Health-Damaging Inputs, Workers' Health Status and Productivity Measurement

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Abstract

In many sectors technological conditions of firm production require the use of specific inputs that are at the same time hazardous for firm workers, *i.e.*, *health-damaging* inputs. Safety rules on the application of these health damaging inputs are not always followed due to lack of knowledge on the adverse long-run health effects and improper firm management. This in turn implies that firms suffer from important productivity losses due to deterioration of their human capital. In this paper, we develop a primal decomposition framework to analyze the effects of human capital on individual productivity growth rates while considering the adverse effects of health-damaging inputs. Workers' health indices are estimated using the recently developed generalized propensity score (GPS) methods with continuous treatments (Hirano and Imbens, 2004). The approach is implemented in a unique dataset of greenhouse producers in Western Crete, Greece that combines individual worker health with production data.

Keywords: health-damaging inputs; workers' health index; TFP growth; greenhouse farms
JEL Codes: *I12*, *I30*, *Q12*, *D24*.

1 Introduction

Since the seminal papers of Schultz (1961) and Becker (1962), a vast literature emerged analyzing the role of human capital on productivity growth rate. Using Griliches (1963, 1964) and Mincer (1974) theoretical developments, empirical research at a micro level concluded that indeed improvements in human capital account for significant gains in observed productivity rates among individual firms (*e.g.*, Bartel and Lichtenberg,1987; Katz and Murphy, 1992). At the same time studies based on the endogenous growth model of Lucas (1988) and Romer (1986) attributed significant productivity improvements to human capital accumulation for a broad set of countries around the world (*e.g.*, Hall and Jones, 1999; Bils and Klenow, 2000). A common ground throughout this literature, is that human capital is mainly determined by two factors: worker's educational level and health status. The intuition behind this assertion is simple. Formal or informal education decreases the marginal cost of acquiring production related information and the benefit of such information improves the allocative ability of firm workers. On the other hand, improved health status enhance workers' (skilled and unskilled) productivity by increasing their physical capacities, such as strength and endurance, as well as their mental capacities, such as cognitive functioning and reasoning ability.

Another common feature of these empirical studies, is that they all assume that workers' health status is determined exogenously. Regardless the choice of variables used to proxy individual health status, this is assumed to be independent of working environment and production decisions made within the firm. The majority of empirical work commonly hypothesizes a strong relationship between nutritional intakes and wages to examine the effects of health on labor productivity mainly in rural areas in both developed and developing countries (Bliss and Stern, 1978; Deolalikar, 1988; Croppenstedt and Muller, 2000). A set of wage function estimates provides solid evidence that higher nutrition leads to increased productivity rates. This nutrition-productivity hypothesis is further confirmed by production function approaches using instrumental variables to correct for simultaneous equation bias (Strauss, 1986). Using different proxies for workers' health status, more recent micro-level research verifies the positive relationship between health variables and productivity for both skilled and unskilled workers (Strauss and Thomas, 1998; Schultz, 2002).

However, empirical evidence worldwide rather suggests the opposite. In many sectors (if not all) workers' health status is not irrelevant to the workplace conditions and individual firm decisions. Evidence from medical studies indicates that health impairments account for 12-28 per cent productivity losses in construction sector (Meerding *et al.*, 2005), while the relative figure in Information and Communications Technology (ICT) industry is 15 per cent (Hagberg *et al.*, 2002). Further, according to the *International Labour Organization* (ILO), every year 160 billion workers suffer globally from illnesses due to work-related causes, while the relative total cost of these diseases accounts for approximately 4 per cent of world's GDP. According to a recent study by *Eurostat* (2010), about 8.6 per cent of the workers in the EU-27 face at least one work-related health problem in a period of 12 months, while the total time of lost work due to work-specific health impairments is approximately 367 million calendar days. There are two ways that workplace conditions are affecting workers' health status. First, the nature of working activities involved in firm production (*e.g.*, construction sector) and second, the technological conditions that require the use of specific inputs that are at the same time hazardous for firm workers. Ensuring strict safety standards in a construction site (such as the height of handrails, shoring of trenches, and safe handling procedures) may reduce the adverse effects in workers health status from a potential accident. This is an instantaneous decision made by the firm (mostly imposed by the regulatory framework) and it's impact on individual productivity rates depends on the incidence of work accidents in the future.

In terms of productivity improvements though, it is more important to analyze workers' health status when firms utilize specific inputs in their production process that are at the same time (directly or indirectly) harmful for individual workers, *i.e.*, *health-damaging* inputs. This type of inputs entails a trade-off between firm production and workers' health status. This is particularly acute for hazards that do not have an immediate and recognizable effect. For instance pesticides materials in crop production, chemical substances in many manufacturing sectors, plastic or paint manufacturing, are all cases where health-damaging inputs are extensively used by firms posing serious health risks for their employees. In these sectors, workers seldom have perfect information about the health implications of their jobs and the use of this specific type of inputs. For many hazards, the true probabilities of being killed or getting ill are not known by anyone. Due to the retarded state of occupational medicine, even the underlying medical ramifications of different exposures to aspects of the workplace such as radiation, noise, high temperatures, and chemical vapors are little understood. This uncertainty is compounded by uncertainty with regard to the characteristics of the work situation, for example, the concentration of asbestos fibers in the air.

Hence, in many instances safety application rules are not always followed by individual workers due either to improper firm management or lack of individual knowledge. Although the social cost of such health impairments might not be of the interest of the firms, the associated reductions in effective labor do matter for them since such reductions are accompanied by lower productivity rates. Hence, measuring the indirect effect of health-damaging inputs, through human capital deterioration, may indirectly enforce safety standards in working environments. If these productivity losses are important for individual firms, then indeed improving workers' knowledge or applying more effective management practices would result to significant gains for them.

Along these lines, this paper contributes to the relevant literature by suggesting a theoretically consistent framework to analyze both the direct and the indirect effect of health-damaging inputs on total factor productivity growth. The decomposition framework is based on a primal approach requiring no assumptions about the structure of labor markets. It is applied to a panel of greenhouse producers from Western Crete, Greece observed during the 2003-07 cropping period. Due to the extensive use of chemical pesticides, farming is a particularly interesting example for measuring the adverse effects of health-damaging inputs on individual productivity rates. For measuring employees' health status, individual health indices are estimated using recently developed generalized propensity score (GPS) methods in a continuous treatment setting (Hirano and Imbens, 2004). To our knowledge this is the first attempt to construct an index of workers' health status that is endogenously determined, enabling the analysis of both direct and indirect effects of health damaging inputs on individual total factor productivity growth rates. Our empirical results may contribute to the ongoing debate for improving working conditions and reducing work-specific health impairments in many sectors.

The next section develops a primal decomposition framework taking into account the dual effect of health-damaging inputs on productivity growth rates. Section 3 presents the empirical setting developing at the same time a theoretically consistent index for measuring workers' health status by using the generalized propensity score method. Next section 4 presents the empirical results of our case study discussing their policy implications. Finally, the last section concludes the paper.

2 Human Capital and TFP Growth

According to the relevant literature, effective labor input may be defined through the following general function (*e.g.*, Griliches, 1963; Bliss and Stern, 1978; Strauss, 1986; Deolalikar, 1988):

$$l^e = l^e\left(l, \epsilon, h\right) \tag{1}$$

where $l \in \Re_+$ stands for actual labor hours devoted to firm production, $\epsilon \in \Re_+$ and $h \in \Re_+$ denote workers' educational level and health status, respectively, and $l^e\left(l, \epsilon, h\right) : \Re^3_+ \to \Re_+$ is a continuous and twice differentiable concave function, non-decreasing in h and ϵ, representing effective labor hours utilized in firm production.

Assuming that the only source of impairment in workers' health is the use of hazardous inputs in the production process, then actual workers' health status is given by:

$$h = h(z) \tag{2}$$

where $z \in \Re_+$ is the amount of hazardous input utilized in production and, $h\left(z\right)$ is a continuous and twice differentiable convex function, non-increasing in z representing workers' actual health status.

Under this general setup, we can describe the firm's technology in period t from the following closed, non-empty production possibilities set:

$$T(t) = \left\{ (\mathbf{x}, l, z, \epsilon, y) : y = f\left(\mathbf{x}, l^e, z, t\right), l^e = l^e\left(l, \epsilon, h\right), h = h\left(z\right) \right\} \tag{3}$$

where $y \in \Re_+$ is the realized firm output, $\mathbf{x} \in \Re_+^J$ is a vector of the j non-labor variable inputs, and $f\left(\mathbf{x}, l^e, z, t\right) : \Re_+^{j+3} \rightarrow \Re_+$, is a continuous and, strictly increasing, twice differentiable concave production function, representing maximal output from variable inputs, effective labor, and health damaging input use given worker's education.

Taking logarithms of both sides of the production function, $y = f\left(\mathbf{x}, l^e, z, t\right)$, totally differentiating with respect to t and, using relations (1) and (2), yields:

$$\dot{y} = \frac{\partial \ln f}{\partial t} + \sum_j \frac{\partial \ln f}{\partial \ln x_j}\dot{x}_j + \frac{\partial \ln f}{\partial \ln l^e}\left[\frac{\partial \ln l^e}{\partial \ln l}\dot{l} + \frac{\partial \ln l^e}{\partial \ln \epsilon}\dot{\epsilon} + \frac{\partial \ln l^e}{\partial \ln h}\frac{\partial \ln h}{\partial \ln z}\dot{z}\right] + \frac{\partial \ln f}{\partial \ln z}\dot{z}$$

or in elasticity form

$$\dot{y} = TC + \sum_j e_j^x \dot{x}_j + e^l \dot{l} + e^\epsilon \dot{\epsilon} + e^d \dot{z} + e^h e^{hz} \dot{z} \tag{4}$$

where a dot over a variable indicates its time rate of change, $TC = \dfrac{\partial \ln f}{\partial t}$ is the primal rate of technical change, $e_j^x = \dfrac{\partial \ln f}{\partial \ln x_j}$ and $e^l = \dfrac{\partial \ln f}{\partial \ln l^e}\dfrac{\partial \ln l^e}{\partial \ln l}$ are the output elasticities of the non-labor and labor inputs, respectively, $e^\epsilon = \dfrac{\partial \ln f}{\partial \ln l^e}\dfrac{\partial \ln l^e}{\partial \ln \epsilon}$ is the output elasticity of workers' educational level and, $e^d = \dfrac{\partial \ln f}{\partial \ln z}$ and $e^z = e^h e^{hz}$ are the direct and indirect output elasticities of the health damaging input, respectively. The latter is the product between the output elasticity with respect to workers' health status, $e^h = \dfrac{\partial \ln f}{\partial \ln l^e}\dfrac{\partial \ln l^e}{\partial \ln h}$ and the health elasticity with respect to the hazardous input utilized in production, $e^{hz} = \dfrac{\partial \ln h}{\partial \ln z}$.

Following Chan and Mountain (1983), it can be shown that the cost shares can be related to the scale elasticity as follows: $s_j^x = \dfrac{e_j^x}{E}$, $s^l = \dfrac{e^l}{E}$, and $s^z = \dfrac{e^z}{E}$ where $E = \sum_j e_j^x + e^l + e^z$. Plugging these relations into the conventional *Divisia* index of TFP growth (*i.e.*, $TFP = \dot{y} - \sum_j s_j^x \dot{x}_j - s^l \dot{l} - s^z \dot{z}$) and substituting it into (4) results, after slightly rearranging terms, in:

$$T\dot{F}P = TC + e^\epsilon \dot{\epsilon} + \left(\frac{E-1}{E}\right)\left(\sum_j e_j^x \dot{x}_j + e^l \dot{l} + e^z \dot{z} + e^h e^{hz} \dot{z}\right) \tag{5}$$

Under the assumptions made on firms' production technology, the above formula shows that calculated TFP growth is a biased measure of technical change captured by the first term in (5). The most familiar source of this bias in human capital literature emerges from how changes in worker's educational level affect output growth. Intertemporal changes in the educational level cause changes in observed output due to changes in effective labor units and not due to the traditional scale concerns. In this instance measured TFP growth will conflate the amount of technological progress occurring with output changes caused by intertemporal changes in the educational level of firm workers. Apart of the effect of education, measured TFP growth contains a scale component that must be disentangled from observed growth in variable, labor and health damaging inputs. In expression (5), the scale component of the technology is captured by the third term.

Scale bias is not present if returns to scale are one (*i.e.*, $\sum_j e_j^x + e^l + e^z = 1$) or if variable factors of production, labor hours worked on firm and health damaging inputs do not change over time. Scale bias is positive (negative) under increasing (decreasing) returns to scale as long as inputs increase over time and *vice versa*. The first term of the scale bias reflects the impact of non-labor inputs ($\sum_j e_j^x \dot{x}_j$), the second that of labor hours devoted in firm production ($e^l \dot{l}$) and, the last two the direct ($e^z \dot{z}$) and indirect ($e^h e^{hz} \dot{z}$) effect of the hazardous input on individual productivity rates. The indirect effect reflects productivity changes caused by the impact of the hazardous input on worker's health. Given the monotonicity properties of the health function in (2), increases in the hazardous input use, cause impairment in worker's health reducing effective labor units. These decreases in effective labor emanating from higher levels of the hazardous input contribute in turn negatively (positively) to TFP growth under increasing (decreasing) returns to scale. Nevertheless, under constant returns to scale, changes in the hazardous input use will still affect health and consequently the effectiveness of labor inputs but the later will have no impact on observed productivity rates.

3 Empirical Illustration: Chemical Pesticides

Due to the extensive use of chemical pesticides, the agricultural sector is a particularly interesting example for measuring the effects of health damaging inputs on individual productivity growth rates through their impact on farm workers' health. Exposure to chemical pesticides is one of the most important occupational risks in both developed and developing countries (Konradsen *et al.*, 2003; Coronado *et al.*, 2004). The *World Health Organization* (WHO) and the *UN Environment Programme* estimate that each year 3 million farm workers in agriculture experience severe poisoning from pesticides (WHO, 2004). Chemical pesticides are vital in farming practices due to their damage preventing nature. Pesticides are used extensively in crop production under conventional farming practices since they mitigate damage and reduce output losses caused by the presence of harmful pests. Hence, unlike conventional inputs which enhance directly the volume of produced output, pesticides application reduce the pest incidence which in turn affects the level of realized farm output (Saha *et al.*, 1997; Chambers *et al.*, 2010).

However, chemical pesticides besides preventing crop damage are at the same time hazardous for farm workers. Both anecdotal evidence and available data worldwide indicate that pesticide use in various farming activities has often been associated with significant health problems (Jeyaratnam, 1990; Cowan and Gunby, 1996). Low education levels of the rural population, lack of information and training on pesticide safety, poor spraying technology, and inadequate personal protection during pesticide application have been reported to play a major role in pesticide intoxication. As a result, farm workers exposed systematically to hazardous ingredients over the past decades experienced significantly higher rates of illnesses compared with workers in any other sector of the economy (Coye, 1985). These distinct characteristics make the empirical analysis of farm production particularly interesting.

Our empirical illustration involves a data set of Greek farmers cultivating vegetables in greenhouses. The survey was undertaken within the context of the Research Program TEAMPEST financed by the European Commission.[1] Specifically, our dataset includes 50 small-scale greenhouse farms randomly selected from the Chania region in the Western part of the island of Crete, Greece. In this specific area of Crete vegetable cultivation under greenhouses is flourishing in the last twenty years. The survey covers five cropping seasons from 2003 to 2007 resulting in a balanced panel dataset of 250 total observations. Crop protection in greenhouses became strongly chemically oriented since the early 60's. The micro-climate inside greenhouses is excellent for fast reproduction of pests and diseases demanding high spray frequencies. This implies that pesticide applicators (farmers or farm workers) are heavily exposed in this type of farming activities, insofar as applications are more frequent than in open-air fields, environmental conditions are extreme (high temperature and relative humidity), and ventilation is poor in partially-closed spaces.

The survey contains farm-level information on three different pesticide ingredients used against the greenhouse whitefly *Trialeurodes Vaporariorum* (Westwood). The greenhouse whitefly has been focused on as a 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. All identified types of pesticide materials were found to belong in the second

[1]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

category of the most hazardous pesticides according to the WHO classification containing highly toxic ingredients such as *propetamphos*, *sodium cyanide*, *fluoroacetamide*, *carbofuran*, and *methomyl*. Information on pesticide use consists of data on expenditures and quantities used in litres. We use these data to construct an aggregate pesticides input quantity index using *Tornqvist* procedures with cost shares of each ingredient to total pesticides expenditures being the relevant weights. Greenhouse whitefly population levels are measured using chemical traps installed approximately every 250 squared meters. The number of whiteflies captured in the traps were then used to extrapolate the average number of whiteflies per greenhouse farm.[2] Summary statistics of the variables are presented in Table 2.

Prior to the definition of farm workers' health index, we first need to distinguish among various farm working activities. Given that the health damaging effect of chemical pesticides arises through the labor input, improper measurement of farm labor may result in biases in estimated productivity growth rates. Thus, we distinguish the two major types of work activities involved in farm production: i) *field labor* including working hours devoted to field tasks (*e.g.*, harvesting, spraying, fertilisation, irrigation), and, ii) *management labor* including the hours devoted to supervision and organizational activities. According to Bliss and Stern (1978) and Strauss (1986) these two distinct types of farm labor inputs are not perfect substitutes having a different impact on productivity growth. Human capital increases field workers' physical ability to engage in work at the field increasing their skills and their physical strength and endurance. On the other hand, such increases enhance managers' organizational and supervision capabilities in a different manner, increasing their mental and reasoning abilities. Hence, the distinction among the two types of farm labor will improve our estimates on the adverse productivity effects of pesticide application among greenhouse farmers.

3.1 Farm Workers' Health Index

According to Strauss and Thomas (1998) there are two major problems in defining an appropriate health index for farm workers. First, unlike educational level, health status is a fundamental multidimensional concept. Different dimensions of health are having different impact on individual productivity rates and these effects may significantly vary over time. Respiratory problems have different and rather short-run effects on productivity compared with many chronic diseases. Second, many health indicators are measured with errors that are systematically related with individual farm or market characteristics and farmers behavior. For instance, the body mass index-BMI

[2] 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 color. 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 situation in each greenhouse.

(weight measured in kilograms divided by height squared measured in meters) used frequently in the relevant literature, has been found by Strauss and Thomas (1996) to be structurally related with individual income. Weil (2007), trying to overcome these problems, proposed three conditions that an "ideal" health indicator should satisfy in any empirical setting: first, it should be related with aspects of farmer's health that are relevant in productivity measurement; second, it should have a structural relationship of the returns to these health characteristics and; third, data for the construction of the indicator are indeed available (and free of systematic measurement errors).

Along this line of argument, we follow the same approach with Antle and Pingali (1994) who also analyzed empirically the adverse effects of pesticides on farmers' health. In this context the proposed index overcomes the theoretical problems underlined by Strauss and Thomas (1998) and at the same time satisfies the Weil's (2007) "ideal" conditions. Using WHO definitions we first identify the five most serious pesticide-related diseases that arise from organophosphate compounds and 2,4-D that exist in all types of pesticide materials utilized by greenhouse farmers in Western Crete. These include *eye*, *dermal*, *respiratory*, *neurological* and, *kidney* problems that together with their associated specific clinical symptoms are linked directly with exposure to those chemical compounds.[3] These specific health problems capture different dimensions of health status, while at the same time are directly or indirectly structurally related with individual productivity levels (Pingali *et al.*, 1993). In particular, pesticide application results in chronic eye irritation problems and diminished vision. On the other hand, dermal contamination takes place during application and mixing resulting to chronic dermal disorders. Bronchial asthma is the most common chronic lung abnormality due to long-term pesticide exposure. Organophosphate compounds and 2,4-D are known neurotoxicants associated with sensory loss and diminished reflexes. Finally, circulating toxins through human body due to pesticide materials lead to significant kidney abnormalities.

Greenhouse farmers were surveyed periodically by a team of experts consisting of a specialist doctor, an agronomist and two economists. The team examined in detail the medical and social security records of all farm workers[4] (including the owner) during the 2003-07 period in order to obtain accurate information on the above list of health problems and their associated clinical symptoms. These records include personal prescription books as well as medical records kept at the University of Crete Hospital. This disease-oriented construction of farm workers' health index

[3]Obviously this is not an exhaustible list. Pesticides are also responsible for non-specific illnesses that affect farm workers' general health status (*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 a general index for health status. We can reasonably assume though that these effects are closely related with the above list of pesticide-related diseases and therefore measurement errors are kept random. In addition, we do not take into account cancer incidences and reproductive problems. These are associated with very long-term effects and difficult to assign to pesticide use in our sample survey.

[4]Farms in the sample used to occupy permanent field workers which facilitates the identification of health information. In cases of past-employed field workers, the survey team contacted via telephone the potential respondents in order to arrange personal interviews.

lessens significantly the potential biases arising from systematic measurement errors. Farm workers and farm owners belong to a rather homogenous rural population having all access to the National Health System enjoying the same health-related benefits. Hence, they do not have incentives to over- or under-report morbidity rates and illnesses. The survey also contains information on the medical cost of treatment for each disease together with the associated work days lost for each farm worker. Both information were gathered from the personal prescription books. All five pesticide-related diseases were found to account for approximately 75% of the total health incidences recorded. Table 1 presents summary statistics of the pesticide-related health problems suffered by farm managers and field workers together with their associated medical and impairment costs.

Over the five-year period, 486 cases of illnesses were recorded among Cretan greenhouse farms. The most common types of health problems were the respiratory problems (325 cases), followed by dermal (77 cases) and eye problems (53 cases). Incidences of neurological and kidney problems were also observed but in a lesser extent constituting together only the 6.4 per cent of the total number of incidences recorded. The frequency distribution of the recorded incidences for the five categories of health problems was quite similar for farm managers and field workers. Nevertheless, the relative impairment cost was found to vary significantly across the two labor types. In particular, field workers suffered from each disease for about 10.8 days on average before they fully recover, while the average recovery period for farm managers was substantially shorter, 8.3 days.[5] For more than half of these days, both field workers and farm managers abstained totally from working activities while during the remaining recovery days, they were involved in work tasks but their effectiveness was lower by 52.3 and 54.0 per cent, respectively.[6] The average medical cost of treatment was approximately 253 and 134 Euros for field workers and farm managers, respectively. In total, the medical cost from pesticide-related health problems was 94,396 Euros over the period while the total time of work lost was approximately 2,621 days.

In order to combine all these information into a single index of health status we use the sum of the annual direct and indirect costs concerning pesticide-related health problems as a proxy of individual worker's health impairment. Direct costs include the medical costs of treatment, while the indirect costs involve the opportunity cost from the work days lost including the value of work loss due to lower efficiency. These indirect costs were calculated using the average wage for field workers in Western Crete. Based on these assumptions, the health index was defined as the logarithm of the reciprocal of health impairment cost and it was constructed on an annual basis for the manager (*i.e.*, farm owner) and every field worker in the farm. Since each farm employs

[5]As Schultz and Tansel (1997) noted, this difference between farm workers and farm manager may arise due to differences in their opportunity cost of time.

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

more than one field workers (including family members) an aggregate health index of field labor was constructed as the weighted sum of all individual health indices with field labor time shares used as the relevant weights.

3.2 Pesticide Intensity and Health Index

Once an appropriate health index for farm workers has been defined, the problem still remains of how to measure the effect of pesticide use on the health index. In an ideal situation a researcher would like to have data on the health status for the same individual at different levels of treatment or pesticide use, *i.e.*, data on all potential outcomes. Unfortunately, the only available data is based on observed outcomes and only the health status for a single level of pesticide use is observed for each individual when collecting survey data. A potential problem that may arise in this case is that the amount of pesticides used by each farm in the sample has not been randomly assigned to each farm. The fact that the assignment of pesticide levels is not random implies that farms applying different levels of pesticides may systematically differ from one another for reasons other than the level of pesticide use. Therefore observed differences in the health status corresponding to different levels of pesticide use could depend on baseline characteristics that affect pesticide use and not so much on the level of pesticide itself.

The study undertaken by Antle and Pingali (1994) relates the health impairment index to the number of applications and some demographic variables without taking into account that the assignment of farmers to different levels of the number of applications is not random. On the other hand, Antle *et al.*, (1998) partially correct the problem of non random assignment by using data both from framers and from a referent group not exposed to pesticides where both groups are matched by age and education. However their health index depends on other covariates related to farmers' intelligence for which no matching was performed. Baseline characteristics affecting the choice of pesticide level could be related to demographic characteristics such as the education level as well as to structural characteristics such as the pest incidence or the quality of spraying equipment. In addition, the amount of pesticides is likely to be correlated with background baseline variables and the potential status of the individual's health habits (*e.g.*, smoking or drinking). In order to adjust for such differences, a key assumption is that treatment assignment is independent of the outcomes given the covariates or in the present case that conditional on observed covariates V the level of pesticides z is independent of the potential health status (weak unconfoundedness assumption) and is given by,

$$h(z) \perp Z|V \quad \text{for all z} \in Z$$

Under the unconfoundedness assumption, propensity score methods can be used to remove any potential bias arising from differences in the observed characteristics between workers. Following

Hirano and Imbens (2004) and Bia and Mattei (2012) we employ in our empirical analysis the recently developed generalized propensity score method in a continuous treatment setting. The weak unconfoundedness assumption adjusting for differences in covariates removes all biases in comparisons by pesticide application levels. In other words, this assumption implies that the baseline covariates which affect both the health and the likelihood of applying pesticides are all observed while the remaining ones are perfectly correlated with the observed ones. Combined with this assumption, the propensity score defined as the conditional density of the actual level of pesticides can be used to eliminate any bias arising from differences in the covariates and hence, to approximate the true health damaging effect of pesticides.

The approximation of farm workers' health index is done in two-steps. In the first step, the conditional distribution of the pesticide application intensity is estimated given a set of covariates assumed to affect application rates. Following Hirano and Imbens (2004) and Bia and Mattei (2012), the logarithmic transformation of pesticides application intensity, z_{it}, is used to reduce the skewness of the variable. The logarithm of the pesticide variable is then assumed to have a normal distribution conditional on the covariates, as follows:

$$\ln z_{it} \mid \mathbf{V_{it}} \sim N\left(\delta' \mathbf{V_{it}}, \sigma^2\right) \tag{6}$$

where i is used to index farms, t indicates the time period, $\mathbf{V_{it}}$ is a vector of covariates, δ is a vector of parameters to be estimated and σ^2 is the variance of the conditional density of the logarithm of pesticide application rates. The model in (6) is estimated using standard maximum likelihood technique and the estimated generalized propensity score-GPS is obtained from:

$$\hat{r}_{it} = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}\left[\ln z_{it} - \hat{\delta}' \mathbf{V_{it}}\right]^2\right] \tag{7}$$

where $\hat{\sigma}^2$ and $\hat{\delta}$ indicate the estimated parameters.

Using these generalized propensity scores, we estimate in the second step farm workers' actual health index. Specifically, the conditional expectation of the health index is expressed as a quadratic function of the form:

$$E\left[\ln h_{it} \mid z_{it}, \hat{r}_{it}\right] = \alpha_0 + \alpha_z z_{it} + \alpha_{zz} z_{it}^2 + \alpha_r \hat{r}_{it} + \alpha_{rr} \hat{r}_{it}^2 + \alpha_{zr} z_{it} \hat{r}_{it} \tag{8}$$

where $h_{it} = H_{it}^{-1}$ is the farm workers' health index defined as the reciprocal of health impairment cost, z_{it} are the pesticide application intensity rates, $\hat{r}_{it}$ are the estimated GPS scores obtained from (7) and, α's are the parameters to be estimated by simple OLS.

Using the estimated parameters, the average health index is computed for each level of pesticide application intensity rate utilized by surveyed farms during all time periods in order to obtain a farm- and time-varying estimate of farm workers' health index from:

$$E\left[\ln h(\bar{z})\right] = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{\alpha}_0 + \left[\hat{\alpha}_{\bar{z}} + \hat{\alpha}_{zz}\bar{z}\right]\bar{z} + \left[\hat{\alpha}_r + \hat{\alpha}_{zr}\bar{z} + \hat{\alpha}_{rr}\hat{r}_{it}\left(\bar{z}, \mathbf{V_{it}}\right)\right]\hat{r}_{it}\left(\bar{z}, \mathbf{V_{it}}\right)\right) \quad (9)$$

Intensity in pesticides use was proxied by the ratio of applied pesticides measured in litres divided by the size of cultivated land measured in stremma (one stremma equals 0.1 ha). Concerning farm manager, three demographic and four general health and pesticide-related covariates were used for the estimation of individual health indices. These include *age* measured in years, *experience* defined as the number of years involved in greenhouse cultivation and, *educational level* proxied by years of formal education and participation in training seminars.[7] All of these variables affect individual farmer's awareness and behavior on health issues and therefore pesticide application intensity. The remaining five covariates considered were manager's *smoking*, and *drinking* habits, *pest population* and, the *stock of spraying equipment*. The first two variables reflect his/her health habits, while pest population and spraying equipment is assumed to influence pesticide application intensity. Smoking habits were proxied as the average number of cigarettes smoked per day multiplied by the tar milligrams contained, while drinking habits were proxied by the average consumption of alcohol per week measured in units of alcohol (Stampfer, *et al.*, 1993).[8] Finally, the stock of spraying equipment was computed using the perpetual-inventory method as described by Ball *et al.*, (1993) and data on depreciation rates obtained from the Greek Ministry of Agriculture for different farming equipment.

Five of these covariates were also used in the econometric estimation of field workers' health index. Specifically, manager's age, education and experience together with pest population and the stock of spraying equipment were included in (6) when estimated for field workers. Farm manager usually makes all farm decisions and thus, his/her level of awareness affects directly pesticide application intensity that depends on pest incidence and available spraying equipment on farm. The remaining covariates include field workers' *age*, *education*, and *smoking* or *drinking* habits measured as described before. Field workers' characteristics and health habits are likely to affect pesticide intensity as field workers are responsible to apply manager's decisions. These four covariates were

[7]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. Concerning training seminars, extension agents from the local Agricultural Experimental Stations run for many years a continuous scheme of training seminars for both farmers and farm workers in greenhouses. These training seminars are crucial as they enhance significantly their abilities particularly in intensive farming practices like greenhouses. To aggregate both variables into a single education index we assume that one month participation in training seminars corresponds to one year of formal schooling.

[8]One unit of alcohol equals approximately 8 gms of ethanol which corresponds to half pint of beer or a small glass of wine.

calculated at aggregate level for each farm as a weighting sum using field labor time shares as the relevant weights. Summary statistics of all these variables are also presented in Table 2.

3.3 Farm Production Model

For the effective labor function in (1) we adopt Griliches (1963) multiplicative separable specification that presumes perfect substitutability between actual labor hours and human capital variables (*i.e.*, health and education).[9] In logarithmic form, the effective labor functions for both types of farm labor input have the following form:

$$\ln F^e = \ln F + \ln \hat{h}^F(z) + \ln \epsilon^F \quad \text{and} \quad \ln M^e = \ln M + \ln \hat{h}^M(z) + \ln \epsilon^M \tag{10}$$

where i is used to index farm, t indicates the time periods and, $\hat{h}^F_{it}(z)$ and $\hat{h}^M_{it}(z)$ are field workers' and farm manager's health indices obtained from the econometric estimation of (8) and relation (9).

Next, we need to take into account the asymmetric role of pesticides in farm production which is the only health damaging input considered.[10] According to the damage control literature (*e.g.*, Lichtenberg and Zilberman, 1986; Chambers and Lichtenberg, 1994; Fox and Weersink, 1995), the impact of pesticides on farm production involves a two-stage process which consists of the effect of pesticides on pest infestation and the subsequent effect of the remaining pests on output. Thus, farm production function can be written as:

$$y_{it} = f\big(\mathbf{x_{it}}, F^e_{it}, M^e_{it}, t; \beta\big)\big(1 - g\left(b_{it}; \lambda\right)\big) \exp\left(v_{it}\right) \tag{11}$$

with

$$\begin{aligned} g\left(b_{it}; \lambda\right) &= 1 - \exp\left(-\lambda b_{it}\right) && (12)\\ b_{it} &= b^r_{it}\big[1 - \phi\left(z_{it}; \beta^z\right)\big] && (13)\\ \phi\left(z_{it}; \beta^z\right) &= 1 - \exp\left(-\beta^z z_{it}\right) && (14) \end{aligned}$$

where β, β^z and λ are the parameters to be estimated and, $v^p_{it} \sim N\left(0, \sigma^2_v\right)$ is a normally distributed error term representing the omitted explanatory variables and measurement errors in the dependent variable. $g(b_{it}; \lambda) : \Re_+ \to [0, 1]$ is a non-decreasing and concave pest damage function measuring the proportion of farm output loss for any given level of pest incidence (density). If the damage agent is

[9] Bliss and Strauss (1986) and Deolalikar (1988) relaxed the assumption of perfect substitutability in the same methodological framework. The validity of this assumption can be examined using formal statistical testing also suggested by Griliches (1963, 1964).

[10] If the damage-control nature of pesticides is not considered in modeling production technology, then the estimated marginal product of pesticides tends to be upward biased (Lichtenberg and Zilberman, 1986).

absent, $b_{it} = 0$, then realised output equals effective output. If, however, the level of damage agent incidence tends to infinity, $b_{it} \to \infty$, then realised output approaches a minimum level which reflects the maximum destructive capacity of damage agents. On the other hand, pest incidence depends on the initial level of pest population, b^r, and the proportion of the damage agent that is not controlled for a given level of treatment, that is, $b_{it} = b^r_{it}\big(1 - \phi\left(z_{it}; \beta^z\right)\big)$, where $\phi(z_{it}; \beta^z) : \Re_+ \to [0, 1]$ is a non-decreasing and concave pest control function measuring the proportion of pest eradication. If $\phi(z_{it}; \beta^z) = 0$, pesticides have no effect on damage agent incidence and the level of damage agent affecting farm production is equal to its initial population, $b_{it} = b^r$. If, however, $\phi(z_{it}; \beta^z) = 1$, there is a complete eradication of the damage agent and realized and effective output coincide.

Assuming a translog specification for the production function in (11) and using relations (12) through (14), our empirical model turns into the following:

$$
\begin{aligned}
\ln y_{it} &= \beta^0_i + \sum_j \beta^x_j \ln x_{jit} + \beta^F \ln F^e_{it} + \beta^M \ln M^e_{it} + t\Big[\beta_t + 0.5\beta_{tt} t + \sum_j \beta^x_{jt} \ln x_{jit} + \beta^F_t \ln F^e_{it} \\
&+ \beta^M_t \ln M^e_{it}\Big] + 0.5\Big[\sum_j \sum_\rho \beta^{xx}_{j\rho} \ln x_{jit} \ln x_{\rho it} + \beta^{FF} (\ln F^e_{it})^2 + \beta^{MM} (\ln M^e_{it})^2 \\
&+ \beta^{FM} \ln F^e_{it} \ln M^e_{it} + \sum_j \beta^{xF}_j \ln x_{jit} \ln F^e_{it} + \sum_j \beta^{xM}_j \ln x_{jit} \ln M^e_{it}\Big] - \lambda b^r_{it} \exp\left(-\beta^z z_{it}\right) + v_{it}
\end{aligned}
\tag{15}
$$

where $\ln F^e$ and $\ln M^e$ are defined in (10).

Using (15), all terms appearing in the decomposition formula in (5) can now be identified. First, the primal rate of technical change is calculated from:

$$
TC = \beta_t + \beta_{tt} t + \sum_j \beta^x_{jt} \ln x_{jit} + \beta^F_t \ln F^e_{it} + \beta^M_t \ln M^e_{it} \tag{16}
$$

Griliches (1963) augmentation scheme in (10) implies that the elasticity of effective labor with respect to labor hours utilized and human capital variables equals to one. Keeping this in mind, the elasticities necessary for the calculation of all terms appearing in relation (5) are obtained from:

$$
\begin{aligned}
e^x_{jit} &= \beta^x_j + \beta^x_{jt} t + 0.5\left(\sum_\rho \beta^{xx}_{\rho j} \ln x_{\rho it} + \beta^{xF}_j \ln F^e_{it} + \beta^{xM}_j \ln M^e_{it}\right) \\
e^F_{it} &= \beta^F + \beta^F_t t + 0.5\left(\beta^{FF} \ln F^e_{it} + \beta^{FM} \ln M^e_{it} + \sum_j \beta^{xF}_j \ln x_{jit}\right) \\
e^M_{it} &= \beta^M + \beta^M_t t + 0.5\left(\beta^{MM} \ln M^e_{it} + \beta^{FM} \ln F^e_{it} + \sum_j \beta^{xM}_j \ln x_{jit}\right) \\
e^d_{it} &= \beta^z \lambda b^r_{it} z_{it} \exp\left(-\beta^z z_{it}\right)
\end{aligned}
$$

$$e_{it}^{z} = e_{it}^{F} e_{F}^{hz} + e_{it}^{M} e_{M}^{hz}$$

where e_{jit}^{x} is the output elasticity of non-labor inputs, e_{it}^{F} is the output elasticity of field working hours, e_{it}^{M} is the output elasticity of management working hours, e_{it}^{d} is the direct output elasticity of pesticides (*i.e.*, the damage control effect of pesticide materials), e_{it}^{z} is the indirect output elasticity of pesticides through changes in effective labor hours and, e_{F}^{hz}, e_{M}^{hz} are the health elasticities of pesticides use for both types of labor which are obtained from (9) as:

$$\begin{aligned} e_{F}^{hz} &= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{\alpha}_{z}^{F} + 2\hat{\alpha}_{zz}^{F}\bar{z} + \hat{\alpha}_{r}^{F}\frac{\partial \hat{r}_{it}^{F}(\cdot)}{\partial \bar{z}} + 2\hat{\alpha}_{rr}^{F}\hat{r}_{it}^{F}\frac{\partial \hat{r}_{it}^{F}(\cdot)}{\partial \bar{z}} + \hat{\alpha}_{zr}^{F}\hat{r}_{it}^{F} + \hat{\alpha}_{zr}^{F}\bar{z}\frac{\partial \hat{r}_{it}^{F}(\cdot)}{\partial \bar{z}}\right)\bar{z} \\ e_{M}^{hz} &= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\hat{\alpha}_{z}^{M} + 2\hat{\alpha}_{zz}^{M}\bar{z} + \hat{\alpha}_{r}^{M}\frac{\partial \hat{r}_{it}^{M}(\cdot)}{\partial \bar{z}} + 2\hat{\alpha}_{rr}^{M}\hat{r}_{it}^{M}\frac{\partial \hat{r}_{it}^{M}(\cdot)}{\partial \bar{z}} + \hat{\alpha}_{zr}^{M}\hat{r}_{it}^{M} + \hat{\alpha}_{zr}^{M}\bar{z}\frac{\partial \hat{r}_{it}^{M}(\cdot)}{\partial \bar{z}}\right)\bar{z} \end{aligned}$$

where $\dfrac{\partial \hat{r}_{it}\left(\bar{z}, \mathbf{V_{it}}\right)}{\partial \bar{z}}$ is the partial derivative of equation (7) with respect to pesticides intensity, $\bar{z}$ for each type of farm labor. Again health elasticities are estimated for each level of pesticides application intensity, $\bar{z}$, utilized by farms during the cropping periods. In that respect, the health elasticities of pesticides are farm- and time-varying as long as the level of pesticides application intensity varies across farms and years as well.

For the empirical approximation of farm technology, we consider one output and three variable inputs together with labor inputs and chemical pesticides. 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 *Tornqvist* output index with the revenue shares of each crop defining the relevant weights. The three non-labor variable inputs are *land*, *fertilizers* and, other *intermediate inputs*. Land input includes the value of the total acreage (rented or owned) under greenhouses measured in Euros. Concerning fertilizers, farmers use a mixture of nitrate, phosphorous, and potassium ingredients. These different fertilizers were aggregated again into a single *Tornqvist* fertilizer index with the cost shares of each type of fertilizer defining the relevant weights. Finally, intermediate inputs consist of goods and materials used during the crop year, whether purchased off-farm or withdrawn from beginning inventories. These include seeds, fuel and electric power, storage expenses, and irrigation water also measured in Euros.

Management labor was defined as the total working hours devoted by the manager (*i.e.*, farm owner) to supervision and organizational activities. *Field labor*, on the other hand, is measured as the total hours devoted to field activities such as harvesting, planting, fertilization and pesticide application. It includes both farm owner, family members and hired workers with either permanent or seasonal occupation.[11] The *education* variable, for both types of labor, includes years of formal schooling and informal training on farming practices (as defined in section 3.2). For field workers a single education index was constructed using *Tornqvist* procedures with working hours shares of each farm worker (farm owner, family members, hired workers) as the relevant weights.

All monetary variables were converted into 2000 constant prices. Finally, prior to econometric estimation, and to avoid problems associated with units of measurement, all variables were converted into indices, with the basis of normalization being the representative greenhouse farm. The representative farm was the one with smallest deviation of all variables from the sample means. Summary statistics of all variables are presented in Table 2.

4 Empirical Results

Health Index

First, the conditional distribution of pesticides application intensity is estimated given the covariates for each type of labor using the ML estimation procedure. The estimation results reported in Table 3 indicate that manager's education and experience along with pest population and stock of spraying equipment are significant determinants of treatment, *i.e.,* pesticides intensity. As expected, manager's education and experience are both negatively related with the level of pesticides applied per unit of land. Additionally, higher pest population increases pesticides intensity while better spraying equipment reduces the level of pesticides applied per stremma. Innovative equipments enable effective spraying methods, such as, target spray applications, which minimize pesticide waste resulting in this way in lower pesticide intenstity rates. On the other hand, field workers' education does not exhibit any significant association with pesticides intensity which is expected given that farm production decisions including pesticides application rates are made by the farm manager. Similar results are also found for the health-related covariates *i.e.*, age, smoking, drinking. These covariates used for matching purposes are assumed to be determinants of potential outcomes (*i.e.*, potential health indexes) rather than determinants of treatment levels. The ML estimates presented here are used next to compute the GPS for both field workers and farm manager.

Before proceeding with the estimation of the continuous dose response function (*i.e.* average health index), the effectiveness of the specification of the propensity score in (8) was examined by testing the balancing properties of covariates before and after adjusting for the estimated GPS. Specifically, the range of pesticides intensity measured in litres per stremma is divided into three intervals, $(0, 0.27]$, $(0.27, 0.50]$ and, $(0.50, 1.33]$ which represent light-, medium- and intensive-pesticide

[11] Our analysis is simplified by assuming that family and hired field labor are perfect substitutes implying that returns to farm and off-farm work are equal under competitive labor markets. Given the structure of local labor markets this assumption is realistic.

user groups, respectively. The first and second groups include 92 and 73 observations and the third group 85 observations. Next, a conventional two-sided t-test was performed for each one of the covariates to examine whether the mean in one of the three treatment groups was different from the mean of the other two groups combined. The test was repeated before and after adjusting for the estimated GPS for both field workers' and farm manager's vector of covariates. The results indicate that adjusting for GPS improves significantly the models as balancing property is found to be satisfied at the 10 per cent level. Table 4 reports the balance properties of covariates after adjusting for GPS. For all three groups in both models, adjusted mean differences are found statistically insignificant at the 10 per cent level providing evidence in favor of the effectiveness of the GPS specification adopted.

As an additional check for the balancing property, the *Bayes Factor Test* for equality of means was performed for all covariates in the two models. The Bayes factor test statistics for unadjusted and GPS-adjusted mean differences are reported in table 5. The values of the Bayes factor can be interpreted as the odds in favor of the equality of the means and therefore of the balancing property. The results indicate that the GPS improves the balance in both models providing strong support for the choice of the GPS specification. In particualr, regarding field workers' covariates, 12 Bayes factors are found less than one and 3 less than 0.01 before adjusting for the GPS while after the adjustment all of them are well above unity. Similar results hold for farm managers' covariates. In particular, prior to adjustment, 9 out of 21 Bayes factors are less than one whereas after adjusting for the GPS again all Bayes factors are found to exceed unity. This increasing trend characterizes all Bayes factors after the adjustment since for all covariates in both models unadjusted Bayes factors were found to be lower than the corresponding GDP-adjusted ones.

Given the t-test and Bayes factor results, the GPS was used to remove the bias arising from systematic differences in covariates. The OLS parameter estimates of the conditional expectation of health status in (8) are reported in Table 6. Based on these estimates, the average potential health index at each level of pesticide intensity was calculated for field workers and farm managers in our sample using equation (9). Figure 1 illustrates the estimated dose response functions (*i.e.*, average health indexes) at each level of pesticide application per unit of land. As is apparent in the Figure, the estimated average health index declines for both types of labor as pesticide intensity rises. For low application levels, increases in the pesticides intensity lead to serious health impairments while for higher levels the corresponding effects are substantially lessened. The estimated average health index for field workers almost equals the corresponding health index of farm managers for low application rates. Nevertheless, as pesticide intensity rises, field workers' health deteriorates with a faster pace resulting in a constantly lower health index for field workers. These findings are more apparent in Figure 2 presenting the average marginal effects of pesticides application intensity.

Farm Production

Prior to the econometric estimation of the translog production function and the empirical approximation of farm production technology, we examined the hypothesis of the multiplicative separable specification for the effective labor function. Using Griliches (1964) approach, the estimated health index and education level were included as separate inputs in the production function along with actual labor hours for both field workers and farm manager. Then, a simple t-test was employed to examine whether the coefficients of labor input and human capital variables were equal for both types of farm labor. The results failed to identify statistically significant differences in the coefficients implying perfect substitutability between labor inputs and human capital variables as Griliches approach implies. This finding suggests that the adopted functional specification for effective labor function is a statistically accepted approximation of the true relations in our sample of greenhouse farms.

Farm production model in (15) was estimated using the standard *fixed effect* estimation procedure. Because of the nonlinearity imposed by our damage-control specification in the use of pesticides materials, the model was estimated using a grid search procedure around the 0-2 range for the values of the β^z parameter. All parameter estimates are presented in Table 7 along with their corresponding standard errors. The estimated parameters were found to be statistically significant at least at the 10 per cent significance level. All input coefficients have the anticipated magnitude and sign and the majority of them are statistically significant at least at the 10 per cent level. Concavity of the production technology with respect to non-labor, labor and damage preventive inputs is satisfied at the point of normalization. Hence, marginal products of non-labor, labor and damage-control inputs are positive and diminishing.

Three additional hypotheses concerning farm production structure were statistically examined using the generalized LR-test statistic. First, the assumptions of zero (*i.e.*, $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_t^F = \beta_t^M = 0$) and *Hicks*-neutral technical change (*i.e.*, $\beta_{jt}^x = \beta_t^F = \beta_t^M = 0$) were statistically tested by imposing the corresponding parameter restrictions in (15). Both hypotheses were rejected by the LR-test indicating that technical change was present during the cropping periods in our sample contributing to TFP growth rates. Annual rate of technical change was estimated to be 0.9561 per cent driven mainly from neutral shifts of the production technology. Regarding technological biases, technical change is found to be labour-saving, land-using and neutral with respect to the remaining two variable inputs (fertilisers and intermediate inputs) as the relevant parameters are found to be statistically insignificant. Finally, the assumption of constant returns to scale was also tested and rejected by the LR-test. For the whole period under consideration, returns to scale were found to be increasing (1.0957 on the average) implying that greenhouse farmers operate at a sub-optimal scale. In any case, the scale effect is present and constitutes an important source of

TFP growth.

Using the parameter estimates of the translog production function, crop output elasticities along with their corresponding standard errors, computed using block resampling techniques, are presented in Table 8. On average, both labor inputs (field workers and farm manager) together with land have the greater impact on farm's crop production. Labor elasticity is 0.3356 (0.2065 for field workers and 0.1291 for farm manager), whereas that for land input is 0.4039. On contrary, the overall output elasticity of pesticide materials is substantially lower, 0.0863. This low point estimate for pesticides is mainly due to their high negative indirect impact on the effective labor units rather than the result of their damage-control effect on production. Assuming that chemical pesticides have no impact on workers' health, an increase in pesticides use by 1 per cent would increase, *ceteris paribus*, crop output by 0.2369 per cent. This difference underlines the importance of the adverse health effects of pesticides on output production which are not negligible.

To investigate the patterns of the direct effect of pesticides on production, two measures of output damage were computed for each level of pesticides use. These measures are: the actual damage measured as the percentage damage in crop production for any given level of pesticides use and the potential damage measured as the percentage damage that would have occurred in crop production assuming zero pesticide use. Table 9 presents the two computed measures calculated at sample means as well as at pesticide-quartiles means. As it was expected, actual damage follows a decreasing pattern over pesticide-quartiles. Farms in the first quartile realize significantly greater output losses due to pest infestation (14.19 per cent) compared with intense pesticide users in the fourth quartile (5.40 per cent). On average, farms in the sample experienced a 10.14 per cent reduction in the attainable output because of the uncontrolled pest population. On the other hand, potential damage estimates exhibit positive patterns across pesticide-quartiles implying higher potential output losses for heavier pesticide applicators. Farms who would potentially experience more serious output losses are actually those who realized the lower ones as a result of their production decision to apply higher pesticide levels. In particular, assuming zero use of pesticides, the additional percentage damage for farms in the first and fourth quartile is estimated at 5.09 per cent and 17.63 per cent, respectively, while the corresponding figure for all farms is 9.90 per cent.

TFP Growth

The empirical results concerning the decomposition of TFP changes based on equation (5) are reported in Table 10. The average annual productivity growth rate is found to be 1.4167 per cent during the 2003-07 cropping periods. The greatest part of that growth is due to technical change (67.48 per cent) and to a lesser extent due to the presence of scale economies and aggregate variable input growth (24.69 per cent). Increases in educational level account for the remaining 7.83 per cent of observed TFP growth constituting the third most important contributor to productivity rates. Neutral technological innovations are the driving force of TFP growth among greenhouse farms as they account for the 58.44 per cent of the observed productivity changes.

The average education effect is 0.1109 per cent over the period analyzed including the overall impact of changes in both field workers' and farm manager's educational levels on productivity growth. Increases in field workers' education account for the 4.12 per cent of observed productivity changes whereas the corresponding figure for farm managers is quite similar, 3.71 per cent. The later is due to the increasing participation of farm managers in training seminars over the last years which probably reflects their perspectives about the long-term benefits of learning. On contrary, improvements in field workers' educational level is attributable mainly to changes in the composition of hired field workers rather than increases in informal education revealing the farm owners' willingness to hire more educated workers over time.

The average contribution of non-labor variable inputs is 0.1170 per cent accounting for the 8.26 per cent of observed productivity growth rates. Intermediate inputs (4.49 per cent) have the highest contribution due to the gradual intensification of greenhouse production over years. Land input changes account only for the 1.83 per cent of observed TFP growth as changes in the total acreage due mainly to crop sharing contracts among farmers have been limited during the period analyzed. Increases in field working hours account for the 6.01 per cent of TFP growth, whereas the corresponding figure for farm managers is considerably lower, 3.22 per cent. Operation at a sub-optimal scale for greenhouse farms induced intensification of farm production, increasing variable input use (for both labor and non-labor inputs) which was translated into significant productivity improvements during the five cropping periods analyzed.

The overall effect of pesticide materials accounts for the 7.20 per cent increase in observed productivity growth rate (0.1021 per cent). This includes both the direct damage control effect through eradication of harmful pests in crop production and the indirect effect through the deterioration of farm workers health index. Specifically, the direct damage effect is 0.2630 per cent as the use of pesticide materials was increased under increasing returns to scale in crop production. Farm intensification and the associated increase in pesticide application rates resulted in TFP gains as farm size is lower than that maximizing ray average productivity. Nevertheless this significant positive effect has been lessened from the adverse effects that pesticides materials had on farm workers health index. Deterioration of field workers' health index account for the 8.82 per cent decline in annual TFP growth rates, whereas the corresponding figure for farm owners is only 2.54 per cent.

In total, adverse health effects of pesticides materials account for the 11.36 per cent of TFP slowdown during the whole period analyzed. Although productivity gains from the associated reductions in crop damage due to pesticides utilization slightly exceed the productivity losses caused from impairments in workers health, still the adverse health effects are indeed significant and it should be taken into consideration in analyzing productivity growth rates in the presence of health damaging inputs. If farmers applied pesticides taking all precautionary measures, then the associated gains would have been higher resulting to improved productivity rates.

5 Concluding Remarks

In this paper, we developed a theoretical consistent decomposition framework to analyze the dual effects of health-damaging inputs on total factor productivity growth. Unlike previous studies, the proposed methodology allows the constructed workers' health indices to be affected by the working environment and not determined exogenously by nutritional intakes. The decomposition framework was based on a primal approach requiring no assumptions about the structure of labor markets. The empirical illustration involves a panel data set of greenhouse farms from Western Crete, Greece covering the 2003-07 cropping periods. Greenhouse farming provides a good example for the analysis of the dual role of health-damaging inputs on productivity growth rates as pesticide materials are used extensively for many years. The dataset is unique including detailed information concerning pesticide-related health problems recovery days and health impairment costs.

For proxying workers' health status, we estimated individual health indices using the recently developed generalized propensity score methods in a continuous treatment setting suggested by Hirano and Imbens (2004). This empirical approach allows to take into account the potential biases arising from differences in farm workers' characteristics. Empirical results suggest that chemical pesticides are vital for greenhouse production. Potential crop losses would have been 21.04 per cent on the average if chemical pesticides were not utilized. At the same time pesticides account on average for 14.8 days lost from work and to a 53.2 per cent reduction in farm workers effectiveness.

Average annual rate of TFP growth was 1.0027 per cent during the analyzed period. The greatest part of that growth is due to technical change (78.23 per cent) and to a lesser extent due to the presence of scale economies (24.28 per cent). Work-related health problems due to the use of chemical pesticides were found to account for 12.92 per cent productivity losses during the period under consideration. This figure, besides being case specific, underlines that health-damaging inputs have indeed a significant impact on observed productivity growth rates and it should be taken into account in empirical analysis. Farms and farm workers should realize that important gains can be achieved under more efficient management practices and improving individual perceptions about the long-term effects of chemical substances.

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Tables and Figures

Table 1: Pesticide-Related Health Problems and their Associated Economic and Medical Cost (Average Values)

Health Problem	No of Cases	Recovery Days	Days of Absence	Effectiveness Change (%)	Treatment Cost (in €)
Field Workers					
Eye	33	10.8	6.0	-52.8	241
Dermal	50	11.5	6.3	-54.0	256
Respiratory	193	10.4	5.9	-52.1	238
Neurological	10	11.7	8.0	-43.3	400
Kidney	9	14.3	7.2	-55.0	428
All problems	295	10.8	6.1	-52.3	253
Farm Managers					
Eye	20	8.6	3.9	-58.0	135
Dermal	27	7.7	4.1	-54.1	106
Respiratory	132	8.3	4.4	-53.8	132
Neurological	4	12.5	6.5	-49.9	443
Kidney	8	8.4	4.8	-50.1	104
All problems	191	8.3	4.4	-54.0	134

Table 2: Summary Statistics of the Variables

Variable	Mean	Min	Max	Std.Dev.
Health Index Data				
Field Workers:				
Log of Health Impairment	4.41	0.00	7.37	2.28
Age (years)	47.97	25.11	72.00	10.10
Education (years)	9.48	4.25	17.54	2.72
Smoking (tar units)	15.57	0.00	42.49	11.22
Drinking (alcohol units)	18.70	0.00	44.69	12.27
Farm Manager:				
Log of Health Impairment	4.31	0.00	7.24	2.45
Age (years)	50.88	26.00	72.00	10.87
Education (years)	9.36	6.00	17.25	2.76
Experience (years)	19.82	2.00	40.00	7.45
Smoking (tar units)	16.15	0.00	50.00	12.43
Drinking (alcohol units)	17.94	0.00	39.19	12.22
Farm Production Data				
Output (euros)	42,556	9,111	222,360	31,937
Land (euros)	46,048	12,844	264,982	44,163
Fertilizers (euros)	2,621	468	11,129	2,005
Intermediate Inputs (euros)	5,778	600	15,450	3,059
Management Labor (hours)	508	40	1,580	291
Field Labor (hours)	4,286	423	21,599	4,861
Pesticides (litres)	2.71	0.62	12.41	1.90
Pest Population (pests per m^2)	1.28	0.45	3.01	0.54
Spraying Equipment (euros)	193	148	284	19

Table 3: ML Estimates of Conditional Distribution of Pesticides Application

Variable	Estimate	St.Error	Variable	Estimate	St.Error
Field Workers			Farm Manager		
Constant	0.6269	0.5937	Constant	0.6931	0.5881
Field Workers_Age	0.0849	0.3542	Manager_Age	0.5313	0.3167
Field Workers_Education	0.1446	0.1953	Manager_Education	-0.3239	0.1694*
Field Workers_Smoking	-0.0127	0.0741	Manager_Experience	-0.4494	0.1738**
Field Workers_Drinking	0.0581	0.0957	Manager_Smoking	-0.0177	0.0702
Manager_Age	0.4308	0.4267	Manager_Drinking	0.0343	0.0852
Manager_Education	-0.4291	0.2156**	Pest Population	0.2399	0.1019**
Manager_Experience	-0.4498	0.1746**	Spraying Equipment	-0.9268	0.4550**
Pest Population	0.2436	0.1020**		-	
Spraying Equipment	-0.9162	0.4360**		-	
Log Likelihood	-246.2790			-246.5913	

* and ** indicate statistical significance at the 10 and 5 per cent level, respectively.

Table 4: Balancing Properties Tests given the Generalized Propensity Score

Variable	Treatment Intervals (litres/stremma)					
	$(0, 0.27]$		$(0.27, 0.50]$		$(0.50, 1.33]$	
	MD	St.Error	MD	St.Error	MD	St.Error
Covariates-Field Workers						
Field Workers_Age	0.0098	0.0280	-0.0268	0.0314	0.0007	0.0286
Field Workers_Education	0.0433	0.0335	0.0072	0.0436	0.0290	0.0353
Field Workers_Smoking	-0.0342	0.0964	-0.0648	0.1104	0.0035	0.0985
Field Workers_Drinking	-0.0227	0.0876	-0.0400	0.1009	0.0105	0.0892
Manager_Age	-0.0015	0.0273	-0.0366	0.0316	0.0106	0.0285
Manager_Education	-0.0003	0.0337	0.0219	0.0443	0.0138	0.0335
Manager_Experience	-0.0011	0.0454	-0.0401	0.0572	-0.0057	0.0498
Pest Population	0.0077	0.0457	-0.0200	0.0636	-0.0033	0.0442
Spraying Equipment	-0.0037	0.0127	-0.0072	0.0152	0.0081	0.0131
Covariates-Farm Manager						
Manager_Age	-0.0045	0.0265	-0.0152	0.0296	0.0095	0.0275
Manager_Education	-0.0012	0.0322	0.0116	0.0413	0.0017	0.0332
Manager_Experience	-0.0148	0.0445	-0.0160	0.0539	-0.0013	0.0479
Manager_Smoking	0.0165	0.0993	-0.0087	0.1117	-0.0098	0.1009
Manager_Drinking	0.0150	0.0897	-0.0155	0.0982	-0.0017	0.0885
Pest Population	0.0277	0.0445	-0.0473	0.0607	-0.0314	0.0443
Spraying Equipment	-0.0011	0.0123	-0.0078	0.0145	0.0161	0.0126

Note: MD stands for mean difference.

Figure 1: Estimated Average Potential Health Index and Pesticide Application

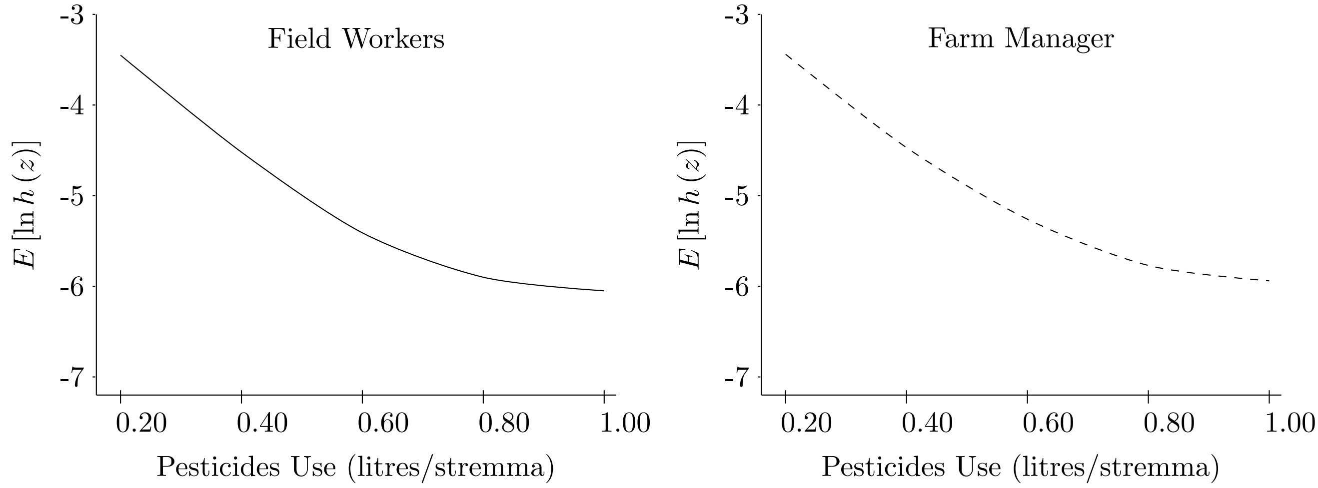

Table 5: Bayes Factor Statistics for Equality of Means

Variable	Treatment Intervals (litres/stremma)					
	$(0, 0.27]$		$(0.27, 0.50]$		$(0.50, 1.33]$	
	Ad BF	UAd BF	Ad BF	UAd BF	Ad BF	UAd BF
Covariates-Field Workers						
Field Workers_Age	4.4455	3.1374	3.2368	2.6457	4.6744	3.8938
Field Workers_Education	2.1246	1.2364	4.5171	2.4642	3.3796	2.1012
Field Workers_Smoking	4.4399	4.0938	3.8742	3.1102	4.6732	4.0985
Field Workers_Drinking	4.5671	3.2783	4.2446	3.9898	4.6445	2.2892
Manager_Age	4.7093	2.1423	2.4134	1.27537	4.3772	2.4285
Manager_Education	4.7163	0.3564	4.0602	0.5546	4.3125	0.4335
Manager_Experience	4.7155	0.9643	3.6202	0.7762	4.6471	0.6498
Pest Population	4.6588	0.0004	4.3706	0.0018	4.6637	0.0002
Spraying Equipment	4.5208	0.2162	4.1171	0.3152	3.8887	0.3131
Covariates-Farm Manager						
Manager_Age	4.6508	4.0265	4.0407	3.7296	4.4152	4.1275
Manager_Education	4.7114	0.9322	4.4078	0.6413	4.6699	0.7332
Manager_Experience	4.6981	1.0445	3.9802	1.3539	4.6740	1.0479
Manager_Smoking	4.6588	2.9993	4.5651	4.1117	4.6547	3.5009
Manager_Drinking	4.6586	3.9897	4.5269	2.2982	4.6748	3.9885
Pest Population	3.9172	0.0025	3.4446	0.0067	3.6721	0.0143
Spraying Equipment	4.6981	0.5123	3.9994	0.4145	2.3072	0.1126

Note: UAd BF and Ad BF stand for unadjusted and GPS-adjusted Bayes Factor, respectively.

Table 6: Parameter Estimates of Conditional Health Index

Parameter	Estimate	St.Error	Parameter	Estimate	St.Error
	Field Workers			Farm Manager	
α_0^F	0.0594	0.1401	α_0^M	0.0127	0.0458
α_z^F	-0.6107	0.2096**	α_z^M	-0.1253	0.0735*
α_r^F	-1.6477	0.7149**	α_r^M	-0.5698	0.2355**
α_{zz}^F	0.1025	0.0586*	α_{zz}^M	0.0134	0.0205
α_{rr}^F	1.6029	0.8732*	α_{rr}^M	0.6265	0.2908**
α_{zr}^F	0.2008	0.3046	α_{zr}^M	0.0182	0.1052
R^2	0.3161			0.2719	

F and M stand for field workers and farm manager, respectively, z for pesticides and r for propensity score. * and ** indicate statistical significance at the 10 and 5 per cent level, respectively.

Figure 2: Average Marginal Effect of Pesticides on Health Index

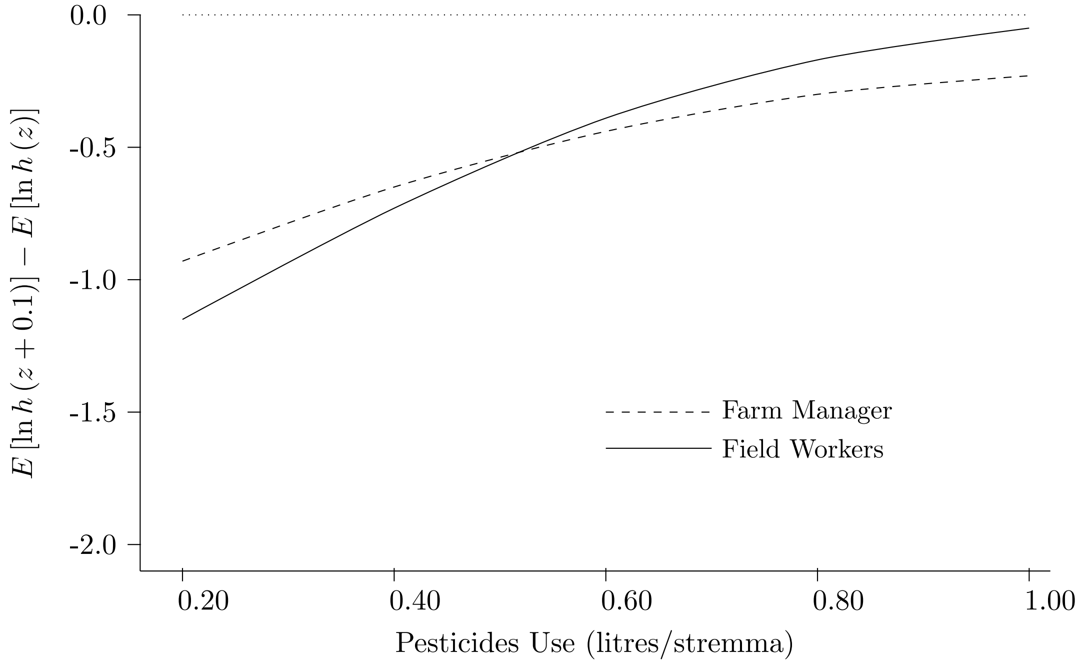

Table 7: Parameter Estimates of the Translog Production Function

Parameter	Estimate	St.Error	Parameter	Estimate	StError
β^0	0.1124	0.4149	β^{xx}_{II}	-0.0775	0.0547
β^x_A	0.4468	0.1939**	β^{xx}_{AC}	0.0979	0.1340
β^x_C	0.0943	0.0542*	β^{xx}_{AI}	0.1998	0.1219*
β^x_I	0.1347	0.0647**	β^{xx}_{CI}	-0.1690	0.0815**
β^F	0.1656	0.0681**	β^{FF}	0.1257	0.0497**
β^M	0.0577	0.0330*	β^{MM}	0.0495	0.0316
β_t	0.0719	0.0217**	β^{FM}	0.0182	0.0452
β_{tt}	0.1107	0.0197**	β^{xF}_A	-0.0168	0.0945
β^x_{At}	0.0313	0.0169*	β^{xM}_A	-0.0301	0.0760
β^x_{Ct}	-0.1370	0.1408	β^{xF}_C	-0.0047	0.0777
β^x_{It}	-0.1710	0.1244	β^{xM}_C	0.1363	0.0446**
β^F_t	-0.1637	0.0356**	β^{xF}_I	0.1114	0.1008
β^M_t	-0.1872	0.1016*	β^{xM}_I	0.0838	0.0530*
β^{xx}_{AA}	0.1113	0.3143	λ	0.2414	0.1481*
β^{xx}_{CC}	0.0239	0.0761	β^z	0.9138	0.5118*
R^2			0.8385		

A refers to land, I to intermediate inputs, C to fertilizers use, F to field workers working hours, M to farm manager working hours, z to pesticides and t to time. Asymptotic errors were computed using block re-sampling techniques (Politis and Romano, 1994). * and ** indicate statistical significance at the 10 and 5 per cent level, respectively.

Table 8: Output Elasticities and Returns to Scale

Output Elasticity	Value	St.Error	Output Elasticity	Value	St.Error
Non-Labor Inputs	0.6738	0.2924**	Pesticides	0.0863	0.0311**
Land	0.4039	0.1226**	Direct	0.2369	0.1214**
Fertilizers	0.1272	0.0361**	Indirect	-0.1506	0.0501**
Intermediate Inputs	0.1427	0.0625**	Field Workers	-0.1199	0.0453**
Labor Inputs	0.3356	0.1514**	Farm Manager	-0.0307	0.0162*
Field Workers	0.2065	0.0826**			
Farm Manager	0.1291	0.0702*	Returns to Scale	1.0957	0.3146**

Standard errors were obtained using block resampling techniques (Politis and Romano, 1994). * and ** indicate statistical significance at the 10 and 5 per cent level, respectively.

Table 9: Output Damage Measures (Average Values per Quartile)

	Pesticide Use Quartiles				Mean
in %	1st	2nd	3rd	4th	Values
Actual Crop Damage ($z \neq 0$)	14.19	11.65	9.36	5.40	10.14
Potential Crop Damage ($z = 0$)	19.28	20.33	21.49	23.03	21.04

Table 10: Decomposition of TFP Growth (Average Annual Values for the 2003-07 period)

Components	Rate of Change	Percentage
TFP Growth	1.4167	(100.00)
Technical Change:	0.9561	(67.48)
Neutral TC	0.8279	(58.44)
Biased TC	0.1282	(9.04)
Education Effect	0.1109	(7.83)
Field Workers	0.0584	(4.12)
Farm Manager	0.0525	(3.71)
Scale Effect:	0.3498	(24.69)
Non-labor Inputs	0.1170	(8.26)
Land	0.0259	(1.83)
Fertilizers	0.0275	(1.94)
Intermediate Inputs	0.0636	(4.49)
Labor Input	0.1308	(9.23)
Field Workers	0.0852	(6.01)
Farm Manager	0.0456	(3.22)
Pesticides	0.1021	(7.20)
Direct	0.2630	(18.56)
Indirect	-0.1609	(-11.36)
Field Workers	-0.1249	(-8.82)
Farm Manager	-0.0360	(-2.54)