Pesticide Use, Health Impairments and Economic Losses Under Rational Farmers Behavior

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Abstract

The present paper develops a novel methodology for measuring the economic losses resulting from the negative health impacts of pesticides while taking into account their role as a damage control agent. To this effect a production model is presented that takes into account both the effect of the health impairment caused by pesticides on labor units and the pest control and crop enhancing properties of pesticides. The supply-responses and optimal cost adjustments made by rational farmers in the absence of health effects are examined, which facilitates the proper measurement of the private economic losses associated with the health effects of pesticides. The biases in previous pest-damage measures that ignore the presence of health effects are also examined. The model is empirically applied to a unique panel dataset of Greek greenhouse producers where the use of health-hazardous pesticides is particularly prominent. Moreover the estimation of health impairment indices takes into account the observational nature of the data collected, applying recently developed treatment effects methods. The results show that farmers suffer considerable quasi-rent losses due to the negative effect of pesticides on health with the average being 1,511 Euros.

Keywords: chemical pesticides; farmer's health; economic losses; greenhouse farms
JEL Codes: *I12*, *I30*, *Q12*, *D24*.

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Introduction

The adverse effects of chemical pesticides on food safety and consumers' health have been at the centre of public discussions and policy regulation over the last two decades. However, one important effect of pesticides that was rather neglected from this policy debate, is the impact that these chemicals have on the health of farm workers. Chemical pesticides besides being toxic for pests, are also toxic for humans posing serious threats to the health of farm operators (Antle and Pingali, 1994; Sunding and Zivin, 2000; Calvert *et al.*, 2004; Thundiyil *et al.*, 2008; Huang *et al.*, 2016). Each year approximately one million farm workers experience severe unintentional poisoning from pesticides with pesticide applications listing amongst the top level of the most health-risky occupational activities in both developed and developing countries (WHO, 2009; Abdalla *et al.*, 2017). Besides the obvious social cost, health impairments due to pesticides entail also private costs for individual farms in the form of productivity losses arising from decreases in effective farm work (Crissman *et al.*, 1998; Loureiro, 2009; Sheahan *et al.*, 2017). Absenteeism from work due to illness, decreases in the physical capacities of farm workers, such as strength and endurance, and decreases in their mental capabilities, such as cognitive functioning and reasoning ability, are the most common paths through which pesticide-related health impairments decrease effective farm work.

The existing research in developing countries' agriculture[1] suggests that pesticide-related decisions are made by farmers in a sub-optimal way due to misinformation and myopic behaviour about the health risks of pesticides (Zilberman and Castillo, 1994). Low education levels of the rural population, poor spraying technology, and ignorance of safety rules are pointed out to play a major role in explaining farmers' bounded rationality and sub-optimal decisions in the rural areas of the developing world (Cropper, 1994; Athukorala *et al.*, 2012).[2] However, although these behavioural conditions have been empirically tested and confirmed in a set of developing countries, both casual scepticism and empirical evidence question their validity in developed countries' agriculture. In developed countries, educational levels are much higher and information about pesticide-related diseases is widespread. At the same time, pesticide application technologies are more advanced and safety rules and methods are likely to be well understood by farmers (FAO, 2019).

Thus, if farmers are indeed aware about both the health effects of pesticides and the available protection methods, then lack of averting behaviour is the only reason for the high rates of pesticide-related illnesses observed in rural populations of developed countries. According to Zilberman and

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[1] A series of studies by Antle and Pingali (1994), Antle and Capablo (1994), Pingali *et al.* (1994), Crissman *et al.* (1994), Antle *et al.* (1998) and others have provided valuable insights on the economic consequences of the trade-offs between farm productivity and farmer's health status.

[2] Under misinformation and myopic behaviour, the health effects of pesticides can be perceived as exogenous to farm operations. Farmers apply pesticides even when their total private costs exceed total benefits simply because they ignore the health costs of pesticides. Hence, the health effects of pesticides take the form of a negative externality for farms.

Castillo (1994) and Cropper (1994), there are three reasons for the lack of averting behaviour: (a) the cost of protective equipment, (b) the inconvenience cost that these practices entail for farm operators, and (c) the personal traits of individual farmers such as how careless they are.[3] While the cost of protective equipment seems to be trivial in most cases, the latter two reasons provide a significant non-arbitrary rationale in explaining why protection actions are not always undertaken by farmers in developed countries. In either case, under informed decision-making and rational behaviour, pesticide-related impairments in farmer's health are endogenous implying that farmers equate marginal costs to marginal benefits while accounting for the expected health costs of pesticides and the personal inconvenience costs related to the use of protective equipments.

Along these lines, based on the work of Antle and Pingali (1994), we extend Chambers *et al.*, (2010) theoretical framework developing a model to measure quasi-rent losses associated with the health effects of pesticides under rational producer behavior. Although the social cost of health impairments might not be of the interest of the farmers, the associated reductions in effective labor do matter for them since such reductions are accompanied by lower productivity rates. Hence, measuring the economic losses due to the negative effects of pesticides on human capital, may indirectly enforce safety standards in farm working environments reducing the associated social cost. If these economic losses are important for individual farms, then indeed improving farm workers' knowledge or applying more effective management practices would result to significant gains for them internalizing at the same time social costs.

The model is empirically applied to a unique panel dataset of Greek greenhouse producers. The data come from a primary survey covering five consecutive cropping seasons during the 2003-07 period and include rich information on pesticide-related health problems and costs faced by greenhouse producers. Using this information, health impairment indices are estimated for individual farm workers using the recent treatment effects estimation method developed by Cerulli (2015). More importantly, this approach accounts for treatment endogeneity and restores consistency making use of an instrumental variable approach. The endogeneity issue arises from the fact that pesticide application levels and pesticide-related health effects may depend on unobserved personality traits of farmers resulting in inconsistent estimates. This important source of endogeneity has been largely overlooked by previous studies in the field.

The rest of the paper is structured as follows. Next section develops the theoretical framework for measuring economic losses associated with the health effects of pesticides and economic losses due to pests. This is followed by the description of the survey and a discussion on the behavioral implications arising from the analysis of the farmers in the sample. The next two sections present

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[3] For many pesticide-related hazards, the true probabilities of getting ill (or even getting killed) are not known by farmers. Due to the underdeveloped state of occupational medicine, even the underlying medical ramifications of different exposures to aspects of the farming environment including chemical vapors are little understood.

the econometric specification of the health impairment and profit model, respectively, along with information on the variables used. The estimation results are then presented. Finally, the last section concludes the paper.

Theoretical Framework

Farm Crop Technology

The crop production technology in period t for a farm household with specific characteristics $s \in \Re^r_+$ is represented by the following closed, non-empty production possibilities set:

$$T(s,t) = \{(\ell, x, k, z, y) : \ (\ell, x, k, z) \text{ can produce } y \text{ for a given level of } (s,t)\}$$

where $\ell \in \Re_+$ are the hours worked by family members[4], $x \in \Re^n_+$ is a vector of variable-inputs used in farm production, $k \in \Re^m_+$ is a vector of quasi-fixed inputs, $z \in \Re_+$ are the pesticide materials applied on field, and $y \in \Re_+$ is crop output.[5] Farmers make typically their choices about pesticide use at the beginning of each cropping period. They observe pest population, market conditions such as pesticide costs and crop price, consider the health costs related to pesticide use and form expectations about farm profit flows. Based on this information set, farmers make next their decisions about the level of pesticide use. Although changes in application schedules in later stages can happen, these changes do not constitute a common practice. This is because in later stages of the production process, the use of pesticides is largely ineffective since damage is largely irreversible. Hence, pesticide materials are considered as a pre-determined input in crop production.

Exposure to pesticides affects equally both family and hired farm workers. Assuming though that farmers remunerate hired labor in effective units, this should have an impact on hired workers' income but not on the productivity of the farm as long as farmers face an elastic supply of hired labor (Antle and Pingali, 1994).[6] Hence, our focus is on the health effects arising only from impairments in the health of family workers. According to Antle and Pingali (1994) impairments in family members' health status due to application of pesticide materials, can be described from the following general function:

$$h = h(z, s) \tag{1}$$

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[4] In a farm household setting, the total hours of family work devoted to crop production are highly correlated with the number of family members which is a fixed resource endowment of the household. Therefore, family labor is treated as a quasi-fixed input in crop production.

[5] To keep the notation simple, we develop the model for a scalar output technology which is consistent with our empirical application focusing on a single crop. However, the extension to a multi-output case is largely an issue of notation.

[6] In other words, hired workers are paid the market wage for every unit of effective labor provided.

where $h \in \Re_+$ is the health impairment variable, and $h(z,s)$ is a continuous and twice differentiable function, non-decreasing and concave in z.[7] Then, following Bliss and Stern (1978), Strauss (1986) and Deolalikar (1988), effective family labor (ℓ^e) is proportional to hours worked on-farm as follows:

$$\ell^e = q\left(h(z,s)\right)\ell \tag{2}$$

where $q\left(h\right) \in (0,1]$ is a continuous and twice differentiable decreasing in h concave function. When $h = 0$ it holds that $q = 1$ and when $h \to +\infty$ then $q \to 0$. It also holds that $\partial\ell^e/\partial\ell \geq 0$ and $\partial^2\ell^e/\partial\ell^2 = 0$, that is a linear relationship.

Finally, following Lichtenberg and Zilberman (1986), Fox and Weersink (1995), and an extensive biological literature, our specification of the technology simultaneously recognizes the asymmetric role that damage-control agents play in the production technology. Thus, crop farm technology may be now defined as:

$$T(s,t) = \left\{(\ell,x,k,z,y) : y \leq f\left(\ell^e,x,k,t\right)g\left(b^r,z,\ell^e,k,t\right),\ \ell^e = q(h)\ell,\ h = h(z,s)\right\} \tag{3}$$

where $f\left(\ell^e,x,k,t\right)$ is a continuous and, strictly increasing, twice differentiable concave production function, representing maximal output obtainable from family labor input, variable inputs and quasi-fixed inputs with application of pesticides at z. Because our empirical application is for greenhouse farms, we assume that the long-run maximal output technology exhibits constant returns to scale in ℓ^e, x and k.[8] Finally, $g\left(b^r,z,\ell^e,k,t\right)$ whose range is restricted to lie in the unity interval represents the percentage of maximal output realized in the presence of pest infestation $b^r \in \Re_+$ with application of pesticides at z.[9] It is non-increasing and convex in b^r and non-decreasing and concave in (z, ℓ^e, k, t) as long as damage-control technology is improved over time.

Using (3) for a farmer facing crop $p \in \Re_{++}$ and variable-input $w \in \Re^n_{++}$ prices, the quasi-rents obtained from the endowment of family labor and quasi-fixed inputs with application of pesticides at z is

$$\begin{aligned}
\Pi\left(p,w,\ell,k,b^r,z,s,t\right) &\equiv \max_{x,y}\left\{py - w'x : y \leq f\left(\ell^e,x,k,t\right)g\left(b^r,z,\ell^e,k,t\right),\ \ell^e = q(h)\ell,\ h = h(z,s)\right\} \\
&= \max_{x}\left\{pg\left(b^r,z,\ell^e,k,t\right)f(\ell^e,x,k,t) - w'x,\ \ell^e = q(h)\ell,\ h = h(z,s)\right\} \\
&= \pi\left(pg\left(b^r,z,q\left(h(z,s)\right)\ell,k,t\right),w,q\left(h(z,s)\right)\ell,k,t\right) \qquad (4)
\end{aligned}$$

where $\pi(\cdot)$ is the restricted profit function. By standard results $\pi(\cdot)$ is sublinear (positively linearly

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[7] It's monotonicity properties with respect to farm-specific characteristics are discussed in the following sections.

[8] This assumption does not imply that $T(s,t)$ exhibits constant returns to scale as marginal returns in the damage-control agents, z, can be either increasing or decreasing.

[9] Accordingly, $1 - g\left(b^r,z,\ell^e,k,t\right)$, measures the percentage of output lost due to pests.

homogenous and convex) in (p, w), non-decreasing in p, and non-increasing in w. Because $f(\cdot)$ exhibits constant returns to scale, $\pi(\cdot)$ is also positively linearly homogeneous in the endowment of quasi-fixed factors of production. Thus, if the technology is smooth, the quasi-rent to the fixed input endowment can be decomposed into returns to each of the quasi-fixed factors of production as $\pi(\cdot) = \pi_k(\cdot)'k + \pi_\ell(\cdot)\ell$, where $\pi_k \in \Re^m_+$ and $\pi_\ell \in \Re_+$ denote the gradient of $\pi(\cdot)$ in k and ℓ, respectively. They define the shadow price for the relevant quasi-fixed factor while the inner product of the shadow-price vector and the vector of fixed factors completely exhausts quasi-rents.

Some useful insights can be gained by looking more carefully at relation (4). If there are no health impairments, then farmers utilize ℓ units of family labor with $\ell \geq \ell^e$. In this case, farmers collect revenues which are equal to $pg\left(b^r, z, \ell, k, t\right) f(\ell, x, k, t)$, with $pg\left(b^r, z, \ell, k, t\right) f(\ell, x, k, t) \geq pg\left(b^r, z, \ell^e, k, t\right) f(\ell^e, x, k, t)$. There are two reasons for which revenues increase if health impairments are absent: first, maximal output increases, $f(\ell, x, k, t) \geq f(\ell^e, x, k, t)$, given that $\ell \geq \ell^e$, and second, effective output price increases, $pg\big(b^r, z, \ell, k, t\big) \geq pg\big(b^r, z, \ell^e, k, t\big)$, as $g(\cdot)$ is non-decreasing in family labor input.

If there is a unique quasi-rent maximizing variable-input demands and supply, then through *Hotelling's Lemma* the profit function above is differentiable in p and w providing:

$$\begin{aligned} y\left(p, w, \ell, k, b^r, z, s, t\right) &= \Pi_p\left(p, w, \ell, k, b^r, z, s, t\right) \\ &= \pi_1\left(pg\left(b^r, z, q\left(h(z,s)\right)\ell, k, t\right), w, q\left(h(z,s)\right)\ell, k, t\right) \\ &\quad \times g\left(b^r, z, q\left(h(z,s)\right)\ell, k, t\right) \qquad \text{(5a)} \\ x\left(p, w, \ell, k, b^r, z, s, t\right) &= -\Pi_w\left(p, w, \ell, k, b^r, z, s, t\right) \\ &= -\pi_w\left(pg\left(b^r, z, q\left(h(z,s)\right)\ell, k, t\right), w, q\left(h(z,s)\right)\ell, k, t\right) \qquad \text{(5b)} \end{aligned}$$

where $\Pi_w \in \Re^n_-$ and $\pi_w \in \Re^n_-$ are the gradient of $\Pi(\cdot)$ and $\pi(\cdot)$ with respect to w, respectively, $\Pi_p(\cdot)$ denotes the partial derivative of $\Pi(\cdot)$ with respect to p, and $\pi_1(\cdot)$ is the partial derivative of $\pi(\cdot)$ with respect to its first argument.

Quasi-Rent Losses due to Health Impairments

To simplify notation, we first drop function arguments and then we denote with g^e, g^d, y^e and y^d crop damage and crop supply with and without the health effects, respectively.[10] We also denote with ℓ^e effective family labor as defined by (2). Then in the absence of health effects, a farmer

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[10] Crop supply without the health effects of pesticides is obtained by applying *Hotelling's Lemma* to the solution of the maximization problem in (4) excluding last two constraints.

applying pesticides at z, realizes a quasi-rent of:

$$\begin{aligned}\Pi(\cdot) &= \pi\left(pg^d, w, \ell, k, t\right)\\ &= pg^d\pi_1\left(pg^d, w, \ell, k, t\right) + w'\pi_w\left(pg^d, w, \ell, k, t\right)\\ &= py^d - c^d\left(w, \frac{y^d}{g^d}, \ell, k, t\right)\end{aligned} \tag{6}$$

where $c^d(\cdot)$ is the minimal variable cost associated with production in the absence of health effects. Similarly, with health effects present, quasi-rents from farming are:

$$\begin{aligned}\Pi(\cdot) &= \pi\left(pg^e, w, \ell^e, k, t\right)\\ &= pg^e\pi_1\left(pg^e, w, \ell^e, k, t\right) + w'\pi_w\left(pg^e, w, \ell^e, k, t\right)\\ &= py^e - c^e\left(w, \frac{y^e}{g^e}, \ell^e, k, t\right)\end{aligned} \tag{7}$$

where $c^e(\cdot)$ is the minimal variable cost associated with production in the presence of health effects. Subtracting (7) from (6), we obtain a complete measure of the economic losses related to the health effects of pesticides as:

$$Q^h\left(p, w, \ell, k, b^r, z, s, t\right) = \pi\left(pg^d, w, \ell, k, t\right) - \pi\left(pg^e, w, \ell^e, k, t\right) \geq 0 \tag{8}$$

which is non-negative as the restricted profit function is non-decreasing in output price and non-decreasing in family labor input. It captures both changes in the revenues realized by farmers and changes in the variable costs associated with the optimal adjustments of supply and variable inputs demand, respectively, *i.e.*,

$$Q^h\left(p, w, \ell, k, b^r, z, s, t\right) = R^h\left(p, w, \ell, k, b^r, z, s, t\right) - C^h\left(p, w, \ell, k, b^r, z, s, t\right) \tag{9}$$

where

$$R^h(\cdot) = p\left[\pi_1\left(pg^d, w, \ell, k, t\right)g^d - \pi_1\left(pg^e, w, \ell^e, k, t\right)g^e\right] \geq 0 \tag{10a}$$

$$C^h(\cdot) = w'\left[\pi_w\left(pg^e, w, \ell^e, k, t\right) - \pi_w\left(pg^d, w, \ell, k, t\right)\right] \geq 0 \tag{10b}$$

where $R^h(\cdot)$ is the difference between revenues in the absence of health effects and revenues realized by farmers in the presence of health effects. Note that in the absence of health effects, supply increases directly due to the increase in the endowment of family labor input but also indirectly due to the decrease in pest-damage. Therefore, this difference which is non-negative can been thought as the supply effect measuring revenue losses due to the health effects of pesticides. Moreover, $C^h(\cdot)$

is the difference between the minimal variable cost in the absence of health effects and the optimal variable cost in the presence of health effects. This difference is also non-negative since $w'\pi_w$ is decreasing in output price with $pg^d \geq pg^e$ and non-increasing in family labor input with $l \geq \ell^e$. This cost saving component tends to mitigate the revenue loss associated with the adverse health effects. Farmers realizing that variable-input use necessarily involves losses due to the presence of health impairments curtail the use of variable factors of production, and that input curtailment brings with it a variable-input cost saving that would not exist if there were no health effects.[11]

Some interesting insights can be gained by examining more carefully relations (10a) and (10b). Assuming that farmers have perfect information on the health effects of pesticides and the use of protective equipment is fully efficient, then $Q^h(\cdot)$ can be used as a measure of how farmers implicitly price the inconvenience of using protective equipment.[12] If farmers do not understand the health consequences of exposure to the pesticides they are using, then health impairments increase exogenously in the model. In this case, pesticide-related choices are made in a way that is sub-optimal from a private perspective due to misinformation. The later suggests a utilization of pesticides beyond their optimal level.[13]

Quasi-Rent Losses due to Pest Incidence

Apart from the adverse health effect of pesticide application, it is important to identify the total economic losses suffered by farmers in the presence of pests. In the absence of pests, $b^r = 0$, farmers do not apply pesticides, $z = 0$ and realize a maximal possible quasi-rent of $\Pi(p, w, \ell, k, 0, 0, t) = \pi(p, w, \ell, k, t)$. In this case, there are no pesticide-related health impairments and therefore $q = 1$ indicating that farmers utilize effectively ℓ units of family labor. If pests are present, a farmer who applies pesticides at z realizes quasi-rents $\Pi(p, w, \ell, k, b^r, z, s, t) = \pi(pg^e, w, \ell^e, k, t)$.

Therefore, a complete measure of the private quasi-rent losses associated with pest infestation can be obtained from:

$$Q^b(p, w, \ell, k, b^r, z, s, t) = \pi(p, w, \ell, k, t) - \pi\Big(pg^e, w, \ell^e, k, t\Big) \tag{11}$$

Quasi-rent losses related to the health effects of pesticides, $Q^h(\cdot)$, is a component of $Q^b(\cdot)$. To

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[11] Given that expressions $Q^h(\cdot)$,$R^h(\cdot)$, and $C^h(\cdot)$ are non-negative, it follows that $R^h(\cdot) \geq Q^h(\cdot)$.

[12] A complete measure of farmers' inconvenience would require to account also for the cost of buying the protective equipment. However, this cost is considered in many cases as trivial for farmers. For instance, parts of safety equipment are commonly included for free in pesticide packages purchased by farmers.

[13] Note though that even if health impairments are exogenous to farmers, rational farmers would still make adjustments in variable inputs use in the presence of the unexpected reductions in the endowment of family labor input.

demonstrate this, we solve relation (8) for $\pi\left(pg^e, w, \ell^e, k, t\right)$ and substitute it into (11):

$$Q^b\left(p, w, \ell, k, b^r, z, s, t\right) = Q^h\left(p, w, \ell, k, b^r, z, s, t\right) + \left[\pi(p, w, \ell, k, t) - \pi\left(pg^d, w, \ell, k, t\right)\right] \geq 0 \quad (12)$$

which is composed of two terms: the first captures the quasi-rent losses due to the health effects of pesticides, and the second is the difference between maximal possible quasi-rent and quasi-rent realized in the presence of pests assuming no health effects. This second component is identical with the measure of quasi-rent losses due to pests proposed by Chambers *et al.*, (2010). If health effects are present but ignored in the measurement of the quasi rent-losses due to pests, then the later measurement underestimates total quasi-rent-losses.

A measure of output-damage caused by pests can be obtained by dividing the revenue component of (11) by the crop price:[14]

$$\frac{R^b\left(p, w, \ell, k, b^r, z, s, t\right)}{p} = \pi_1\left(p, w, \ell, k, t\right) - \pi_1\left(pg^e, w, \ell^e, k, t\right) g^e \quad (13)$$

Dividing relation (10a) by output price, solving it for for $\pi\left(pg^e, w, \ell^e, k, t\right)$ and then substitute it into (13), yields:

$$\frac{R^b\left(p, w, \ell, k, b^r, z, s, t\right)}{p} = \frac{R^h\left(p, w, \ell, k, b^r, z, s, t\right)}{p} + \left[\pi_1\left(p, w, \ell, k, t\right) - \pi_1\left(pg^d, w, \ell, k, t\right) g^d\right] \quad (14)$$

implying that output damage due to pests consists of two components. The first captures the output losses caused by the health effects of pesticides. These losses are due to the decrease in optimal supply caused by the lower endowment of family labor input. The second is the difference between maximal potential output in the absence of pests and output realized in the presence of pests assuming no health effects which is identical with the measure of output-damage due to pests proposed by Chambers *et al.*, (2010). This is higher than the traditional output-damage measure given by $\left(1 - g^e\right) \pi_1\left(pg^e, w, \ell^e, k, t\right)$ for two reasons. First, in the presence of pests, effective output price decreases. As a result, a rational farmer realizing that the use of variable inputs is less profitable responds by lowering maximal potential output (*i.e.*, maximal potential supply adjusts downwards). Second, in the presence of pests, a farmer who applies pesticides faces a decrease in effective family labor due to health impairments caused by exposure to pesticides. In turn, the reduction in the endowment of family labor decreases further maximal potential supply.

The quasi-rent loss due to pest infestation in (11) can be expressed in percentage terms as:

$$1 - \frac{\pi\left(pg^e, w, \ell^e, k, t\right)}{\pi\left(p, w, \ell, k, t\right)}$$

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[14] Relation (11) can be distinguished between a revenue and a cost component in a similar manner with (9).

The difference between the expression above and the traditional percentage output damage, $1-g^e$, measures the bias inherent in the traditional percentage output damage measure:

$$\begin{aligned}
D^b(\cdot) &= g^e - \frac{\pi\left(pg^e, w, \ell^e, k, t\right)}{\pi\left(p, w, \ell, k, t\right)} \\
&= \frac{g^e \pi\left(p, w, \ell, k, t\right) - \pi\left(pg^e, w, \ell^e, k, t\right)}{\pi\left(p, w, \ell, k, t\right)} \\
&= \frac{\pi\left(pg^e, wg^e, \ell, k, t\right) - \pi\left(pg^e, w, \ell^e, k, t\right)}{\pi\left(p, w, \ell, k, t\right)} \\
&= \frac{Q^h\left(p, w, \ell, k, b^r, z, s, t\right)}{\pi\left(p, w, \ell, k, t\right)} + \frac{\pi\left(pg^e, wg^e, \ell, k, t\right) - \pi\left(pg^d, w, \ell, k, t\right)}{\pi\left(p, w, \ell, k, t\right)} \geq 0
\end{aligned}$$

In the above expression, the third line is obtained from the second as a result of the sub-linearity of the restricted profit function in input and output prices, while the last line of the expression is due to relation (8). It follows that $D^b(\cdot)$ is non-negative since the restricted profit function is non-increasing in input price with $g^e \leq 1$ and non-decreasing in family labor input with $q \leq 1$. This implies that the traditional percentage output-damage measure underestimates the true percentage damage caused by pests. One source of bias is the health effects of pesticides captured by term $\frac{Q^h(p,w,\ell,k,b^r,z,s,t)}{\pi(p,w,\ell,k,t)}$ measuring percentage quasi-rent losses due to the adverse health effect of pesticide materials on family workers. As health impairments become small, $Q^h(\cdot)$ approaches zero and the associated bias tends to zero as well. The other source of bias is the profit adjustment component for the economic losses realized by individual farmers due to pest incidence and reduction of effective labor hours. Farmers realizing that decreased revenues from crop due to variable input use necessarily involves revenue losses due to the presence of the pest curtail the use of variable factors of production, and that input curtailment brings with it a variable-input cost saving that would not exist if there were no pest infestation.

In the presence of health impairments, the shadow price of pesticides decreases due to the adverse health effects of pesticides. Assuming a smooth technology, with quasi-fixed input endowment of k and ℓ, the shadow prices are the marginal contributions to quasi-rent (variable profit):

$$\begin{aligned}
\nu^z(\cdot) &= \Pi_z\left(p, w, \ell, k, b^r, z, s, t\right) \\
&= \pi_1\left(pg^e, w, \ell^e, k, t\right) p \left[\frac{\partial g^e}{\partial z} + \frac{\partial g^e}{\partial \ell^e}\frac{\partial \ell^e}{\partial z}\right] + \pi_3\left(pg^e, w, \ell^e, k, t\right)\frac{\partial \ell^e}{\partial z} \qquad (15)
\end{aligned}$$

where $\Pi_z \in \Re_+$ is the gradient of $\Pi(\cdot)$ in z, and $\pi_3(\cdot)$ is the partial derivative of $\pi(\cdot)$ with respect to its third argument. The first term measures marginal changes in revenues due to changes in the effective price of crop. Effective crop price changes with changes in z for two reasons: first, changes in pesticides affect directly g^e altering effective crop price, and second, changes in pesticides affect indirectly g^e as a health-hazardous input changing effective family labor. Finally, the last term in

(15) measures marginal changes in revenues due to changes in effective family labor.

Another more informative interpretation is available here using the shadow price of family labor, $\nu^{\ell}(\cdot) = [\pi_1(\cdot) p \frac{\partial g^e}{\partial \ell^e} + \pi_3(\cdot)] q\big(h(z,s)\big)$. Solving this for $\pi_3(\cdot)$, replacing it into (15), and multiplying both sides by z, yields:

$$\nu^z(\cdot) z = \pi_1 \left(pg^e, w, \ell^e, k, t\right) pg^e \frac{\partial \ln g^e}{\ln z} + \nu^{\ell}(\cdot) \ell \frac{\partial \ln \ell^e}{\partial \ln z}$$

where, the first term in the right-hand side measures the quasi-rent gains associated with application of pesticides at z. The second term captures decreases in the quasi-rent of pesticides due to reductions in effective family labor caused by application of pesticides at z. The magnitude of these losses depend on the elasticity of effective family labor with respect to pesticides.

Survey Design

Our empirical application focuses on a panel of greenhouse farmers cultivating vegetables in the Western part of the island of Crete in Greece. All data used in the empirical analysis were obtained through a survey undertaken within the context of the Research Program TEAMPEST financed by the European Commission.[15] In this part of the island, vegetable cultivation under greenhouses is flourishing mainly due to the favorable climatic conditions prevailing in the area. Crop production under greenhouses became strongly chemically oriented over the last three decades. It is indicative that at the time of the survey (2003-2007), more than 90% of the greenhouse producers were relying heavily on the use of pesticides. Hence, greenhouse farmers in this area are likely to have been exposed heavily to dangerous pesticide ingredients during farming activities, insofar as applications are more frequent in greenhouses than in open-air fields, environmental conditions are extreme (high temperature and relative humidity), and ventilation is poor in partially-closed spaces.

The survey consisted of three parts, namely, the *main*, the *complementary* and the *preliminary* survey. The *main survey* covered a sample of 50 randomly selected conventional farms for five cropping seasons during the 2003 to 2007 period. Farms in the sample were visited twice per year by a survey team of experts consisting of two specialised doctors, two agronomists and four economists. The visits took place both at the beginning of the cropping season (end of August) and the end (end of May). During the first visit, on-field measurements of pest populations were made in each farm. In addition, personal interviews were conducted with farmers to gain information about their personal characteristics and their expectations about the forthcoming cropping

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[15] The TEAMPEST project (Theoretical Developments and Empirical Measurement of the External Costs of Pesticides) was financed within the EU 7th Framework Programme under Theme 2 on Food, Agriculture and Fisheries, and Biotechnology. More information on the TEAMPEST project can be found in http://www.eng.auth.gr/mattas/teampest.htm

season. In the second visit, farm-level information on output volumes, gross revenues, inputs usage and expenditures including pesticides were retrieved directly from farmers' accounting books. In addition, the medical and social security records of all family members working at the farm were examined to obtain information on pesticide-related health problems and medical costs faced by farmers[16]

The *complementary survey* covered a sample of 26 randomly selected organic farms from the same area and for the same five-year period as the main survey. The sample of organic farmers was only used as a control group to lessen potential biases arising from mis-identification of pesticide-related diseases and errors in the measurement of the health costs of pesticides in the sample of conventional farmers.[17] The *preliminary survey* included the same 50 conventional farmers as the main survey and took place at the beginning of the project, shortly before the beginning of the main survey (early of August 2003). The preliminary survey was designed to examine farmers' awareness about the health effects of pesticides and the timing of pesticide-related decisions. In addition, it was aimed at evaluating farmers' knowledge about methods for safe storage, handling and usage of pesticide materials.

Results from the main survey revealed that convetional farmers in the sample use systematically pesticides to target a specific pest, namely, the greenhouse whitefly, *Trialeurodes Vaporariorum* (Westwood). The greenhouse whitefly is considered by farmers as the major harmful pest responsible for about 80% of the total damage in greenhouse production. Adults and immature flies are phloem feeders and reduce productivity of plants. Furthermore, they produce large amounts of honeydew on the leaf reducing plants' photosynthesis. Under greenhouse conditions whiteflies can multiply quickly many generations increasing dramatically crop damage. To deal with the threat of greenhouse whitefly, convetional farmers rely mainly on the use of four types of pesticides which they consider as highly effective. The types of pesticides utilized by farmers contain six highly toxic ingredients, namely, *propetamphos*, *sodium cyanide*, *fluoroacetamide*, *carbofuran*, and *methomyl.*

Results from the preliminary study indicated four notable findings with respect to the behavior of convetional farmers in the area. First, farmers indicated that application of the specific class of pesticide ingredients is essential for the control of the main pest since there are no effective substitutes in the local market. Second, farmers presented a high understanding of the health consequences of pesticide exposure while they were also able to associate correctly health problems and medical symptoms with application methods and specific pesticide ingredients. Likewise, farmers demonstrated a very good knowledge on how to avert exposure although they recognised that

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[16] Details on the methods used to identify pesticide-related health problems and measure medical costs are presented in the next section.

[17] The procedures used to collect information on health problems and medical costs are the same with those used for conventional farmers.

they do not always follow safety guidelines due to the inconvenience of using protective equipment related mainly to the intense heat prevailing inside the greenhouses.

Third, farmers indicated that pesticide-related decisions including pesticide dose levels and number of applications are made at the beginning of the cropping season based on their personal observations on the level of pest infestation. Although changes in the application schedule of pesticides can happen in case of extreme pest incidences, these changes do not constitute a common practice among farmers. This is because farmers use pesticides for precautionary purposes. In later stages of the production process, the use of pesticides is perceived by farmers as ineffective since damage is considered as irreversible. Finally, farmers indicated that diminished work capacity of hired workers is accompanied with a lower wage since hired workers are paid according to the daily hours worked and not a fixed daily wage. In cases of reduced work time because of illness, farmers do not bear any of the associated health costs of the hired workers.

Health Impairment Index

Econometric Approach

The main problem related to the consistent measurement of the health effects of pesticides is that observations on farm worker's health are made only after exposure to a specific level of pesticides. In an ideal situation, we would like to have data on health impairments for the same farm worker from exposure to different levels of pesticides. Unfortunately, the only available data are based on observed outcomes; health impairments from exposure to a specific level of pesticides are observed for each farm worker when collecting survey data. The later has important implications for the measurement of the health effects of pesticides since observed differences in health impairments across farm workers could be further attributed to systematic differences in their baseline characteristics (e.g., educational levels) and not only to differences in pesticide levels. More importantly, if pesticide application levels depend also on these baseline characteristics, then the assignment of farm workers to different pesticide application levels is not random.

Under these conditions, traditional linear regression models fail to provide consistent estimates of the parameters of interest. Therefore, matching methods have been proposed to estimate *Average Treatment Effects* (ATE) models which restore the consistency of estimates. When treatment is continuous as in our case study, treatment levels (pesticide levels) and outcome responses (health impairments) can be directly correlated and the effects of treatment on outcome can be consistently estimated without the use of the non-treated units (Hirano and Imbens, 2004). One basic problem related to the Hirano and Imbens' (2004) method is the possible endogeneity of the treatment variable. Endogeneity arises from the fact that that pesticide application levels and pesticide-related health effects may depend on unobserved personality traits of farmers and other unobservable factors (*e.g.*, knowledge about pesticide effects and/or about correct dosages).[18] To deal with this problem, Cerulli (2015) proposed an estimation approach that accounts for treatment endogeneity and restores consistency making use of an instrumental variable approach. Moreover, it takes advantage of the continuous treatment while considering both treated (organic farm workers in our case) and untreated units (conventional farm workers in our case) making therefore complete use of existing information in the dataset.

Let N_f denote the total number of family farm workers in the two samples (conventional and organic). Define d_{it} a binary variable which takes the value 1 for conventional farms and 0 for organic farms, h_{it} is the health impairment variable, and $\xi_{it} \in \Re^r_+$ is a vector of exogenous observable characteristics. Finally, assume that z_{it} is a continuous variable indicating the level of pesticides applied in the farm. Following Cerulli's (2015), we specify the following system of equations consisting of the *baseline outcome* equation, the *treatment selection* equation and the *treatment level* equation, respectively:

$$\text{Baseline Outcome:} \quad h_{it} = \mu_0 + \xi_{it}'\delta^{\xi} + d_{it}\text{ATE} + d_{it}(\xi_{it} - \bar{\xi})'\delta + d_{it}r(z_{it}) + \eta_{it} \tag{16a}$$

$$\text{Treatment Selection:} \quad d^*_{it} = \xi^{d\,\prime}_{it}\beta^d + \eta^d_{it} \tag{16b}$$

$$\text{Treatment Level:} \quad z_{it} = \xi^{z\,\prime}_{it}\beta^z + \eta^z_{it} \tag{16c}$$

where $r(z_{it})$ is a polynomial function of the treatment level, z_{it}, which is different from zero only when treatment is positive and in the present application it is given by, $r(z_{it}) = \beta_1 Z_{1it} + \beta_2 Z_{2it}$, where $Z_{1it} = z_{it} - E(z_{it})$ and $Z_{2it} = z^2_{it} - E\left(z^2_{it}\right)$[19] . Moreover, μ_0, δ^{ξ}, ATE, δ, β_1, β_2, β_3, β^d, and β^z are parameters to be estimated, $\bar{\xi}$ is a vector of averages of exogenous variables over time and farmers, and d^*_{it} is the latent unobservable counterpart of the binary variable; $\xi^d_{it} = \left(\xi_{it}, u^d_{it}\right)$ and $\xi^z_{it} = (\xi_{it}, u^z_{it})$ are two vectors of exogenous regressors with u^d_{it} and u^z_{it} being the vectors of instrumental variables used to explain treatment selection (organic or conventional) and treatment levels (pesticide levels), respectively. The instruments in vectors u^d_{it} and u^z_{it} are assumed to be directly correlated with d^*_{it} and z_{it}, respectively, but not with h_{it}. Finally, η_{it}, η^d_{it}, and η^z_{it} are error terms with zero unconditional mean. The error terms are assumed to be uncorrelated with the instruments but freely correlated with one another.

The treatment selection and treatment level equations (16b-16c) were estimated using the *Heck-*

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[18] Although, the Hirano and Imbens (2004) approach reduces the risk of endogeneity, when the status treated versus not treated rather than the level of treatment is endogenous, by omitting the non-treated units from the analysis, the latter means that the non-treated units are dropped and relevant information between observed covariates and treatment assignment is completely ignored.

[19] A polynomial parametric form of second degree has been assumed here. This specification has been statistically tested against the first-degree (linear) and third-degree polynomial.

man two-step procedure under the assumption that the errors are jointly normally distributed and homoskedastic (see Cerulli, 2015). Finally, the outcome equation (16a) was estimated using a two-stage least squares method using the following exogenous variables as instruments: ξ_{it}, $\hat{d}_{it}$, $\hat{d}_{it}(\xi_{it} - \bar{\xi})$, $\hat{d}_{it}\hat{Z}_{1it}$, and $\hat{d}_{it}\hat{Z}_{2it}$, where a hat over a variable indicates its predicted value. Under this estimation set-up, the two-stage least squares approach provides consistent estimation of the basic coefficients of the model, μ_0, δ^{ξ}, ATE, δ, β_1, β_2, and β_3.

Based on these estimates, the dose response function was then estimated as:

$$\hat{\text{ATE}}(z_{it}) = d_{it}\left(\hat{\text{ATE}}_1 + \hat{\beta}_1\left(z_{it} - \bar{z}\right) + \hat{\beta}_2\left(z_{it}^2 - \bar{z}^2\right)\right) + (1 - d_{it})\hat{\text{ATE}}_0 \tag{17}$$

where $\hat{\text{ATE}}_1 = \hat{\mu}_0 + \bar{\xi}'_{z\succ 0}\hat{\delta} + \bar{r}_{z\succ 0}$ and $\hat{\text{ATE}}_0 = \mu_0 + \bar{\xi}'_{z=0}\delta$ are the estimated average treatment effects for the treated and untreated units, respectively, $\bar{z}$ and $\bar{z}^2$ are the sample means for the level and the square level of pesticides, respectively, $\bar{\xi}'_{z\succ 0}$, $\bar{r}_{z\succ 0}$ are the average of the exogenous variables in ξ and the $r(\cdot)$ response function defined above taken over $z_{it} > 0$, respectively, and $\bar{\xi}'_{z=0}$ is the average of the exogenous variables taken over $z_{it} = 0$. The marginal effect of pesticides is also estimated as the first derivative of the dose response function with respect to pesticides as: $\dfrac{\partial \hat{\text{ATE}}(z_{it})}{\partial z_{it}} = \hat{\beta}_1 + 2\hat{\beta}_2 z_{it}$.

Data Construction

To measure pesticide-related health impairments, we followed Pingali's *et al.*, (1994) and Antle and Pingali's (1994) approaches focusing exclusively on diseases and clinical symptoms associated with exposure to specific pesticide ingredients.[20] According to them, the most serious health problems that arise from exposure to the toxic ingredients found in pesticide materials include *eye*, *dermal*, *respiratory*, *neurological* and, *kidney* problems that together with their associated clinical symptoms are linked directly to exposure to those chemical compounds.[21] The health problems listed above capture different dimensions of health impairments, while at the same time they are directly related to farm activities. Eye irritation problems and diminished vision often occur during application activities. On the other hand, dermal contamination is likely to occur during application and mixing of pesticides resulting in dermal disorders. Systematic exposure to pesticide ingredients during different farm activities is also likely to result in bronchial asthma that is the most common lung disease associated with long-run exposure to pesticide ingredients. In

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[20] Strauss and Thomas (1998) provide a similar approach to proxy health status.

[21] Obviously this is not an exhaustible list. Pesticides are also responsible for non-specific illnesses that affect farm workers' general health (*e.g.*, a simple flu may be related to weak immune efficiency due to pesticides use). However, it is not possible to identify all these minor clinical symptoms in constructing an index for measuring pesticide-related health impairments. We can reasonably assume though that these effects are closely related to the above list and therefore measurement errors are random. In addition, we do not consider cancer incidences and reproductive problems. These are associated with long-term effects which are difficult to be correlated with pesticide use.

addition, specific toxic ingredients found in pesticides can act as neurotoxicants resulting in sensory loss and diminished reflexes. Finally, circulating toxins through human body may lead to significant kidney abnormalities.

At the second visit of each season, specialised doctors examined in detail the medical and social security records of all family members working in the farm in order to obtain information on the above list of health problems and their associated clinical symptoms.[22] These records included personal prescription books as well as medical records kept at the University of Crete Hospital.[23] Once pesticide-related health diseases were identified, data on medical treatment costs along with information on working days lost for each identified disease were gathered from the personal prescription books. The same process was used also to identify pesticide-related health problems and measure medical costs in the sample of organic farms. The sum of the annual direct and indirect costs concerning pesticide-related health problems was used to measure pesticide-related health impairments for every family member working on-farm. Direct costs include the medical costs of treatment, while the indirect costs involve the opportunity cost from the work days lost. Indirect costs were calculated using the average wage in the local labor market. The health impairment variable was constructed on an annual basis for every family member and was used as the dependent variable in the estimation of the outcome equation in (16a).

Exposure to pesticide ingredients was proxied by the ratio of the total amount of active ingredients applied during the crop season to the size of cultivated land measured in stremmas (one stremma equals 0.1 ha). All identified types of pesticide ingredients were found to belong in the second category of the most hazardous pesticides according to the classification of pesticides provided by WHO (2004). The later enables the aggregation of the pesticide ingredients identified into a single index. To aggregate pesticide ingredients, a weighted pesticide quantity index was constructed using the cost shares of pesticide ingredients as weights. The index was next divided by the size of cultivated land. The resulting index was used as the dependent variable in the estimation of the treatment level equation in (16c).

The vector of instrumental variables used in the estimation of the treatment selection equation in (16b), includes: (*a*) the size of farm measured in stremmas, and (*b*) the amount of decoupled subsidies received by farmers measured in Euros. Both of these variables have been shown to exhibit significant explanatory power in explaining farmers' choice related to the type of farming (*i.e.*, conventional or organic) while not related to health outcomes. Hence, these variables affect directly the selection variable but are not correlated with the health impairment variable that makes them

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[22] Medical doctors were not aware of the distinction between conventional and organic farm workers to retain objectivity when identifying pesticide-related health problems.

[23] Farmers belong to a rather homogenous rural population having all access to the National Health System enjoying the same social security benefits. Hence, they do not have incentives to over- or under-report morbidity rates and illnesses.

valid instruments in the econometric estimation. Similarly, the vector of instrumental variables used in the estimation of the treatment level equation in (16c) includes the following: (a) pest density, (b) price of pesticides, (c) crop price, and (d) variable-input prices. Measurements on pest populations were obtained using chemical traps installed approximately every 250 squared meters in each field. The number of whiteflies captured in the traps were then used to extrapolate the average number of whiteflies per greenhouse farm.[24] The ratio of this number to the size of the greenhouse farm was used to measure pest density. Finaly, the vector of exogenous observable characteristics includes the following variables: (a) family worker's age measured in years, (b) family worker's educational level proxied by years of schooling,[25] (c) family worker's smoking habits measured as the average number of cigarettes smoked per day multiplied by the tar milligrams contained, and (d) family worker's body mass index-BMI constructed as the ratio of weight in kilograms to height in meters squared.

The inclusion of education in the vector of exogenous factors deserves some attention here. Studies in the health economics literature highlight that education might be endogenous to health outcomes due to two reasons. First, health in earlier ages may affect investments in education suggesting a possible inverse causality from health to education. The rationale behind this view is that individuals in good health at the earlier years of their lives are more likely to invest in education since the corresponding returns are expected to accrue for a longer period of time (Schultz, 1961). Second, unobserved factors such as genetic factors are likely to affect both health and educational achievements (Brunello *et al.*, 2016). Although this reasoning implying endogeneity is valid when general health outcomes are considered, it does not seem to entail plausible concerns for our analysis which focusses on specific health impairments related to a certain occupational activity. It is rather unlikely that pesticide-related health impairments experienced by family workers affect their investments in education which commonly have been made in a much earlier stage. It seems also equally unlikely that genetic factors which explain educational achievements explain at the same time pesticide-related diseases experienced by family workers.

Table 1 provides a summary of pesticide-related health problems suffered by family farm workers along with information on medical costs and work days lost. The information presented in the Table refers solely to conventional family workers. In total, 585 cases of pesticide-related health problems were recorded over the five-year period. The most frequent types of health problems observed were the respiratory problems (257 cases), followed by dermal (155 cases) and eye problems (106 cases).

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[24] Adult fly populations are typically monitored using yellow sticky traps (*McPhail traps*) that are baited with sex pheromone and ammonium bicarbonate. The sex pheromone is attractive to male flies while the ammonium bicarbonate is primarily attractive to females. Both sexes are attracted to the trap's yellow colour. Thus, the population numbers used in our empirical analysis are not biased with respect to fly gender and can be expected to reflect, as closely as possible, the actual pest incidence in each greenhouse.

[25] As Griliches (1963) pointed out the use of specific or more elegant variables than educational level does not alter significantly the econometric results as all these variables are highly correlated with years of schooling.

Incidents of neurological and kidney diseases were also observed but with a lower frequency (29 and 38 cases, respectively). The average recovery period from each disease was 11.1 days. For more than half of these days, family farm workers abstained totally from working activities while during the remaining recovery days, they were involved in work tasks but their effectiveness was lower by 52.5 per cent.[26] Finally, average treatment cost per disease was 117 Euros.

Table 2 presents summary statistics of the variables used in the estimation of the health impairment model. First, it is evident that health impairments, measured as the annual total direct and indirect costs arising from pesticide related health problems for the average family worker, are significantly lower in the sample of organic farmers. This implies that our method used to identify and measure pesticide-related health problems can indeed distinguish health impairments arising from exposure to pesticides from health impairments attributed to other factors. Concerning the exogenous variables used in the estimation of the health impairment model, statistical results indicate that conventional farmers are in general older and less educated than organic farmers. The average age and educational level of the family workers in the sample of conventional farms were 51.3 years of age and 11.1 years of schooling, respectively, while the corresponding figures in the sample of organic farms were 34.6 years of age and 15.3 years of schooling. Focusing on the two instrumental variables used in the estimation of the treatment selection equation, results indicate that conventional farmers operated larger farms cultivating on average in an area of 7.14 stremmas, which is considerably higher than that of their organic counterparts, 2.89 stremmas. Finally, organic farmers received a larger amount of decoupled subsidies.

Profit Function

Econometric Specification

Following Strauss (1984), we adopt a negative exponential in health impairments specification to approximate the factor of proportionality function in relation (2).[27] However, apart from health status, education level may also influence effective labor input. One way to include education in the specification of the effective labor function is by assuming perfect substitutability between labor input and education which in turn would allow the direct multiplication of education variable with labor input (Griliches, 1963). However, this process would require to inflate the labor input by "quality per man" measures estimated by weighting each school-year completed class by the corresponding income share in this class. Given that this information is not available, we relax the

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[26] The reported reductions in efficiency reflect farm workers' personal perceptions, since this variable could not be directly retrieved from their medical records.

[27] Two more specifications (quadratic and cubic) suggested by Strauss (1986) have been statistically tested but results fail to show any statistical improvement over the negative exponential specification.

assumption of perfect substitutability between labor input and education which allows us to use directly educational levels as observed. In addition, farm worker's age and Body Mass Index may also influence the effective labor units (Wouterse, 2016). Following Deolalikar's (1988), we introduce education and other farm-specific human capital variables multiplicatively in the specification of the effective labor function by assuming a semi-log functional form. Under this set-up, the effective labor function in logarithmic form is expressed as:

$$\ln \ell^e_{it} = \ln \ell_{it} - \gamma^h \hat{h}_{it} + \gamma_{Edu} \ln Edu_{it} + \gamma_{Age} \ln Age_{it} + \gamma_{BMI} \ln BMI_{it} \tag{18}$$

where subscripts i and t indicate the farm and the time period, and $\hat{h}_{it}$ is the health impairment index obtained from the econometric estimation of the system in (16a-16c). Since more than one family member may perform work tasks in each farm, an aggregate health impairment index of family labor was constructed as the weighted sum of health impairment indexes of family workers in each farm using labor time shares as weights. The same aggregation process was used for the remaining human capital variables observed for each family member working at the farm.[28]

Our econometric specification of the damage control function follows the contribution of Fox and Weersink (1995), which decomposes $g^e(\cdot)$ into two components allowing for the possibility of increasing returns to the damage-control agent:

$$g^e_{it} = 1 - exp\big(\lambda b^r_{it}(1 - \phi_{it})\big) \tag{19}$$

with

$$\phi_{it} = 1 - exp\big(- \beta^z z_{it} - \beta^{zt} z_{it} t - \beta^{z\ell} z_{it} \ell^e_{it} - \sum_u \beta^{zk}_u z_{it} k_{uit}\big)$$

where β's and λ are parameters to be estimated.

Using (18) and (19), the econometric specification of the profit function in (4), has the following flexible transcendental logarithmic (translog) specification:

$$\begin{aligned}
\ln \pi_{it} \quad = \quad & \alpha_0 + \alpha^p \ln \tilde{p}_{it} + \sum_n \alpha^w_n \ln w_{nit} + \alpha^\ell \ln \ell^e_{it} + \sum_u \alpha^k_u \ln k_{uit} + \alpha^t t + \frac{1}{2}\Bigg[\alpha^{pp}(\ln \tilde{p}_{it})^2 \\
+ \quad & \sum_n \sum_q \alpha^{ww}_{nq} \ln w_{nit} \ln w_{qit} + \alpha^{tt} t^2\Bigg] + \frac{1}{2}\Bigg[\alpha^{\ell\ell}(\ln \ell^e_{it})^2 + \sum_u \sum_r \alpha^{kk}_{ur} \ln k_{uit} \ln k_{rit}] \\
+ \quad & \sum_u \alpha^{\ell k}_u \ln \ell^e_{it} \ln k_{uit}\Bigg] + \ln \tilde{p}_{it}\Bigg[\sum_n \alpha^{wp}_n \ln w_{nit} + \alpha^{\ell p} \ln \ell^e_{it} + \sum_u \alpha^{kp}_u \ln k_{uit}\Bigg] \qquad (20) \\
+ \quad & \sum_n \alpha^{w\ell}_n \ln w_{nit} \ln \ell^e_{it} + \sum_n \sum_u \alpha^{wk}_{nu} \ln w_{nit} \ln k_{uit} + t\Bigg[\alpha^{pt} \ln \tilde{p}_{it} + \sum_n \alpha^{wt}_n \ln w_{nit}
\end{aligned}$$

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[28] Days lost due to illnesses were taken into consideration while constructing labor time shares.

$$+\alpha^{\ell t}\ln \ell^e_{it} + \sum_u \alpha^{kt}_u \ln k_{uit}\Bigg]$$

where $\ln\tilde{p} = \ln p_{it} + \ln g^e_{it}$, t is the usual time trend, a's are parameters to be estimated with $a^{ww}_{nq} = a^{ww}_{qn}$, $a^{kk}_{ur} = a^{kk}_{ru}$, $a^p + \sum_n a^w_n = 1$, $a^{pp} + \sum_n a^{wp}_n = 0$, $a^{kp}_u + \sum_n a^{wk}_{nu} = 0$ for each u, $a^{\ell p} + \sum_n a^{w\ell}_n = 0$, and $a^{pt} + \sum_n a^{wt}_n = 0$. We also impose that $\sum_u a^k_u + a^\ell = 1$, $\sum_u a^{kk}_{ur} + \sum_r a^{\ell k}_r = 0$ for each r, $a^{\ell\ell} + \sum_u a^{\ell k}_u = 0$, $a^{w\ell}_n + \sum_u a^{wk}_{nu} = 0$ for each n, and $a^{\ell p} + \sum_u a^{kp}_u = 0$.

The associated supply and variable input demands in quasi-rent share forms are obtained using *Hotelling's Lemma*:

$$S^y_{it} = \alpha^p + \alpha^{pp}\ln\tilde{p}_{it} + \sum_n \alpha^{wp}_n \ln w_{nit} + \sum_j \alpha^{\ell p}_j \ln \ell^e_{jit} + \sum_u \alpha^{kp}_u \ln k_{uit} + \alpha^{pt} t \tag{21}$$

$$-S^x_{nit} = \alpha^w_n + \sum_q \alpha^{ww}_{nq} \ln w_{qit} + \alpha^{wp}_n \ln\tilde{p}_{it} + \sum_j \alpha^{w\ell}_{nj} \ln \ell^e_{jit} + \sum_u \alpha^{wk}_{nu} \ln k_{uit} + \alpha^{wt}_n t \tag{22}$$

For the identification of the β parameters, a grid search procedure was used. Then, the system consisting of equations (20) to (22) was estimated conditional on β's as a seemingly unrelated regression model using the two-step *Feasible Generalized Non-Linear Least Squares* estimator (FGNLS).

Data

The data used in the estimation of the profit function were retrieved from the main survey including only the sample of convetional greehnouse farms. One output and three variable inputs were considered. Greenhouse farmers produce four different kinds of vegetables, namely, tomatoes, cucumbers, peppers and aubergines. Different crops (including quantities sold off the farm and quantities consumed by the farm household during the crop year) were aggregated into a single aggregate output index with revenue shares of each crop defining the relevant weights. Likewise, output prices were aggregated into a single aggregate *Tornqvist* output price index using again revenue shares as weights. The output prices used are those obtained by farmers at the time that production was sold to the local market after subtracting indirect taxes.

The variable inputs considered in the analysis are fertilizers, hired labor and intermediate inputs. Farmers use different types of fertilizers which include a mixture of nitrate, phosphorous, and potassium ingredients. The cost shares of each type of fertilizer were used as weights to aggregate the prices of the different fertilizers into a single price index. Compensation of hired workers was computed as the average hourly wage plus social security taxes paid by farmers. Intermediate inputs consist of goods and materials used during the crop year and include expenditures on seeds, fuel and electric power, and irrigation water along with storage expenses. Again, the corresponding cost shares were used as weights to aggregate the different categories into one price index.

The quasi fixed inputs considered in the analysis are family labor, land, and capital. Family labor was measured as the total hours devoted by family members to farm activities, e.g., harvesting, spraying, fertilisation, irrigation. Land includes the total acreage (rented or owned) under greenhouses devoted to vegetable production measured in stremmas. Capital stock was computed using the perpetual-inventory method. Finally, pesticides were measured as the total quantity of active ingredient of pesticides applied during the season. Since different types of pesticides were applied, the cost shares of each type were used to aggregate them into a single quantity divisia index. All monetary variables were converted into 2000 constant prices. To avoid problems associated with units of measurement, all variables were normalized by their mean values. Intermediate inputs and land were used as *numeraires* in imposing linear homogeneity in crop and variable input prices and quasi-fixed inputs, respectively. Summary statistics of the variables are presented in Table 2.

Empirical Results

As explained previously when describing the health impairment model given by (16a-16c) different polynomial specifications were compared when estimating the outcome equation. In particular, the first-order (linear) and the third-order polynomial specifications were examined against the second-order polynomial using goodness of fit measures. None of these specifications showed any statistical improvement over the second-order polynomial. Therefore, the second-order polynomial specification was adopted. One basic advantage of this particular functional form is that it does not impose a priori a concave or convex relationship between pesticide intensity and health impairments but instead allows the data to choose the type of relationship.

The estimation results of the treatment selection equation are presented in the upper panel of Table 3. Estimation results indicate statistical significant parameters for the majority of the variables. Focusing first on the two instrumental variables, the results show that land size and decoupled subsidies exhibit strong statistical power in explaining treatment selection. Large farms are found to use conventional farming practices while the amount of decoupled subsidies received by farms is found to be positively correlated with the use of organic farming practices implying that financial incentives have a significant impact on the selection of family workers towards organic farming. Likewise, family workers' age and education were found to exhibit a significant positive and negative relationship with treatment selection, respectively.

The estimation results of the treatment level equation are presented in the middle panel of Table 3. Starting again from the instrumental variables, the results indicate a strong and positive effect of pest density on pesticide intensity which is an expected result. In addition, the price of pesticides is found to have a significant negative impact on pesticide intensity. Likewise, the prices of all variable inputs were identified to affect negatively pesticide levels suggesting a possible complementarity between pesticide input and variable inputs. Focusing on the exogenous factors, age exhibits a positive relationship with pesticide intensity while education was found to have a significant negative effect on pesticide levels.

The parameter estimates of the outcome equations are reported in the lower panel of Table 3 and show that the estimate of the parameter ATE is positive and highly significant, showing that overall pesticide use has a positive effect on health impairment. Based on these estimates, the average health impairment index at each level of pesticide intensity was calculated for family workers. Figure 1 illustrates the estimated dose response function (*i.e.*, average health impairment) at each level of pesticide intensity together with the 95% confidence bands, while Figure 2 replicates the same information using though bootstrapped standard errors. Pesticide intensity is scaled in these figures over the $[0, 100]$ interval.[29] The estimated dose response function appears to be statistically significant as standard errors are small and confidence intervals narrow. Estimates are very precise for low and middle levels of pesticide intensity but become less reliable for high levels. Health impairments respond positively to increases in pesticide intensity and these responses are concave which is consistent with findings of previous studies (Antle and Pingali, 1994). Figure 3 presents the average marginal effect of pesticide intensity on health impairment which verifies the concavity of the health impairment function with respect to pesticide intensity.

The parameter estimates of the restricted profit function are presented in table 4. Estimates for the key parameters of the model appear to be statistically significant and have the expected signs. Table 5 presents the supply and input demand elasticities estimated at sample means. Starting from the supply elasticity with respect to output price, it is positive and close to unity (1.069) ensuring that supply is upward sloping in output price. As expected, the own-price elasticity of demand is negative for all three variable inputs, e.g., hired labor, fertilizers, and intermediate inputs. Concerning the magnitude of these point estimates, the own-price elasticity of intermediate inputs exhibits the highest value (-2.028) which is quite large compared to that of hired labor and fertilizers (-0.545 and -00607, respectively). Note though that the supply elasticity with respect to the price of intermediate inputs is also large indicating that this high value could be largely driven by an output effect. The cross-price elasticity of demand is negative in all cases implying that variable inputs are gross complements.

To further examine the strength of complementarity or substitutability between variable inputs, we compute the compensated demand elasticities by removing the supply-expansion effect from input demand. The lower panel of table 5 presents the compensated input demand elasticities estimated at sample means. The own-price compensated elasticity of demand for all variable inputs is again negative as expected. Moreover, the magnitude of the compensated elasticity of

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[29] A value of z=10 in the figures corresponds to 78 grams/stremma.

demand for intermediate inputs drops significantly to -0.093 verifying our initial suspicion that the high value of the uncompensated own-price elasticity of intermediate inputs is largely driven by an output effect. Concerning the cross-price compensated elasticities of demand, they are all found to be positive suggesting that variable inputs are output-compensated (net) substitutes.

Using the parameter estimates of the restricted profit function, the quasi-rent losses associated with the health effects of pesticides were estimated and the sample mean was computed for each one of the four profit quartile regions as well as for the whole sample. Results on quasi-rent loss, $Q^h\left(p, w, \ell, k, b^r, z, s, t\right)$, along with its decomposition into the revenue, and cost effect are presented in the upper panel of table 6. Quasi-rent losses due to the health effects of pesticides are estimated at 1,511 Euros on average following a steadily increasing trend across profit quartiles. Revenue losses associated with the health effects of pesticides are estimated at 2,829 Euros that is 1,318 Euros higher than quasi-rent losses. This deviation is consistent with the predictions of our theoretical model. Revenue losses are partly attributed to the reduction in effective output price and the corresponding downward adjustment of optimal supply made by rational farmers caused by the increase in output damage triggered in turn by the lower endowment of family labor input. The later decrease in family labor input has also a direct negative impact on output production explaining the remaining revenue losses. The difference between quasi-rent and revenue loss which represents the cost effect indicates that adjustments in the use of variable inputs were quite fruitful in terms of lessening the economic losses of the health effects of pesticides leading to an average saving of 1,318 Euros.

Quasi-rent losses due to pests, $Q^b\left(p, w, \ell, k, b^r, z, s, t\right)$, are estimated at 7,648 Euros following an increasing trend across profit quartiles. This loss is decomposed into two components. The first component, $Q^h\left(p, w, \ell, k, b^r, z, s, t\right)$, is related to the health effects of pesticides accounting for the 20% of the estimated quasi-rent loss due to pests which is undoubtedly an important share. The second component, $\pi\left(p, w, \ell, k, t\right) - \pi\left(pg^d, w, \ell, k, t\right)$, is the difference between maximal possible quasi-rent and quasi-rent realized in the presence of pests assuming no health effects. This second component which is identical to the measure of quasi-rent loss due to pests proposed by Chambers *et al.* (2010) captures quasi-rent losses associated with pest infestation ignoring though the associated health effects induced by pesticide application. The second component predicts an average loss of 6,136 Euros accounting therefore for the remaining 80% of the total quasi-rent loss due to pests.

Two measures of output loss due to pests are reported in the middle panel of table 6. The first measure is the one used in Chambers' *et al.* (2010) analysis defined as revenue loss due to pests divided by output price, $\frac{R^b(p,w,\ell,k,b^r,z,s,t)}{p}$. The other is the traditional output-damage measure defined as maximal potential output in the presence of pests times damage, $(1-g^e)\pi_1(pg^e, w, l^e, k, t)$. Output loss due to pests, as measured by $\frac{R^b(p,w,\ell,k,b^r,z,s,t)}{p}$, is estimated at 21,325 kgs and is again decomposed into two components. The first component refers to the health effects of pesticides on maximal production, $\frac{R^h(p,w,\ell,k,b^r,z,s,t)}{p}$, indicating an average output loss of 4,099 kgs attributed to decreases in the endowment of family labor. The lower endowment of family labor input decreases directly output but also indirectly by reducing effective output price leading to a downward supply response by farmers. The second component is the difference between maximal potential output in the absence of pests and output realized in the presence of pests assuming no health effects, $\pi_1(p, w, \ell, k, t) - \pi_1(pg^d, w, \ell, k, t)g^d$. Therefore, it measures output losses associated with pest infestation ignoring though the health effects emerging from the use of pesticides. It indicates an average output loss of 17,226 kgs accounting for the 80% of the output damage due to pests.

The traditional output damage measure, $(1 - g^e)\pi_1(pg^e, w, l^e, k, t)$, suggests an average output loss of 6,581 kgs which is 14,744 kgs lower compared to that predicted by the $\frac{R^b(p,w,\ell,k,b^r,z,s,t)}{p}$ measure. This substantial deviation which quantifies the bias introduced in the traditional output-damage measure is due to the fact that the latter fails to account for the optimal supply adjustments made by rational farmers in the absence of pests. These optimal supply adjustments ignored by the traditional measure are further triggered by the higher utilization of family labor implied by the absence of health effects.

Finally, estimates on the percentage quasi-rent losses due to pests, $1 - \frac{\pi(pg^e,w,\ell^e,k,t)}{\pi(p,w,\ell,k,t)}$, along with those on traditional percentage damage measure, $1 - g^e$, are reported at the lower panel of of table 6. The quasi-rent loss due to pest infestation is estimated to be 32.10% while the traditional percentage damage measure indicates a percentage loss of 15.71%. This difference of 16.39 percentage units is substantially high implying that the traditional percentage damage measure underestimates percentage losses due to pests by almost 50% in our analysis. Optimal adjustments made by farmers related to the health effects of pesticides ignored by the traditional measure explain an important share of this bias (5.23 percentage units). Both percentage damage measures follow a general decreasing trend across profit quartiles. This result is mainly attributed to a higher utilization of pesticides by larger farms which is also verified by our data.

Table 7 reports estimates on the shadow price of pesticides along with its components. The shadow price of pesticides increases steadily across profit quartiles indicating that marginal returns to pesticides are larger for more profitable farms. On average, the shadow price of pesticides is estimated at 0.5372 Euros. The largest share is due to marginal increases in revenues arising from increases in effective output price triggered in turn by small increases in pesticides use. These marginal increases in revenues are estimated at 0.5682 Euros and include both the direct positive effect of pesticides on effective output price (first term in the bracket) and the indirect negative effect of pesticides on effective output price through their impact on effective family labor (second term in the bracket). The latter indirect effect, albeit not reported in the table, is found to decrease the shadow price of pesticides by 0.0986 Euros, on average. Moreover, marginal increases in pesticide use decrease also the shadow price of family labor reducing further marginal revenues. This latter negative effect is found to reduce the shadow price of pesticides by 0.0310 Euros.

Conclusions

In this paper, we developed a method for measuring quasi-rent losses associated with the health effects of pesticides under informed decision-making and rational farmer behavior. Starting from a production model modified to account for the health effects of pesticides on effective labor units, we developed a restricted profit model which enables to identify the optimal supply-response and optimal cost adjustments made by farmers in the presence and absence of pesticide-related health effects. Using this model, we showed how to measure economic losses associated with the health effects of pesticides when endogeneity of health effects is induced by informed decision-making. As an important by-product of the analysis, we demonstrated how ignoring the health effects of pesticides when those are present, introduces bias in pest damage measures and in the measurement of the marginal returns to pesticides.

The model was empirically applied on a unique panel dataset of Greek greenhouse producers where the use of health-hazardous pesticides is particularly prominent. The survey covered a five-year period making it the longest survey exploring the effects of pesticides on farmers' health. Using this unique dataset, health impairment indices were estimated for family workers using recent treatment effects estimation methods. To measure quasi-rent loss due to health effects, a translog profit function was estimated augmented to account for the asymmetric role of pesticides as a damage control input.

Empirical results attributed significant quasi-rent losses to the health effects of pesticides. Although cost adjustments made by farmers in the sample lessened significantly these adverse effects, estimated economic losses were found to remain substantially high. Moreover, results indicated that impairments in farmers' health due to exposure to pesticides constitute an important component of quasi-rent and output loss due to pests suggesting that ignoring the health effects of pesticides may bias downward pest-damage measures. In our case study analysis, this bias was quantified to be approximately 20%. Finally, the health effects of pesticides were also found to affect significantly the marginal returns to pesticides decreasing significantly the shadow price of pesticides.

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Tables and Figures

Table 1: Health Problems and Associated Economic and Medical Costs

Health Problem	No of Cases	Recovery Days	Days of Absence	Effectiveness Decrease (%)	Medical Cost (in €)
Eye	106	10.8	6.0	52.8	118
Dermal	155	11.5	6.3	54.0	112
Respiratory	257	10.4	5.9	52.1	109
Neurological	29	11.7	8.0	43.3	255
Kidney	38	14.3	7.2	55.0	86
All problems	585	11.1	6.2	52.5	117

Table 2: Summary Statistics of the Variables

	Conventional Farmers			Organic Farmers		
Variable	Mean	Max	Min	Mean	Max	Min
Pesticide intensity (grams/stremma[1])	199	797	46	0	0	0
Land size (in stremmas[1])	7.14	31.40	2.40	2.89	9.00	1.60
Decoupled subsidies (in €)	1,121	1,905	390	1,551	2,280	892
Pest density (pests per m^2)	1.36	3.40	0.32	–	–	–
Price of output (in €)	0.65	0.99	0.35	–	–	–
Price of pesticides (in €)	0.48	0.85	0.24	–	–	–
Price of fertilizers (in €)	0.35	0.55	0.16	–	–	–
Price of hired labor (in €)	4.02	7.51	2.20	–	–	–
Price of intermediate inputs (in €)	5.36	7.46	3.04	–	–	–
Capital stock (in €)	1,934	7,672	695	–	–	–
Family labor (in hours)	1,042	2,981	234	–	–	–
Age (in years)	51.3	70.0	18.0	34.6	59.0	18.0
Education (in years)	11.1	18.0	6.0	15.3	20.0	9.0
Smoking habits (tar units)	15.3	50.0	0.0	13.9	50.0	0.0
BMI (kg/m^2)	27.1	33.4	21.8	25.5	31.4	19.8
Health impairment (in €)	584	1,281	190	34	154	0

[1] One stremma equals 0.1 ha.

Table 3: Estimation of the Health Impairment Model

Variable	Estimate	St.Error
Treatment Selection Equation:		
Constant	2.0878	(1.9290)
Land Size	0.6670	(0.0842)**
Subsidies	-0.0029	(0.0005)**
Age	0.0626	(0.0112)**
Education	-0.3983	(0.0577)**
Smoking habits	0.0064	(0.0108)
BMI	0.0672	(0.0617)
Treatment Level Equation:		
Constant	35.835	(12.330)**
Pest density	6.8799	(1.2928)**
Price of output	26.556	(5.7851)**
Price of pesticides	-21.534	(5.4515)**
Price of fertilizers	-3.4339	(0.6839)**
Price of hired labor	-1.2880	(0.6883)*
Price of intermediate inputs	-42.738	(9.0626)**
Age	0.3220	(0.0748)**
Education	-2.5115	(0.3182)**
Smoking habits	0.1225	(0.0634)*
BMI	0.7528	(0.3668)*
Mill's λ	2.4250	(2.9114)
ρ	0.1834	–
σ	13.221	–
Outcome Equation:		
Constant	299.63	(52.529)**
d-(ATE)	530.50	(15.865)**
z-(β_1)	12.882	(2.2638)**
z^2-(β_2)	-0.0611	(0.0234)**
Age	-4.2618	(0.4828)**
Education	-3.5529	(3.1123)
Smoking habits	-0.0230	(0.3431)
BMI	-2.7864	(1.9144)

* and ** indicate statistical significance at the 5 and 1 per cent level, respectively.

Figure 1: Dose-Response Function

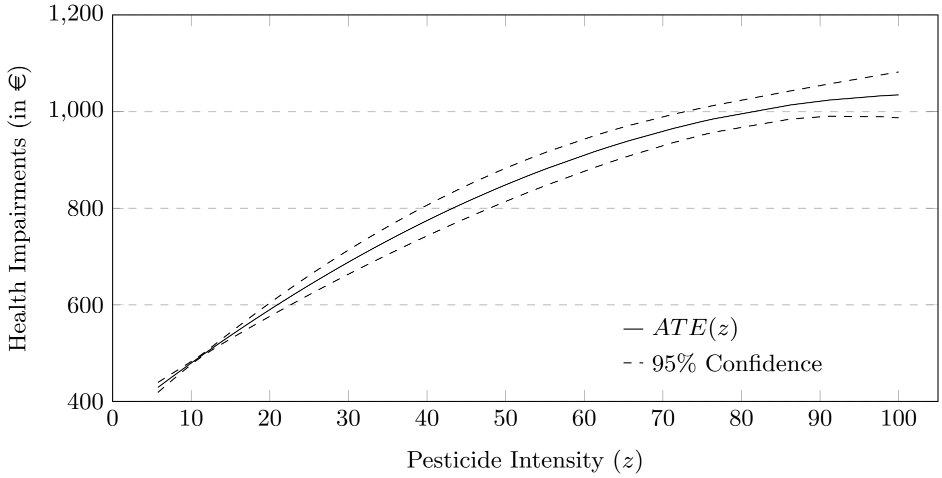

Figure 2: Dose-Response Function with Bootstrapped Standard Errors

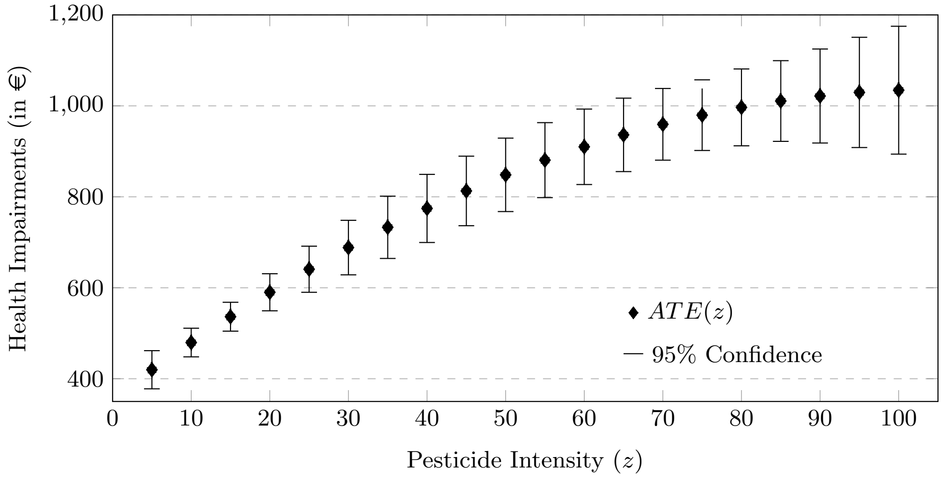

Figure 3: Derivative of the Dose-Response Function

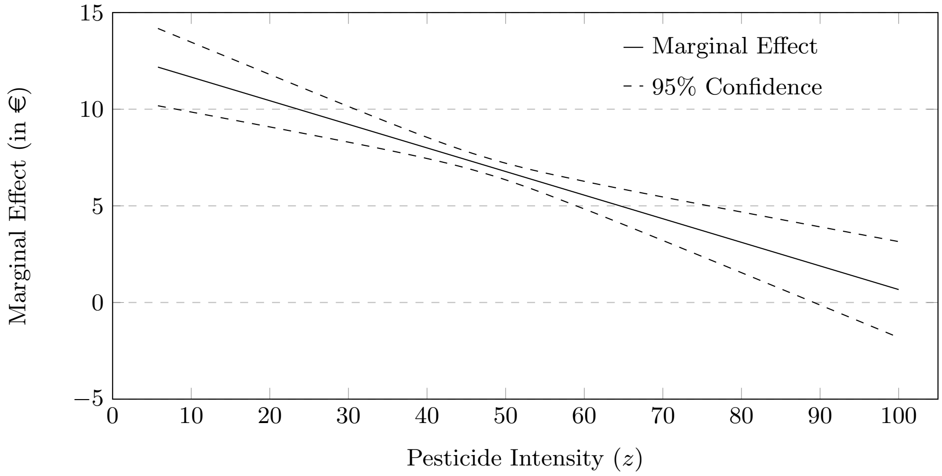

Table 4: Parameter Estimates of The Restricted Translog Profit Function

Par.	Estimate	StError	Par.	Estimate	StError	Par.	Estimate	StError
α_0	2.0695	(1.1761)*	α^{ww}_{DI}	0.1826	–	α^{wk}_{IC}	0.3401	–
α^p	1.8580	(0.1435)**	α^{ww}_{FI}	0.0294	–	α^{wk}_{IA}	-0.3386	–
α^w_D	-0.3197	(0.0693)**	$\alpha^{\ell\ell}$	0.2163	(0.1109)*	α^{pt}	-0.0817	(0.0441)*
α^w_F	-0.0978	(0.0117)**	α^{kk}_{CC}	-0.0018	(0.1384)	α^{wt}_D	0.0053	(0.0200)
α^w_I	-0.4406	–	α^{kk}_{AA}	0.2568	–	α^{wt}_F	-0.0059	(0.0066)
α^ℓ	0.3772	(0.1507)**	$\alpha^{\ell k}_C$	0.0212	(0.0379)	α^{wt}_I	0.0823	–
α^k_C	0.3084	(0.1626)*	$\alpha^{\ell k}_A$	-0.2374	–	$\alpha^{\ell t}$	0.0281	(0.0252)
α^k_A	0.3144	–	α^{kk}_{CA}	-0.0194	–	α^{kt}_C	0.0500	(0.0979)
α^t	0.4790	(0.2437)*	$\alpha^{\ell p}$	0.0099	(0.0054)*	α^{kt}_A	-0.0781	–
α^{tt}	0.2937	(0.3248)	α^{kp}_C	-0.4922	(0.0427)**	γ^h	-0.2067	(0.0649)**
α^{pp}	0.3258	(0.1207)**	α^{kp}_A	0.4823	–	γ^s_E	0.5396	(0.1097)**
α^{ww}_{DD}	-0.2732	(0.0454)**	$\alpha^{w\ell}_D$	-0.0083	(0.0031)**	γ^s_B	-0.1061	(0.8837)
α^{ww}_{FF}	-0.0488	(0.0115)**	α^{wk}_{DC}	0.1095	(0.0198)**	γ^s_G	0.4184	(0.2014)*
α^{ww}_{II}	-0.2120	–	α^{wk}_{DA}	-0.1013	–	λ	-0.6566	(0.3128)*
α^{wp}_D	0.1093	(0.0401)**	$\alpha^{w\ell}_F$	-0.0001	(0.0009)	β^z	-0.3500	(0.1013)**
α^{wp}_F	0.0380	(0.0140)**	α^{wk}_{FC}	0.0426	(0.0073)**	β^{zt}	-0.1000	(0.0511)*
α^{wp}_I	0.1786	–	α^{wk}_{FA}	-0.0425	–	$\beta^{z\ell}$	-0.0500	(0.0212)**
α^{ww}_{DF}	-0.0187	(0.0104)*	$\alpha^{w\ell}_I$	-0.0015	–	β^{zk}_C	-0.1000	(0.0524)*

where D stands for hired labor, F for fertilizers, I for intermediate inputs, C for capital, A for land, E for education, B for Body Mass Index (BMI), and G for age. * and ** indicate statistical significance at the 5 and 1 per cent level. Standard errors were estimated using bootstrapping techniques.

Table 5: Crop Supply and Variable-Input Demand Elasticities

	Hired Labor	Fertilizers	Intermediate Inputs	Crop Output
Uncompensated Demand and Supply Elasticities:				
Hired Labor	-0.5452	-0.0447	-0.9888	1.5787
Fertilizers	-0.1545	-0.6073	-0.7526	1.5144
Intermediate Inputs	-0.7431	-0.1638	-2.0287	2.9355
Output	-0.2850	-0.0792	-0.7052	1.0693
Compensated Demand Elasticities:				
Hired Labor	-0.1241	0.0720	0.0521	–
Fertilizers	0.2490	-0.4952	0.2463	–
Intermediate Inputs	0.0392	0.0543	-0.0934	–

Table 6: Quasi-Rent Losses, Output Losses and Pest-Damage Measures

	Profit Quartiles				Mean Values
	1st	2nd	3rd	4th	
Quasi-Rent Loss (in €)					
$Q^b\left(p, w, \ell, k, b^r, z, s, t\right)$	5,398	5,684	7,728	11,635	7,648
$Q^h\left(p, w, \ell, k, b^r, z, s, t\right)$	456	853	1,337	3,335	1,511
$R^h\left(p, w, \ell, k, b^r, z, s, t\right)$	844	1,534	2,433	6,376	2,829
$-C^h\left(p, w, \ell, k, b^r, z, s, t\right)$	-388	-681	-1,097	-3,041	-1,318
$\pi\left(p, w, \ell, k, t\right) - \pi\left(pg^d, w, \ell, k, t\right)$	4,942	4,831	6,392	8,300	6,136
Output Loss (in kgs)					
$\frac{R^b(p,w,\ell,k,b^r,z,s,t)}{p}$	16,182	16,347	21,281	31,103	21,325
$\frac{R^h(p,w,\ell,k,b^r,z,s,t)}{p}$	1,408	2,402	3,641	8,777	4,099
$\pi_1\left(p, w, \ell, k, t\right) - \pi_1(pg^d, w, \ell, k, t)g^d$	14,774	13,945	17,640	22,326	17,226
$(1-g^e)\pi_1(pg^e, w, l^e, k, t)$	4,687	5,460	6,902	9,214	6,581
Crop Damage (in %)					
$1 - \frac{\pi(pg^e,w,\ell^e,k,t)}{\pi(p,w,\ell,k,t)}$	0.3890	0.3090	0.3122	0.2720	0.3210
$1 - g^e$	0.1965	0.1578	0.1562	0.1177	0.1571
$\frac{Q^h(p,w,l,k,b^r,z,s,t)}{\pi(p,w,l,k,t)}$	0.0338	0.0461	0.0524	0.0766	0.0523
$\frac{\pi(pg^e,wg^e,\ell,k,t)-\pi\left(pg^d,w,\ell,k,t\right)}{\pi(p,w,\ell,k,t)}$	0.1587	0.1050	0.1037	0.0777	0.1116

Table 7: Marginal Returns to Pesticides

	Profit Quartiles				Mean Values
	1st	2nd	3rd	4th	
$\nu^z\left(p, w, \ell, k, b^r, z, s, t\right)$	0.0937	0.2061	0.4741	1.3750	0.5372
$\pi_1\left(pg^e, w, \ell^e, k, t\right) p \left[\frac{\partial g^e}{\partial z} + \frac{\partial g^e}{\partial \ell^e}\frac{\partial \ell^e}{\partial z}\right]$	0.0991	0.2181	0.5015	1.4542	0.5682
$\pi_3\left(pg^e, w, \ell^e, k, t\right) \frac{\partial \ell^e}{\partial z}$	-0.0054	-0.0120	-0.0273	-0.0792	-0.0310