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Effects of Insurance Adoption and Risk Aversion on Agricultural Production and Technical Efficiency: A Panel Analysis for Italian Grape Growers

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Abstract: This article aims to evaluate the effect of insurance on production, technical efficiency, and input use of Italian specialised-quality grape growers. A panel instrumental variable stochastic frontier approach is applied over the years 2008–2017 using data from the Farm Accountancy Data Network. The results show the requirement to correct for the endogeneity that stems from insurance adoption. Insurance has an enhancing effect on production and efficiency and reduces the use of intermediate inputs. It suggests that insurance helps to diminish the risk-averse farmers' suboptimal input use due to the presence of uncertainty. Crop insurance leads risk-averse farmers to behave as if they were risk neutral and employs the profit-maximising input vector. Therefore, by reducing the risks linked to the uncertainty of outcomes, crop insurance leads grape growers to go in the direction of profit maximisation.

Keywords: endogenous stochastic frontier; crop insurance; viticulture

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1. Introduction

Agricultural production has always had to cope with uncertainty (Moschini and Hennessy 2001). Farmers make their resource allocation decisions in a complex environment made up of poorly controllable biological (diseases, insects, pests, weeds), environmental (i.e., weather, soil, and water conditions), and institutional (i.e., markets, legislation) factors. Additionally, economic, and financial markets, as well as the political and institutional environment, can be sources of uncertainty. In the future, it is expected that the exposure to risk in agriculture is likely to increase due to upcoming challenges related to land degradation and climate change (IPCC 2013; Raimondo et al. 2021). Such a situation explains the wide array of farming practices and management approaches available to the farmers to manage their risks at the farm level, basically involving three broad areas of farming decisions: production, marketing, and financial (Boehlje and Trede 1977; McConnell and Dillon 1997). These management approaches and practices include, among others: on- and off-farm diversification of income-generating activities (Chavas and Kim 2010; Corsi and Salvioni 2012; Bellon et al. 2020), inputs intensification (Foudi and Erdlenbruch 2012; Pagnani et al. 2021), varietal diversification (Di Falco and Chavas 2006; Gotor et al. 2021), vertical integration and contract farming (Hennessy 1996; Otsuka et al. 2016), forward contracting and futures hedging (Asplund et al. 1989), and finally crop insurance (Ahsan et al. 1982; Nelson and Loehman 1987; Ramaswami 1993). In this paper, we specifically focus on the latter, since crop insurance has recently been gaining the attention of policymakers, especially in the European Union with the recent development of the Common Agricultural Policy (CAP) (Enjolras et al. 2012; Santeramo et al. 2016;

Vigani and Kathage 2019). Furthermore, crop insurance might cover different sources of uncertainty, supporting farmers in the process of adaptation to climate challenges (Di Falco et al. 2014).

Crop insurance represents one of the most investigated subjects in agricultural economics. There is a large amount of literature addressing crop insurance demand (Enjolras et al. 2012; Santeramo et al. 2016), pricing and subsidies (Skees et al. 1997; Lusk 2017), impact on farming decisions (Ahsan et al. 1982; Nelson and Loehman 1987; Ramaswami 1992; Mieno et al. 2018) and moral hazards (Horowitz and Lichtenberg 1993; Quiggin et al. 1993; Smith and Goodwin 1996). Additionally, there is wide range of literature examining the effect of crop insurance on input use (Wu 1999; Goodwin et al. 2004; Möhring et al. 2020a, 2020b) and input demand under crop insurance (Ramaswami 1993; Babcock and Hennessy 1996). More recently some attention, though still limited, has been directed towards the effective economic impact of crop insurance in terms of farming productivity (Vigani and Kathage 2019) or technical efficiency (Roll 2019). For instance, Roll estimated a stochastic production frontier to investigate whether insurance affects Norwegian salmon farming in terms of inputs use, productivity, and technical efficiency. Looking at the literature, the effects of insurance on input use are largely an empirical issue. Some authors found that insurance is positively related to input intensity (e.g., Horowitz and Lichtenberg 1993), while other studies found a negative relation (e.g., Quiggin et al. 1993; Smith and Goodwin 1996; Babcock and Hennessy 1996). Finally, Goodwin et al. (2004) found a positive and negative effects depending on the crop analysed.

In this paper, we intend to add to this latter stream of literature. Similar to Roll (2019), we explore the effect of expenditure in crop insurance on the production and technical efficiency of a nationally representative sample of Italian grape growers. More specifically, this paper aims to clarify whether insurance adoption might solve the risk-averse farmers' suboptimal input use due to the presence of uncertainty. Of course, there is no simple answer to this: on one hand, crop insurance, by making risk-averse farmers prone to being risk neutral (Nelson and Loehman 1987; Ramaswami 1993), should facilitate optimal resource allocation, allowing farmers to maximise profit, enhance the production level, and to specialise their production (Ahsan et al. 1982), consequently improving their technical efficiency (Roll 2019). However, on the other hand, insurance adoption may incentivise farmers in reducing the number of safety measures against harm as a consequence of moral hazard (Horowitz and Lichtenberg 1993; Quiggin et al. 1993). This would result in a major exposure to risk and might reduce the production level and technical efficiency.

From a methodological point of view, using data from the Farm Accountancy Data Network (FADN), a panel stochastic frontier estimation approach is implemented on a sample of commercial Italian farms specialising in the production of quality grapevines[1] over the period 2008–2017. Different from previous studies, we account for the potential endogeneity of insurance, therefore providing more reliable parameter estimates (Karakaplan and Kutlu 2017a).

The dominant insurance schemes in Italian agriculture, as for grape growing, are single-peril (mainly hail) and multi-peril crop insurance (ISMEA 2018). Farmers pay a premium to cover yield damages caused by one or more eligible events listed in the Italian Insurance Plan. Premium per hectare varies in relation to the risk exposure of the farmer. A specific focus has been given to the grape growers because crop insurance has been widely adopted in this sector in Italy, which represents around 27% of the Italian crop insurance market in terms of monetary values and 14% in terms of land (ISMEA 2018). Additionally, it is widely assumed that the viticulture sector is exposed to many risks which are progressively increasing due to climate change. Global warming causes increases in temperature in grapevine regions. This may cause changes to the grape chemistry, and an increase in insects and insect-borne diseases (Mozell and Thachn 2014). Additionally, the increase in the frequency of extreme weather events such as rainfall, late frost, or hailstorms (IPCC 2013) has potentially negative effects on yields and wine quality, and increases income variability (Holland and Smit 2010).

The rest of this article is organised as follows. In the next section, we present a brief literature review on the role of risk in production choices. Then we introduce the methodology utilised with a focus on the endogeneity problem. Successively, we show the dataset and the model specification. We then show and discuss the results. The conclusions are presented in the final section.

2. Theoretical Background

Farmers choose the level of inputs to maximise profit before knowing the true state of nature; therefore, productive factors are allocated according to farmers' risk perception and aversion (Roosen and Hennessy 2003). Risk-taking or risk-loving farmers would take an opportunity to gain a higher profit rather than taking a safer position, with the chance of sustaining a large loss. Vice versa, the risk-averse farmers prefer to avoid the worst possible outcome. Finally, risk-neutral farmers would hypothetically consider the weighted expected outcome of the different expected states of nature. Thus, risk aversion has direct consequences on the optimum resource-use level. To maximise profit, farmers should operate at the profit-maximising point, i.e., where the expected marginal value product of input equals the marginal factor cost. This is the risk-neutral farmer's choice, while the risk-averse farmer operates at the position where profit is not being maximised except in "bad" seasons. In other words, risk aversion results in suboptimal economic decisions with respect to input allocation. The difference in input use of risk-averse and risk-neutral farmers depends on the marginal risk premium (MRP) (MacMinn and Holtmann 1983), which is the wedge between input cost and expected marginal product at the optimum level of input use. In general, the sign of MRP depends on risk preferences and technology. MRP is positive if the use of the input increases the production uncertainty (risk increasing input). MRP is negative when the input is risk-decreasing (MacMinn and Holtmann 1983; Ramaswami 1992). Consequently, in the single-input single-output case, the risk-averse level of input use is higher (lower) than the risk-neutral level of input use if the input is risk-decreasing (increasing) (Nelson and Loehman 1987). In farm decision-making, fertilisers are often considered risk-increasing inputs (Just and Pope 1979; Pope and Kramer 1979) while pesticides and herbicides are usually considered risk-decreasing (Möhring et al. 2020b).

This study aims to evaluate the effect of crop insurance on grape producers' decision-making process. Crop insurance has the potential to affect both the input (Nelson and Loehman 1987; Ramaswami 1993) and output choices (Ahsan et al. 1982) with consequences for production and technical efficiency (Roll 2019). On one hand insurance may enhance the farming results, allowing input choice independent of the farmer's preference function over uncertain outcomes (Nelson and Loehman 1987). The purchase of insurance induces risk-averse farmers to behave as if they were risk neutral and choose the optimal quantity of inputs by setting the expected marginal product of inputs to its opportunity cost (Ahsan et al. 1982). According to Ramaswami (1993), this is due to the risk reduction effect of the insurance adoption, which reduces the wedge between expected marginal product and input price and makes farmers adjust input application in the direction of risk-neutral levels, i.e., to increase the level of input if risk-increasing and to decrease the input use if risk-decreasing. The risk reduction effect implies that the mean output could increase or decrease depending on the nature of the production technology.

On the other hand, the possible existence of a moral hazard may alter insured farmers' optimal decisions (Quiggin et al. 1993). More specifically, a moral hazard may reduce the input used independently of whether it is risk-reducing or risk-increasing (Ramaswami 1993). Moral hazard decreases the mean expected output because the insurance contract reduces the loss associated with the insured event and may change the farmer's behaviour. As a result, farmers reduce the precautions to cope with risk since there are much fewer consequences for an incident. Therefore, when the input is risk-decreasing, insurance increases the riskiness of output and decreases the expected output, while if it is risk-increasing this effect will depend on the effect of moral hazard and risk reduction effects.

With regards to output choice, farmers tend to allocate more resources to insured cultivation and, in more detail, will specialise in the production of higher-value risky activities that can be insured (Ahsan et al. 1982) According to this view, Roll (2019) found that insured farmers might gain from greater specialisation since they do not need to diversify their activities to manage their idiosyncratic risk. The higher specialisation achieved by insurance adoption might explain the increase in technical efficiency. On the other hand, the moral hazard could lead to a change in the farmers' ordinary behaviour, influencing the quality and the intensity of the production factors. These actions, including the managerial effort devoted to farming activities, will have a direct consequence on technical efficiency, limiting the impact of the specialisation achievable by insurance (Kirkley et al. 1998).

This paper aims to tackle the above-mentioned dilemma about the effect of crop insurance on inputs use and technical efficiency of a nationally representative sample of Italian grape growers. The following section will clarify the methodological approach employed and the data used for the analysis.

3. Data and Methodology

3.1. Methods

The foundations of efficiency analysis started from the contribution of Farrell (1957), and since the 1960s it was extensively applied to analyse the way production inputs are combined into valuable outputs. Efficiency analysis can involve a parametric estimate of the production function as independently proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977) through the stochastic frontier models. These models are composed of a deterministic part identifying the frontier (i.e., the maximum output obtainable, given the available technology and input levels) and of a stochastic part including a two-sided error term, and a one-sided inefficiency error term: the latter identifies the distance from the stochastic frontier. Battese and Coelli (1995) implemented a stochastic frontier production function for panel data, which accounts for potential unobserved heteroscedasticity, and includes environmental variables in the inefficiency distribution. Accordingly, the frontier equation was specified as:

$$\ln y_{it} = \beta_0 + \sum\nolimits_k \beta_k \ln x_{kit} + v_{it} - u_{it} \tag{1}$$

where y_{it} is the logarithm of the output of the i-th farm at time t; x_{kit} is a vector of k inputs and other explanatory variables of the i-th farm at time t; β is a vector of k unknown parameters to be estimated; v_{it} is a two-side error term capturing the standard random errors, and u_{it} is a non-negative error term associated with the technical inefficiency effects. In turn, the variance of technical inefficiency (u_{it}) can be assumed to be a function of a set of s explanatory variables (z_{sit}), a conformable vector of coefficients to be estimated (δ), and a random term (ω) as in the following equation:

$$\sigma^2{}_{uit} = \delta_0 + \sum\nolimits_s \delta_s \ln z_{sit} + \omega_{it}. \tag{2}$$

When analysing production and efficiency it is important to account for the potential endogeneity of the explanatory variables to obtain unbiased estimates of technical efficiency (Shee and Stefanou 2014; Amsler et al. 2016; Karakaplan and Kutlu 2017b). According to Vigani and Kathage (2019), there are different potential endogeneity sources regarding insurance adoption in the estimation of the production frontier. Potential endogeneity may arise due to reverse causality between the adoption of risk management tools and productivity (Ramaswami 1993). For instance, bigger farms are more likely to have the financial and human resources to adopt risk-management practices (Vigani and Kathage 2019). As for Italian farmers, the adoption of crop insurance has been demonstrated to be influenced by farm performance, total assets, and financial leverage (Enjolras et al. 2012; Santeramo et al. 2016). Furthermore, insurance adoption is voluntary and not randomly assigned and therefore may be adopted by farms that find it most useful. This means that insured farmers are self-selected, i.e., they have common unobservable characteristics influencing both the performance and adoption choice. This will lead to inconsistent estimates of the impact of insurance on farm production (Di Falco and Veronesi 2013). To deal with endogeneity issues, we follow the general maximum likelihood-based approach proposed by Karakaplan and Kutlu (2017a). These authors start from the model proposed by Battese and Coelli (1995) described in Equations (1) and (2) above and developed an endogenous panel stochastic frontier model which handles endogenous variables in both the frontier and/or in the inefficiency by using an instrumental variable approach. Unlike the standard control function methods where estimations are performed in two stages, authors estimated the parameters using a single maximum likelihood function, gaining statistical efficiency[2]. Additionally, a potential source of endogeneity may arise from the substitution effect between insurance and inputs since the adoption of insurance can increase the use of risk-increasing inputs and decrease the level of risk-decreasing inputs (Nelson and Loehman 1987; Ramaswami 1992). The most popular production functions used in the stochastic frontier analysis are Cobb-Douglas and translog. In this study we consider the translog functional to capture the substation effect of insurance.

Finally, to avoid the potential endogeneity due to omitted variables, we included other risk management tools in the model specification, namely irrigation and on-farm diversification. Previous studies have shown that farmers often adopt different risk management strategies and that the global risk mitigation effect is not necessarily equal to the sum of the effects of adopting each strategy separately (Wu and Babcock 1998).

3.2. Data

We used farm-level data for vine growers specialising in quality grape production, located in Italy and observed from 2008 to 2017. The data have been extracted from the FADN, which provides high-quality and consistent datasets of commercial farms, i.e., farms with an economic size, in terms of *standard output*[3], exceeding EUR 8000 in the case of Italy. FADN consists of an annual survey aimed to provide representative data, harmonised among EU member states, along three dimensions: the region, economic size, and type of farming. Due to the rotation over the years of the observed farms in the sample, the dataset is an unbalanced panel.

By excluding observations with null or inconsistent values on the main variables of interest, our dataset was composed of 9419 observations of 2587 farms. The descriptive statistics of the variables included in the model are reported in Table 1.

Table 1. Descriptive statistics.

Variable and Abbreviation		Description	Mean	Standard Deviation
		Output and Inputs		
y	Production	Total Gross Production (EUR)	57,338	136,247
x_1	Land	Utilised Agricultural Area (ha)	8.92	17.30
x_2	Capital	Amount of Capital (EUR)	472,696	1,446,921
x_3	Intermediate Inputs	Intermediate Inputs Costs (EUR)	11,908	37,635
x_4	Labour	Total number of hours worked per year (h)	2418	4511
		Risk Management Strategies		
ins	Insurance	Expenditure on crop insurance (EUR)	891	5168
d_{ins}	Insurance Dummy	One for insured farm, zero otherwise	0.22	0.41
irr	Irrigation	Percentage of irrigated land over total land (%)	0.28	0.43
d_n	Non-agricultural Diversification	Dummy for services diversification	0.11	0.32
d_a	Agricultural Diversification	Dummy for crop or livestock diversification	0.74	0.44

Table 1. *Cont.*

	Variable and Abbreviation	Description	Mean	Standard Deviation
		Control Variables		
es_1	Economic Size (1) [base category]	One for small farms, zero otherwise	0.13	0.33
es_2	Economic Size (2)	One for medium-small farms, zero otherwise	0.21	0.41
es_3	Economic Size (3)	One for medium farms, zero otherwise	0.28	0.45
es_4	Economic Size (4)	One for medium-large farms, zero otherwise	0.32	0.47
es_5	Economic Size (5)	One for large farms, zero otherwise	0.06	0.24
alt_1	Altimetry (1) [base category]	One if located in the plain, zero otherwise	0.24	0.42
alt_2	Altimetry (2)	One if located in the hill, zero otherwise	0.59	0.49
alt_3	Altimetry (3)	One if located in the mountain, zero otherwise	0.17	0.37
loc_1	Location (1) [base category]	One for farms located in the South, zero otherwise	0.12	0.33
loc_2	Location (2)	One for farms located in the Central, zero otherwise	0.25	0.43
loc_3	Location (3)	One for farms located in the Northeast, zero otherwise	0.32	0.47
loc_4	Location (4)	One for farms located in the Northwest, zero otherwise	0.31	0.46

Production refers to the total gross production of the grape, measured in euros. We use the monetary value of the output produced considering that grape growing in Italy evolved significantly towards higher-quality production (Urso et al. 2018). Land is measured in hectares and refers to the Utilised Agricultural Area (UAA). Capital is an aggregate, measured in euros, formed by working capital and real estate, less the farmland value to avoid problems of multicollinearity with land. Intermediate inputs, measured in euro, refer to expenditures on water, crop certification, fertilisers, pesticide, services, energy (fuel, electricity, and heating), marketing (materials, transport, and intermediation), and other generic expenses. Labour[4] refers to the total number of hours worked per year in grape growing.

To investigate the insurance's relation to production and efficiency we use expenses in crop insurance. Many previous studies used dummy variables to represent the farmers' insurance decisions (e.g., Horowitz and Lichtenberg 1993; Smith and Goodwin 1996). Similar to Weber et al. (2016) and Möhring et al. (2020b), we use the intensity of insurance (measured by the amount of insurance premiums paid) to capture changes in the input use at different levels of insurance expenditures. Given that a significant number of observed farms have no expenses in crop insurance, we added the value one for uninsured farms to obtain the logarithm and not to incur biased results as suggested by Battese (1997). Battese (1997) has also shown that simply adding a small number may not be the most appropriate solution and proposed the inclusion of a dummy variable that takes a value of one when the input, insurance in our case, is not used. If the coefficient of such a dummy is statistically significant, then the intercepts of insured and uninsured farms are not equal, and the absence of the dummy will provide biased results. Additionally, to mitigate possible omitted variables bias we include a set of variables referring to risk-management tools that are an alternative to insurance, namely irrigation and on-farm agricultural and non-agricultural diversification. Irrigation is the percentage of irrigated over total land. Non-agricultural diversification is a dummy variable taking a value of one when the farm is producing non-agricultural services (agritourism, educational, etc.) in addition to farming. Agricultural diversification is a dummy variable taking a value of one when the farm produces other crops or livestock in addition to grape, and the value zero otherwise. The inclusion of such different risk mitigating strategies in addition to insurance allows us to avoid omitted variables bias since the global effect of adapting different risk strategies is not necessarily equal to the effect of adopting each strategy separately (Wu and Babcock 1998).

We also included a set of variables to control for additional sources of heterogeneity due to the environmental and economic characteristics of the farm. As for the location of the farm, there are three dummy variables referring to altimetry (plain, hill, and mountain) and four dummy variables for farms located in the Southern, Central, North-eastern, and North-western regions. Economic size is defined based on standard output and is divided into five classes: small (less than 25,000 euros), medium-small (25,000–50,000 euros), medium (50,000–100,000 euros), medium-large (100,000–500,000 euros), and large farms (over than 500,000 euros).

Table 2 shows the mean and standard deviation values of all variables included in the model, dividing the sample into insured and uninsured farms. As shown in Figure 1, production and input use are larger in terms of absolute value in insured than uninsured farms. Insured farms have a higher percentage of irrigated land, while there is no difference in the participation in both the agricultural and non-agricultural diversification strategies of the larger the economic size and the greater the percentage of insured farms. Finally, most of the insured farms are in the North-Eastern regions while insurance is less diffused in the South.

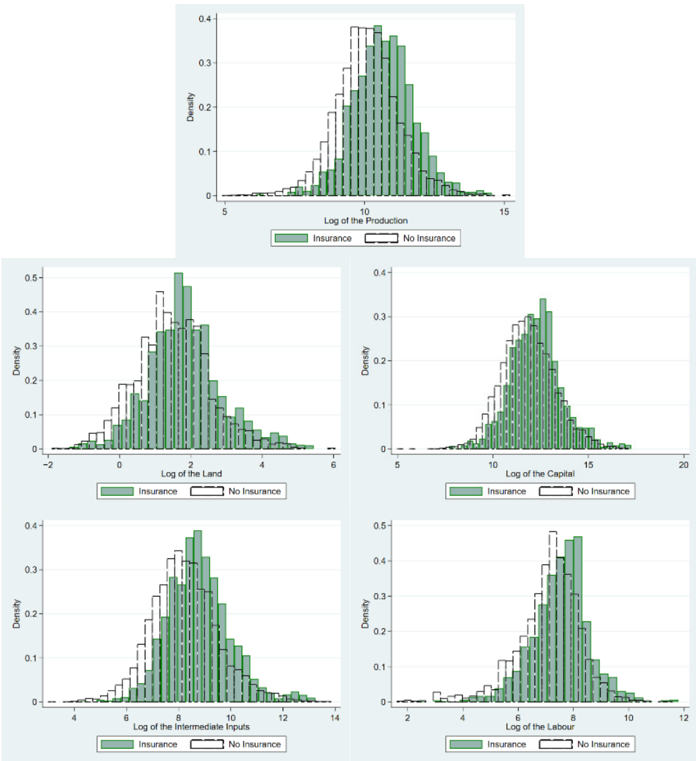

Figure 1. The graphs show the distribution of the mean values of the logarithm of output and input levels for insured and uninsured farmers over all observations from 2008 to 2017.

Table 2. Descriptive statistics (insured vs. uninsured farms).

Variable	No Insurance		Insurance	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
	Output and Inputs			
Production	50,024	130,627	83,761	151,990
Land	8.07	16.03	11.98	20.99
Capital	410,406	1,116,236	697,727	2,256,782
Intermediate Inputs	10,439	33,155	17,215	47,099
Labour	2146	3462	3399	7025
	Risk Management Strategies			
Insurance	0	0	4110	10,489
Irrigation	0.24	0.41	0.39	0.47
Non-agricultural Diversification	0.11	0.31	0.11	0.31
Agricultural Diversification	0.74	0.44	0.73	0.44

Table 2. *Cont.*

Variable	No Insurance		Insurance	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Control Variables				
Economic Size (1)	0.15	0.35	0.07	0.25
Economic Size (2)	0.23	0.42	0.15	0.35
Economic Size (3)	0.28	0.45	0.29	0.45
Economic Size (4)	0.29	0.46	0.40	0.49
Economic Size (5)	0.05	0.22	0.09	0.29
Altimetry (1)	0.23	0.42	0.26	0.44
Altimetry (2)	0.62	0.48	0.49	0.50
Altimetry (3)	0.15	0.35	0.25	0.43
Location (1)	0.15	0.35	0.06	0.24
Location (2)	0.24	0.43	0.28	0.45
Location (3)	0.28	0.45	0.46	0.50
Location (4)	0.33	0.47	0.20	0.40

3.3. Empirical Strategies

The translog production frontier is specified as follows:

$$\ln y_{it} = \beta_0^{*} + \sum_k \beta_k \ln x_{kit} + \tfrac{1}{2} \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \beta_{ins} \ln ins_{it} + \tfrac{1}{2} \beta_{ins}{}^{2} \ln ins^{2}{}_{it} + \sum_k \beta_{kins} \ln x_{kit} \ln ins_{it} + \beta_{irr}\, irr_{it} + \beta_{dn}\, d_{nit} + \beta_{da}\, d_{ait} + \beta_t\, t + \tfrac{1}{2} \beta_{tt}\, t^2 + \sum_k \beta_{kt} \ln x_{kit}\, t + \beta_{tins} \ln ins_{it}\, t + v_{it} - u_{it} \quad (3)$$

where the dependent variable is the gross production of the i-th farm at time t. β are the parameters to be estimated. β_0^{*} contain the effects of constant term and control factors, i.e., economic size, altitude, and location. Four inputs (x_{kit}) are included in the model: land, labour, capital, and intermediate inputs. Since the translog functional form, we also include inputs squares and interactions. In addition, we included the effect of the insurance expenditures (ins_{it}), its square, and the interactions with other inputs. The other risk management strategies, i.e., the percentage of irrigated land (irr_{it}) and the two dummy variables referred to non-agricultural (d_{nit}) and agricultural diversification (d_{ait}), are also included. Finally, a time trend (t) has been added to control for any technological change or innovations during the period analysed and to measure the effect of insurance on technological change (β_{tins}).

The variance of technical inefficiency is specified as follows:

$$\sigma^2{}_{uit} = \delta_0^{*} + \delta_{ins} \ln ins_{it} + \delta_{irr}\, irr_{it} + \delta_{dn}\, d_{nit} + \delta_{da}\, d_{ait} + \delta_t\, t + \omega_{it} \quad (4)$$

where the variance of the non-negative error term u_{it} is a function of expenditure in insurance (ins_{it}), irrigation (irr_{it}), non-agricultural (d_{nit}) and agricultural diversification (d_{ait}), and time trend (t) As before, δ_0^{*} includes the effects of constant term and other control factors, i.e., economic size, altitude, and location. The coefficient δ_{ins} indicates the effect of insurance on technical efficiency. Since we estimate an inefficiency effect, a negative sign indicates that insurance increases efficiency and vice versa.

Finally, to deal with the potential endogeneity of insurance, we need to identify proper instrumental variables. Valid instruments need to be correlated with the endogenous variables, insurance expenditure, but uncorrelated with the error or inefficiency terms. Enjolras et al. (2012) have shown that the cost of insurance, i.e., the premium per hectare, has an influence on the demand for crop insurance in Italy. At the same time, the decision to become insured does not affect the overall demand for crop insurance at the provincial level. Hence, the insurance premium paid by each farmer affects both the production and efficiency. On the contrary, the average insurance premium at the provincial level is correlated with the endogenous variable (insurance), but it is uncorrelated with the error or inefficiency terms. Therefore, the average premium per hectare measured at the province level has been used to instrument insurance in the frontier and the efficiency equations.

As proposed by Karakaplan and Kutlu (2017a), another equation is estimated simultaneously to include the relationship between the endogenous variable, the instrumental variable, inputs included in the production frontier, time trend, and other risk-management tools. As in the previous equations, the effect of control variables is in the constant term.

4. Results

The endogeneity test indicates that insurance is endogenous, and correction is needed ($X^2 = 21.25$; $p < 0.0001$)[5]. Therefore, we implemented the IV panel approach as proposed by Karakaplan and Kutlu (2017a). First, we assessed the instrument's strength. The chi-squared statistic of the instrument in the prediction equation of insurance is 484.13, which is greater than 10 and passes the rule of thumb for not being a weak instrument. Additionally, we checked if the inclusion of the dummy variable is needed to allow for different intercepts for insured and uninsured farms and avoid biased results, as proposed by Battese (1997). The z statistic of the coefficient estimated for the dummy is −0.47 (p = 0.635). This indicates that the intercepts of insured and uninsured farms are equal, and the inclusion of the dummy is not necessary to obtain unbiased coefficient estimates.

The estimated parameters of the production frontier are presented in Table 3 while output elasticities with respect to inputs are calculated and reported in Table 4. Estimated output elasticities are statistically significant and positive for all inputs. The estimated elasticity of the time trend shows that there is a positive and significant technological change during the period under analysis.

Table 3. Production function.

Variable	Parameter	Estimate	Standard Error	z	P > |z|
		Inputs			
Land	β_1	0.3457	0.1447	2.39	0.017
Capital	β_2	0.3934	0.0898	4.38	0.000
Int. Inputs	β_3	0.2889	0.0806	3.58	0.000
Labour	β_4	−0.0158	0.0638	−0.25	0.805
Trend	β_t	−0.0196	0.0251	−0.78	0.437
Land^2	β_{11}	−0.0560	0.0238	−2.35	0.019
Capital^2	β_{22}	−0.0018	0.0087	−0.20	0.838
Int. Inputs^2	β_{33}	0.0124	0.0084	1.47	0.140
Labour^2	β_{44}	0.0031	0.0057	0.54	0.586
Trend^2	β_{tt}	0.0038	0.0015	2.61	0.009
Land ∗ Capital	β_{12}	0.0216	0.0112	1.94	0.053
Land ∗ Int. Inputs	β_{13}	0.0227	0.0109	2.09	0.036
Land ∗ Labour	β_{14}	−0.0075	0.0093	−0.81	0.420
Land ∗ Trend	β_{1t}	−0.0084	0.0035	−2.38	0.017
Capital ∗ Int. Inputs	β_{23}	−0.0297	0.0080	−3.72	0.000
Capital ∗ Labour	β_{24}	0.0072	0.0057	1.27	0.204
Capital ∗ Trend	β_{2t}	−0.0113	0.0021	−5.27	0.000
Int. Inputs ∗ Labour	β_{34}	−0.0026	0.0066	−0.39	0.694
Int. Inputs ∗ Trend	β_{3t}	0.0211	0.0026	8.14	0.000
Labour ∗ Trend	β_{4t}	−0.0015	0.0021	−0.71	0.479
		Risk-Management Strategies			
Insurance	β_{ins}	**0.0640**	**0.0260**	**2.46**	**0.014**
Insurance^2	${\beta_{ins}}^2$	**0.0076**	**0.0019**	**3.92**	**0.000**
Land ∗ Insurance	β_{1ins}	**−0.0018**	**0.0034**	**−0.53**	**0.594**
Capital ∗ Insurance	β_{2ins}	**−0.0006**	**0.0020**	**−0.33**	**0.745**

Table 3. *Cont.*

Variable	Parameter	Estimate	Standard Error	z	P > ∣z∣
		Risk-Management Strategies			
Int. Inputs ∗ Insurance	$\boldsymbol{\beta_{3ins}}$	**−0.0056**	**0.0027**	**−2.05**	**0.041**
Labour ∗ Insurance	$\boldsymbol{\beta_{4ins}}$	**−0.0021**	**0.0020**	**−1.04**	**0.300**
Trend ∗ Insurance	$\boldsymbol{\beta_{tins}}$	**0.0002**	**0.0007**	**0.32**	**0.750**
Irrigation	β_{irr}	0.0389	0.0301	1.29	0.196
Non-Agr. Diversification	β_{dn}	−0.0983	0.0350	−2.81	0.005
Agr. Diversification	β_{da}	−0.0731	0.0253	−2.89	0.004
		Control Variables			
Medium-Small	β_{es2}	−0.0782	0.0371	−2.11	0.035
Medium	β_{es3}	−0.0781	0.0445	−1.75	0.079
Medium-Large	β_{es4}	−0.0493	0.0529	−0.93	0.352
Large	β_{es5}	0.0549	0.0792	0.69	0.488
Hill	β_{alt2}	0.1468	0.0288	5.10	0.000
Mountain	β_{alt3}	0.2830	0.0447	6.34	0.000
Centre	β_{loc2}	−0.1345	0.0385	−3.49	0.000
Northeast	β_{loc3}	0.1731	0.0388	4.46	0.000
Northwest	β_{loc4}	0.2391	0.0399	6.00	0.000
Constant	β_0	4.4803	0.6203	7.22	0.000

Note: The coefficients related to insurance expenditure are shown in bold.

Table 4. Output elasticity.

Variable	Estimate	Standard Error	z	P > ∣z∣
Land	0.5926	0.0284	20.87	0.000
Capital	0.1427	0.0145	9.85	0.000
Int. Inputs	0.1312	0.0194	6.78	0.000
Labour	0.0358	0.0150	2.38	0.017
Insurance	0.1065	0.0156	6.85	0.000
Trend	0.0219	0.0056	3.98	0.000

The output elasticity with respect to insurance (ϵ_{ins}) has been calculated as the partial derivative of the logarithm of the production function with respect to the logarithm of the crop insurance expenditure:

$$\epsilon_{ins} = \delta \ln y_{it} / \delta \ln ins_{it} = \beta_{ins} + \beta_{ins}{}^{2} \ln ins_{it} + \sum\nolimits_{k} \beta_{kins} \ln x_{kit} + \beta_{tins}\, t \quad (5)$$

ϵ_{ins} mean value is positive and statistically significant, indicating an enhancing effect of insurance on production.

We are also interested in investigating whether insurance affects the use of inputs. We intend to analyse the substitutability between insurance and other inputs, i.e., the ability to substitute insurance for another input without affecting the output level, in more detail. The technical relationship between insurance and other inputs depends on the curvature of the isoquant. Measures of substitution possibilities between inputs are obtained with elasticities of intensity (Diewert 1974). As shown by Roll (2019) the elasticity of intensity between insurance and other inputs is given by:

$$\delta\, \epsilon_{ins} / \delta \ln x_{kit} = \beta_{kins} \quad (6)$$

where k are the inputs land, capital, intermediate inputs, and labour. Negative elasticity indicates a substitute relationship, while positive elasticity indicates a complementary one. We find that the coefficients of the interaction terms are all statistically non-significant apart from the interaction term between insurance and intermediate inputs, which is statistically significant, negative, but close to zero. This latter finding indicates that insurance is a very weak substitute for intermediate inputs. This presumes right-angled isoquant with inputs used in nearly fixed proportions to each other. As for the interaction among inputs, the signs of these coefficients show that land is complementary for capital and intermediate inputs, while capital is a substitute for intermediate inputs. Finally, land and capital usage decreased over time, while the use of intermediate inputs increased. The parameter β_{tins} measures the effect of insurance on technological change. As seen from Table 3, this is found to be positive but not statistically significant, indicating that insurance expenditures have not affected the technological change. Regarding risk-management tools different from insurance, the percentage of irrigated land has a positive but not significant effect on production, while both agricultural and non-agricultural diversification negatively affect production in accordance with what was previously found (Vidoli et al. 2016). Furthermore, in terms of economic size, medium and medium-small farms are less productive with respect to the smaller farms. The production level grows with the growing of altimetry and farms located in the South produce more than farms located in the Centre and less than farms located in the North.

The results of the efficiency function are presented in Table 5. Since we are estimating the inefficiency function, a negative parameter indicates that the variables considered have a positive effect on technical efficiency. Like Roll (2019), our estimates show that insurance has an enhancing effect on efficiency. Irrigation has a statistically significant and positive effect on efficiency. This may be related to the fact that irrigation decreases the variability of yields, and hence the variability of income (Foudi and Erdlenbruch 2012) allowing farmers to invest to enhance efficiency. Agricultural and non-agricultural diversifications do have not a statistically significant effect on efficiency. The estimated parameter of the time trend indicates that efficiency decreased during the analysed period. This result may be due to some events such as pests, rainfall, and drought, etc., that negatively influenced the efficiency. As for economic size, the significant coefficient of the medium-smaller farms shows that this group of farms is more efficient than the smaller farms[6]. The coefficients of the other size classes are not statistically significant. This result could be due to the fact that there is an important presence of small and highly specialised farms in the market (Kim et al. 2012). Farms operating in Southern areas of Italy were found to be more efficient compared to the farms operating in Northern areas, similar to what was found by Urso et al. (2018). Finally, farms located in the hilly areas are less efficient compared to those located in the plain areas. There is no statistical difference in the mountain compared to the lowland areas.

Table 5. Inefficiency estimates.

Variable	Parameter	Estimate	Standard Error	z	P > |z|
Insurance	δ_{ins}	−0.0226	**0.0111**	**−2.03**	**0.042**
Irrigation	δ_{irr}	−0.2783	0.1188	−2.34	0.019
Non-Agr. Diversification	δ_{dn}	−0.0119	0.1168	−0.10	0.919
Agr. Diversification	δ_{da}	0.0416	0.0931	0.45	0.655
Trend	δ_{t}	0.0617	0.0134	4.62	0.000
Medium-Small	δ_{es2}	−0.2647	0.1176	−2.25	0.024
Medium	δ_{es3}	−0.1670	0.1212	−1.38	0.168
Medium-Large	δ_{es4}	−0.0034	0.1260	−0.03	0.978
Large	δ_{es5}	0.0881	0.2024	0.44	0.663
Hill	δ_{alt2}	0.4653	0.1271	3.66	0.000
Mountain	δ_{alt3}	−0.1931	0.1878	−1.03	0.304
Centre	δ_{loc2}	−0.0439	0.1586	−0.28	0.782
Northeast	δ_{loc3}	0.4336	0.1553	2.79	0.005
Northwest	δ_{loc4}	0.2443	0.1593	1.53	0.125
Constant	δ_{0}	−1.6218	0.2227	−7.28	0.000

Note: The coefficients related to insurance expenditure are shown in bold.

5. Discussion

This article aims to clarify the effect of expenditure in crop insurance on the production, technical efficiency, and input use of commercial grape-growing farms in Italy. Crop insurance might be an important tool for enhancing farm performances by reducing suboptimal input use (Ahsan et al. 1982; Nelson and Loehman 1987; Ramaswami 1993). On the contrary, insurance adoption may lead to inefficient farming actions driven by moral hazard, which causes non-optimal economic results (Horowitz and Lichtenberg 1993; Kirkley et al. 1998; Quiggin et al. 1993).

The net result of risk reduction and moral hazard effects on input use and output is indeterminate and remains an empirical issue. Our study intends to add to this stream of the empirical literature. We focus on the Italian grape growers' sector because it is the type of farming with the highest participation in the crop insurance program in Italy (ISMEA 2018). Using FADN data, we estimated the impact of crop insurance on input use, production, and efficiency by using the endogenous panel stochastic frontier model proposed by Karakaplan and Kutlu (2017a).

Similar to Roll (2019), our results show that insurance has a boosting effect on both production and technical efficiency. With regards to the insurance effect on input use, we find that insurance does not have a statistically significant impact on labour, land, and capital while it has a significant influence on the use of intermediate inputs. The non-significant effect on labour and land was expected as labour is a quasi-fixed input in household farms and the quantity of land is fixed in the short-medium term in the case of perennial crops as grapevines. The results on land are not in line with those of Enjolras and Aubert (2020), who found a reduction in land allocated to grape production in France. Moreover, the statistically insignificant effect on capital does not confirm the enhancing investment effect of insurance found by Vigani and Kathage (2019) in French and Hungarian farms specialising in wheat. Finally, the negative, significant effect of insurance on intermediate inputs indicates that insurance is a substitute for intermediate goods. In our sample, most of the expenses in intermediate inputs are tied to the purchase of crop protection chemicals. Hence, the choice to purchase intermediate inputs in our sample is largely dominated by the choice about the use of crop defence chemicals, i.e., fungicide, pesticides, and herbicides. Our results contribute to the growing literature on the intensive margin relations of insurance and pesticide use (Horowitz and Lichtenberg 1993; Quiggin et al. 1993; Smith and Goodwin 1996; Babcock and Hennessy 1996; Möhring et al. 2020a, 2020b), showing that, contrary to that which was found by Enjolras and Aubert (2020) in France, in the case of grape production in Italy, insurance decreases the intermediate input use while increasing output. Our results differ from that which was previously found by Enjolras and Aubert (2020) in the case of French grape growers (no insurance effect on chemical inputs) and by Möhring et al. (2020b) for French arable crops (insurance's positive effect on pesticides use). This highlights that insurance and pesticide policies need to account not only for the heterogeneity of pesticide type as showed by Möhring et al. (2020a), but also the heterogeneity due to the specific condition in which each sector operates (Goodwin et al. 2004). Hence, it is not possible to give a policy indication based on the observation of what happens in a single sector (Möhring et al. 2020b).

The causes of the changes found in input use and supply, as explained in Section 2, can be the risk reduction and moral hazard effects induced by insurance. As for the risk reduction effect, as described in earlier work by Ahsan et al. (1982), a Pareto optimal insurance program that provides full coverage has a risk-reduction effect which causes risk-averse farmers to reduce (increase) the use of risk-decreasing (increasing) inputs toward (away from) the optimal level of risk-neutral farmers and improve (reduce) output. However, in reality, crop insurance is often affected by information asymmetries (Just et al. 1999) that lead to opportunistic behaviour. Under such circumstances, farmers undertake actions that change the probability of loss relative to what the losses might be if the farmer were uninsured, in this way deviating from Pareto optimality (Nelson and Loehman 1987). Moral hazard reduces the use of all inputs and decreases mean output (Ramaswami 1993).

Therefore, the net effect of the two adjustments induced by insurance depends on the degree of farmers' risk aversion and the effect of the input on the probability of low yields (Horowitz and Lichtenberg 1993; Ramaswami 1993; Babcock and Hennessy 1996).

As for the risk preferences of grape growers, previous work has shown they are risk averse (Aka et al. 2018). This risk-averse attitude is mainly due to the existence of sunk costs related to high investments in land and capital equipment. In consideration of this aversion to risk, the increase in output found in this study suggests that in the case of grape production, the risk reduction effect dominates the moral hazard effect. In other words, the reduction in input use induced by insurance can be interpreted as a re-optimisation of input use rather than the effect of moral hazard. This conclusion is supported by the fact that when crop insurance targets specific weather hazards, such as insurance contracts in use in Italy and France, moral hazard does not play an important role as a driver of intensive margin effects (Möhring et al. 2020b) because there are hardly any agronomical adjustments possible to cause an insurance pay-out (Quiggin et al. 1993). Moreover, the decision to participate in a crop-insurance program must be made before the beginning of the season to avoid an opportunistic farmer taking out insurance after the observation of unfavourable conditions (Aubert and Enjolras 2014).

The decrease in the use of chemicals induced by insurance in grapevine production in Italy is good news for the success of the EU Commission's strategy aimed at reducing pesticide use. Grape production is characterised by the highest level of pesticide use per hectare (Aka et al. 2018) mainly fungicide (Mailly et al. 2017), followed by insecticides and herbicides. At the same time, the grapevine is the agricultural sector where insurance has been widely adopted both in the EU and Italy (ISMEA 2018). The reduction in the use of defence chemicals induced by insurance can contribute both to reducing production costs and external costs attributed to farmers' health and environment, in addition to preventing pest resistance (Wilson and Tisdell 2001). Moreover, the relevant increase in intermediate input used during the period analysed may be associated with the impact of global warming on grapevine regions (Mozell and Thachn 2014). For example, it may be reasonable for the overuse of pesticides due to the increase in insects and insect-borne diseases. Therefore, insurance may have the potential to be an instrument that contributes to the reduction in environmental and health adverse effects derived from the risk-averse farmers' suboptimal input allocation (Möhring et al. 2020b).

Furthermore, the input use optimisation due to insurance adoption may also explain the increase in efficiency. By changing the use of inputs, insurance allows risk-averse grape growers to decrease the use of efficiency-reducing inputs due to the uncertainty of outcomes. Additionally, insurance may provide farmers with the possibility to invest in efficiency-improving practices. For example, grape growers may invest in precision agriculture to predict the field-specific optimum requirement of resources such as irrigation, fertilisers, pesticides, and herbicides (Bhakta et al. 2019). Likewise, they may change the rate of replanting perennial crops, thereby affecting the age distribution of the orchard and the yield. Moreover, improvement in efficiency may also be related to the fact that insurance allows farms to specialise in insured crop production (Ahsan et al. 1982) since they do not have to diversify to manage their idiosyncratic risk (Roll 2019)

Finally, our findings show the requirement to treat endogeneity of insurance to estimate unbiased parameters. The importance of considering endogeneity is due to different aspects. First, the endogeneity test provided by Karakaplan and Kutlu (2017b) shows the endogeneity presence due to self-selection and reverse causality in our model. Second, the significance of the substitution effect between insurance and intermediate input use shows that the adoption of the translog specification is also necessary. Lastly, the significance of the coefficients of the variables referred to the risk management tools alternative to insurance underlines the importance of including them to avoid omitted variables bias.

6. Conclusions

This article analysed how insurance affects the production decisions of commercial grape-growing farmers in Italy through the estimation of an endogenous panel stochastic frontier. More specifically, we investigated the crop insurance's effect on production, technical efficiency, and input use in Italian grape-growers' farms. Similar to Roll (2019), our findings show that insurance has a positive impact on production and efficiency, while it reduces the use of intermediate inputs. These results are fully consistent with neoclassic theory and indicate that insurance can play an essential role in the reduction of suboptimal input use due to the presence of uncertain outcomes. The increase in output found in this study suggests that in the case of grape production in Italy, the risk reduction effect dominates the moral hazard effect. In other words, the reduction in input use induced by insurance can be interpreted as a re-optimisation of input use rather than the effect of moral hazard. Furthermore, the input use optimisation due to insurance adoption may explain the gain in efficiency. Finally, we find that controlling for endogeneity in the causal relationship between insurance and production is needed to avoid biased parameters estimates.

A limitation of the study is related to the not fully reliable data in terms of labour. First, there is a high rate of missing values in hours worked in grape growing in during the years 2008 to 2010. Second, data referring to labour generally contain measurement errors because of the presence of factors such as illegal employment. Last, we have not considered the quality of labour distinguishing, for example, between skilled and unskilled labour or family and hired labour.

The main limitation of the study, though, is due to the different risk profiles of inputs included in the intermediate inputs that do not allow us to investigate the effect of insurance on the use of input with different attributes.

Since the substitution effect between insurance and intermediate inputs and the different nature of the inputs included in this variable in this study, further studies are needed to investigate the relationship between insurance and specific intermediate inputs used in the grape-growing sector.

Our findings have several policy implications. First, our results differ from that which was previously found in different crops and countries. This suggests that insurance and pesticide policies need to account for heterogeneity due to the specific condition in which each sector operates. Hence, it is not possible to give a policy indication based on the observation of what happens in a single sector. Second, the decrease in the use of intermediate inputs induced by insurance is good news for the success of the EU Commission's strategy aimed at reducing pesticide use. Insurance can contribute to reducing the external costs attributed to farmers' health and environment, in addition to preventing pest resistance.

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Notes

[1] This paper defines "quality grapevines" as those certified by the EU quality certification scheme.

[2] Proofs and more technical details are provided in (Karakaplan and Kutlu 2017a, 2017b).

[3] In the FADN the "standard output" (SO), of an agricultural product (crop or livestock) is the average monetary value of the agricultural output at farm-gate price. The SO excludes direct payments, value added tax and taxes on products.

[4] In total, 27% of the observations for the total number of hours worked on grape growing were missing in the sample. Most of these missing values are related to some specific years and provinces. When the information of farm labour was available for a specific farm in at least one year, then the missing value has been replaced by the hours obtained based on the proportion between hours worked on grape growing and total hours worked on the farm. When hours worked on grape growing were missing in all years for one farm, we replaced them with an approximation based on year and location (province, region, and altimetry) specific mean.

[5] A test similar to the Durbin–Wu–Hausman test has been used to assess the correlation between the instrumented variables and the two-side error term vit. This test examines the joint significance of the components of the bias correction terms (see Karakaplan and Kutlu 2017a, 2017b for more details). If the bias correction terms components are not jointly significant, one would conclude that correction for endogeneity is not necessary, and the variables can be estimated by the traditional frontier models.

[6] Please note that being more efficient does not necessarily imply that farms are more productive. In fact, technical efficiency is a part of productivity, along with technical change and scale economies (Coelli et al. 2005). We find that smaller farms are more productive but less efficient than the medium-small farms. The explanation of such differences in the productivity and efficiency of different size classes deserves a specific study that is beyond the scope of our analysis.

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