants of inefficiency:

$$\delta_i = \mathbf{z}_\mathbf{i}\beta + \varepsilon_i \ge 1 \tag{2}$$

where β are parameters to be estiamted and ε_i is an independent and identically distributed (i.i.d.) error term.

For estimation, δ_i has to be replaced by $\hat{\delta}_i$ (the estimated efficiency scores from the first stage):

$$\hat{\delta}_i = \mathbf{z}_\mathbf{i}\beta + \xi_i \ge 1 \tag{3}$$

Usually a Tobit regression is applied to estimate the parameters of β. This procedure become necessary because the error term e_i is truncated and not symmetrically distributed with mean zero. Examples of the z variables – and as such also used in this study – are R&D intensity, capital intensity, time, country dummies (capturing different institutional settings), etc.

Simar and Wilson (2007) point to several problems with this approach and advocate for the use of a truncated regression, instead. The $\hat{\delta}_i$ are serially correlated in an unknown way since each $\hat{\delta}_i$ depends on all observation in T. Thus the δ_i are not independent of each other which induces biased estimates in the second step since the usual assumption regarding the error term does not hold.

Moreover, since x_i and y_i are correlated with z_i (otherwise the second step would make no sense), z_i is correlated with ξ_i. The correlation disappears asymptotically, however, at a very slow rate.

As a solution to this bias they suggest a two-step bootstrap algorithm (Simar and Wilson, 2007). First, we correct the bias in (in)efficiency (in DEA). Second, we get unbiased estimates for (in)efficiencies (in the truncated regression). That is, the bootstrap allows to bias-adjust coefficient estimates and also for calculating proper confidence intervals for the statistical inference.

Bootstrapping tends to affect the structure of the data, potentially generating other forms of bias through an 'over-manipulation' of the data. A possible alternative is to develop an instrumental variable to control for the bias. However, this alternative was not seen as operational taking in consideration the available data.

3. Data and variables

Considering strengths and limitations of several potential sources of data,[1] Standard & Poor's (S&P) COMPUSTAT data set (S&P, 2014) was favoured which contains data at firm level collected from companies' audited annual/quarterly reports.

The selection process of firms from the available population of companies entailed several steps. The first consisted in retrieving firms classified as belonging to agriculture (industry code: 0xxx) as well as those to the food-industry (industry code: 2xxx); covering the period 1991-2009. Data had to cover revenue, sales, net income, capital and R&D expenditures (if any); number of employees and/or wage sum, industry code, and region/country (i.e. info on the location of the company's headquarter/where it is registered). However, as most companies from agriculture did not report R&D expenditures, they were dropped from the final sample.

Labour input is critical when considering firm performance. In the case of missing 'number of employees' but available labour expenditures, the number of employees was approximated by using average wage levels taken from International Labour Organisation (ILO) and for values of labour costs vice versa.

The dataset does not allow distinguishing whether R&D was conducted domestically or abroad. All companies' R&D expenditure was assigned to the country where the company is registered.

The DEA approach applied in this paper is sensitive to outliers. Moreover, presuming a common production frontier for companies across countries implicitly assumes that all companies have access to the same technology and produce under virtually the same technological restrictions. Hence, reducing the sample to a sub-sample comprising of rather homogeneous countries/companies appeared advisable in order to ensure widely unbiased empirical results. Outlier observations, however, still need to be excluded from the sample.

After carrying out a final outlier check (checking for consistency and order of magnitude across observations as well as along the time series) some further firms/observations had to be dropped. Thus, outliers were excluded based on the results of Grubbs' tests centred on the sectoral average growth rates of firms' R&D stock intensity (K/revenue) over

[1] For instance, the AMADEUS database may contain sufficient cross-section and time series firm level data, but provides information on R&D (if at all) only for very recent years. The presumed emergence of the food-processing sector as medium-tech, evolving from formerly low-tech, could not be investigated accordingly based on such data. Another possible source of data could be the EU Industrial R&D Scoreboard (released by EC Joint Research Centre). This database comprises of fully consolidated firm level data of top R&D investors in Europe and elsewhere (year of last audited report + 3 years back in time). However, among the listed companies, there are too few belonging to the food-industry.

the investigated period.[2] Moreover, some further observations were dropped for reasons related to the computation of the R&D and capital stocks.

In accordance with the literature (see Hulten, 1991; Jorgenson, 1990; Hall and Mairesse, 1995; Bönte, 2003; Parisi *et al.*, 2006), stock indicators (rather than flows) were used as impact variables. It is thus implicitly assumed that a firm's productivity is affected rather by the cumulated stocks of capital and R&D expenditures and not only by current or lagged flows.[3] Accordingly, our main impact variable is a firm's R&D stock (K) and the second impact variable is 'capital expenditures' (C) captured as capital stocks. By considering the per capita values of these variables (i.e. per number of employees), it allows us both to standardise the data and to eliminate firms' size effects (see, for example, Crépon *et al.* 1998). In this framework, knowledge (R&D) and physical capital stocks were computed using the perpetual inventory method based on the following formulas:

$$K_{t0} = \frac{R\&D_{t0}}{g_{s,c}(K) + \delta} \tag{4}$$

$$K_t = K_{t-1} \cdot (1-\delta) + R\&D_t \text{ with t = 1991, … , 2009} \tag{5}$$

$$C_{t0} = \frac{I_{t0}}{g_{s,c}(C) + \phi_j} \text{ and} \tag{6}$$

$$C_t = C_{t-1}(1-\phi) + I_t \tag{7}$$

where *R&D* is R&D expenditure and *I* is gross investment (capital expenditure).

The OECD ANBERD and the OECD STAN databases were used to provide growth rates $g(K)$ and $g(C)$ for K and C, respectively. We computed the compounded average rates of change in R&D and fixed capital expenditures in the food-processing sector and per country (c). For some European countries the mentioned databases did not report or allowed calculating specific growth rates for R&D- and capital-stocks. The corresponding European averages were assumed in these cases instead. For the US, Canada, and Japan, however, the growth rates were taken from the literature.[4]

In general, different depreciation rates (δ) and (ϕ) for K and C should be assumed depending on whether the industry is high-, medium-high, medium-low/low-R&D intensity. In fact, more technologically-advanced sectors are characterised (on average) by short-

[2] Grubbs' test – also known as maximum normalised residual test – assumes normality (which is a desirable property anyway). Accordingly, we ran normality tests on the relevant variables (assumption was never rejected).
[3] Using cumulated R&D and capital stocks – as in the previous relevant literature – overcomes a potential endogeneity problem which can arise if flows are used.
[4] For capital growth from OECD (Capital Services, total; mean percentage change 1985-2009; see: http://stats.oecd.org/Index.aspx) and for R&D growth rates the average over the period 1980-1998 was taken from (http://www.ulb.ac.be/cours/solvay/vanpottelsberghe/resources/DGBVP_OES.pdf

er product life cycles and by a faster technological progress which together accelerates the obsolescence of the current knowledge and physical capital. In this light, Ortega-Arquiles *et al*. (2009) suggested sectoral depreciation rates of 20%, 15% and 12% to the knowledge capital and 8%, 6% and 4% to the physical capital respectively for the high, medium-high-, and medium-low/low-tech sectors, with the latter (δ=12%, ϕ=4%) to be applied here to the food-processing industry. These are similar to the 15% and 6% commonly used in the literature (Musgrave, 1986; Nadiri and Prucha, 1996; Pakes and Schankerman, 1986; Hall, 2007).

All variables in monetary units were transformed into 2007 Euro using the end of year exchange rate. In cases where no direct exchange rate to Euro was provided by COMPUSTAT, for a certain year, the corresponding currency was transferred into USD first and then into Euro.

After processing the data, the sample used in this paper consists of 307 companies (2948 observations) for the period 1991-2009 registered in either of the following country groups: EU (557 observations), North America (USA and Canada, 1,050 observations), and Japan (1,341 observations), as shown in Table 1.

Europe is less represented than Japanese and North-American counterparts. There is no information on Japanese firms prior to 1999 and most regions are less represented for this period. However, the period starting in 2000 is more balanced, including for Europe. To control for this data structure we use a dummy variables in our estimations to distinguish these two periods.

As shown in Table 1, there is observed significant heterogeneity among the 307 firms. The mean number of employees varies between 2211 in Japan to 15293 in the EU. Nev-

Table 1 Descriptive statistics of main variables

Variable	Mean	Std. Dev.	Min	Max	Firms	Obs.
Total sample					307	2948
Revenue	2308.3	5192.3	0.4	51514		
COGS-costs	1443.5	3295.6	0.4	47137		
R&D expenditure	89.7	451.7	0	7290.3		
Capital expend.	1286.4	2996.3	0	25846		
Employees	10610	31443	2	486000		
EU companies					85	557
Revenue	2705.8	6602.6	0.4	51514		
COGS-costs	1561.2	3323.9	0.4	22873		
R&D expenditure	175.6	926.9	0	7290.31		
Capital expend.	1768.9	4020.4	0	25846		
Employees	15292.7	36441.3	2	269000		
US & Canada					79	1050
Revenue	3684.8	6607	1.7	50659		
COGS-costs	2309.5	4578.3	1	47137		
R&D expenditure	72.5	266.4	0	2476		
Capital expend.	1839.9	3584.2	0	24759		
Employees	18054	43375	2	486000		
Japan*					143	1341
Revenue	1065.3	1983.5	5	15913		
COGS-costs	716.6	1330.7	2	9785.7		
R&D expenditure	67.5	181.5	0	1642.2		
Capital expend.	652.6	1497.7	0	13127		
Employees	2211	4203	16	36554		

*(1999-2009 period only)

ertheless, in each macro region, apparently, there are also a number of small and even micro-companies. It has to be stressed that the final sample gathers rather large companies, inherent with stock listed company data. This entails that results cannot be easily generalised as rather small private companies operating in the food-processing sector are not captured, but should be considered pertinent to large firms which, in fact, are inclined to be more active in terms of R&D. Also, this kind of "pick the winner" effect might be particularly severe in medium and low-tech sectors (like food-processing), where the overall company population tends to be dominated by smaller firms which scarcely engage in R&D investment (Becker and Pain, 2002).

The sample mean of R&D-intensity (R&D/sales) is above 1% in all macro-regions with the EU reporting the highest rate (~6%). This would allow classifying the companies/sector as medium-tech (even medium-high), according to the commonly applied classification (Hatzichronoglou, 1997). Considering the median R&D-intensity rather than the mean, the R&D/sales ratios do not change significantly in magnitude in Europe and the US/Can, but they drop below 1% in Japan. However, in the EU and the US/Can only a few firms perform R&D at all (but those which do, however, have significant spending), while in Japan most companies are engaged in R&D activities but modestly at individual level.

In general, the companies active in the food-processing sector in the EU and in the US/Can seem to be fairly similar: EU companies are, in average, a little smaller in terms of revenue (sales) and number of employees but have almost exactly the same ratio of net income/revenue as those from US/Can and also comparable figures in terms of spending on R&D and capital (including their accumulated stocks). In contrast, Japanese firms appear smaller and less profitable, more inclined to do corporate R&D, but, in average, at a lower financial (Table 1). These differences between macro regions need to be taken in consideration when interpreting the estimated results and performing cross-country comparisons.

In terms of sub-sector representation, observations from beverages companies are the most present followed by mixed-activity or generalist food-processing firm and prepared foods, accounting for 53% of the total sample. The remaining subsectors account individually between 4% and 9% the dairy sub-sector which is marginally present in the sample (Table 2).

Table 2 Sample composition - observations per subsector

Subsector	Codes	No. observations
Beverages, including alcohol	2080-2087	561
Mixed/generalist	2000	490
Prepared foods	2090-2099	491
Meat and poultry packing	2010-2015	272
Sugar and confectionery	2060-2068	252
Canned fruits and vegetables	2030-2038	225
Grain	2040-2048	226
Bakery	2050-2053	197
Dairy	2020-2026	18
Oils	2070-2079	116
Total		2948

4. Results

4.1 The size of inefficiency

An output-oriented efficiency model (variable returns to scale-VRS) was run with a simple specification made of one output and three inputs. Inputs consist of capital stock (*C*), labour (number of employees, *E*) and total cost of goods sold (*COSD*). The output was measured as the value of total revenues assumed to be total food related sales, although firms may have sales revenue from other lines of activity and streams of income such as asset management (Fuglie *et al*., 2011).

The distribution of efficiency scores by frequency is displayed in Figure 1. In general, the figure shows that the inefficiency distribution is skewed to the left indicating that most of the companies operate relatively close to their frontier (panels b and c). Very high inefficiencies could only be found for a few companies. Moreover, panel (a) shows an estimate of the bias of the inefficiency estimate. The distribution reveals that the bias is considerable. Thus conducting an analysis without bootstrapping would have led to largely biased estimated parameters in the second step. Panel (b) gives an example of the inefficiencies calculated with the adjusted technology T^*. Finally, panel (c) give the unbiased estimator (distribution) of the inefficiency.

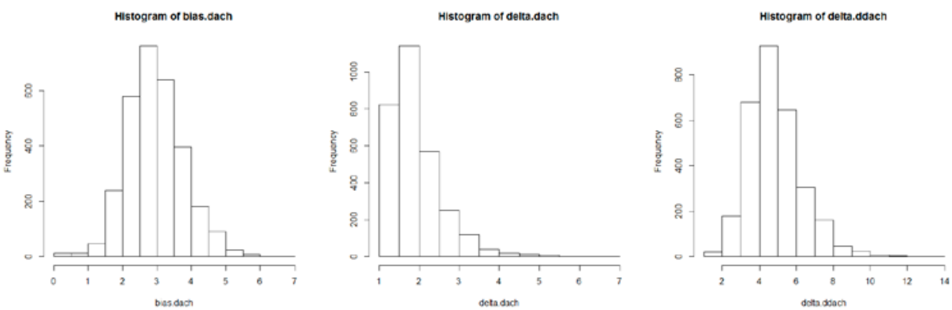
4.2 The determinants of inefficiency

The basic hypothesis of the second stage is that R&D has a positive impact on firm performance. In general, the determinants of inefficiency will be captured by the knowledge base of a company which depends on (a) on own R&D and (b) knowledge created elsewhere (universities, research institutes, companies) and diffuses to the public domain.

The main objective of this paper is to capture the effect of the first type of knowledge. As a result, we include the variable own (private) R&D expenditure of companies

Figure 1. Illustration of inefficiency estimates and estimated bias, frequencies.

(a) (b) (c)



Inefficiency units | Inefficiency units | Inefficiency units

$BI\hat{A}S(\hat{\delta}_i) = BIAS(\hat{\delta}_i) + v_i$ $\qquad$ $\hat{\delta}_i^* = \delta(\mathbf{x}_i, \mathbf{y}_i \mid T^*)$ $\qquad$ $\hat{\hat{\delta}}_i = \hat{\delta}_i - BI\hat{A}S(\hat{\delta}_i)$

(without distinguishing whether it is internal or external R&D) in the set of explanatory variables (z) considered in the second stage estimations. Usually the information is available when the companies are required to publish their investments. Although it can be safely assumed that large companies in all countries have some R&D, however, they have no spontaneous incentive to report it since this would reveal information about the firm's strategy and threaten the firm's competitive position.

This lack of data may bias the result. However, no information on R&D is less severe than expected. Given the basic hypotheses, the impact of R&D on performance might be less significant since firms which do not report but conduct research should be more efficient than expected.

Regarding the knowledge created elsewhere (technological opportunities), firm R&D impacts not only the revenues directly but in addition also affects the technological opportunities of the firm. The firm's technological opportunities consist of two parts: the knowledge external to the sector (universities, public research institutes) and the existing knowledge at the competitors which diffuses to some extent into the public domain (Cohen and Levinthal, 1989). The degree of openness depends on the institutional regulations regarding the protection of firm specific knowledge but also from the type of technology.

The use of public knowledge depends on the absorption potential. This absorption depends on the height of the R&D expenditure as well the characteristics of the scientific and technological foundations. In addition it is determined by the ease how this knowledge can be absorbed.

In order to account for differences in the knowledge and research infrastructure we consider regional dummy variables in the estimation. We expect that the US and Japan have a favourable knowledge base to conduct R&D and this knowledge base also finds its expression in better firm performance. Some indication of this can be seen Table 1 which shows that Japan and the US have the highest research expenditures related to outputs. The same effect can be expected for the old EU Member States ("EU15"). Similar to Japan and the US, they belong to the group of countries with a highly developed research infrastructure. Given the structural difficulties of EU New Member States ("NMS") from Eastern Europe in particular related with their past history of planned economy, the research systems in these countries are likely less developed thus attaining lower productivity levels. The reference region for these regional dummy variables is Canada. Note that, some studies find that Canada reports lower performance of food-processing firms than their peers from other developed countries such as US (Chan-Kang *et al.* 1999; in Fuglie *et al.* 2011)

To further control for the knowledge and research infrastructure beyond the regional dummies, the contemporaneous general public R&D investments per capita is also introduced in the regression (GERD of government sector, Euros equivalent, 2007 constant prices).

The time lags and dynamic effects (e.g. see Andersen & Song, 2013) are not controlled for in the analysis, given that the availability of data in the sample for different years varies strongly across firms and regions. However, to account for the differences in the sample structure over time, dummy variables are used for the 1990s period and the period 2004-2009 with the 2000-2004 period serving as reference.

Table 3. Truncated regression estimates of the determinants of efficiency.

Independent variables	1A (biased)	1A	1B	2A	2B	3A	3B	4A	4B	5A	5B
Constant	*2,2880*	5,7321*	5,7437*	4,9921*	5,0246*	5,9101*	5,7705*	5,7044*	5,8331*	5,9844*	6,0773*
R&D, perpetual inventory	*-0,8243*	-0,7931*	-1,0606*	-0,8684*	-1,1703*	-0,6639*	-0,9157*	-10,7639*	-10,8921*	-0,9767*	-1,1729*
(R&D, perpetual inventory)^2			0,0447*		0,0532*		0,0386*		0,1176*		0,0810*
GERD, gov. sector/ capita	*-0,0023*	-0,0026*	-0,0028*	-0,0040*	-0,0041*	-0,0062*	-0,0054*	-0,0052*	-0,0057*	-0,0063*	-0,0066*
Japan	*-0,7098*	-0,9469*	-0,9248*			-1,2181*	-1,1465*	-1,1878*	-1,2033*	-1,2020*	-1,2328*
USA	*-0,7378*	-1,0090*	-1,0082*			-1,0157*	-1,0204*	-1,0542*	-1,0579*	-1,1013*	-1,1263*
EU12, NMS	*0,9666*	1,6572*	1,6479*			1,4837*	1,5142*	1,4666*	1,4820*	1,5267*	1,6351*
EU15	*-0,2256*	-0,2823*	-0,3052			-0,5035*	-0,4022*	-0,4321*	-0,3465*	-0,4832*	-0,5173*
1990s dum.	*0,1187*	0,1938*	0,1852*	0,2708*	0,2827*	0,0904	0,1029	0,0904	0,0768	0,0861	0,0790
After 2004 dum.	*0,2399*	0,2815*	0,2763*	0,3897*	0,3990*	0,1697*	0,1843*	0,1781*	0,1808*	0,1950*	0,1965*
Dairy				0,3069*	0,3273*	-0,0636	-0,0556	-0,0901	-0,1270	0,1876	0,2057
Canned				0,1105	0,1026	0,2952*	0,2545*	0,2593*	0,2313*	0,2500*	0,2280
Beverages				-0,5804*	-0,5828*	-0,7585*	-0,7190*	-0,7069*	-0,7598*	-0,7698*	-0,7936*
General				0,1760	0,1583	0,1551	0,1461	0,1676*	0,1292	0,1108	0,1826
Meats				0,3146*	0,2854*	0,4265*	0,3832*	0,4036*	0,3487*	0,6228*	0,6248*
Oils				-0,5020*	-0,5396*	-0,3130*	-0,3251*	-0,2887*	-0,3198*	-0,0022	-0,0199
Bakery				0,3042*	0,2958*	0,4644*	0,4124*	0,3915*	0,3527*	0,4686*	0,4696*
Prepared foods				0,3893*	0,3919*	0,4236*	0,4049*	0,3870*	0,3786*	0,3461*	0,3603*
Sugar				-0,1587	-0,1696	-0,0466	-0,0952	-0,0758	-0,0792	0,0155	-0,0030
Japan x R&D								10,2002*	9,9897*		
USA x R&D								10,1015*	9,8361*		
(EU12, NMS) x R&D								-0,2317	-0,5675		
EU15 x R&D								9,9956*	8,7063*		
Dairy x R&D										-1,5265*	-1,5851*
Canned x R&D										-0,1390	-0,0883
Beverages x R&D										0,2183	0,1948
General x R&D										0,1830	-0,4624
Meats x R&D										-9,0025*	-9,1332*
Oils x R&D										-4,4689*	-4,5715*
Bakery x R&D										-0,8573	-0,8754
Prepared foods x R&D										0,5644*	0,4738*
Sugar x R&D										-1,2186*	-1,1682*

NMS: EU New Member States. * indicates stat. significance at 5%. Source: own calculations on R v2.14 with FEAR package.

The estimated results of the second stage pooled truncated regression are reported in Table 3. We have estimated several alternative and complementary model specifications to avoid potential collinearity between explanatory variables. Model 1A starts with a simple specification of the estimated equation which includes private R&D (perpetual inventory), public R&D (GERD/per capita), time dummies, and regional dummies (US, Japan, EU, etc.) with Canada serving as the reference country. For comparison purposes, we also report the results obtained with the biased estimators for the first model (1A biased). The remaining models are only presented with their unbiased estimators. The extended first model (1B) also considers squared value of private R&D with the aim to capture the change in marginal gains from additional investment in private R&D.

The second set of models (2A, 2B) considers sectoral dummies instead of regional dummies with firms specialised in grain processing being used as the reference sub-group. Model 2B expands 2A with adding squared value of private R&D. The third set of models (3A and 3B) add both regional and sectoral dummies in the estimated equation. Again, model 3B expands 3A with adding squared value of private R&D.

The remaining model sets (4 and 5) consider interaction variables between private R&D and regional and sectoral dummy variables, alongside the variables considered in the first three model sets, in order to capture whether the impact of private R&D vary across regions or sectorial circumstances, respectively. That is, the fourth set of models (4A, 4B) includes interaction variables between private R&D and regional dummies, while the fifth set of models (5A, 5B) interacts private R&D and sectoral dummies.

The estimates largely confirm the hypothesis that private R&D has a positive effect on performance (i.e. it reduces inefficiency) of the food-processing firms (Table 3). However, the variable controlling for marginal gain of additional investment does systematically capture decreasing marginal returns of R&D investments on performance at firm level. Public R&D has also statistically significant contribution to performance, in line with country specific studies such as for the Spanish food sector by Acosta *et al* (2015). However, the relationship is complex as hinted by Maietta *et al* (2017) whose analysis of the R&D sector in Europe over the 2007-2009 period suggest a displacement effect on *intra-muros* (internal) R&D by government R&D. These results are consistent across all estimated models.

Private R&D investing seems to more positively affect performance in Canada (the reference country) than in the USA, Japan or EU15 countries (4A and 4B). The estimated coefficient for new EU member states is not significant in both models where the interaction variables between private R&D and regional dummies are considered (i.e. 4A and 4B). These results suggest that additional R&D investment in Canada and NMS would produce greater firm efficiency gains than in in the USA, Japan or EU15. With regards to sub-sectorial sensitivity to R&D investment on firm performance (5A and 5B), some sub-sectors (dairy, meat processing, oils and sugar) seem to be more responsive to R&D investment and statistically significant compared to the reference sector (grain). In contrast, processed food sectors are less sensitive to R&D investment, while the remaining sub-sectors were found to be statistically insignificant relative to the reference sector.

The performance of food-processing firms during the period after 2004 is significantly lower compared to the 1990s and especially compared to the reference period (2000-2004). In terms of regional variation of firm performance, the estimates suggest that Japanese, US, and EU15 firms are more efficient that Canadian firms which corroborates with previous studies comparing US and Canadian firms (Chan-Kang *et al.* 1999, Fuglie *et al.* 2011). The food-processing firms from the NMS tend to underperform the Canadian peers, and hence the firms from other countries.

Firm operating as generalist of the food-processing sector tend not to indicate a statistically significant difference with the reference group (grains). In most models, this is also the case for dairy and sugar-related firms, while for oil and canned producers the results are mixed in terms of statistical significance. However, firms specialised in meats, bakery and prepared foods tend to be less efficient than those involved in grains; these resulte are statistically significant across all models.

5. Conclusions

This paper confirms the hypothesis that R&D investment influences firm performance: food-processing firms which invest in R&D tend to be closer to the efficiency frontier compared to those that do not invest in R&D (i.e. private R&D has a negative effect on inefficiency). Estimates of this paper also point to decreasing marginal returns in reducing (increasing) inefficiency (efficiency) by private R&D as well as that that the general public R&D has a positive effect on efficiency of food-processing firms.

When looking at the drivers of firm performance, country/region dummies do capture differences and similarities in knowledge systems and nature of the sector. Similarities can be detected in the US and Japanese contexts. Further, as expected, less favourable eastern European (NMS) context is indentified in the estimated results as compared to the performance of firms from old EU Member States. However, the results suggest that gains from additional investment in R&D could be greater in NMS than old EU Member States or the US.

The findings of this paper have to be considered, however, with some caution on the account of the data limitations. The persistent lack of reporting R&D in certain countries in the EU may create biases in the estimated effects. Further, the sample contains rather larger firms from the food-processing industry (a key factor determining R&D, as illustrated by Acosta *et al* (2015) for the Spanish food sector), while small firms are underrepresented. This data limitation does not allow to fully extrapolate the results obtained in this paper to the whole food-processing industry.

Overall, the results of this paper show that R&D in food-processing industry is associated with higher firm performance. At the same time, the sample used in this paper includes medium-high-tech (and larger) food-processing firms, questioning the generally held view on the sector as being rather low-tech. By prioritising high-tech sectors, emerging technologies, knowledge-based services, etc., the current backbone of the European economy, mainly constituted by industries that are often rather medium- and even low-tech, tend to be somewhat marginalised from the policy attention perspective (Hanse and Winther, 2011). Results of this paper show that growth opportunities could also be expected and encouraged from this type of non-high-tech innovative sectors. Further, the results of this paper suggest heterogeneity in R&D effects across EU Member States, hence innovation policies may have different implications across EU regions.

6. Acknowledgements

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7. Disclaimer

The authors are solely responsible for the content of the paper. The views expressed are purely those of the authors and may not in any circumstances be regarded as stating an official position of the European Commission.

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Full Research Article

Can menu labeling affect away-from-home-dietary choices?

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Abstract. This study aims to evaluate the impact of two menu-labeling formats on changes in dietary choices in an away-from-home meal, specifically in a university cafeteria. A field experiment at a university cafeteria in Italy was conducted providing two different types of nutritional labels. The experiment lasted four days, spread over two weeks during which a total of 930 observations were collected. During each day of the experiment, only in one food line (*treated* line) a label indicating the healthy options was displayed, while in the other line no label was presented (*control* line). The paper describes two indexes to measure how the selected food choices for each participant are in line with what suggested by the labels. We define five different classes of these indexes and we test our hypothesis using an ordered logit model. Results show the labels we provided had no significant impact on changing the tray composition, in accordance with other previous experiments suggesting that adding only nutritional information in a restaurant setting does not necessarily encourage healthier choices. The paper concludes highlighting the need of a multifaceted approach to design effective public policies enhancing healthier choices in a self-service restaurant. Specifically, the provision of nutritional information by itself can have zero or low impact unless it synergizes with others instruments such as nutritional education, social norm provision and nudges. In the conclusions, some suggestions on public policies addressing the promotion of healthy food habits are given.

Keywords. Menu Labels, Food away-from-home, Healthy food policies, Food labeling.

JEL Codes. I12, I18, D12.

1. Introduction

Food away from home (FAFH) consumption plays an increasing role in the daily diets of many people worldwide. In Italy, the share of FAFH on total food expenditure was 33% in 2015, versus 46% in Spain, 44% in the United Kingdom, 27% in Germany, and 26% in

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France (Agrifood Monitor, 2016). In 2015, about 12 million Italians (around 20% of the entire population) had lunch away from home 3-4 times a week (Fipe-Commercio, 2015). These patterns are actually similar for all industrialized and many developing countries (Mottaleb *et al.*, 2017). In the USA, the share of FAFH on total yearly food expenditure rose from 25.9% in 1970 to 43.1% in 2012 (USDA). In the 2007-2008 National Health and Nutrition Survey data 41% of adults said they had consumed foods and/or beverages from fast food-type restaurants during the previous 24 hours, and 27% of them from full-service restaurants (Seguin *et al.*, 2016).

While the rising in FAFH consumption is not a bad habit *per se*, researchers have found that the frequency of eating FAFH is positively correlated with some unhealthful outcomes, such as overweight and obesity (Binkley *et al.*, 2000; McCrory *et al.*, 1999; Satia *et al.*, 2004, Todd *et al.*, 2010).

The link between FAFH and obesity can be explained because people tend to underestimate calories and fat content when they select their meal in an away-from-home environment (Backstrand *et al.*, 1997). Indeed, restaurants and cafeterias typically use caloric dense ingredients (butter or dressings) to gain palatability[1]; yet, it is almost impossible for consumers to detect those "hidden" fats and overall taste remains a major force driving food choices (Glanz *et al.*, 1998).

The positive relationship between FAFH expenditure and BMI has also been found in children. According to a study by Bowman *et al*. (2004), on a typical day when eating at quick-service food, children (aged 4-19) tended to consume more fat (+ 9 g), added sugars (+ 26 g), sugar-sweetened beverages (+ 228 g), and less fiber (-1.1 g), milk (-65 g) and fruits and non-starchy vegetables (-45 g), compared to those who did not, leading to 187 extra calories compared to a meal consumed at home.

Given the increasing trend in eating away from home, policy makers have considered the urgency of finding policy instruments which can lead to healthier consumption behavior. Labeling[2] is among the information-based instruments extensively used to lead consumers towards more informed and possibly healthier choices (Galizzi, 2014; Traill, 2012). We can think that in a FAFH environment providing some nutritional information may limit the misperception on nutrients' content when consumers are choosing their meal. However, while the introduction of nutritional information in a restaurant menu is supported by many researchers and health officials, their provision is mainly due to private sector or local government initiatives (Brambilla-Marcias *et al.*, 2011). In fact, the implementation of a mandatory policy in a catering environment would require the

[1] Elaborating data from household food consumption surveys conducted by the U.S. Department of Agriculture (USDA) during the period 1977-2008, Biing-Hwan *et al.* (1999; 2012) have shown a reduction of the share of saturated fat to the overall caloric intake of Americans. However, from their analysis, FAFH is still richer in saturated fat than food at home: in 2005-2008, fat contributed to 30.5% and 37.2% of the caloric intake from food at home and from FAFH, respectively (Biing-Hwan *et al.*, 2012; Kozup *et al.*, 2003). Moreover, the FAFH has been found higher in saturated fat, sodium and cholesterol and resulted in lower calcium content and dietary fiber than food at home (BiinHwan *et al.* 2012). Todd *et al.* (2010) estimated that in the USA each meal consumed away from home results in 134 additional calories.

[2] In the United States, under provisions of the Affordable Care Act of 2010, restaurant chains with twenty or more locations operating under the same brand are required to provide detailed nutritional information to consumers and to display calories on their menus. In the European Union (EU), with Regulation no. 1169/2011, new rules regarding nutritional information for food, both pre-packed and non-pre-packed, have been introduced. However, this regulation does not impose stringent rules for restaurants, unless differently required by each member state.

capacity of standardizing ingredients and portions, which is not a trivial task especially for smaller size and not-chained restaurants. As a consequence, requiring stringent adoptions of nutritional labels in a catering environment can have the side effect of pushing smaller, non-chain business out of market, and can reduce options for consumers (Mazzocchi *et al.*, 2009).

The aim of this study is to analyze if the provision of some nutritional information in a university cafeteria has an effect on the composition of the meal chosen. Specifically, it can be expected that, by providing some nutritional information using labels, consumers might be facilitated to reduce the bias of "hidden calories" and consequently to identify healthier options. At this end, the authors conducted a field experiment in a university cafeteria in Italy, where two types of informative labels were alternatively provided.

This article proceeds as follows: after a literature background, first the experimental design and the indicators used to evaluate the quality of the meal are described; then the model and the empirical results are presented, followed by some discussion and policy implications.

2. Background

Previous literature showed the provision of nutritional information can lead to mixed findings. In a systematic review, Mazzocchi and Trail (2005) evaluated the effect of food label in portion size consumption and they found varying impacts, from increasing, to decreasing or no effect. However, none of the studies examined found an effect on reducing energy-dense foods (Mazzocchi and Trail, 2005). Similarly, a literature review by Swartz *et al.* (2011) and another by Kiszko *et al.* (2014) have shown the provision of caloric labels had none effect on the caloric intake of the food ordered and consumed. Further, Harnack and French (2008) concluded that, even if some studies support the evidence of a relation between the provision of caloric labeling and food choices, these effects are weak or inconsistent.

Similarly, empirical studies have shown mixed results. Some have found the provision of nutritional information in a restaurant menu helps reducing the caloric intake (Roberto *et al.,* 2010, Wisdom *et al.,* 2010), others have measured no significant effect (Elbel *et al.,* 2009, Finkelstein *et al.*, 2011). Ellison *et al.* (2014) showed that numeric labels alone (i.e. labels where nutrients content was shown as grams or mg per 100 grams of products or as percentage) have no influence on food choices, unless reinforced by traffic light symbols. In fact, traffic light labels (i.e. labels where some nutrient contents are classified with colors red, orange or green based on some thresholds with respect to dietary recommendations) may lead restaurant patrons to introduce in the menu lower-calorie options. Marette *et al.* (2019) showed that the appearance of traffic light labels significantly impacts the Willingness to Pay of products offered in the experiment.

On the other side, an experimental study conducted by Seward *et al.* (2016), where traffic labels where provided in a university cafeteria setting, has shown that, while students reported to use the traffic light regularly and support their use, the intervention had no effect in improving dietary quality. Vasiljevic *et al.* (2015) have shown that, on selecting different snacks, emotion labels (such as smiling faces) yields stronger effect on the perception of the healthfulness of the snack than colored label; and overall frowning labels are more effective than smiling ones.

Using a random control trial, Oliveira *et al.* (2018) find the provision of a menu labeling displaying different food information being positively associated with healthy food choices. Elbel *et al.* (2009) find that the provision of caloric labels on fast food menus in New York had no effect on the caloric content of the purchased meal.

In general, the literature has found paternalistic interventions (nudges), eventually combined with information provision, being more effective in producing behavioral changes (Downs *et al.*, 2009; Thapa and Lyford, 2014; Thunström and Nordtröm, 2013; Castellari and Berning, 2016). Other studies have shown the importance of providing social descriptive norms to encourage change in food choices (Burger *et al.* 2010).

This work evaluates the effect of nutritional labels' provision on the menu items selections, rather than the caloric content of the meal choices. Nutritional information may have little effect on the caloric content of the overall meal but might impact its composition inducing a shift from 'worse' to 'better' choices[3]. Other studies have found only a small portion of consumers (between 16% and 29%) have responded to nutritional labels changing their menu selections (Balfour *et al.* 1996, Yamamoto *et al.* 2005). We evaluate two different label intervention: (1) a label where the green color is matched with a positive emotion (smile) to identify the item within the same food group (first, second, side dish, fruit and dessert) that has the lowest caloric intake among the available options; (2) a label which ranks within the same food group (first, second, side dish, fruit-dessert) the options available based on their caloric composition using a medal (gold, silver and bronze).

3. Methods

3.1 Experimental design

The hypothesis behind the experiment is that displaying some nutritional labels (i.e. indicating either a partial or a complete ranking of dishes in terms of their caloric content) in a self-service restaurant may influence consumer when selecting food options. We expect the presence of the label would help consumers to identify the hidden calories and thus the less caloric options.

At this end, we collected data at a university cafeteria located in Piacenza, Italy; the experiment lasted four days, spread over two weeks (with a four-week break between them) between March and April 2016. The cafeteria is a self-service caterer, presenting two lines, each one providing identical food choices. The cafeteria meal has a fixed price and it allows to select one option within each menu category: first dish; second dish; side dish; fruit-dessert..

To test our hypothesis we provided (in separate settings) two different types of labels:

1) Less Caloric Labels (LCL): within each menu category (first dish; second dish; side dish; fruit-dessert.) the label indicates the option with the lowest level of calories[4] per portion (Fig. 1, left panel);

[3] Within each food category (first dish, side dish, second dish, fruit-dessert), we rank food choices based on their caloric content from best (less caloric content) to worse (higher caloric content).

[4] The canteen staff provided us the recipes of the dishes and, with their supervision, we used the website http://www.myfitnesspal.com to rank every dish in each category, from the less to the most caloric.

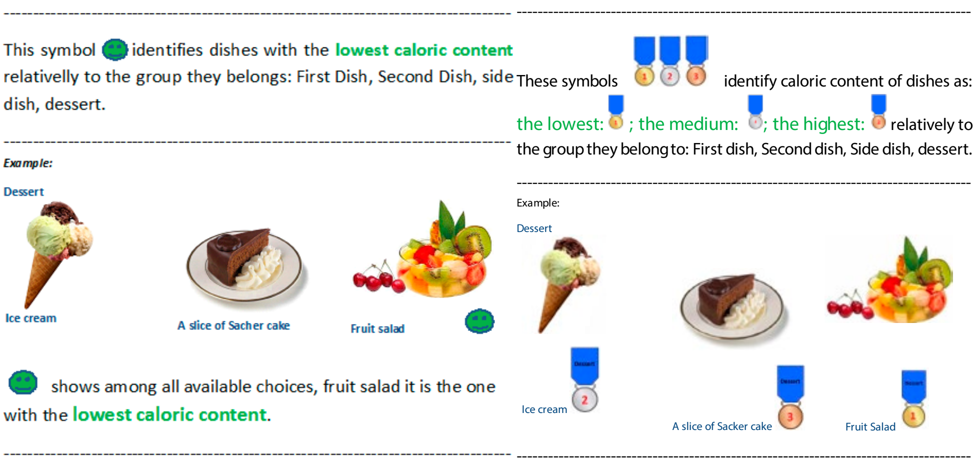
2) Calories Ranking Labels (CRL): within each meal category (first dish; second dish; side dish; fruit-dessert.) the labels indicate a ranking among options based on the level of calories from the least (gold medal, 1st place) to the most (bronze medal, 3rd place) caloric (Fig. 1, right panel).

The labels were chosen together with the canteen managers. We proposed different types of labeling selected from previous studies. During the first week (1st and 2nd day) the effect of providing a LCL was tested, whereas the CRL was used in the second week (3rd and 4th day).

During each day of the experiment only one food line (*treated* line) displayed a label while in the other line no label was present (*control* line). It is assumed people randomly choose between the two lines, although to account for a possible self-selection bias the treated and the control lines from day one to day two (LCL) and from day three to four (CRL) were switched.

Participants were not aware to be part of the experiment before selecting the food choices. The first contact with the labels took place at the beginning of the treatment line, where a flier explained the meaning of the label (LCL in day 1 and 2: CRL in day 3 and 4 as in Fig. 1). Individuals taking the control line did not receive any nutritional information during the meal selection. The recruitment of participants to the experiment took place at the end of the lines (both control and treatment), where, with the support of a flier, two recruiters explained to users how to take part to the experiment. If they accepted, they were asked to take a picture of their tray using their smartphone *before* starting to eat and to share it using a digital platform. Moreover, after lunch, participants were asked to complete a survey including both demographic and behavioral questions. All participants were rewarded with a coupon redeemable at the university coffee shop. We collected 459 observations during the first week (1st and 2nd day) and 471 during the second week (3rd and 4th day). The final dataset contains 930 observations recording tray composition,

Figure 1. Explanation of LCL (left panel) and CRL (right panel).



demographics and behavioral characteristics for each individual. The final sample is mostly composed by university students (around 84% of the sample), and in small percentage by university faculty and staff. For a detailed description of the participants, please refer to the model and empirical results sections.

3.2 Indexes of meal composition

To summarize the food selections made by participant i at day t we computed two different indicators of the tray's meal composition. The purpose of this index is to measure how close the composition of the meal is to an "optimal meal", which in the case of LCL would correspond to a tray with all green labeled choices, while in the case of CRL to a tray with all gold medals. Two different indexes for both the treatment and the control subsamples were computed: (a) a *uniform index* (UI) where we attributed the same weight to each of the dish selections; (b) a *weighted index* (WI) where we attributed different weights to dishes of different categories (first dish, second dish, side dish and dessert).

The UI was computed as follows:

$$UI_{i,t} = \sum_{j=1}^{N_{i,t}} S_{jit} \frac{1}{N_{it}} \tag{1}$$

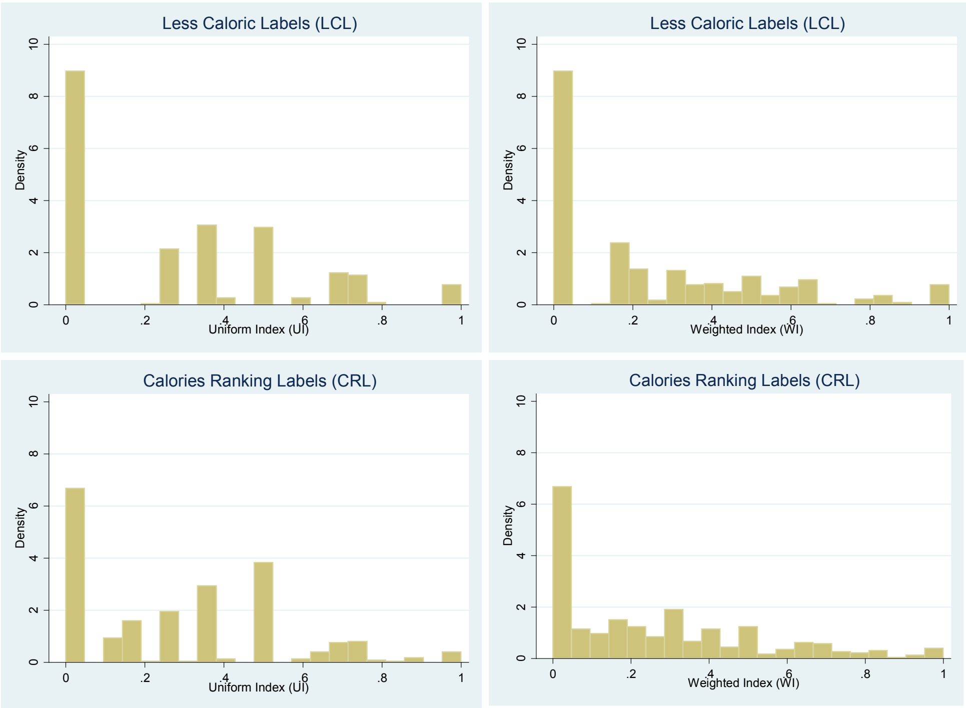
where N_{it} is the total number of dishes composing the tray of individual i at day t while S_{jit} is the score, which in the case of the LCL would be equal to one if individual i at day t made a choice j labeled as healthy (green label), and zero otherwise. In the case of the CRL S_{jit} has a value equal to 1 if the choice j made by individual i at day t was labeled as gold, equal to 0.5 if choice j was labeled as silver, and zero if it was labeled as bronze.

Similarly, to compute the WI we used the following:

$$WI_{i,t} = \sum_{j=1}^{N_{i,t}} S_{jit} \frac{P_{jit}}{\sum_{j=1}^{N_{i,t}} P_{jit}} \tag{2}$$

where P_{jit} is the weight attributed to each dish selected by individual i at day t The weight P_{jit} depends on the meals' category. Specifically, a weight of 0.35 was attributed to the first and second dishes, since they are typically more caloric, and a weight of 0.15 to side dish and dessert. Both indexes (UI and WI) range from one, when an "optimal tray" was chosen, to zero, when all choices are not the one "suggested" by the labels. Fig. 2 shows the distribution of the two indexes (WI and UI) under both label treatments (LCL and CRL). The index computed using the uniform approach is more concentrated around some specific values. Moreover, the distribution of all indexes is concentrated around zero: for the LCL indexes the zeros account for more than 80% of the observations, while for the CRL indexes this share reduces to around 60%.

Figure 2. Distribution of the Weighted Index (WI) and Uniform Index (UI) for the Less Caloric Label (LCL) and Calories Ranking Labels (CRL).



Source: Own data elaboration.

4. Results

To test whether the label provision had an effect on the food selections, we generated a variable indicating the propensity to select an "healthy option" (PHO), using the UI and the WI. Specifically, based on the index values, we compute the PHO as an ordinal variable with five possible outcomes as described in Table 1. The probability of being in a PHO class (k), is given by:

$$\Pr(PHO = k \mid \mathbf{Z}) = \Phi\,(\beta_k + [\mathbf{Z}]`\boldsymbol{\beta}) - \Phi\,(\beta_{k+1} + [\mathbf{Z}]`\boldsymbol{\beta}) \tag{3}$$

where Φ (.) is the standard logistic density function (CDF), k= [0,…,4], β_0 = - ∞ and β_5 = + ∞; **Z** is a set of covariates influencing PHO and **β** is a conformable set of parameters. Specifically, **Z** includes the following variables: a) T is a dummy variable equal to one if participant i in day t belongs to the treated sample; b) X_i is a set of demographics and behavioral variables collected for each person i, as described in Table 2.

Summary statistics are presented in Table 3. In both weeks, the sample is almost equally split between treated and non-treated observations. Students are the largest share

Table 1. Definition of the classes of PHO.

Outcomes	Classes
PHO=0	UI or WI = 0
PHO=1	0 < UI or WI ≤ 0.25
PHO=2	0.25 < UI or WI ≤ 0.50
PHO=3	0.50 < UI or WI ≤ 0.75
PHO=4	0.75 < UI or WI ≤ 1

Table 2. Demographic and behavioral variables.

Variable name	Variable Description
Student	One if student, zero otherwise
Female	One if female, zero otherwise
Commuter	One if commuter, zero otherwise
Frequent User	One if he/she eats at the cafeteria at least 3 times a week, zero otherwise
Cook	One if he/she prepares his/her own dishes often or sometime, zero if rarely or never
Label	One if he/she reads the label of the food consumed often or sometime, zero if rarely or never
FV5	One if he/she consumes at least 5 portions of Fruit or vegetables per day, zero otherwise
Water	One if during the meal he/she never or rarely substitutes water with other drinks, zero if often or always
Weight	One if in the last six months he/she had a weight increase, zero otherwise
Nutritionist	One if he/she ever visits a nutritionist for a diet, zero otherwise
Active	One if he/she practices physical activity at least once-twice a week, zero otherwise

Source: Own data collection.

of the sample (around 84%) and females are around half of the sample. Around 40% of the sample is commuting from nearby areas and almost 90% of the participants use the cafeteria at least three times a week. A large share of the sample declared to usually pay attention to the labels of the food they purchase (around 80%), to prepare its own meal often or sometimes (around 70%), to practice regular physical activity at least once a week (around 70%), and to not substitute water with other drinks during a meal (around 70%). More than 30% of the sample experienced some weight gain in the last six months and more than 20% sometimes visited a nutritionist to receive diet advises. Surprisingly, only 2.6% of the whole sample reported to consume at least five portions of fruit and vegetables daily.

Given the nature of the dependent variable, model (3) was estimated in STATA using an ordered logit model. Equation (3) was estimated for both LCL and CRL samples, using both uniform and weighted indexes. Results are reported in Table 4.

All parameters on the treatment line variable (T) are not statistically significant, suggesting that all our specifications fail to identify any significant positive effect of the label

Table 3. Summary Statistics.

Variable	Less Caloric Label (LCL) N=459		Calories Ranking Label (CRL) N=471	
	Mean	Std. Dev.	Mean	Std. Dev.
Uniform Index (UI)	0.279	0.289	0.286	0.262
Weighted Index (WI)	0.245	0.279	0.256	0.261
PHO (from UI)	1.251	1.243	1.314	1.122
PHO (from WI)	1.203	1.278	1.306	1.167
Treated line (T)	0.468	0.500	0.482	0.500
Student	0.843	0.364	0.851	0.356
Female	0.525	0.500	0.501	0.501
Commuter	0.397	0.490	0.372	0.484
Frequent User	0.854	0.353	0.868	0.338
Cook	0.786	0.410	0.769	0.422
Label	0.806	0.396	0.794	0.405
FV5	0.026	0.160	0.030	0.170
Water	0.778	0.416	0.726	0.446
Weight	0.327	0.470	0.344	0.476
Nutritionist	0.255	0.436	0.225	0.418
Active	0.691	0.463	0.705	0.457

Source: Own data elaboration.

provision on the level of the index (UI and WI)[5]. These results are in line with several other studies which found information based policies are effective on improving consumer awareness but not necessarily to significantly impact behavior (Galizzi, 2014).

Results show students tend to be more reluctant to change their food selections (for all models coefficients are negative and significant). In line with previous studies (i.e. Krieger *et al.*, 2013), this paper also finds women have a different attitude towards menu labeling, with specifications (3) and (4) of table 4 showing positive and significant coefficients.

Frequent users of the canteen service do not seem to respond differently than less frequent users (i.e. coefficients are not significant). This study also finds people who sometimes or often cook their own meal tend to have a higher index under the LCL approach, while for the CRL the difference is not significant.

Variables associated with more attention to the diet, as the attitude on reading food labels, or consuming more fruit and vegetables, are significantly correlated with higher PHO under the CRL scheme, but not under the LCL. Similarly, people who declare to never substitute water with other drinks, or having required the opinion of a nutritionist, tend to have higher PHO, with a positive improvement of the index, only under the LCL scheme. Furthermore, results show variables such as having gained weight in the previous six months, or practicing sport at least once a week, are not associated with different PHO.

[5] This study considers only a selected sample of a university cafeteria in Italy, for regulatory purpose and policy interventions an extended study with a more representative sample need to be consider.

Table 4. Results - Ordered Logit model.

VARIABLES	(1) (UI LCL)	(2) (WI LCL)	(3) (UI CRL)	(4) (WI CRL)
T	0.019	-0.121	0.260	0.146
	(0.175)	(0.175)	(0.171)	(0.170)
Student	-1.024***	-1.263***	-1.387***	-1.366***
	(0.232)	(0.235)	(0.251)	(0.246)
Female	0.008	-0.046	0.310*	0.368**
	(0.179)	(0.178)	(0.182)	(0.183)
Commuter	-0.139	-0.189	-0.786***	-0.769***
	(0.184)	(0.183)	(0.186)	(0.185)
Frequent User	-0.025	0.091	0.021	0.076
	(0.264)	(0.262)	(0.269)	(0.268)
Cook	0.500**	0.514**	0.216	0.252
	(0.222)	(0.222)	(0.214)	(0.212)
Label	0.044	0.024	0.399*	0.430**
	(0.229)	(0.229)	(0.216)	(0.216)
FV5	0.544	0.671	1.042**	1.188**
	(0.568)	(0.559)	(0.482)	(0.475)
Water	0.550**	0.493**	0.305	0.280
	(0.220)	(0.219)	(0.204)	(0.201)
Weight	0.120	0.041	-0.018	-0.073
	(0.190)	(0.189)	(0.180)	(0.179)
Nutritionist	0.396*	0.469**	0.345	0.199
	(0.203)	(0.202)	(0.211)	(0.209)
Active	-0.052	-0.066	-0.003	0.175
	(0.192)	(0.190)	(0.201)	(0.199)
Constant cut1	-0.254	-0.554	-1.222***	-1.064**
	(0.461)	(0.470)	(0.456)	(0.450)
Constant cut2	0.195	0.245	-0.200	0.151
	(0.461)	(0.469)	(0.452)	(0.448)
Constant cut3	1.753***	1.503***	1.734***	1.745***
	(0.470)	(0.476)	(0.460)	(0.457)
Constant cut4	3.333***	2.534***	3.306***	2.963***
	(0.512)	(0.495)	(0.508)	(0.484)
Observations	459	459	471	471

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5. Discussion

The main objective of this research was to analyze whether the provision of nutritional information influenced the meal composition in an away-from-home environment. To this end, we conducted a field experiment at a university cafeteria.

The use of information based policies is among the most debated instruments when policy makers look for solutions to promote behavioral changes towards healthier and more sustainable food choices. Yet, effects of these information-based policies on actual behavioral changes are mixed. While some previous studies have found some potential benefits of menu labeling in a restaurant setting, in terms of calorie intake reduction and healthier food choices (Oliveira *et al.,* 2018; Ellison *et al*., 2013; Roberto. *et al*., 2010), this paper did not find any statistically significant effects of caloric labeling on food selections, in accordance with several other studies (Elbel. *et al*., 2009; Swartz *et al*., 2011; Downs *et al*. 2009; Mazzocchi and Trail, 2005; Swartz *et al.* 2011; Kiszko *et al*., 2014; Harnack and French, 2008).

While these results can also be driven by the experimental settings, they suggest that compulsory nutritional labeling in a dining-out environment may not be effective per se. First the effect of a label on dietary choices depends on many unobservable or not-recorded factors, such as the environment characteristics, the sample composition, the way the labels have been explained and communicated, the type of labels, and many behavioral characteristics. Most of the studies are referred to relatively small sample and to selected group (such as university students), so it becomes difficult to generalize the results from this type of studies to the whole population, as well to find ad hoc recipe valid for all settings. Further, even if a strong link between nutritional label and caloric intake reduction as well as food environment improvement would be found, there would still be the need to consider the final outcomes of this policy interventions on health and BMI (Jaime and Lock, 2009).

Bonanno *et al.* (2018), using a quantile regression approach, have shown that the relationship between reading food labels and BMI highly differs among demographics groups. Krieger *et al.* (2013) have measured the effect of calories posting in fifty restaurants, and after eighteen months, have found a decrease of menu calories only in some sites and in women, but not in men. These previous studies highlight the difficulties to find a "best for all" policy. Thus, some ad-hoc interventions are needed to set up eating environments where healthy food choices are enhanced.

In this sense, the synergies among different actions can be valuable to reach broader demographic groups. However, in general, especially in cafeterias linked to educational or working environments, a sure action that need to be reinforced is the setup of common protocols to monitor the nutritional quality of the service and to measure the effect of any in-site healthy initiative. Only continuously and carefully monitoring the nutritional quality of food options and the effects of interventions can ensure their effectiveness on enhancing healthier behavioral changes.

6. Conclusions and policy implications

The provision of nutritional labels in a food canteen have many practical difficulties. First, recipes need to be standardized and carefully followed; second, dish sizes need also to be standardized, with additional burdens on the food preparation process. However, asking to provide nutritional labels without enforcing the use of standard procedures on food preparation might lead to misleading information signaling, while, at the same time, enforcing this standardization might push out of business small no-chained restaurants (Mazzocchi *et al.*, 2009). Given these practical issues, applying the requirements for the labels only to chain restaurants, as experimented in the USA, is probably the easiest option to be applied in Europe. Moreover, chain restaurants are usually chosen to dine out by people driven by time and price constraints, which represent a population group most likely to be targeted by policy makers.

However, even if nutritional labels alone will not be the solution to the obesity problem, their provision can increase consumer awareness and lead to some beneficial spillover effects, such as encouraging restaurants to offer healthier food and meal "reformulation" (Schulman, 2010). As nutritional information is presented to consumers, restaurants might find incentives to offer lower calorie and healthier options, as observed by Ellison *et al.* (2014).

In this scenario, if the final goal of these policies is to improve the healthiness of food choices, our results, together with the existing literature, suggest the need of continuous monitoring of behaviors in order to design effective policies. However, we can also think of label policies for only their information value "per se", independently from their effect on final food choices and health outcomes. In this sense, Marette *et al.* (2019) have found a traffic light label significantly impacts the willingness to pay for the different types of products offered in an experiment, showing that consumer positively evaluate the provision of an easily readable label. An analysis sizing the cost and the benefits of implementing a labeling policy could be valuable to understand to what extent this policy is economically feasible and if it can be potentially sustained under a voluntary scheme. However, at this end, it is also important to consider that the literature has previously mentioned that an overload of information reduce the marginal effect related to it (Keller and Staelin,1989), at the point that consumers can even lose any interest, which is a big challenge for regulators.

In accordance with previous findings, we believe that, in order to encourage behavioral changes in an away-from-home food environment, public policies need to rely on a multifaceted approach, where the provision of nutritional information synergizes with other instruments such as nutritional education, social norms provision and nudges (Downs *et al.*, 2009; Thapa and Lyford, 2014; Thunström and Nordtröm, 2013, Burger *et al.* 2010, Storcksdieck genannt Bonsmann and Wills 2012, Castellari and Berning, 2016). Moreover, the discussion highlights the importance of reinforcing common protocols to ensure the nutritional quality of the food options in cafeterias, and to constantly monitor any intervention promoting healthy food styles. Moreover, further research needs to evaluate if the implementation of a "health related" intervention in a cafeteria, such as the introduction of nutritional label, has an effect on the sustainability of the food environment and on the produced waste. Overall, it is important for regulators to follow a multidisciplinary and systemic approach to the food system where all possible spillovers from the demand and supply side are evaluated in order to promote a more sustainable and healthy food environment.

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Short Communication

A preliminary test on risk and ambiguity attitudes, and time preferences in decisions under uncertainty: towards a better explanation of participation in crop insurance schemes

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Abstract. The exposure of farmers to different (and increasing) risks has been recognized by the EU policy, which supports several risk management tools through the Common Agricultural Policy (CAP). Despite the vulnerability of the agricultural sector, and the attention paid at the EU level, the uptake of such tools is generally low across EU countries. The Italian case is emblematic: the uptake of subsidized crop insurance contracts is low, limited to few products, and concentrated in few areas. Coherently, the interest of policy makers toward explaining these characteristics and in gaining insights on the interventions that may help promoting participation is intense. This contribution investigates behavioral aspects linked to choices under risk and ambiguity, and account for time preferences in order to mimic the scenario faced by the potential adopters of the subsidized crop insurance contracts in Italy. Data are collected through questionnaires submitted to students from agricultural colleges in three administrative regions located in northern, central and southern Italy. Results show that attitude toward risk, ambiguity, and impatience are correlated with the intrinsic characteristics of respondents. In addition, some of those attitudes may help explaining decisions under uncertainty. Despite the empirical analysis is preliminary and focused on students, it allowed to validate a promising methodological approach capable of explaining farmer's willingness to adopt (or renew) insurance contracts. By accounting for (currently under-investigated) behavioral aspects, it is likely to prove useful to re-design or implementing, more effectively, the current policies.

Keywords. Insurance, subjective probabilities, risk preferences, choice experiment.

JEL codes. D81, D83, Q18.

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1. Introduction

Risk affects all economic activities, and the agricultural sector shows specific factors that make yields, input and output prices highly variable. The increased volatility of these variables was shown in recent years, and it is possibly due to frequent adverse phenomena and extreme climatic events. At European level all countries are affected, and Italy seems one of the most spoiled country. The Italian agricultural sector is largely exposed to risky events, as shown by Trestini *et al.* in 2017. Among EU members, from 1998 to 2006 Italy registered the highest number of farms experiencing a decline in farm income exceeding -30% (on average) (European Commission, 2009); moreover, 35% of Italian farmers experienced income decrease events from 2007 to 2013 (European Commission, 2017).

According to the economic theory, price volatility should incentivize farmers to adopt risk management tools (RMT): put differently, the increasing uncertainty should increase the latent demand for RMT. The increasing uncertainty and the availability of new instruments introduced by the 2008 CAP Health Check should have favoured the diffusion of these policy instruments (e.g., mutual funds and subsidized insurance contracts). However, the implementation of risk management tools is limited, and the adoption of these instruments is currently rather scarce. Such a contingent scenario is worrisome, provided that a correct use of risk management policies would allow EU countries to increase the resilience of their agricultural sector to external shocks. The EU Regulation 1305/2013 promotes three types of measures, respectively under art. 37, 38 and 39: crop insurance, mutual funds, and the income stabilization tool. The Italian Ministry has budgeted a large amount of financial resources to promote these measures but, despite a great attention and a large turmoil, the experiences on mutual funds and Income Stabilization Tool are scant (Severini *et al.*, 2018; Trestini *et al.*, 2018), and subsidized single crop insurances are still the most adopted RMT. However, the subsidized insurance programs are not always stories of success. In Italy, participation in crop insurance programs is low, heterogeneous, and (recently) declining (Santeramo, 2019), making it a pressing issue for policymakers. This decline is also associated to recent policy changes. The last CAP reform has moved the support to RMT to the Rural Development Policy, changing the administrative rules of the system. In Italy this transition has resulted in a lack of familiarity with the rules, in delays in payments for subsidies and indemnifications and, at the end, in a reduced uptake of crop insurance schemes.

The current literature falls short in explaining the peculiarities of crop insurance adoption in Italy, and more precisely, it has not explored the potential role of ambiguity aversion and time preferences on participation in crop insurance programs.

Understanding the behavioral aspects of potential adopters of RMT is crucial to both design and implement effective policy interventions and avoid low and sparse uptake. The Italian case is an emblematic one and it allows to focus on long-standing issues that need to be solved at national and EU level. The Italian (subsidized) crop insurance system is characterized by high adoption rate in the north, and low participation rate in central and south regions.

Apart from the main drivers of farmer behavior under uncertainty and of adoption of risk management tools, several attitudinal aspects are likely to matter. Departures from rationality and non-coherent choices with respect to risk perception help explaining farmers' choices. A recent study (Sutter *et al.*, 2013) suggests that attitudes toward ambiguity, due to incomplete information, as well as differences in risk perception, and in time preferences are likely to play a pivotal role for decisions under uncertainty.

This paper is a preliminary attempt to assess the validity of an empirical methodology to evaluate if and how behavioral factors (risk and ambiguity attitudes and time preferences) may affect the decision-making process under uncertainty. Our setup has been inspired by the framework faced by potential adopters of crop insurance. The analysis, conducted on a sample of students of agricultural disciplines allows to conclude on whether the methodological approach is worth replication to a set of Italian farmers, representative of the latent demand for crop insurance contracts.

The analysis is divided in two steps. First, we investigate how socio-economic characteristics tend to influence risk aversion, ambiguity aversion and time preferences. Second, we explore how socio-economic characteristics as well as risk aversion, ambiguity aversion and time preferences may help explaining choices under uncertainty (smoking, practicing sport and playing lottery).

2. On Italian insurance market and factors affecting farmers' adoption

2.1 The Italian market for subsidized crop insurance contracts

Risks linked to natural disasters have been recognized since long-time in agriculture as unexpected sources of losses for farmers, especially for those highly vulnerable that are not adopters of risk management strategies. The shift from ex post compensations to ex-ante measures, and to subsidized crop insurance contracts, has been a concrete effort to promote the diffusion of risk management strategies.

According to ISMEA (2018), the Italian market (2004-2010) is characterized by a limited adoption of insurance contracts. Subsidized insurance market reached a maximum of 265,000 contracts in 2008, followed by declines in the number of contract subscriptions. Differently, total compensation rose constantly, signalling the low (economic) sustainability of the system, exacerbated by an adversely selective participation process: as contacts' prices rise, farmers with lower probability of facing adversities quit the market, contributing to the increase of the total amount of compensations paid by insurers (and by public funds). Since 2010 the public contribution to contracts decreased to 65% (according to EU Reg. 73/2009) and has been devoted (since 2014) to contracts that cover at least three climatic adversities. These changes do not seem to push the market too far. Last (public) data referred to 2015 (ISMEA, 2018) depicts a similar picture: from 2010 to 2015 contracts have decreased by 20% (from 210,000 to 168,000), while the insured area remained unaltered (+5%); the insured value raised by 20% as well (from 4.8 to 5.6 billion euro), and it has generated a 4% increase in the premium paid by farmers and through public funds (from 279 to 381 mil euro). The geographical distribution of contracts tends to be concentrated in northern regions, which account for more than 80% of the insured value (ISMEA, 2018). In addition, only few products account for most of the total insured value: indeed, apple, corn, rice, grapes, and tomatoes account for 2/3 of the covered value.

2.2 On the drivers of crop insurance uptake

The identification of the drivers of crop insurance uptake is still open and vivid (Enjolras *et al.*, 2011; Santeramo *et al.*, 2016). More important, there has been a limited effort in investigating how farmers' behavioral aspects may help explaining the adoption and/or renewal of crop insurance contracts, exception made for Menapace *et al.* (2015).

Key drivers of uptake are the age and the income level: Ogurtsov *et al.* (2009) found a positive correlation for age and adoption of crop insurance contracts, while Wąs and Kobus (2018), Liesivaara and Myyrä (2017) and van Winsen *et al.* (2016) suggested that the opposite is true; as for the income level, Menapace *et al.* (2015) found a positive correlation with uptake, while Wąs and Kobus (2018) and Farrin *et al.* (2016) concluded on the opposite direction for correlation.

Ambiguous results have also been found for risk aversion, which has been found positively correlated with age, according to Nielsen *et al.* (2013) and van Winsen *et al.* (2016), and negatively correlated according to Franken *et al.* (2017) and Goldstein *et al.* (2008). Heterogeneous results are also reported for the farm size, positively correlated with risk awareness in Franken *et al.* (2017), and negatively correlated with risk awareness according to van Winsen *et al.* (2016).

Furthermore, the low participation level may be due to a low level of familiarity with the instrument (Santeramo, 2018 and 2019; Santeramo *et al.*, 2016). Subscription of new contracts tend to be influenced by size, degree of crop diversification and irrigated area (Enjolras and Sentis, 2011; Finger and Lehmann, 2012); moreover, Santeramo *et al.* (2016) argued that farmers tend to consider crop diversification (and irrigation) and insurance contracts as alternate management strategies with a high degree of substitutability. The policy framework is also playing a role: for instance, greening requirements push toward crop diversification to help preserving the environment; measures of income support (e.g. direct payments or agri-environmental measures) are aimed at reducing famers' income instability and may prove substitutes for other risk management tools (Severini *et al.*, 2017).

A contingent scenario, faced by Italian farmers, is that the bureaucratic aspects related to subscription and reimbursement procedures, and the delays in refunds (ISMEA, 2018), may have discouraged participation and renewal of crop insurance contracts. From 2010 to 2014 the share of new adopters (14%) of (subsidized) crop insurance contracts has exceeded the number of farmers who gave up (11%). Differently, and possibly due to the delays in payments and to the (perceived) ambiguity of the newly adopted rules, in 2015 the quitters overcame new adopters, and the net balance between new entrants and leavers was largely negative (-11%).

3. Methodology and data collection

The above presented scenario has emphasized the importance of focusing on three specific aspects: risk aversion, ambiguity aversion, and time preferences. This paper investigates how attitudes toward uncertainty (risk and ambiguity) as well as time preferences influence risky decisions. The dataset includes data on 50 students from three different universities (Faculty of Agricultural Sciences) in Italy: namely, the University of Padova

(Padova) in the North, Tuscia University (Viterbo) in Central Italy and University of Foggia (Foggia) in the South. The research is part of a wider ongoing study aiming at investigating Italian farmers' decision making under uncertainty: particularly, the broader aim is to study the factors influencing the insurance schemes' uptake. The experimental methodology is inspired by the canonical Holt and Laury (2002) choice lists and, more specifically, by the approach proposed by Sutter *et al.* (2013). In order to elicit individual preferences related to risk aversion, ambiguity aversion and time preferences, respondents received a structured questionnaire with three experiments and ten control questions.

More specifically, the first and the second experiments (Fig. 1) are made by a list of 11 choices with two options each: at any given choice respondents choose between a sure payoff (option A), and a gamble (option B). The sure payoff is iteratively decreased (from 100 to 1€) so to elicit the indifference point between the lottery and the sure payoff. The lottery has been simulated by extracting a random number from a uniform distribution ranging from 1 to 100 being the number 50 excluded (in order to have symmetrical probability distributions between the two outcomes). In the first experiment, aimed at eliciting risk preferences, respondents may win (for instance) 100€ if the randomly extracted number ranges between 1 and 49, or nothing, if the randomly extracted number is larger than 51. In order to get respondents acquainted with the functioning of the lottery, respondents have been exposed to a computer simulation of ten random draws from 1 to 100 (the extraction of the number 50 implies a further extraction), and have been informed on the cases in which they would have won the lottery. The second experiment, aimed at eliciting ambiguity aversion, compares the choices for a sure payoff and a (ambiguous) lottery. The lottery pays out if, by extracting two random draws, the second extraction gives a larger number than the one extracted in the first place. The ambiguity arises by a peculiarity: the result of the first extraction is not revealed, whereas only the second extraction (and the outcome of the lottery) is revealed. For instance, by drawing the number 20 and successively the number 35, the lottery results in a winning outcome.

Finally, in the third experiment aiming at measuring time preferences (Fig. 2), respondents received two lists (blocks) of ten choice sets each. Each choice set consisted in two sure payoffs (A and B) that respondents may receive in different periods: option A is a "early payoff" of 100€, whereas option B is a "late payoff" which is increased from 100€ to 190€. Depending on respondents' preference for receiving a sure payoff earlier (i.e., "now") or later (i.e., "in 12 months"), we elicited respondents' attitude in delaying the win (or, put differently, their impatience).

Prior to the survey, we paid attention to ensuring that participants were able to understand the questions, and that the experiments were correctly explained. We design a *ran-*

Figure 1. Example of a choice list for experiment 1 (risk attitude) and 2 (ambiguity attitude)

	Option A	Option B
1	Sure payoff (100€)	Lottery
2	Sure payoff (90€)	Lottery
3	Sure payoff (80€)	Lottery

Source: own elaboration.

Figure 2. Example of a choice list for experiment 3 (time preference).

	Option A	Option B
1	Receive 100€ today	Receive 100€ in 12 months
2	Receive 100€ today	Receive 110€ in 12 months
3	Receive 100€ today	Receive 120€ in 12 months

Source: own elaboration.

dom lottery incentive system (Cubitt *et al.*, 2019), often used in individual choice experiments, to motivate respondents to reveal their true preferences: at the end of the experiments we ran a real lottery with the ten percent of (randomly selected) respondents: if their questionnaires did not present incoherent answers (as found in all cases), they played the game included in the questionnaire with the possibility of winning part of the money of the bet (more precisely, 10% of the money at stake), in case of favourable outcome.

The individual Certainty Equivalent (CE) has been calculated for experiment 1 and 2 (CEr and CEa, respectively), as midpoint between the two consequent payoffs for which the interviewee switched from option A (i.e., sure payoff) to option B (i.e., gamble). Accordingly, CE represents the payoff that makes the individual indifferent between receiving the sure amount and gambling. To measure risk attitude (experiment 1), we calculated the coefficient of risk aversion (r) as follows (Sutter *et al.*, 2013):

$$r = 1 - \frac{CE_r}{\pi} \tag{1}$$

with π representing the prize of the gamble (i.e., 100€). This coefficient ranges from 0 to 1, with values of r larger than 0.5 indicating risk aversion, whereas smaller than 0.5 risk loving and equal to 0.5 risk neutrality. Moreover, in the second experiment we measured the coefficient of ambiguity attitude (a) as follows:

$$a = \frac{CE_r - CE_a}{CE_r + CE_a} \tag{2}$$

The coefficient a ranges from -1 to 1, with negative numbers representing ambiguity loving, 0 standing for ambiguity neutrality and positive numbers indicating ambiguity aversion. As regards the third experiment, we calculated the Future Equivalent (FE) of the fixed payoff as the midpoint between the two consequent later payoffs where the interviewee decided to switch from option A to B. The larger the FE, the larger the aversion for delayed payments (i.e., impatience). Finally, in order to control for the main drivers of decisions under uncertainty, we collected information on age (age), gender (gender), number of university credits achieved (ECTS credits), average grade (max 30) (average grade), and on whether the respondent does not have a technical high school degree (degree), on smoking habits (being a smoker), on habits to practice physical activity (sport practicing), and on habits to play lottery or sport betting at least once a month (playing lottery). Finally, we recorded whether the respondent is owner (or son of the owner) of a farm (family farm) and, whether the respondent has ever worked on a farm even for a short period of time (farmworker).

The empirical strategy is admittedly simple, yet rigorous and comparable with the approach suggested in Sutter *et al.* (2013). First, we use a linear regression to conclude on the effects of some socio-demographic variables on: i) the coefficient of risk aversion (r), ii) the coefficient of ambiguity aversion (a), iii) time preferences (i.e., future equivalent at 12 months). Second, we use a linear regression to investigate how risk aversion, ambiguity aversion and time preferences (FE_12m) influence behaviors characterized by decisions under uncertainty: i) being a smoker; ii) sport practicing; iii) playing lottery.

4. Hypothesis testing and results

As shown in Table 1, the sample consists of 78 observations, mostly male students (78%). Most participants have not a technical high school background (51%), are not smokers (64%), practice sports activities (60%), and do not play lotteries (80%). The average number of credits acquired by sampled students is 132, while the average grade is 26. In terms of coefficients of risk aversion and risk ambiguity, we have quite heterogeneous results: the coefficient of risk aversion ranges from 0.05 to 0.95 and the coefficient of ambiguity aversion ranges from -0.50 to 0.83. Similarly, we have time preferences computed at 12 months ranging from 105 to 185.

The sample is mainly composed of risk averse (51%) and ambiguity averse students (51%), whereas the future equivalent shows a greater impatience for risk neutral and ambiguity averse subjects (Table 2).

We regress attitudes toward risk and ambiguity on control factors (Table 3). The considered observable characteristics do not allow to explain these attitudes. Regarding risk aversion, only the variable "degree" is positively correlated with risk aversion, regardless of students' career characteristics (number of credits acquired) and average grade, and of respondent's social characteristics (gender, age, farm owner and farming experience). There are no significant coefficients in the case of ambiguity aversion.

Results seems to be in line with studies (e.g. Sutter *et al.*, 2013) that refer risk attitude and ambiguity not influenced by ordinarily observable characteristics.

As shown in Table 4, we also found a positive significant correlation between the degree of impatience and gender, degree and past experience in farm work, showing that males with non-technical degree are less impatient, while subjects who already had a work experience related to agricultural sector are more impatient. Conversely, we did not find any relevant effect for risk and ambiguity aversion. In general, we found that attitudes toward uncertainty (risk aversion, ambiguity aversion, and impatience) are correlated with intrinsic characteristics of the students, hereafter referred as control factors.

Following Sutter *et al.* (2013) we use the control factors (age, gender, degree, ECTS credits, average grade, family farm, and farmworker) and the attitudes toward risk, ambiguity and time, to explain decisions under uncertainty. We regress "being a smoker", "sport practicing" and "playing lottery" on control factors and variables on attitudes.

We found that average grade and risk aversion are statistically significant having a negative effect on being a smoker, whereas impatience has a slight positive effect on the

Table 1. Descriptive statistics of the sample (N = 78).

Variable	Type		%	Mean	Std	Min	Max
Age	Continuous			23.39	2.22	20	29
Gender	Dummy	1 = male	78.20				
		0 = female	21.80				
Degree[1]	Dummy	1 = yes	51.30				
		0 = no	48.70				
ECTS credits[2]	Continuous			131.51	57.99	23	300
Average grade (max 30)	Continuous			25.72	2.04	21	29.7
Family farm	Dummy	1 = yes	28.20				
		0 = no	71.80				
Farm worker	Dummy	1 = yes	61.50				
		0 = no	38.50				
Being a smoker	Dummy	1 = yes	35.90				
		0 = no	64.10				
Sport practicing	Dummy	1 = yes	60.30				
		0 = no	39.70				
Playing lottery	Dummy	1 = yes	20.50				
		0 = no	79.50				
r	Continuous			0.48	0.16	0.05	0.95
a	Continuous			0.08	0.22	-0.50	0.83
FE_12m	Continuous			146.54	20.83	105	185

[1] Subjects without a technical high school background ("Liceo" in Italy).
[2] ECTS credits express the volume of learning based on the defined learning outcomes and their associated workload. 60 ECTS credits are allocated to the learning.

Table 2. Risk and ambiguity attitude (%) and future equivalent (N = 78).

Category	%	Average FE_12m[1]
Risk averse	51.3%	146.50 (20.07)
Risk neutral	24.4%	149.21 (24.79)
Risk seeker	24.4%	143.95 (18.83)
Ambiguity averse	51.3%	148.00 (20.78)
Ambiguity neutral	19.2%	147.00 (23.36)
Ambiguity seeker	29.5%	143.70 (19.84)

[1] Standard deviations are reported in parentheses.

same characteristic (Table 5). Impatience seems to play a slight role on sport practicing too, being instead negatively correlated. Regarding playing lottery, a significant positive correlation emerged for gender (all respondents that practice gambling are males), num-

Table 3. OLS - Risk Aversion (r) and Ambiguity Aversion (a).

	Dep. Var.					
	Risk Aversion (r)			Ambiguity Aversion (a)		
	β	S.E.	P>|t|	β	S.E.	P>|t|
Age	0.003	0.010	0.756	-0.012	0.013	0.355
Gender	0.033	0.046	0.476	0.008	0.063	0.900
Degree	0.068	0.040	**0.088***	-0.082	0.055	0.137
ECTS credits	-0.001	0.001	0.185	0.001	0.001	0.448
Average grade	0.008	0.010	0.456	0.015	0.014	0.307
Family farm	-0.032	0.046	0.486	-0.036	0.064	0.568
Farmworker	0.006	0.042	0.888	0.024	0.058	0.678
cons	0.278	0.328	0.401	-0.036	0.457	0.983
Obs		78			78	
Prob > F		0.574			0.695	
Adj R^2		-0.017			-0.031	

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 4. OLS - Impatience (FE_12m).

	Dep. Var.		
	Future equivalent 12 months (FE_12m)		
	β	S.E.	P>|t|
Age	0.039	1.234	0.975
Gender	-9.918	5.831	**0.094***
Degree	-8.656	5.146	**0.097***
ECTS credits	-0.037	0.053	0.484
Average grade	0.998	1.330	0.455
Family farm	-7.290	5.873	0.219
Farmworker	9.760	5.331	**0.072***
r	11.212	16.183	0.491
a	9.264	11.626	0.428
cons	127.054	42.084	0.004
Obs	78		
Prob > F	0.206		
Adj R^2	0.045		

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 5. OLS Estimates on being a smoker, sport practicing, and playing lottery.

	Dep. Var.								
	Being a smoker			Sport practicing			Playing lottery		
	β	S.E.	P>|t|	β	S.E.	P>|t|	β	S.E.	P>|t|
Age	0.029	0.028	0.310	-0.022	0.030	0.465	-0.010	0.022	0.643
Gender	-0.091	0.136	0.506	0.169	0.146	0.248	0.265	0.108	**0.016****
Degree	0.139	0.120	0.250	-0.071	0.128	0.584	0.116	0.095	0.225
ECTS credits	-0.001	0.001	0.986	0.001	0.001	0.739	0.002	0.001	**0.019****
Average grade	-0.056	0.031	**0.074***	0.038	0.033	0.250	-0.063	0.024	**0.011****
Family farm	-0.036	0.136	0.792	0.078	0.145	0.594	0.215	0.107	**0.050***
Farmworker	0.075	0.125	0.548	-0.033	0.134	0.805	0.021	0.099	0.830
r	-0.914	0.371	**0.016****	0.232	0.397	0.561	-0.247	0.294	0.404
a	-0.394	0.267	0.145	0.242	0.286	0.399	-0.170	0.211	0.423
FE_12m	0.005	0.003	**0.093***	-0.005	0.003	**0.079***	-0.001	0.002	0.523
cons	0.850	1.025	0.410	0.636	1.095	0.563	1.767	0.811	0.033
Obs.		78			78			78	
Prob > F		0.134			0.590			0.008	
Adj R^2		0.069			-0.021			0.179	

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

ber of credits acquired (with a positive slight coefficient close to zero) and being part of a family involved in farming activities. Average grade shows negative correlation indeed.

Respondents showing little risk aversion and high levels of impatience smoke more, whereas less impatient individuals practice sport more. Men are found to play lottery more than women. As shown by "ECTS credits", students up to date with credits play lottery more, whereas "average grade" shows that best students play lottery and smoke to a lesser extent. Interestingly, the higher the impatience (i.e., subjects who have a higher future equivalent with 12 month-delay condition), the less they practice sport. Lastly, ambiguity aversion coefficients don't show significant relations with the analysed dependent variables.

To summarize, both observable characteristics and behavioral characteristics (risk aversion, ambiguity aversion and time preferences) help explaining choices under uncertainty, particularly smoking and playing lottery. It is important to note that, as expected, risk aversion is negatively correlated with smoking while impatience is positively correlated with smoking while negatively with practicing sport.

5. Concluding remarks

Risk management policies for the primary sector are under the spotlight in the EU: large subsidies have been granted for crop insurance programs and mutual funds. The EU Regulation 1305/2013 establishes rules and funds that may be adopted by Member States to promote participation in crop insurance programs (art. 37), to start and manage mutual funds (art. 38) and to enhance the start of the Income Stabilization Tool (art. 39). Despite the clear interest of the policymakers, the academic debate seems behind. The economic literature provides several hints to explain farmers' uptake in crop insurance programs, but several determinants (other than farm size, farmers' education, relationships with other risk management strategies, and insurance premia) are still under-investigated. In particular, while the literature on insurance programs (i.e. health, car and life insurance) has emphasized the role of information, and of individual attitudes toward uncertainty, ambiguity and impatience, there is little evidence on the role of ambiguity and impatience on farmers' decision to adopt crop insurance contracts.

Based on these premises, we tested the validity of a methodology in exploring how risk and ambiguity aversion, and impatience may influence the decision-making process for risky activities. Our test, conducted on a sample of students, has been calibrated on behavioral aspects that are likely to matter for potential adopters of (subsidized) crop insurance contracts. We asked students involved in university programs related to agricultural sciences to declare if they experienced working in a farm. Similarly, we investigated decisions under uncertainty proxying risky decisions such as those related to the adoption of crop insurance programs.

We found that the attitudes toward uncertainty (risk aversion, ambiguity aversion, and time preferences) are weakly correlated with some intrinsic characteristics of the students. These attitudes cannot be satisfactorily explained by few observable characteristics. In contrast, we found evidence that attitudes toward risk and impatience may help explaining agents' decisions under uncertainty. This suggests including agents' attitudes in future research to prevent biased inference due to missing explanatory factors which would lead to ineffective policy recommendations.

Despite the analysis is still preliminary and applied to students, the approach we have taken seems promising in explaining potential residual factors that may affect farmer's willingness to adopt (or renew) insurance contracts. Hence, future research on this latter issue should take into consideration not only farmers' risk aversion but ambiguity aversion and time preferences as well. These factors may be used to explain the limited (and heterogeneous) uptake of insurances. Furthermore, the empirical findings may help to better design and manage future policy measures: understanding the role of time preferences may be useful to address how delayed payments of reimbursements and indemnities may discourage participation.

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