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The Effect of Insurance on Farmers' Production, Technical Efficiency and Input Use: An Endogenous Stochastic Frontier Model to Analyse the Italian Case

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Contents

Abstract

The presence of risk in the agricultural sector has important implications for production decision-making and, therefore, the economic and environmental performance of farms. Given the risky environment, the EU policymakers introduced several risk management tools aimed at the reduction of the income variability of farms. The adoption of risk management tools impacts production decision-making in several ways. Therefore, analysing the interrelation between farm performances and risk management tools is crucial for policymakers to foster both the economic and environmental sustainability of farming.

Despite the significant role of risk and risk management tools in agricultural production decisions, most studies on farm-level performance analysis do not account for them. Moreover, when included, it is usually assumed that risk and risk management tools are independent of the error terms in the model. Therefore, endogeneity issues are often not considered, which could overstate or understate the effect of risk and risk management tools on farm performance. Indeed, producers may modify input use in response to observed adverse events resulting in a correlation between inputs and statistical error. In addition, endogeneity may arise when including the risk management tools. The model misspecifications due to the absence of endogeneity treatment may lead to erroneous inferences about the estimates of input elasticities, economies of scale, and inaccurate estimates of technical efficiency. Consequently, the analysis may lead to incorrect interpretation and, ultimately, to wrong policy advice.

Among the risk management tools, crop insurance represented the most funded instrument in the EU. In spite of recent growth in the scientific literature on crop insurance in agricultural economics, only a few studies have concentrated on the effects of crop insurance expenditure on farm outcomes. Specifically, the impact of insurance on productivity and technical efficiency has received scant consideration. Therefore, the general objective of this thesis is to quantitatively assess the effect of crop insurance on input use, productivity, and technical efficiency of Italian farming producers. In particular, this thesis examines whether insurance adoption could reduce farmers' inefficient input use that results from the uncertainty of the results. Grape farming has been selected as a case study since it is the sector where crop insurance has been most adopted in Italy. The novelty of this research relates to the inclusion of crop insurance adoption endogeneity into the stochastic frontier approach, allowing for the estimation of parameters with a higher degree of accuracy.

The thesis is divided into seven chapters. Each chapter attempts to lay the groundwork for answering the research question. In particular, Chapter 1 introduces the background, the problem, and the research question, while Chapter 2 introduces the Italian crop insurance regulations and the spread of subsidized crop insurance in the grape-producing sector.

Chapter 3 describes the theoretical background. Specifically, the production function is introduced, which is the first step to comparing the performance of producers. Subsequently, productivity, technical efficiency, and their difference are discussed. Following that, the optimal input use and the effects of risk-aversion on production choice have been discussed. Finally, the impact of insurance on farm performance has been reviewed. In particular, the dilemma which regards the re-optimization or the moral hazard effects arising from the insurance adoption has been investigated.

Then, Chapter 4 is based on an in-depth literature review on farm productivity and efficiency, which has been conducted using a scoping review methodology, focusing on studies that have included risk and risk management tools within the stochastic frontier analysis. The main contribution of the review relates to the indication of a literature gap concerning studies accounting for endogeneity and the clarification of methods used to account for it by using a risk-accommodating stochastic frontier approach. Despite the increasing methodologies proposed in the literature to deal with endogeneity, only a few studies have treated it in farm risk-performance evaluations when using the stochastic frontier analysis. According to the findings of the review presented in Chapter 4, it can be concluded that there is a literature gap regarding the adoption of a comprehensive approach capable of dealing with endogeneity when assessing farm productivity/technical efficiency and risk. Neglecting endogeneity in these analyses may lead to biased estimates and, thus, distorted policy recommendations. Endogeneity and risk issues need to be concurrently addressed to make strides in achieving economic and environmental sustainability. The comprehensive approach could help to achieve more accurate estimates that could yield recommendations that ensure improved productivity and technical efficiency of farmers.

Bearing in mind that, a case study has been implemented to assess how insurance affects Italian specialized-quality grape growers' production, technical efficiency, and input use while accounting for the endogeneity of the crop insurance adoption. Therefore, a panel instrumental variable stochastic frontier approach is applied over the years from 2008 to 2017 using data from the Farm Accountancy Data Network. The methodology, the econometric strategy to deal with endogeneity, the dataset, and the model specification are presented in Chapter 5, while the case study is documented in Chapter 6. The findings highlight the need to account for endogeneity brought on by the adoption of insurance. Moreover, it was found that crop insurance increases output and efficiency while decreasing the need for intermediate inputs in Italian grape farming. It implies that insurance assists in reducing the suboptimal input use caused by risk-aversion and the uncertainty of farming outcomes.

Finally, Chapter 7 discuss the results, summarizes the main conclusion of the thesis, and highlights the limitations and future research directions.

1. General Introduction

1.1. Background

Agriculture is one of the sectors where risk plays a crucial role in the production process (Ahsan et al., 1982; Ellis, 1993). Farmers make resource allocation decisions in a complex environment where factors outside their control may seriously affect the final outcomes. In particular, farmers operate in a context where the quantity, quality, and price of output to be produced are unknown when they allocate the inputs. Commonly the agricultural risk is attributed to the length and complexity of the biological production cycle, which exposes farmers to several sources of risk that make yields, input, and output prices highly variable (Moschini and Hennessy, 2001). The nature of the agricultural risks depends on several sources such as diseases, pests, weather, natural calamities, price volatility, and even political and institutional changes. Additionally, in the future, the risk exposure of agricultural production is expected to increase due to upcoming challenges related to climate change, land degradation, and water scarcity. For instance, many regions across the globe will face increasingly difficult conditions characterized by a warming atmosphere, more unpredictable rainfall patterns, and more frequent extreme events (IPCC, 2013, 2018).

Such a situation explains the wide array of farming practices and management approaches available to the farmers to mitigate the 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 crop insurance (Ahsan et al., 1982; Nelson and Loehman, 1987; Ramaswami, 1993).

Ensuring the stability of farm income has been one of the goals of agricultural policies in the EU (Severini et al., 2017). However, despite the relevance of risk in agriculture, the discussion on a common risk management tools strategy has long been on the margin of European debate. The primary causes are related to the structure of Common Agricultural Policy (CAP) past interventions, which have supported the income of agricultural producers with the presence of market-stabilizing measures such as the production quota system and guaranteed prices (Huirne et al., 2000). With the phasing out of CAP guarantees provided to farmers for the market stabilization, following the international trade agreements, the need for risk management tools at the farm level was becoming increasingly more important (Cortignani and Severini, 2012; Capitanio et al., 2013). After many years of debate on the development of public interventions which target to reduce the income variability of farmers, the concern of risk management instruments obtained legislation consideration in the Community with the approval of the EU Regulation 73/2009 (Art. 68).

Finally, the EU Regulation 1305/2015 has established a multi-annual funding program in the Rural Development Policy 2014-2020, proposing three types of tools such as crop insurance (art. 37), mutual funds (art.38), and income stabilization tool (art. 39). During the years from 2014 to 2020, among these three instruments, expenditure on crop insurance represented about 82% of the total expense on agricultural risk management measures (Bardají et al., 2016).

Since public expenditure on agricultural crop insurance policies is gaining importance in the toolbox of the CAP, researchers and policymakers have many reasons to be interested in whether the provision of this risk management tool affects farm outcomes. The effectiveness and efficient design of crop insurance schemes may contribute to achieving the United Nations Sustainable Development Goals, which aim to reduce poverty (SDG 1), hunger (SDG 2), and climate impact (SDG 13) (Khanal et al., 2021; Vyas et al., 2021). More specifically, crop insurance may play a key role in achieving SDG 1, which aims to enhance the resilience of vulnerable farmers and reduce their exposure to economic, social, and environmental adverse events and disasters. It is particularly relevant in areas where agriculture is a principal source of the gross domestic product and is essential in employment creation too. Moreover, crop insurance may lead to higher agricultural outcomes to ensure safe, nutritious, and sufficient food for all individuals and to face the increasing demand for food due to the expected population growth (Fukase and Martin, 2020) in line with the SDG 2 targets. For example, by reducing the impact of uncertainty of outcomes, the purchase of insurance may lead risk-averse farmers to move toward optimal levels of input allocation (Ahsan et al., 1982; Nelson and Loehman, 1987; Ramaswami, 1993) and raise the investments (Vigani and Kathage, 2019), which result in an increase of output produced. Finally, crop insurance may support farmers in the process of adaptation to climate challenges (Di Falco et al., 2014) and improve the environmental sustainability of agricultural production by inducing farmers, for instance, to reduce the use of detrimental input (Capitanio et al., 2014), aiming to pursue SDG 13 targets. Thus, crop insurance has the potential to foster economic and environmental sustainability of farm production, also impacting the social aspects.

Yet, there also can be intended and unintended side-effects associated with crop insurance uptake that policymakers should account for to design adequate policies. By diminishing the impact of a loss associated with the insured event, the insurance contract may change farming practices increasing the likelihood of the insured event occurring and the severity of the loss. Moreover, the farmers that are more likely to experience the insured event are more willing to insure at a given premium. Previous literature defined these challenges accordingly as moral hazard and adverse selection (Nelson and Loehman, 1987; Ramaswami, 1993; Moschini and Hennessy, 2001). For both, the underlying conclusion for the outcome is the same. Insured farmers are more likely to produce lower yields than uninsured farmers with comparable observable characteristics (Quiggin et al., 1993).

1.2. Problem Statement

The presence of risk in the agricultural sector has important implications for the production decisions and thus the economic and environmental performance of farms. Given the risky environment, farmers operate in a situation where input use decisions are made before knowing the future state of nature. For example, it may be considered the lag between land allocation and climate conditions. Therefore, farmers allocate inputs according to their subjective risk preferences, which usually are separated into risk attitudes and perceptions (Pennings and Garcia, 2001; Bozzola and Finger, 2021). Risk perception is related to the fact that farmers allocate the inputs according to their personal beliefs about the occurrence of events and the relative expected impact on yields, prices, and, in general, agricultural outcomes.

On the other hand, risk attitude reflects the individual predisposition to risk. It implies that risk-averse farmers' production decisions differ from risk-neutral choices. In particular, while risk-neutral farmers employ the input vector intending to maximize profits, risk-averse ones also try to avoid income loss by minimizing the impact of risk on production (Just and Pope, 1978; Antle, 1983). Hence, the risk-aversion introduced by the uncertainty of outcomes causes a more conservative input use, which results in non-profit-maximizing input allocation and, consequently, lower farm performance (Nelson and Loehman, 1987; Ramaswami, 1992).

As mentioned in the previous paragraph, crop insurance may represent an instrument to guide farmers to improve production choices by reducing the effect of risk aversion that may cause inefficient use of the inputs. More in general, crop insurance may substitute other risk management strategies, such as, for example, pesticide use and diversification, with a subsequent impact on farm outcomes. Indeed, the adoption of insurance is potentially interlinked with the input allocation. Previous literature has identified two main mechanisms through which the adoption of crop insurance may affect the input use decisions named intensive and extensive margin effects (Wu, 1999; Graveline and Mérel, 2014; Möhring et al., 2020b). First, the insurance adoption may change input application rates reflecting a re-optimization of input use (Nelson and Loehman, 1987; Ramaswami, 1992) or moral hazard (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996). Second, insurance may impact the cropping pattern decisions of farmers (Wu, 1999; Goodwin et al., 2004). For example, it may induce farmers to increase the land devoted to the insured risky crops (Ahsan et al., 1982), further enhancing the specialization in such crops (Vigani and Kathage, 2019). Due to the different input use levels between crops, land use decisions are related inextricably to input use levels. As a result, changes in input use will directly affect farm outcomes (Kirkley et al., 1998; Roll, 2019).

Crop insurance represents one of the most investigated tools when considering the risk implication in agricultural economics. A large amount of literature aims to study the factors influencing the demand for insurance, insurance pricing, and contract design (Vyas et al., 2021). Moreover, a wide range of literature aims to study the effects of crop insurance on input use which shows contradictory conclusions. According to the empirical literature, some authors found that crop insurance is positively related to input use (e.g., Horowitz and Lichtenberg 1993), while other studies found that the adoption of insurance tends to decrease input use (e.g., Quiggin et al. 1993; Smith and Goodwin 1996; Babcock and Hennessy 1996). Therefore, the effects of insurance on input use are an empirical issue. For instance, Möhring et al. (2020a) showed that pesticide application might increase or decrease depending on the crop, cropping system, and type of pesticide analysed. Despite somewhat discrepancies in the results, little effort is made to explain the underlying causes (Roll, 2019).

Even though the scientific literature on crop insurance in agricultural economics has grown over the last years, only a few studies have focused on the consequences of crop insurance expenditure on farm outcomes. Specifically, little attention has been paid to the impact of insurance on productivity (Vigani and Kathage, 2019) and technical efficiency (Roll, 2019).

1.3. Research Objectives

The aim of the present work is to investigate how insurance adoption impacts the input use and outputs of Italian farm production. In particular, the objectives of the current study are to examine the effects of insurance adoption on the input use, productivity, and technical efficiency of Italian agricultural producers.

To analyse the above mentioned relationships, firstly, the literature that assesses the impact of risk and uncertainty on production decision-making has been examined. Subsequently, the literature aimed to investigate the effect of insurance on input allocation and farm output has been reviewed. Then, the literature to explore the methods to handle risk in the agricultural productivity and efficiency analysis has been reviewed systematically using the Scoping review methodology proposed by Tricco et al. (2018). Additionally, a specific focus was dedicated to the applied methods that account for the endogeneity sources while investigating the effect of risk and risk management tools on production decision-making. Finally, to estimate the impact of insurance on input use, productivity, and technical efficiency, a stochastic frontier model was implemented following the approach proposed by Roll (2019) that studied these relationships in Norwegian salmon farming. In particular, grape farming was selected as a case study since grapevine is the main product of the Italian subsidized crop insurance market (ISMEA, 2018).

The contribution of this research refers to the inclusion of insurance expenditure in the stochastic production frontier framework model to investigate the potential relationship between crop insurance, input use, and farm performances. More specifically, this thesis seeks to determine if insurance adoption might alleviate risk-averse farmers' suboptimal input use that arises from the uncertainty of the outcomes. Certainly, there is no simple answer to this question due to the multifaceted nature of the relationship between the insurance coverage status of farms and farming outcomes (Roll, 2019), while the likely existence of moral hazard/adverse selection for insurance adoption makes the above mentioned relationship particularly worthy to being analysed (Quiggin et al., 1993). However, this is not a sufficient reason to justify the lack of this kind of study. According to Vyas et al. (2021), which mapped the literature on agricultural insurance over the world during the years from 2000 to 2019, research with a focus on this topic at the European level is scarce, while most studies on the relation of crop insurance and farm outcomes are conducted in the context of Northern American agriculture. The novelty of this research relates to the inclusion of potential endogeneity of crop insurance purchases into the stochastic frontier approach, providing the estimate of more reliable parameters (Karakaplan and Kutlu, 2017b).

The findings of this thesis may guide the policymakers in the design of proper crop insurance policies which target to increase the results of farms in economics and environmental terms. Moreover, it may convince farmers to increase the adoption of crop insurance. Even though the Italian government provides one of the highest subsidies in the world, the participation to insurance programmes is quite scarce and concentrated in some regions (Enjolras et al., 2012; Santeramo et al., 2016). Finally, this work aims to inform insurance companies and policymakers in determining the effect of insurance on production results. One of the main problems related to the diffusion of this instrument is the asymmetric information and the lack of trust among agents (Santeramo, 2018). The problems referred to as moral hazard and adverse selection might represent a clamp down on the growth of the insurance supply. Therefore, studies that purpose to investigate these relationships may provide results to measure the net effect of the risk reduction or moral hazard impact resulting from the insurance uptake.

1.4. Thesis Outline

The remainder of the thesis is composed of six chapters. Each chapter aspires to build the path to arrive at to reply to the central research question. First, it is described the Italian crop insurance market. Then, the theoretical background related to the production function, the productivity and technical efficiency, and the uncertainty effect on production decisions have been introduced. Subsequently, the methodological framework which refers to the inclusion of risk and endogeneity in the stochastic frontier analysis has been reviewed. Later, the methodology, the Farm Accountancy Data Network, and model specification implemented to examine the case study of the present work are presented. Finally, the last chapters contain the results and the discussion and conclusion.

Specifically, Chapter 2 describes the Italian crop insurance legislation and the diffusion of subsidized crop insurance in the grape growing sector.

Chapter 3 describes the theoretical background related to the research question. First, the production function and the key performance indicators to evaluate farm performances, such as productivity and technical efficiency, are introduced. Subsequently, the optimal input use and the consequences of risk-aversion on production decision-making are described. Finally, the insurance effect on farm performances is reported.

Chapter 4 reviews the literature on the different methods proposed to deal with risk in the stochastic frontier approach. In particular, a scoping review is performed to study the methods proposed to investigate how risk and risk-management tools were included in this framework in agricultural economics. Moreover, a particular focus aims to analyse the techniques to deal with endogeneity while accounting for risk and risk management tools in the stochastic frontier approach.

Chapter 5 first presents the methodology implemented in this thesis, based on a model developed in the recent literature. In particular, it describes the stochastic frontier approach and the model proposed by Karakaplan and Kutlu (2017b) to handle endogeneity by using an instrumental variable method. Moreover, it describes the dataset used in this work. Finally, the model specification is explained.

Chapter 6 assesses the role of insurance in Italian grape production. Then, the descriptive statistics of the Farm Accountancy Data Network sample are reported, as well as the results of the estimated model. Finally, the findings of this analysis are discussed, providing some conclusions.

Finally, Chapter 7 summarise the analysis conducted in this study and highlights the limitations and future research direction. To conclude, the chapter outlines the implications of the main results and summarises the main conclusions.

2. The Italian Crop Insurance Market

2.1. The Fondo di Solidarietà Nazionale and the Risks Management Plan

In Italy, public intervention in agricultural risk management has a long history. The *Fondo di Solidarietà Nazionale* (FSN) was established in 1970 to compensate farmers harmed by natural disasters. Risk management has been based on ex-post compensations since the early 2000s. Since its inception, the system has undergone numerous reforms. During the first thirty years, compensatory interventions and active protection systems absorbed more than 70% of the public expenditure allocated to FSN interventions, while risk management instruments such as insurance received less attention (ISMEA, 2010).

More recently, Italy adopted the Community Guidelines for State Aid in the Agricultural Sector regarding compensation for damage and insurance premium subsidies in its Legislative Decree N. 102/2004 and subsequent amendments. Consistent with the economic policy guidelines on agricultural risk management adopted in other European countries, the priority objective of the FSN reform introduced with Legislative Decree N. 102/2004 is to shift public interventions, and consequent resources, from ex-post compensatory measures for losses caused by natural disasters to an ex-ante defence system based on risk management tools. More recently, in accordance with Community legislation, the Decree also established the conditions under which it is possible to provide subsidies to agricultural firms. In particular, the interventions that can be activated at the expense of the FSN are primarily of two types: actions to stimulate the adoption of risk management tools and compensatory interventions (only in the case of non-insurable risks) intended to aid in the economic and productive recovery of agricultural enterprises damaged by natural disasters.

The Agricultural Insurance Plan, more recently known as the Risks Management Plan, is one of the most relevant documents for the Italian risk management tools definition. Every year, the document is published by the Decree of the Minister of Agricultural, Food, and Forestry Policies, following the evaluation of proposals discussed by a specific technical commission. Every year the Decree lists the insurable crops, livestock, and farm infrastructure, each year, along with the insurable adverse climatic conditions, plant and animal diseases, and parasitic infections. The Decree also specifies the insurance schemes, premiums, and subsidies.

The Italian system for crop insurance has evolved during the years that the present thesis aims to analyse. As for insurance schemes to cover the adverse conditions, from 2008 to 2014, three different contracts were available for farmers. The insurance coverage may include single adverse weather conditions, plant diseases, parasitic attacks, and epizootic diseases for the events admitted to the subsidized insurance through the stipulation of mono-risk contracts, or it may include two or more harmful events through the stipulation of pluri-risk contracts. Furthermore, multi-risk policies on yields aim to stabilize farm revenues by covering all the adversities admitted to the subsidized insurance. Starting in 2015, a new set of contracts replaced the previous system. The new schemes differentiated the insurable events into infrequent, frequent, and additional adversities. The contract schemes differ according to the different combinations of harmful events. Contract A covers all the perils, such as infrequent, frequent, and additional adversities. Contract B covers the totality of rare perils and at least one of the recurrent damage. Contract C covers at least three among the frequent perils plus possibly one or both additional adversities, while contract D covers all the infrequent perils.

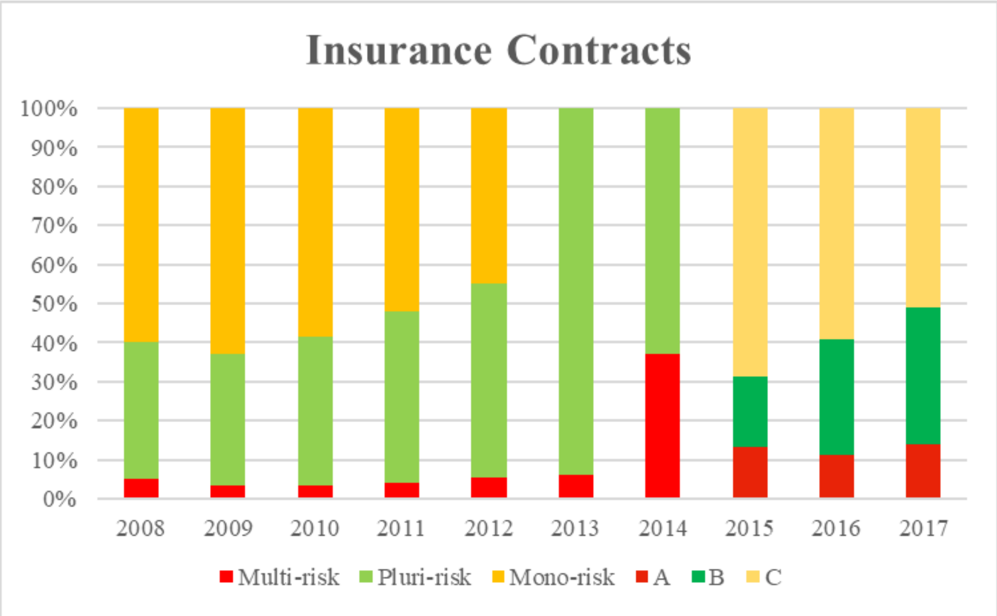
Furthermore, the policy related to premium subsidies, which aims to stimulate the adoption of crop insurance, has also undergone different changes between 2008 and 2017. In general, the public contribution decreased during the period under analysis. In particular, the reduction was related mainly to the contracts that cover fewer adverse climate events. In particular, since 2013, subsidized crop insurance policies must include coverage for at least two climatic adversities, and since 2014, coverage for at least three harmful events. As a result, since 2013, the subsidy is no longer available for mono-risk contracts.

These recent policy adjustments have slowed the diffusion of crop insurance. In particular, the support for risk management tools has been moved to the Rural Development Policy as a determination of the 2013 CAP reform, changing the administrative rules of the system. This transition has resulted in a lack of familiarity with the new regulations and delays in payments of subsidization and, as a result, it caused a lower uptake of crop insurance in Italy (Coletta et al., 2018). However, while there is an extensive literature aiming to investigate the determinants of insurance adoption in Italy, less is known as regards the effect of insurance on farm economic performances, which can explain some of the problems related to the low diffusion of crop insurance.

2.2. The Subsidized Crop Insurance Market in Grape for Quality Wine Production

The distribution of the type of contracts utilized in the grape growing production are reported in Figure 1, while the insured value and the amount of the premium actually paid are reported, respectively, in Figures 2 and 3. Figure 1 shows that, from 2008 to 2012, mono-risk insurance represented the most diffused contract even though its adoption rate decreased from 60% in 2008 to around 45% in 2012. With the ending of subsidies on this contract in 2013, farmers mainly adopted the pluri-risk scheme crop insurance. In 2014, when covering at least three climatic adversities was mandatory to access the public contribution, the multi-risk scheme reached the highest diffusion arriving at around 37% of the subsidised contract. Therefore, the change in the number of perils to be included to access the public subsidies impacted the diffusion of contracts favouring the spread of schemes that cover several adversities. Finally, from 2015 to 2017, farmers mainly adopted the type B and C contracts, which are similar to the pluri-risk, while the A scheme was less diffused than other schemes, as the multi-risk in the previous years. The diffusion of scheme C decreased from 68% in 2015 to 51% in 2017. At the same time, the adoption of scheme B increased from 18% to 35%. However, with the new legislation, the A scheme has a higher spread compared to the past. In fact, it arrived at around 14% of subsidised contracts, compared to the 5 or 6% diffusion rate from 2008 to 2012.

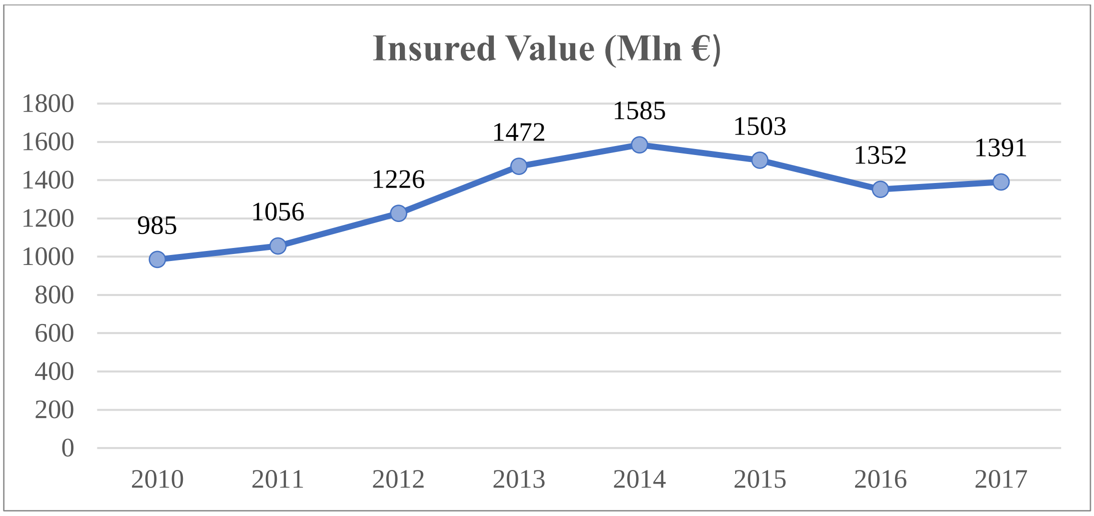
Figure 1. Subsidized Crop Insurance in Grape Production



Source: Own elaboration based on Sicur-Agro (ISMEA) Data

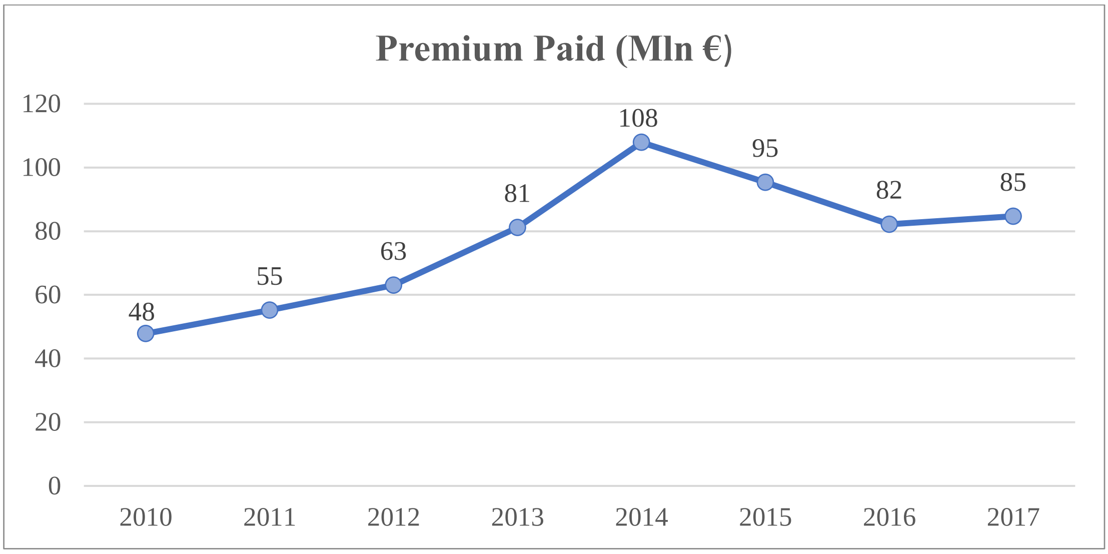
As for the insured value and the premium paid, the Italian grape growers sector follows the whole Italian crop insurance diffusion. From 2010 to 2014, there was a significant increase in both the insured value (Figure 2) and the premium paid (Figure 3). The legislative change of policy insurance schemes in 2014, which entered into force in 2015, has slowed the expansion of crop insurance. As a result, there was a reduction in both the insured value and premium paid.

Figure 2. Insured Value in Grape Production (Current Value)



Source: Own elaboration based on Sicur-Agro (ISMEA) Data

Figure 3. Premium Paid in Grape Production (Current Value)



Source: Own elaboration based on Sicur-Agro (ISMEA) Data

3. Theoretical Background

3.1. Introduction

Risk and uncertainty have a significant influence in production decision- making in the agricultural sector (Ahsan et al., 1982). It is well-known that since farmers make input use decisions before knowing the true state of nature, they choose the input allocation according to their subjective propensity to take a certain level of risk (Roosen and Hennessy, 2003; Cerroni, 2020). In fact, while exerting their typical actions, farmers do not aim only to maximize profits but also try to minimize the risk impact on income loss (Moschini and Hennessy, 2001). Regarding the conceptualization of agricultural risk, it is usually attributed to the length and complexity of the biological production cycle, which exposes farmers to risks such as pests, erratic climatic changes, price fluctuations, and even policy changes (Duong et al., 2019; Komarek et al., 2020). According to Komarek et al. (2020), agricultural risks are classified into production, market, institutional, personal, and financial risks. Production risks stem from the natural growth processes and are also related to weather and climatic conditions. These are factors beyond the farmer's control rendering the stochastic nature of agriculture. Market risks are associated with price volatility for both input and output prices. Factors such as asymmetric information, international trade, and liberalization constitute market risks. Institutional risks are generally associated with abrupt policy and regulation changes, as well as changes in the behaviour of informal institutions that affect transactions. Personal risks are farmer-specific related to health, personal relationships, and well-being, whereas financial risks stem from farm finance factors, credit access, and interest rate payments.

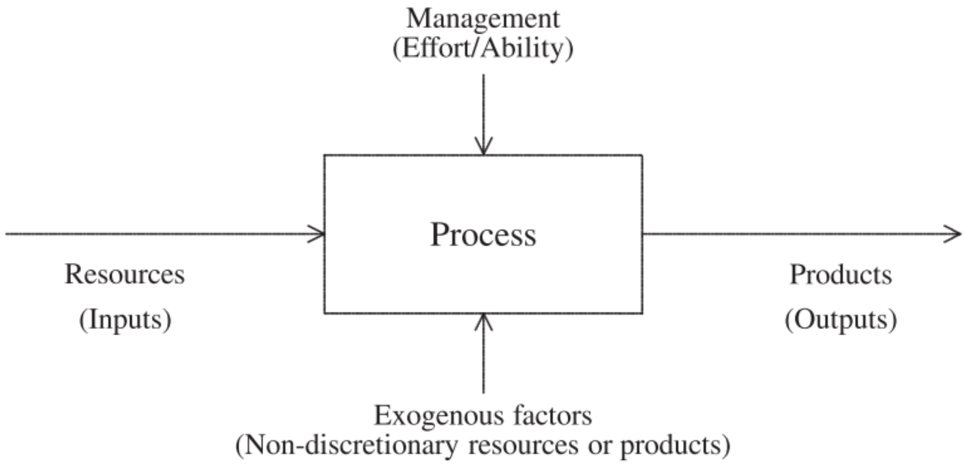
Researchers and policymakers have many reasons to be interested in how risk affects the farmers' decision-making and, thus, economic performances. Farm performance evaluations are fundamental for policymakers and producers to pursue both the economic and environmental sustainability of farming (Farrell, 1957). Moreover, understanding the interrelations between farmers' behaviour in a risky environment and farm performance is essential to enhance the effectiveness of policy measures (Khanal et al., 2021). For example, while risk-neutral farmers aim to maximize profits by considering only the mean effect of production, risk-averse producers account for both mean and higher moments of production function (Antle, 1983). Therefore, risk-averse production decisions differ from risk-neutral ones due to the existence of a marginal risk premium which is the absolute value of the risk effect of input use on output (Ramaswami, 1992). The marginal risk premium may have a positive or negative sign and indicates whether risk-averse producers use more or less input than risk-neutral ones. Thus, risk-averse farmers use less risk-increasing (and more risk-decreasing) inputs to cope with risk compared to risk-neutral farmers, who employ the profit-maximizing input vector (Nelson and Loehman, 1987; Ramaswami, 1993). Hence, the risk-aversion due to the uncertainty of outcomes may result in non-profit-maximizing input use, resulting in lower technical efficiency and productivity. By ignoring the risk impact on production, Battese et al. (1997) conclude that estimates of technical efficacy would be skewed. Consequently, neglecting the interrelation between farm performances and risk-averse deviations from efficient behaviour would lead to misguided policy implications and recommendations (Just, 2003).

Therefore, the present chapter reviews the literature on the theory related to the production function in agricultural economics. It is needed since estimating the production function is the prerequisite to evaluating the performance of farms. Subsequently, productivity and efficiency of farms are introduced since they represent the key performance indicators to investigate the farm performances. Later, it is illustrated the optimal use of input under certainty and uncertainty conditions, which represent the condition in which farms operate. Finally, the risk-aversion consequences on production decision-making and the crop insurance effect on productivity and efficiency are illustrated.

3.2. The Production Function in Agricultural Economics

Farmers are economic agents who continuously have to decide how much input to devote to the growth of crops and animals. While exerting their everyday actions, farmers face decisions concerning how much land, capital, labour, and other inputs to allocate in the production processes. Within a system-orientated approach to the company, the production process is commonly described as a transformation of inputs into outputs, as shown in Figure 4. It is also affected by non-controllable exogenous variables and managerial skills, which play an highly relevant role.

Figure 4. System-orientated approach to the firm



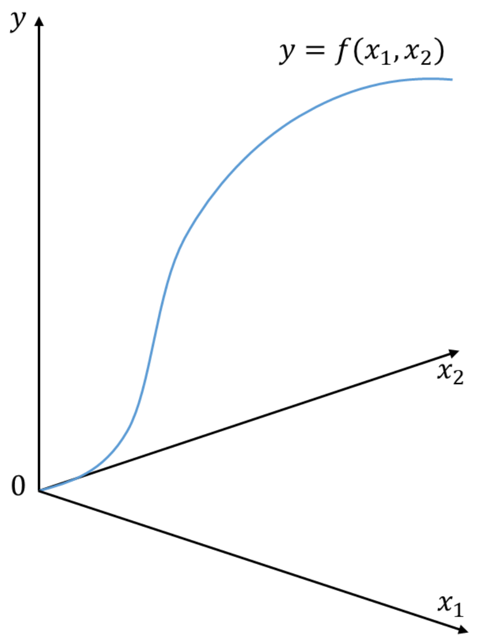
Source: Bogetoft and Otto (2010)

In the economic literature, the production process is represented by the production function, which indicates the level of output that can be produced for given production technology and various levels of input. In other words, the production function describes the transformation relationship which converts inputs into outputs, indicating the maximum output obtainable from a vector of given input quantities in a situation where the technology is used at its full potential (Kumbhakar and Lovell, 2000; Coelli et al., 2005; Kumbhakar et al., 2015).
The production function usually is expressed with a mathematical representation of the technology, such as:

$$y = f(x_1, x_2, \dots, x_k) = f(x) \tag{1}$$

where the function f (·) indicates the production technology which transforms a vector of inputs (*x*) into output (*y*). For example, a production function that refers to a production process that employs two inputs (x_1 and x_2) to produce a single output (*y*) can be shown as illustrated in Figure 5. In this case, the production function represents the maximum output *y* obtainable from the varying combinations of the inputs x_1 and x_2. The surface of the curve and the underlying area define the production possibilities set, which contains all the feasible input-output combinations given the production technology.

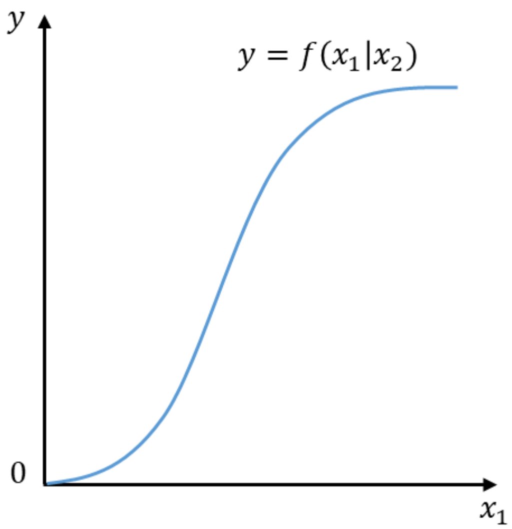
Figure 5. Production function example with two inputs and one output



Source: Own elaboration

However, since it is difficult to interpret the contribution of inputs in a multi-dimensional space, researchers usually refer to the bi-dimension, representing the relation between one input and one output. By slicing the production function at a given value of x_2, it can be shown the relationship between the application level of input x_1 and the output y given a value of x_2, which is often referred to as the total product curve of x_1, as illustrated in Figure 6. In a specular manner, it is possible to obtain the total product curve of x_2 for a given value of x_1.

Figure 6. The total product curve of x_1



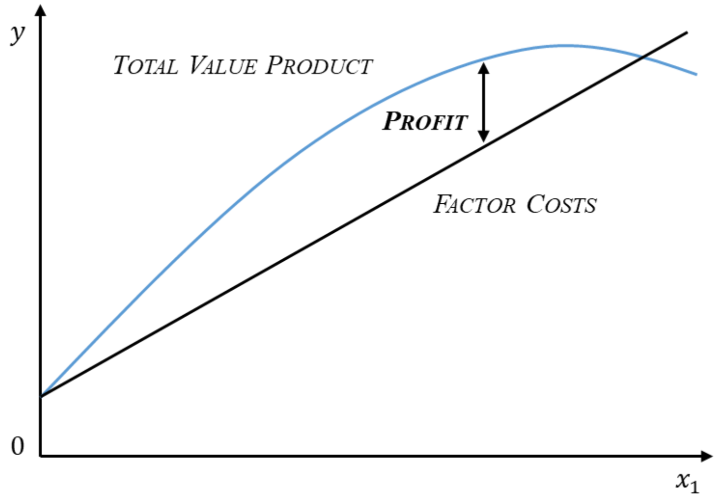
Source: Own elaboration

The production function is assumed to satisfy some properties to approximate the economic behaviour of economic agents, such as: (I) $\delta y / \delta x_i > 0$ implies that the additional use of input increases (or at least does not decrease) the level of output; (II) $\delta^2 y / \delta^2 x_i < 0$ refers to the law of diminishing returns or law of diminishing marginal productivity and implies that the quantity of additional output obtained from the supplemental level of input applied become smaller with the increasing value of input usage. More technical details for all the assumptions related to the production function are provided in Chambers (1998, p. 9).

Although these assumptions almost universally are maintained in economic analysis, most of these restrictions may not hold in the case of the agricultural sector. According to Ellis (1993), the production function and the profit maximization problem in agriculture economics have various specific characteristics and can be represented as shown in Figure 7. The production function is expressed in value terms representing the *total value product* to better explain the production decisions in the farming context. Moreover, the *factor costs* represent the cumulative cost related to the increasing level of input use. They are assumed to be linear to simplify the graphical representation. Finally, the profit is the difference between these values.

As indicated by Ellis (1993), first, in agricultural production, it is possible to find a situation where output occurs in the complete absence of some inputs. For instance, it can be generated output without applying some producing inputs such as fertilizer, irrigation, and pesticide. It implies that the production function may not start from the origin of the axis for some factors. Second, increasing the amount of some inputs such as fertilizer, pesticide, and water increases output, but only up to a certain point. Beyond that threshold, for example, an imbalance between the fertilizer and other plant nutrients in the soil arises, eventually causing output declines when more fertilizer is applied. Therefore, agricultural economics researchers worked to relax some of the properties discussed by Chambers (1998) to estimate the production function in agricultural economics.

Figure 7. The production function for some of the agricultural inputs



Source: Own elaboration based on Ellis (1993)

As for the functional forms of production functions, the most used in the literature are Cobb-Douglas and translog. The translog production function has several desirable properties that make it particularly interesting for this study. The main advantage of adopting a translog production function instead of a Cobb-Douglas is that it is more flexible and allows to investigate of whether the inputs are substitutes or complements (Henningsen, 2020).

3.3. Productivity and Technical Efficiency

To estimate a production function is the prerequisite to investigate the performance evaluations of production business units. Performance evaluations or benchmarking is the systematic comparison of the results of the production business units. Firms, organizations, departments, industries, decision-making units, and individuals are examples of producing units. Benchmarking can be informative in a variety of situations. It may work to explore intra-organizational, i.e., to evaluate the performance of subunits, inter-organizational, i.e., to compare different production entities at the same time, and longitudinal, panel, or dynamic comparisons, i.e., to study the performance of a business unit at different periods (Bogetoft and Otto, 2010).

To evaluate performance in the economic literature, practitioners usually refer to key performance indicators, which are measurements supposed to reflect the producer's goals. When considering the results of producers, it is common to refer to productivity and efficiency. Usually, these terms are used interchangeably, but in economics they have a different meaning.

The productivity of a business unit is the ratio of the output(s) produced to the input(s) employed, as in the following formula:

$$Productivity = output(s) \,/\, input(s) = y/x \tag{2}$$

Practitioners may refer to different measures of productivity, such as partial measures, i.e., land or labour productivity, and total factor productivity, which account for all input used in the production process.

Instead, as proposed by Debreu (1951) and Farrell (1957), efficiency is defined as the ratio of the output produced to the maximum potential output achievable by the production process, given the inputs and technology available. Specularly, efficiency is defined as the ration between the observed applied input and the minimum input required to obtain a specific output. Thus, efficiency definition depends on producers' goals, such as yield or profit maximization and cost minimization. Profit maximization is the goal that better represents the case study investigated in this work. Therefore, efficiency can be defined as the following:

$$Efficiency = output \,/\, output\ max = y/y^{*} \tag{3}$$

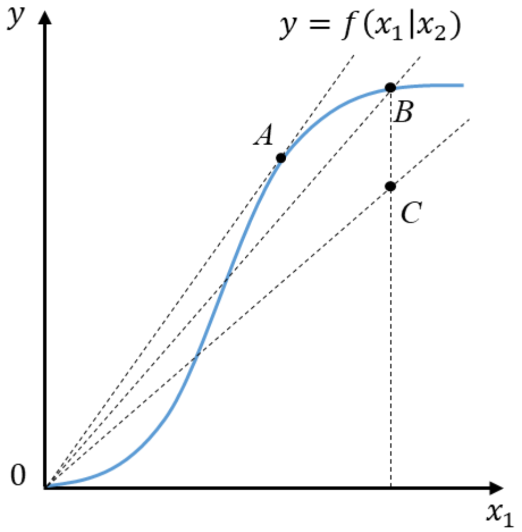
where y is the observed output and y^* is the maximum output obtainable, given a fixed technology and input level.

To illustrate the difference between productivity and technical efficiency is fruitful to present the contribution of Figure 8, representing a production function and the productivity (represented by the lines starting from the origin) of different production choices (A, B, and C). The slope of these lines is *y/x* and provides the measure of productivity. As for efficiency, farms that operate on the frontier are technically efficient, while farms that perform beneath the production frontier are not technically efficient. Thus, a farm operating at point C is inefficient since it is possible to increase the output moving from point C to point B without the increase of the usage of input.

However, a farm that moves from point C to point B boosts both technical efficiency, which is the straight line between point B and C, and productivity because it increases the slope of the line starting from the origin. Instead, as for point A, it is tangent to the production function and defines the point of maximum productivity. While both points A and B are technically efficient, the optimal production choice is where the productivity is maximized. The difference in productivity among technically efficient farms is related to economies of scale, and farms operating at any other point on the frontier with respect to point A are less productive.

As is possible to note, it does exists a relation between productivity and efficiency. In fact, an increase in productivity from one year to another may arise from technical efficiency, technical change, the exploitation of scale economies, or some combinations of these variables (Coelli et al., 2005).

Figure 8. Productivity and Technical Efficiency



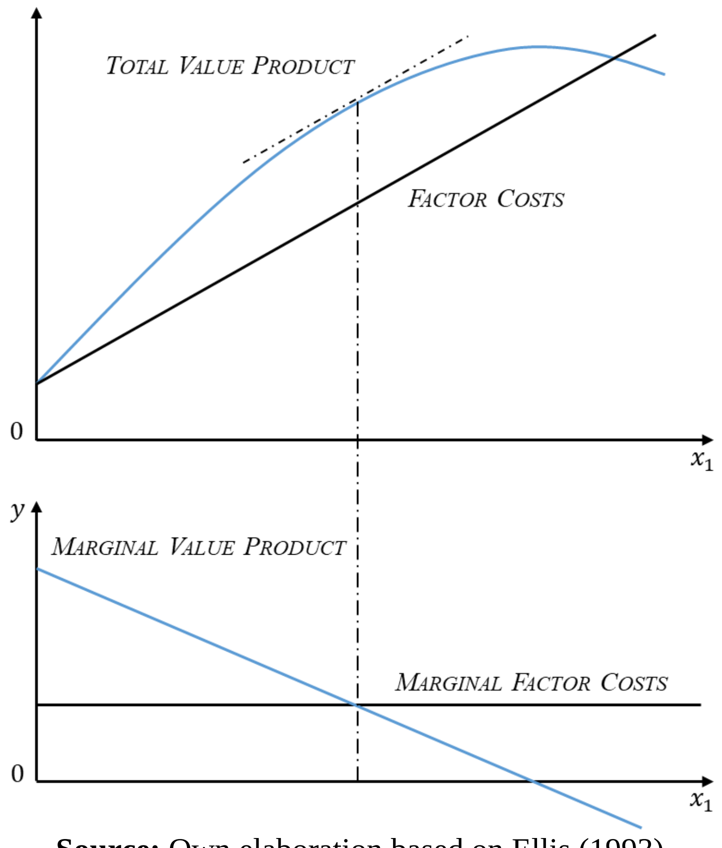
Source: Own elaboration based on Coelli et al. (2005)

3.4. Economic Optimal Use of Input

Farmers are assumed to be decision-makers who rationally take their production choices with the aim of profit maximization. As shown by Ellis (1993), the optimal production decision usually is represented as in Figure 9, where on the top are illustrated the *total value product* and *factor costs* as in Figure 7, and in the lower graph, the respective derivatives, the *marginal value product*, and *marginal factor costs*. The *marginal value product* is the additional return generated by the increment of input use. It is assumed to be linear for a more clear graphical representation. The *marginal factor costs* correspond to the price of the input, and in this example, it is assumed to be constant, and therefore, it does not change with the level of inputs applied.

The optimum level of input use is where the *marginal value product* equals the *marginal factor costs*. It is the position where the *profit* is maximum and corresponds to the rational choice from an economic point of view. In fact, the increased return produced by an extra unit of input is more than the cost of the production factor in the area to the left of this input level, indicating an opportunity to raise profit by increasing the amount of factor usage. On the other hand, in the area to the right of the optimal input level, the increased return produced by an extra unit of input is less than the unit cost of the factor. As a result, the profits are lower and indicate an opportunity to raise profit by diminishing the amount of input used.

Figure 9. Optimal use of inputs under certainty

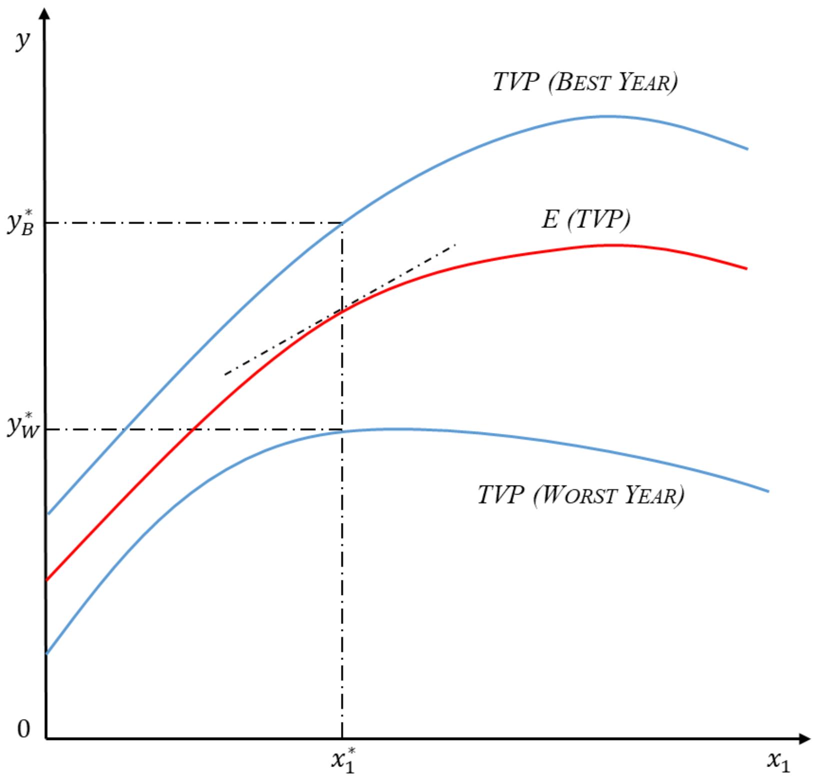


Source: Own elaboration based on Ellis (1993)

Figure 9 describes the so-called optimal input allocation under the certainty conditions, which means that farms face a situation of perfect information. It implies that farmers have the so-called perfect information about the likelihood of future events. However, agricultural production is a complex environment made up of biological (diseases, insects, pests, weeds), environmental (weather, soil, and water conditions), and institutional (markets, regulations) aspects that are difficult to manage (Ellis, 1993; Moschini and Hennessy, 2001; Duong et al., 2019; Komarek et al., 2020). Hence, in the agricultural economics analysis, the production function is assumed to be stochastic because of its unpredictable nature. As a result, the *total value product* obtainable by the production process varies based on factors beyond the farmers control. Therefore, a more appropriate way to describe economic behaviour is the so-called optimal input allocation under the uncertainty conditions, which indicate a situation where the occurrence of events is unknown.

The branch of economic literature that investigates the subjective probabilities relationship with the input decision-making is called the perceived risk or risk perceptions approach to the risk. The implications of uncertainty and risk for the optimal input choice analysis of the farmers can be introduced with the support of a graph, as given in Figure 10.

Figure 10. Optimal use of inputs under uncertainty



Source: Own elaboration based on Ellis (1993)

Here are shown three alternative response curves of *total value product* to increasing levels of a single input. *TVP "best" year* is the *total value product* response to the increasing usage of production inputs with the best environmental conditions. On the contrary, *TVP "worst" year* is the *total value product* response to the higher input level with the worst environmental conditions. They are defined as the outcomes of the states of nature and represent the boundaries of the range of the *total value product* obtainable, considering all the possible outcomes achievable. Finally, *E(TVP)* is a weighted average of the expected production results of the states of nature considering the subjective probabilities associated with the occurrence of good and bad years. The weighted average of the expected outcome (*E(TVP)*) is expressed as:

$$E(TVP) = \Sigma\ (p_s * TVP_s) \tag{4}$$

where p are the subjective probabilities attached by the each farmer to the s outcomes obtainable in every single possible state of nature.

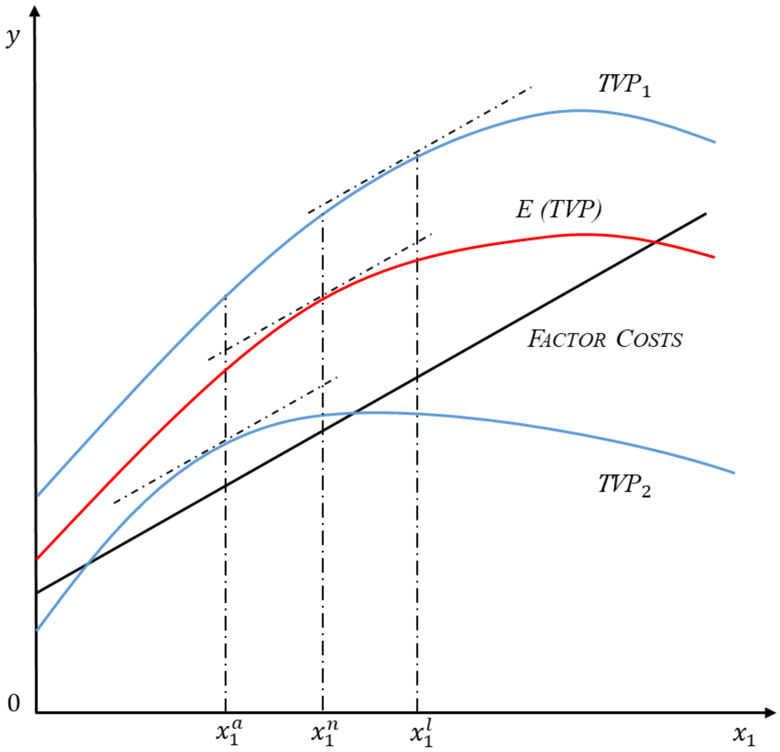
As for the optimal input use under certainty, the optimal input is the point where the derivative of the expected weighted average of the total value product (*E(TVP)*), the expected marginal value product of input, is equal to the marginal factor costs. Therefore, farmers account for all possible outcomes and choose the input level x_1^* to produce a range of output varying from the output y_B^* to y_W^* according to the environmental conditions faced during the season. It is the optimal input choice and represents the profit-maximizing position, which accounts for all the possible environmental conditions over the years.

However, risk perception is not the only effect generated by uncertainty and risk. Since farmers make input applications before knowing the true state of nature, according to the previous literature, they even are assumed to allocate inputs according to their attitudes to risk (Antle, 1987; Cerroni, 2020; Iyer et al., 2020). Risk attitudes reflect the individual predisposition to risk. In the literature, the individuals are divided into risk-averse, risk-neutral, and risk-lover decision-makers. The choice to operate at the optimal input level requires the risk-neutrality of farmers. Yet, previous work has shown that farmers are risk-averse (Kumbhakar and Tveterås, 2003; Aka et al., 2018; Tong et al., 2019). Risk-aversion has several implications for production decision-making. Therefore, also the risk attitudes directly impact optimal input use (Roosen and Hennessy, 2003; Bozzola and Finger, 2021). The role of risk-aversion in production analysis is central to the investigation of the present work, and it will be detailed in the next paragraph.

3.5. The Effects of Risk and Risk-Aversion on Input Choice and Production Output

A branch of the economic literature investigates the risk attitudes effects on production optimal decisions. The impacts of risk attitudes on input choice and production performances in the neoclassical model of farm production can be introduced with the support of a graph, as given in Figure 11.

Figure 11. Risk attitudes effects on optimal use of inputs under uncertainty



Source: Own elaboration based on Ellis (1993)

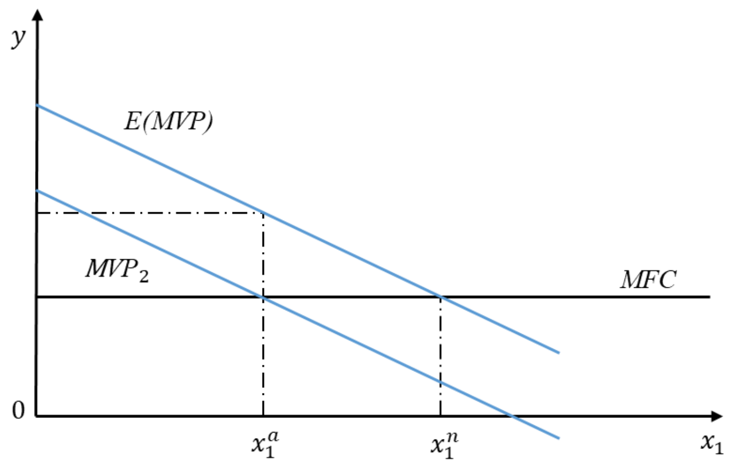
As shown by Ellis (1993), risk attitudes are included in the agricultural production theory assuming, for example, that there could be only two states of nature that can happen due to different environmental conditions, such as weather, pests, etcetera. The weather events may be good to obtain the best crop yields or may be bad, not allowing to achieve the best crop yields. In Figure 11, the graph shows three different response curves of the total value product to increasing levels of a single input. Moreover, the total factor costs are added to show profit and loss. These alternative output response curves represent the outcome of the two events described above, along with the farmer's subjective assessment of the balance between the two events. TVP_1 and TVP_2 are the outcomes of events, and they represent the *TVP* response to increasing the level of input in a good and a bad year, respectively. *E(TVP)* is a weighted average of the two outcomes, TVP_1 and TVP_2, where the weights are the subjective probabilities, p_1 and (1 - p_1), assigned by the farmer to the possibility that the event will happen. Therefore, *E(TVP)* is equal to $p_1 * TVP_1 + (1 - p_1) * (TVP_2)$.

Figure 11 shows three different levels of input choices, x_1^r, x_1^n, and x_1^l. Each input choice is rational according to the farmer's subjective attitudes concerning the risk. Farmers choosing to use the level of input x_1^l are classified as risk-taking or risk-lovers. It is because they would take an opportunity to gain the highest possible profit rather than taking a safer position with the chance of sustaining a substantial loss. In fact, they rise the highest potential profit if TVP_1 occurs. On the contrary, if TVP_2

occurs, a significant loss is suffered. Then, farmers that choose to operate at the level of input x_1^r are described as risk-averse. They prefer the safe choice as in the case the worst possible outcome happens. With this level of input choice, farmers ensure profits in both the states of nature, even if profits are smaller when compared with the other input choices. Finally, farmers choosing to utilize the level of input x_1^n are described as risk-neutral. They consider the weighted expected outcome of good and bad years. Thus, if TVP_1 occurs, a profit is obtained, but this is not the highest profit possible for TVP_1. Similarly, if TVP_2 occurs, a profit is earned, but this is not the highest potential profit for TVP_2.

In other words, due to the risk environment, farmers do not aim only to maximize profits but also try to minimize risk impact on income (Moschini and Hennessy, 2001; Finger, 2013). In particular, while risk-neutral farmers aim to maximize profits considering only the mean effect on production, risk-averse producers take both mean and higher moments of production function into account when optimizing the utility function (Just and Pope, 1978; Antle, 1983). Therefore, risk aversion directly affects the level of optimal resource use. Farmers should operate at the profit-maximizing point, or the point where the *expected marginal value product* (*E(MVP)*) of the input equals the *marginal factor cost* (*MFC*) in order to maximize profit. The risk-neutral farmer makes this decision, whereas the risk-averse farmer chooses to operate in a way where profit is maximized only during "bad" seasons. In other words, risk aversion leads to suboptimal economic decisions regarding the distribution of inputs. Graphically it can be shown in Figure 12. Instead, to operate at the point where *E(MVP)* corresponds to the *MFC*, risk-averse farmers prefer to perform in a situation where MVP_2 equalizes the *MFC*. It implies that the *E(MVP)* is above the *MFC*. Therefore, the use of inputs is not optimal, and profit is not being maximized, except for bad seasons. The consequences of the risk-aversion result in circumstances where, on average, *MVP* > *MFC*.

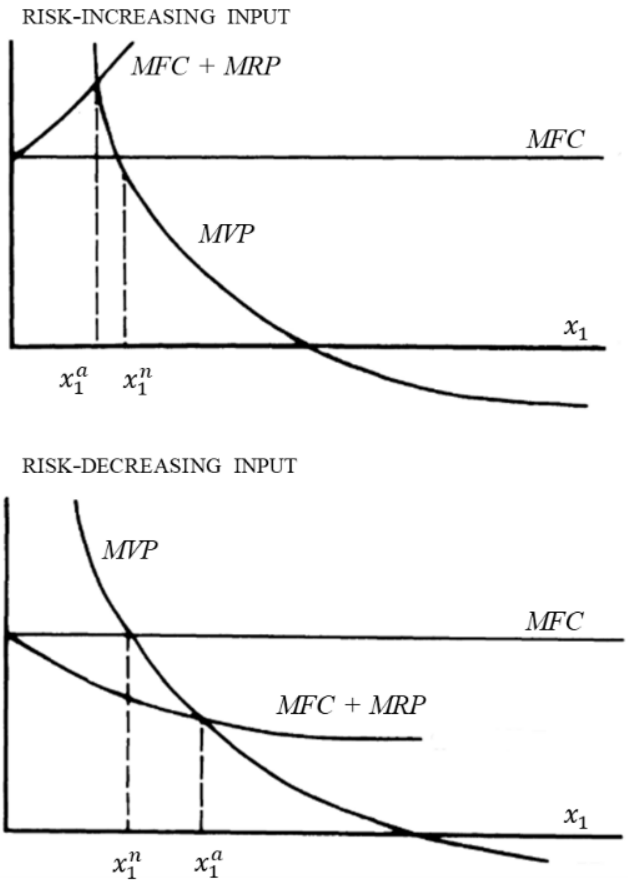
Figure 12. Risk aversion effect on optimal use of inputs under uncertainty



Source: Own elaboration based on Ellis (1993)

More particularly, previous works have shown that the production decisions of risk-averse farmers differ from risk-neutral choices because of the existence of a marginal risk premium (MRP), which is the absolute value of the risk effect of input use (MacMinn and Holtmann, 1983; Nelson and Loehman, 1987; Ramaswami, 1992). In general, the sign of marginal risk premium depends on risk preferences and technology, as shown in Figure 13. The marginal risk premium is positive if the use of the producing factor increases the production uncertainty (risk-increasing input), while it is negative when the producing factor is risk-decreasing (Just and Pope, 1979; MacMinn and Holtmann, 1983; Pope and Kramer, 1979). Consequently, in the case of a single input and a single output, 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; Ramaswami, 1992). In the agricultural sector, fertilizers are frequently regarded as risk-increasing inputs in farm decision-making (Just and Pope, 1979; Pope and Kramer, 1979), whereas pesticides and herbicides usually are reputed as risk-decreasing inputs (Möhring et al., 2020a). As a result, the risk-aversion due to the uncertainty of outcomes results in non-profit-maximizing input use impacting the same time productivity and technical efficiency (Roll, 2019).

Figure 13. The difference in input use for risk-averse and risk-neutral farmers



Source: Nelson and Loehman (1987)

3.6. The Effects of Crop Insurance on Input Choice and Farm Performances

To mitigate the impact of adverse events to production, risk-averse farmers can transfer part of their resources (financial and human) from the production process to risk management activities, which are adopted to minimize the negative impact of risks regarding possible losses (Vigani and Kathage, 2019). Among the vast array of risk management strategies available at the farm level, crop insurance represents an important risk management tool to cope with risk. Yet, there can also be some intended and unintended side-effects of crop insurance adoption. In particular, according to the existing literature, crop insurance adoption may affect input use decisions and thus productivity and technical efficiency in two ways.

First, insurance may change input application rates. In particular, the purchase of insurance may make risk-averse input allocation independent of the farmer's preference function over uncertain outcomes allowing them to behave as risk-neutral in their input choice (Ahsan et al., 1982; Nelson and Loehman, 1987). It is because insurance has a risk-reduction effect, i.e., it reduces the wedge between expected marginal product and input price due to risk aversion. It, in turn, leads risk-averse farmers to move toward optimal levels of input use (Ramaswami, 1993), i.e., to increase the level of input if risk-increasing and to decrease the input use if risk-decreasing. However, insurance adoption reduces the marginal return from an additional unit of input application, as an increase in output may be accompanied by a decrease in expected insurance indemnities. It is described as the moral hazard effect that causes an input use reduction irrespective of whether it is risk-reducing or risk-increasing (Ramaswami, 1993).

Second, insurance adoption may change the cropping patterns. Suppose two different crops are produced using the same input, which is risk-increasing for the first crop while it is risk-reducing for the second crop, i.e., pesticides risk effect on production depends on the crops and type of pesticide considered (Möhring et al., 2020a). The risk-averse farmer would produce less of the first crop and more of the second crop when compared with the risk-neutral farmer (Nelson and Loehman, 1987). Furthermore, insurance induces farmers to allocate more resources to insured risky crops and to enhance their specialization in such crops (Ahsan et al., 1982; Vigani and Kathage, 2019). The higher expertise due to the production specialization, in turn, might boost productivity and technical efficiency (Roll, 2019). On the other hand, moral hazard may cause insured farmers to reduce the use of safety measures to cope with risk (Horowitz and Lichtenberg, 1993; J. C. Quiggin et al., 1993), with a potentially damaging effect on output and the specialization achievable by crop insurance (Ahsan et al., 1982; Ramaswami, 1993; Roll, 2019). In line with previous literature, the two concepts described above can be defined respectively as crop insurance “intensive margin” and “extensive margin” effect on input use (Wu, 1999; Möhring et al., 2020b).

To sum up, the aim of the research reported in this thesis is to tackle the already mentioned dilemma regarding the impact of crop insurance on input use and economic performances of a nationally representative sample of Italian farmers. In particular, starting from the previous crop insurance literature, how the insurance affects the productivity and efficiency of farming was examined, also investigating the crop insurance relationship with the input use. From a methodological point of view, a stochastic frontier approach is implemented on a sample of Italian grapevine producers, using data from the Farm Accountancy Data Network, over the period 2008-2017, following the method proposed by Roll (2019). Besides, a model that accounts for the different sources of endogeneity of insurance adoption was applied, which avoids the problem of inconsistent parameter estimates (Karakaplan and Kutlu, 2017b; Vigani and Kathage, 2019).

4. Methodological Framework

4.1. Introduction

In literature, most productivity and efficiency analyses are conducted through the development of production frontier models. The two commonly used methods in productivity and efficiency analysis are the Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). Although these two methods have their merits, there has been constant debate amongst scholars on which method is better for modelling production technology. A relevant distinction between the two methods is that DEA is deterministic while SFA is stochastic. While in the stochastic frontier model the individual observations may be affected by random noise, in the deterministic approach the potential noise is neglected, and each variation in data is assumed to influence the firm's efficiency and the shape of the frontier (Bogetoft and Otto, 2010). Therefore, one of the principal limits of DEA is that with this methodology is not possible to consider the effect of risk, which could be confused with technical inefficiency. Accordingly, it seems that SFA might be more suitable to model productivity and efficiency in the case of the presence of risk as it is suited to disentangle the inefficiency from the standard statistical error related, for example, to weather events, market volatility, and regulation changes.

Stochastic production functions appeared to be a reasonable solution to account for risk in agricultural economics (Chavas et al., 2010). Just and Pope (1978) introduced a production function specification that can distinguish between the marginal effect of inputs on both the mean and variance of output. Then, Antle (1983) expanded this technique to account for the impact of production inputs on higher moments of production function (i.e., skewness). Later, Battese et al. (1997) extended the model proposed by Just and Pope (1978) to the stochastic frontier production approach developed originally by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). According to the authors, the stochastic frontier production function is more consistent with economic theory and reality with respect to the so-called average production function. More recently, Kumbhakar (2002) generalized the approach proposed by the previous authors by estimating a model which includes production risk, technical efficiency, and producers' attitude toward risk. Given the inevitable consequence of risk effects on producers' technical efficiency, risk sources have to be incorporated into the stochastic production frontier in order to realistically account for and predict producers' technical efficiency (Battese et al., 1997).

The primary motivation paving the way for the present study concerns the purpose that, despite its importance, most of the scientific literature on production at the farm level does not account for risk

(Just, 2003). Moreover, it is worth mentioning that one of the central assumptions of the SFA model is that the input variables should be independent of both the error terms (technical efficiency and random error) in the model. The correlation between explanatory variables and the error terms results in an endogeneity problem which provide biased estimates. However, it is essential to note that endogeneity may occur for several reasons. For instance, farmers may adjust their inputs according to observed adverse events, which are usually included in the random error term. Therefore, the correlation between the production inputs and the statistical error term due to the observed adverse events would result in endogeneity (Latruffe et al., 2017). In Addition, another possible endogeneity issue may arise when farmers, being aware they are inefficient, tend to optimize their input use (Shee and Stefanou, 2014). Finally, other endogeneity sources may occur when farmers cope with risk by adopting risk management tools or risk-mitigation practices (Vigani and Kathage, 2019). The model misspecifications due to the absence of dealing with endogeneity lead to erroneous inferences about the assessment of input elasticities and economies of scale, as well as inaccurate and inconsistent estimates of firm technical efficiency (Karakaplan and Kutlu, 2017b). It is worth noting that endogeneity in SFA is often ignored, which could overstate or even undermine the effects of factors on production, and thus results in key strategies or recommendations being left out to boost farm performance (Amsler et al., 2016; Karakaplan and Kutlu, 2017a, 2017b). The impact on accuracy and consistency of results may be highly relevant when risk analysis is performed (Battese et al., 1997).

Bearing in mind the above mentioned issues related to SFA and endogeneity, a literature review has been performed in the subject area that refers to agricultural productivity and efficiency analysis. The particular focus is on studies that have adopted the SFA method while including the risk. The scoping review method has been adopted for the capability to identify and map out evidence and clarify key concepts in agricultural stochastic frontier literature with the inclusion and consideration of risk. Specifically, this chapter aims to provide insights into how risks and risk mitigation strategies have been factored into SFA. The main contribution of the present research relates to analysing the different methods used to deal with endogeneity while aiming to investigate the risk effects on agricultural production within the SFA approach.

In the following paragraph, it has been presented the scoping review methodology with particular focus on the keywords and eligibility criteria that outline the articles included in the sample. Later, in the results section, the selection process of articles and the insights of the literature analysed are illustrated. Then, the results are shown and discussed. Finally, the conclusions have been presented by highlighting the study's limitations and the path for future research.

4.2. The Scoping Review Method

The scoping review method has been adopted to conduct this study following the guidelines provided by Tricco et al. (2018) in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for scoping reviews (PRISMA-ScR). A scoping review is a form of knowledge synthesis that systematically searches, selects, and synthesizes existing knowledge to map the key concepts, types of evidence, and gaps in research related to a given area or field (Colquhoun et al., 2014).

The advantage of the scoping review method is that it helps to summarise the existing knowledge aiming to develop policy or practice recommendations, as well as to provide practical pathways for future research (Arksey and O'Malley, 2005; Piñeiro et al., 2020). Compared to the traditional literature review, the scoping method aims to be rigorous, transparent, and replicable, including steps to reduce the subjectivity bias resulting from the author's prior knowledge and experience (Munn et al., 2018). The scoping method was thus suitable for this study in exploring how risk has been incorporated in SFA agricultural productivity analysis and how the endogeneity issues have been handled in literature.

After stating the research question, the subsequent steps of this approach are: identification of relevant studies, study selection, data extraction and charting, and reporting of the results. In order to get a representative sample of the literature, an initial set of articles has been identified. The Scopus bibliographic database is used to research the relevant studies, including articles written in English and published in peer-reviewed journals earlier than 30 June 2021.

The search was characterized by a combination of three keyword groups contained in the paper abstract, title, or keywords. The following structured query developed using Boolean operators and wildcards is used for the research:

["stochastic frontier" OR "stochastic production" OR "technical efficiency"] AND ["risk" OR "uncertain"] AND ["farm*" OR "agricultur*" OR "food" OR "crop" OR "livestock"].*

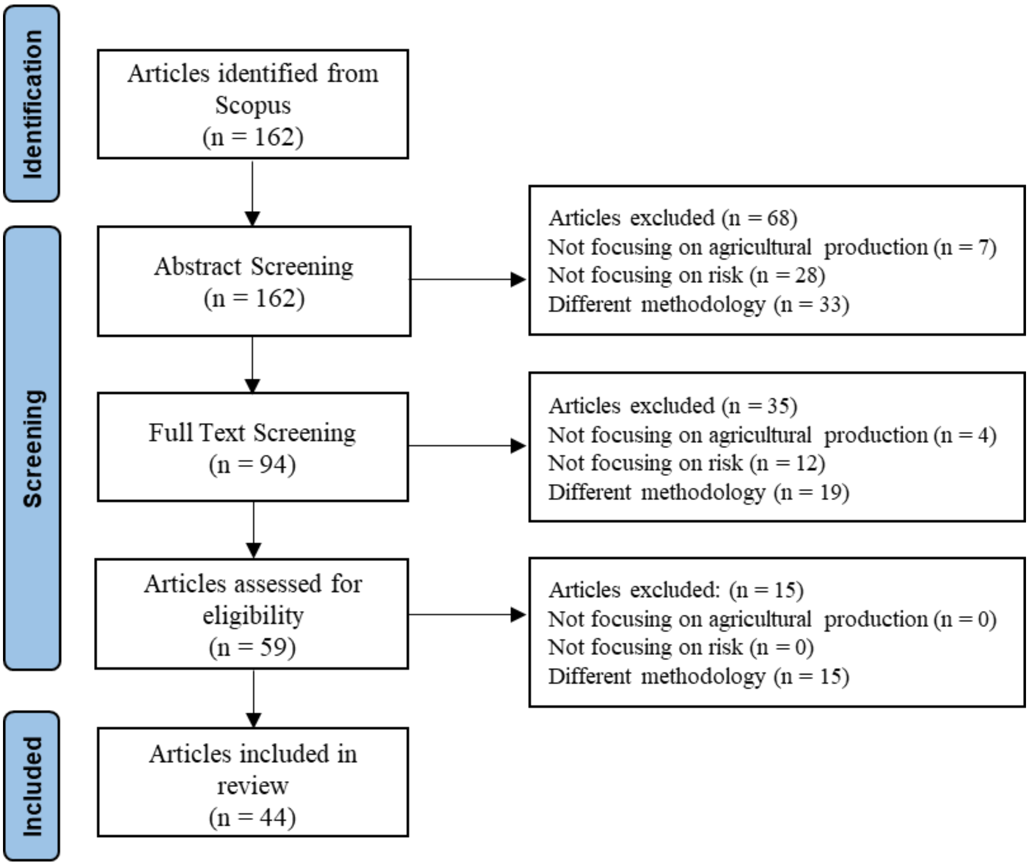
While the first set of keywords included the terms related to the SFA, the second refers to the risk and the third to the agricultural context.

The final set of articles has been exported to the Mendeley referencing tool for assessment. For consistency purposes, a meeting with the Ph.D. supervisors was organized to discuss the chosen studies for this review. To be included in the sample, the eligibility criteria were the following: (i) research topic on agricultural production (ii) inclusion of risk and risk management in farm productivity and efficiency analysis; (iii) studies that adopted the SFA to model technical efficiency and agricultural productivity.

4.3. Results

The selection process followed several steps, as shown in Figure 14, gradually reducing the number of studies according to the eligibility criteria. The search output initially included 162 peer-reviewed articles. In the first screening step, titles and abstracts were examined, retaining only papers focusing on issues related to risk analysis in the agricultural sector using the SFA approach. Then, the full text of the remaining 94 studies was analysed, excluding 35 articles according to the rejection criteria. Finally, in the last screening step, 15 papers were excluded because they utilized a stochastic production function instead of the frontier. However, these papers have been examined to consider their insights as regards the endogeneity issues, reporting this analysis later in this paragraph. At the end of the screening process, 44 articles have been retained. Of the 162 articles, 11 were disqualified because they were not focused on agricultural economics, and 40 were based on the lack of risk considerations. Finally, 67 papers were excluded for their use of methods other than SFA, for instance, stochastic production function (e.g., Griffiths, 1986; Eggert and Tveteras, 2004; Di Falco et al., 2007), or non-parametric approaches such as DEA (e.g., Serra and Oude Lansink, 2014; Chambers et al., 2015; Oude Lansink et al., 2015), or fuzzy mathematical methods (Guo et al., 2019; Wang et al., 2020).

Figure 14. PRISMA-ScR Flow Diagram

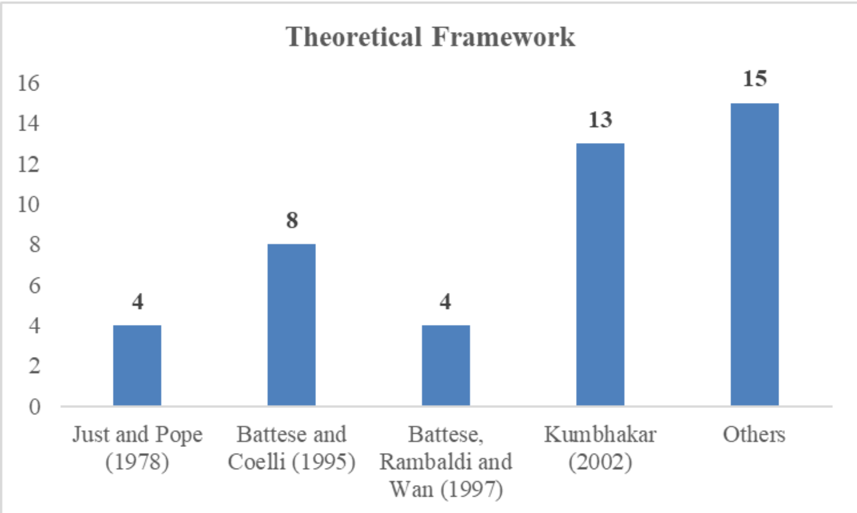


Source: Own elaboration based on Tricco et al. (2018)

Figure 15 below presents the histogram of the distribution of the common approaches employed in the retained articles. The results of this analysis showed that there are several approaches adopted in estimating stochastic production frontiers with risk considerations. The most commonly used methods are those proposed by Just and Pope (1978), Battese and Coelli (1995), Battese et al. (1997), and Kumbhakar (2002). In addition, 15 articles adopted other methods that studied risk in their analysis.

However, not all approaches allow the inclusion of risk within the stochastic production framework, such as Battese and Coelli (1995). Among the techniques that include risk within the production frontier, the most common methods used are the ones proposed by Just and Pope (1978), Battese et al. (1997), and Kumbhakar (2002)[1].

Figure 15. A theoretical framework to estimate the production frontier



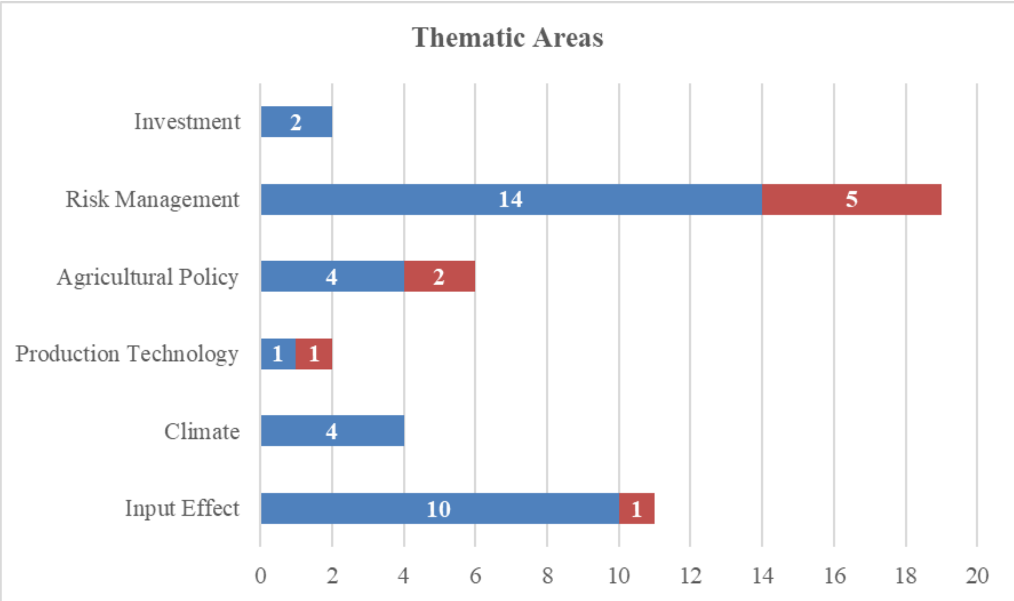
Source: Own elaboration

Six different thematic groups have been identified within the literature analysed, as shown in Figure 16. In this analysis, it was found that two articles incorporated risk in the SFA approach by focussing on the relationship between efficiency, risk aspects, and investment, such as the timing of investment decisions (Lambarraa et al., 2016) or the adoption of new technology (Ghosh et al., 1994). In addition, nineteen articles investigated the effect of farmer risk attitudes, risk mitigation practices, and risk management tools on farm performance. Furthermore, six papers examined the impact of agricultural policies on production risk and technical efficiency. Additionally, two studies investigated the differences in production risk and technical efficiency among distinct production technology, such as intensive or extensive (Nguyen et al., 2020) and organic or conventional production (Tiedemann and

[1] While all the studies consider risk, not all explicitly include it within the estimated production frontier. Some articles assessed it outside the model as a prerequisite or a follow-up step after the estimations.

Latacz-Lohmann, 2013). In addition, four papers investigated the climate effect or market volatility on farm performance and/or risk. Finally, eleven articles focused on the assessment of the impact of input on production risk and technical efficiency. In Figure 16, the articles that dealt with endogeneity and those that did not are differentiated with different colours. The colour red represents the articles that dealt with endogeneity. As a result, only nine studies out of 44 (20.45%) considered the issue of endogeneity. Among them, five articles focused on the risk-management thematic area, two on agricultural policy, one on production technology, and the last one study on input effects.

Figure 16. Literature thematic areas accounting for the articles that dealt with endogeneity issues



Source: Own elaboration

Table 1. Articles dealing with endogeneity in the production frontier estimates

Category/Study	*Frontier Theoretical Framework*	*Endogeneity Source*	*Methodology*
Risk Management			
Chang and Wen (2011)	Kumbhakar (2002)	Self-Selection	Separating Groups
Mishra et al. (2019)	Kumbhakar (2002)	Self-Selection	Separating Groups
Mishra et al. (2020)	Kumbhakar (2002)	Self-Selection	Separating Groups
Rizwan et al. (2020)	Kumbhakar (2002)	Self-Selection	Separating Groups
Khanal et al. (2021)	Greene (2010)	Self-Selection	PSM
Agricultural Policy			
Key and Mcbride (2014)	Karagiannis and Tzouvelekas (2012)	Self-Selection	PSM
Singbo et al. (2020)	O'Donnell (2016)	Input Endogeneity	Meta-Technology
Production Technology			
Tiedemann and Latacz-Lohmann (2013)	Just and Pope (1978)	Self-Selection	PSM
Input Effect			
Nauges et al. (2011)	O'Donnell and Griffiths (2006)	Input Endogeneity	State-Contingent

Source: Own elaboration

Table 1 provides a schematic representation of the different methods implemented to account for endogeneity. Among the articles in the risk management thematic area, Chang and Wen (2011) investigated the off-farm work effect on technical efficiency and production risk in Taiwan rice farming. Mishra et al. (2019, 2020) examined the impact of contract farming on production risk, technical efficiency, and risk attitudes for different crops in Nepal. Rizwan et al. (2020) studied the effect of off-farm employment on production risk and technical efficiency. All these articles developed a stochastic frontier following the model proposed by Kumbhakar (2002), accounting for self-selection by separating farmers adopting and non-adopting the risk management tools investigated. Finally, Khanal et al. (2021) investigated the influence of farmers' climate change adaptations on smallholder farm efficiency and productivity in Nepal rice production. The authors treated the self-selection endogeneity bias among adopters and non-adopters for observed and unobserved characteristics. In particular, they utilized the Propensity Score Matching (PSM) technique to correct for unobserved heterogeneity, obtaining samples of farmers homogenous in terms of socio-economic characteristics. Then, they estimated a stochastic frontier using the model proposed by Greene (2010) to correct for observed heterogeneity.

In the agricultural policy thematic area, Key and Mcbride (2014) estimated the effects on production mean and variance caused by the ban of antibiotics on the US hog industry. They developed a stochastic frontier following the approach proposed by Karagiannis and Tzouvelekas (2012). The authors addressed the potential selection bias due to the fact that the application of antibiotics treatment may be related to other unobserved aspects influencing the production process. In particular, they matched the different treatment effects (antibiotics) to create similar groups based on the observable characteristics. Singbo et al. (2020) analysed the impact of the revenue insurance program and environmental regulations on Canadian hog farmers' behaviour and farm performance indicators. The authors addressed the potential endogeneity of input changes related to adverse events affecting the production by estimating the meta-technology production frontier model developed by O'Donnell (2016).

Within the production technology thematic area, Tiedemann and Latacz-Lohmann (2013) evaluated production risk and technical efficiency in organic and conventional arable crop farms in Germany. The authors developed a stochastic frontier approach stemming from the model developed by Just and Pope (1978). They used the propensity score matching to compare groups, accounting for the self-selection problem due to farm size and soil quality.

Finally, among the input effects thematic area, the only study that dealt with endogeneity is Nauges et al. (2011), who analysed Finnish grain production under both inefficiency and risk condition. They developed a state-contingent production frontier following the model proposed by O’Donnell and

Griffiths (2006). They accounted for the endogeneity of inputs considering the different states of nature. In particular, they considered that farmers allocate inputs differently to manage risk in relation to the meteorological conditions in the relative states of nature.

To summarise, seven articles considered endogeneity bias resulting from self-selection, while two considered endogeneity stemming from input use alterations after adverse environmental events.

Table 2. Articles dealing with endogeneity in the function production instead of the frontier

Category/Study	***Frontier Theoretical Framework***	***Endogeneity Source***	***Methodology***
Risk Management			
Di Falco and Chavas (2009)	Antle (1983)	Self-Selection	Three-Stage Least Squares (3SLS) approach
Di Falco and Veronesi (2014)	Antle (1983)	Self-Selection	Endogenous Switching Regressor
Kassie et al. (2015)	Antle (1983)	Self-Selection	Endogenous Switching Regressor
Mallawaarachchi et al. (2017)	Quiggin and Chambers (2006)	Self-Selection Input Endogeneity	Two-Stage IV approach State-Contingent
Wang et al. (2018)	Antle (1983)	Self-Selection	Two-Stage IV approach
Amondo et al. (2019)	Antle (1983)	Self-Selection	Endogenous Switching Regressor

Source: Own elaboration

In addition to results related to SFA, some other articles emerged from the search string account for the endogeneity in the production function. These papers are reported in Table 2. All these articles were classified into the risk-management thematic area.

Among these articles, Di Falco and Chavas (2009) analysed the crop genetic diversity effects on productivity and production risk in Ethiopian farmers engaged with barley production, following the Antle (1983) approach. The authors estimated the mean function, the variance, and the skewness equations using a three-stage least squares (3SLS) estimator to correct the self-selection bias, treating biodiversity as endogenous in all equations. Following the approach proposed by Antle (1983), Di Falco and Veronesi (2014) investigated the influence of climate change adaptations on farm exposure to downside risk for several crops in Ethiopia. The decision on whether to adapt or not to climate change is voluntary and may result in self-selection bias. The authors accounted for the endogeneity of the adaptation decision by estimating a switching regression model. By using the same approach, Kassie et al. (2015) analysed the effect of sustainable intensification practices on productivity and production risk in maize-legume intercropping production in Malawi, while Amondo et al. (2019) investigated the impact of using drought-tolerant maize varieties on farm productivity, yield variance, and downside risk exposure in Zambian maize-growing farms. The research proposed by Wang et al. (2018) aims to study the importance of irrigation infrastructure in enhancing farmers' ability to adapt to drought and its efficacy in managing drought risk in rice production in China. The authors estimated a production function following the approach proposed by Antle (1983). In addition, they implemented a two-stage instrumental variable method to control for the endogeneity of the adaptation decision. Finally, following the state-contingent method proposed by Quiggin and Chambers (2006), Mallawaarachchi et al. (2017) estimated the production function of dairy farms in Australia to analyse the effect of water allocation on farm performance. They accounted for the endogeneity related to the change in the usage of productive inputs under different states of nature according to the adverse events affecting the productivity. Moreover, they proposed a two-stage instrumental variables approach to correct the endogeneity bias due to self-selection.

4.4. Discussion

The vast majority of the articles using SFA in agricultural production did not consider risk despite its relevance in the field. Consistent with Just (2003), the results of this research confirm the low prevalence of risk-related agricultural production studies, showing the failure of risk researchers in convincing the broader profession of the importance of risk effects on farmers' decision-making. For example, by omitting the keywords related to risk from the search query, the number of articles increases from 162 to 2595. Despite Battese et al. (1997) claimed that by neglecting risk would provide biased estimates of technical efficiency, in fact only relatively few articles accounting for risk by implementing a SFA approach were found. It may be related to the fact that this approach is still in development and the model is rather complex, both as regards the modelling and the estimating procedures (Kumbhakar et al., 2015).

It is worth noting that studies considering risk in the SFA approach do not account for the representation of the complexities of agricultural production modelling, such as endogeneity. Despite methods of dealing with the endogeneity issues in production frontiers have been well documented in the recent literature (Shee and Stefanou, 2014; Amsler et al., 2016, 2017; Karakaplan and Kutlu, 2017; Latruffe et al., 2017), most of the studies analysed in this review, do not generally account for endogeneity bias due to the input relationship with production adverse events.

In addition, other endogeneity sources may arise with the adoption of risk management tools or risk mitigation practices. According to Vigani and Kathage (2019), there are four possible cases. First, it is necessary to account for the possibility of reverse causality between the choice of adopting risk management instruments and productivity. More productive farms, for example, are more endowed with the financial and managerial resources to act for risk mitigation. In addition, the self-selection problem needs to be addressed to avoid inconsistent estimates of the effects of the risk mitigation tools on farm results. In fact, generally, the adoption is voluntary, and a particular strategy may be adopted by farms that have more advantages in adopting, i.e., they have different unobservable characteristics that may have an impact on both the adoption decision and performance. In addition, another potential source of endogeneity may arise from the substitution effect between risk management practices and input use, since the adoption of risk-mitigating practices may change the level of input used. Finally, researchers need to account for omitted variables endogeneity by including the most adopted risk management tools. In fact, the estimates of risk mitigation practice effects may be biased due to the total impact of adopting several risk mitigation practices simultaneously might not be equivalent to the sum of the influences when considering each strategy separately. Among the articles within the risk management thematic area, the few dealing with endogeneity have mainly considered the self-selection bias. None of them have treated the endogeneity arising from the input correlation with adverse events.

The lack of studies dealing with endogeneity by using the SFA approach may be attributed to several reasons. First, the stochastic frontier literature has largely ignored the advances made in the production function framework to control for endogeneity issues (Shee and Stefanou, 2014). Moreover, dealing with endogeneity is relatively more complex in the SFA approach than in the standard regression models. In fact, due to the nature of the error term in the stochastic frontier models, which include both the technical efficiency and statistical error terms, this is a relatively more difficult task with respect to the models involving only the two-sided error term (Karakaplan and Kutlu, 2017b).

Therefore, a gap in the literature appears, regarding the identification of a comprehensive approach capable of dealing at the same time with risk and endogeneity when assessing farm productivity and technical efficiency in the SFA framework. The apparent absence of interest in literature in this field may be related to the lack of consolidated knowledge in terms of standardized methodologies. Indeed, as emerged in the current analysis, the authors applied different production frontier models by using several strategies to deal with either risk and endogeneity issues. In addition, the use of several statistical platforms leads to a situation where the routines are available in a fragmented way. For example, some software may be more appropriate to treat a specific problem, while there is a lack of software capable of providing all the estimators (Kumbhakar et al., 2020). Furthermore, despite the widespread use of SFA, only the most basic implementations are available across the broad array of statistical platforms. As such, the lack of existing routines requires researchers to be able to program these methods to develop a frontier that accounts for all aforementioned issues.

4.5. Concluding Remarks

A scoping literature review technique was used to overview the existing knowledge in farm risk analysis within the SFA framework. In particular, this chapter aimed to investigate the methods proposed in the literature to deal with endogeneity in SFA risk analysis.

The findings of this research highlight the need for more studies that investigate the productivity and efficiency of farming production while dealing with risk and endogeneity issues. Neglecting risk and endogeneity in benchmarking analyses may lead to biased estimates and thus distorted policy recommendations. It is strongly recommended to concurrently address both endogeneity and risk while investigating farm performance to make strides in achieving economic and environmental sustainability. A comprehensive approach might help to achieve more accurate estimates that could yield recommendations that ensure improved productivity and technical efficiency of farmers. However, it is possible to conclude that much still needs to be done in order to get a comprehensive approach to represent the complexity of agricultural production modelling.

The main limitation of this study is the usage of only one database for the research of the articles included in the analysis. However, this was deemed to be enough to highlight the gap in the literature. For future studies of this domain, it is suggested to look at grey literature since the approach proposed in this study is still in development. Finally, expert researchers are strongly encouraged to provide more information to ensure the replicability of their analytical procedures, for example, providing their own programming codes and guidelines for practitioners and policy analysts.

To the aim of the present work, it emerged the need to deal with endogeneity when considering risk in the analysis of agricultural production, especially when considering the risk management tools in this framework. Dealing with endogeneity would lead to estimating consistent parameters, therefore, avoiding to provide misleading interpretations of the crop insurance effect on productivity and efficiency.

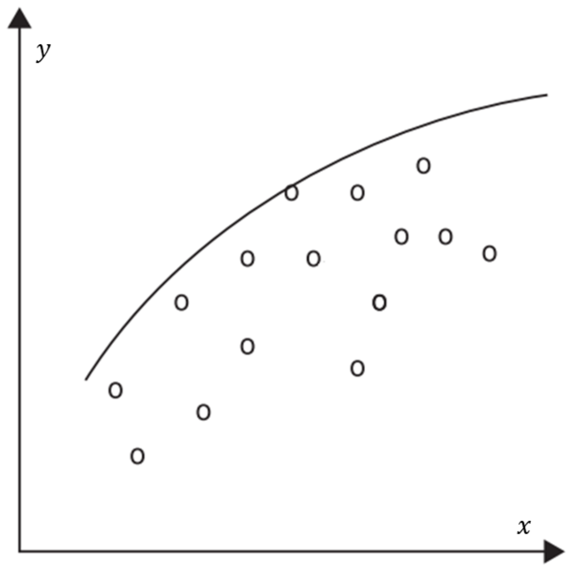
Therefore, the following chapters present a methodology to measure the presence of endogeneity while accounting for the effect of crop insurance on productivity, efficiency, and input use to enrich the knowledge in the literature.

5. Methodology, Data and Model Specification

5.1. Production Frontier Methodology

Since Farrell (1957) formed the basis for efficiency analysis, it has been used widely to examine how production inputs are combined to produce outputs. Through the stochastic frontier models, efficiency analysis can include a parametric estimate of the production function, as separately proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). These models include a stochastic and a deterministic part. The stochastic part is made of a two-sided error term and a one-sided inefficiency error term, the latter of which determines the distance from the stochastic frontier. The deterministic part that identifies the production frontier (i.e., the maximum output achievable given the available technology and input levels). Therefore, the production frontier in microeconomic theory shows the maximum output quantity for each particular set of input quantities. As a result, theoretically, no observation could be above the production frontier, and any point below the production frontier would indicate technical inefficiency, as shown in Figure 17 (Bogetoft and Otto, 2010; Henningsen, 2020).

Figure 17. Production frontier



Source: Bogetoft and Otto (2010)

Starting from the original model, 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 has been specified as:

$$\ln\, y_{it} = \beta_o + \sum_k \beta_k \ln x_{kit} + \, v_{it} - \, u_{it} \tag{4}$$

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, and u_{it} is a one-side error term capturing the inefficiency effects.

In turn, technical inefficiency can be assumed to be a function of a set of s explanatory variables (z_{sit}), a vector of coefficients to be estimated (δ), and a random variable (ω) as in the following equation:

$$\sigma^2_{uit} = \delta_o + \sum_s \delta_s \ln z_{sit} + \, \omega_{it} \tag{5}$$

5.2. Econometric Strategy to Deal with Endogeneity Sources

As highlighted in the previous chapter, when analysing the impact of insurance adoption on production and efficiency, it is necessary to account for the potential endogeneity of insurance 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 within the estimates of the production frontier.

Potential endogeneity may arise due to reverse causality between the adoption of risk management and productivity (Ramaswami, 1993). For instance, the larger 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 thus might be adopted by farms that find it most useful[2]. It means that insured farmers are self-selected, i.e., they have common unobservable characteristics influencing both the performance and adoption choice. It will lead to inconsistent estimates of the impact of insurance on farm production (Di Falco and Veronesi, 2013).

The general maximum likelihood-based approach proposed by Karakaplan and Kutlu (2017a) has been followed to deal with endogeneity issues. The authors, starting from the model provided by

[2] According to the expected utility theory, a farmer will choose to adopt insurance if the expected utility from buying is greater than the expected utility of not buying.

Battese and Coelli (1995), as in equations 1 and 2, 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 done in two stages, authors estimated the parameters using a single maximum likelihood function, gaining statistical efficiency.
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), consistently to what has already theoretically introduced in Chapter 2 (see sections 3.5 and 3.6). A translog functional form has been implemented to capture the substitution effect between inputs.
Finally, to avoid the potential endogeneity due to omitted variables, other risk management tools have been included in the model specification, to take into account of the fact that farmers adopt several risk management strategies aimed at risk mitigation, and the global effect may not necessarily be equal to the impact of adopting each adaptation strategy separately (Wu and Babcock, 1998).

5.3. Dataset

The data used in this thesis study have been extracted from the Italian Farm Accountancy Data Network (FADN - RICA). It is an s an annual sample survey established by the European Commission in 1965, with the European Economic Community (ECC) Regulation 79/56 and updated with the European Community (EC) Reg. 1217/2009 and subsequent amendments. The data collection has been carried out in Italy since 1968, with a similar approach in all Member States of the European Union, and represents the only harmonized source of microeconomic data on the evolution of incomes and the economic-structural dynamics of farms at the European level. The RICA survey does not represent the entire universe of farms surveyed in a given territory, but only those that, given their economic dimension, can be considered professional and market-oriented. In particular, it provides high-quality and consistent data of commercial farms, i.e., farms with an economical size, in terms of *standard output*[3], exceeding 8000€ in the case of Italy. Moreover, it provides representative data along three dimensions: the region, economic size, and type of farming. Currently, the Italian FADN is based on a balanced sample of about 11000 farms, representing 95% of the utilized agricultural area, 97% of the standard production value, 92% of the work units, and 91% of the livestock units.

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

The primary task of the FADN is to satisfy the information needs of the European Union for the definition and evaluation of the Community Agricultural Policy (CAP). The FADN is used to drive the public expenditures to the agricultural sector co-financed by the European Union. The information collected with the FADN also makes it possible to respond to the needs of research and business consultancy services through, by porviding a series of variables and indices on farms' technical, economic, patrimonial, and income characteristics.

For each farm in the sample, information concerning about 2500 variables is collected for the Italian FADN. The variables refer to physical, structural, economic, financial, and asset data. The information framework of the Italian FADN, which is much broader than the institutional needs of the European Commission, makes it possible to carry out analyses on various issues, including the productivity of farms, the production costs, the environmental sustainability, and the role of the family of agricultural producers.

Specifically, farm-level data for farms located in Italy and observed from 2008 to 2017 are used in this study. The dataset is an unbalanced panel since the farms observed in the sample have rotated over the years.

5.4. Model Specification

The translog production frontier has been specified as follows:

$$\begin{aligned}\ln y_{it} = \beta_0^* &+ \sum_k \beta_k \ln x_{kit} + \frac{1}{2}\sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \beta_{ins} \ln ins_{it} + \frac{1}{2}\beta_{ins^2} \ln ins_{it}^2 \\ &+ \sum_k \beta_{kins} \ln x_{kit} \ln ins_{it} + \beta_{irr} irr_{it} + \beta_{dn} d_{nit} + \beta_{da} d_{ait} + \beta_t t \\ &+ \frac{1}{2}\beta_{tt} t^2 + \sum_k \beta_{kt} \ln x_{kit}\, t + \beta_{tins} \ln ins_{it} t + v_{it} - u_{it}\end{aligned} \quad (6)$$

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. Due to the translog functional form, input square and interactions are included in the model too. In addition, the effect of the insurance level (ins_{it}), its quadratic, and the interactions with other inputs are included. The remainder of the risk management strategies, i.e., the percentage of irrigated land (irr_{it}) and the two dummies variables referred to non-agricultural (d_{nit}) and agricultural diversification (d_{ait}), are also included. Finally, a time trend (t) is 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:

$$\sigma_{uit}^2 = \delta_0^* + \delta_{ins} \ln ins_{it} + \delta_{irr} irr_{it} + \delta_{dn} d_{nit} + \delta_{da} d_{ait} + \delta_t t + \omega_{it} \tag{7}$$

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 the 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 the inefficiency effect is estimated, a negative sign indicates that insurance increases efficiency and vice versa.

Finally, following the methods proposed by Karakaplan and Kutlu (2017a), it is necessary to identify proper instrumental variables to deal with the potential endogeneity issues of insurance adoption. Valid instruments need to be correlated with the endogenous variables, the 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 market for crop insurance at the provincial level. Hence, the insurance premium paid by each farmer affects productivity and efficiency. On the contrary, the average insurance premium at the province 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 provincial level has been used to instrument insurance in the frontier and the efficiency equations.

As proposed by Karakaplan and Kutlu (2017a, 2017b) and well documented by Karakaplan (2017), another equation is estimated simultaneously considering crop insurance as endogenous variable. The equation is specified as follows:

$$\ln ins_{it} = \alpha_0^* + \alpha_1 \frac{p}{UAA_{it}} + \sum_k \alpha_k \ln x_{kit} + \alpha_{irr} irr_{it} + \alpha_{dn} d_{nit} + \alpha_{da} d_{ait} + \alpha_t t + \varepsilon_{it} \tag{8}$$

where the endogenous variable insurance (ins_{it}) is expressed as a function of the instrumental variable ($\frac{p}{UAA_{it}}$), inputs comprised in the production frontier (x_{kit}), other risk-management tools such as irrigation (irr_{it}), non-agricultural (d_{nit}) and agricultural diversification (d_{ait}), and time trend (t).

As in the previous equations, the effect of control variables is in the constant term (α_0^*). Therefore, to control for the endogeneity of crop insurance, the insurance demand has been estimated creating a system equation which allows to obtain unbiased estimates of the parameters.

Karakaplan and Kutlu (2017a, 2017b) also proposed a test similar to the Durbin-Wu-Hausman test to check the presence of endogeneity. This test looks at the joint significance of the bias correction terms. One would come to the conclusion that endogeneity correction is not required, and the variables can be estimated by using conventional frontier models if the bias correction terms components are not jointly significant.

6. An Empirical Application to the Italian Grape Production

6.1. Introduction

The case study of this thesis explores the effect of crop insurance expenditure on the production and technical efficiency of a nationally representative sample of Italian grape growers. More specifically, this work aims to clarify whether insurance adoption might solve the suboptimal input use due to the occurrence of the uncertainty of the risk-averse grape growers. Certainly, there is no simple answer to this question. On the one hand, crop insurance should facilitate optimal resource allocation by encouraging risk-averse farmers to become risk-neutral (Nelson and Loehman 1987; Ramaswami 1993), allowing farmers to maximize profit, raise production levels, and specialize their production (Ahsan et al. 1982), ultimately improving their technical efficiency (Roll 2019). On the other hand, moral hazard may induce farmers to take fewer precautions against harm as an effect of the adoption of insurance (Horowitz and Lichtenberg 1993; Quiggin et al. 1993). Therefore, the moral hazard could lower production and technical efficiency while also increasing the exposure of the company to risk. From a methodological point of view, using data from the FADN, a panel stochastic frontier estimation approach is implemented on a sample of Italian commercial farms specialised in producing quality grapevines[4] over the period 2008-2017. Assessing risk consequences on farming is especially important when farms specialize in producing perennial crops, where changing production patterns are severely constrained by high costs and lengthy implementation time (Zinnanti et al., 2019). Finally, different from previous studies, the potential endogeneity of insurance has been taken into account in order to provide more reliable parameter estimates (Karakaplan and Kutlu 2017a).

The analysis has been focused on grape growers since crop insurance has been widely adopted in this sector in Italy. More specifically, grapes represent around 27% of the Italian crop insurance market in terms of monetary values and 14% in terms of insured 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. It may cause changes to the grape chemistry, also augmenting the exposition to insects and insect-borne diseases (Mozell and Thachn 2014). Furthermore, the increase in the frequency of extreme weather events such as rainfall, late frost, or hailstorms (IPCC 2013) has potentially raised the detrimental effects on yields and grapes quality and increased income variability (Holland and Smit 2010).

[4] For the rest of the work, "quality grapevines" are defined as those certified by the EU quality certification scheme.

6.2. Descriptive Statistics of the Grape Growers FADN Sample

This study uses farm-level data to analyse grape producers in Italy observed from 2008 to 2017. Before estimating the production frontier, the observations that contain a null or negative value in the explanatory variables were eliminated, since these values cannot be used with a log-log model. After the data cleaning process, 9419 observations of 2587 farms specialized in grape growing were analysed. Since the surveyed farms of the sample have rotated over time, the dataset is an unbalanced panel. The descriptive statistics of the variables included in the model are reported in Table 3.

Table 3. Descriptive Statistics

Variable and Abbreviation		Description	Mean	Std. Dev
		Output and Inputs		
y	Production	Total Gross Production (€)	57338	136247
x_1	Land	Utilized Agricultural Area (ha)	8.92	17.30
x_2	Capital	Amount of Capital (€)	472696	1446921
x_3	Intermediate Inputs	Intermediate Inputs Costs (€)	11908	37635
x_4	Labour	Total number of hours worked per year (h)	2418	4511
		Risk Management Strategies		
ins	Insurance	Expenditure on crop insurance (€)	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	One for services diversification, zero otherwise	0.11	0.32
d_a	Agricultural Diversification	One for crop or livestock diversification, zero otherwise	0.74	0.44
		Control Variables		
es_1	Economic Size [1] [b. c.]*	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] [b. c.]*	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] [b. c.]*	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

Source: Own elaboration based on FADN data
*** Note:** [b. c.] stay for the base category

Production refers to the total gross production of the grape, measured in euros. The monetary value of the output produced is used considering that grape growing in Italy evolved significantly towards higher quality production (Urso et al., 2018). The variable *Land* is measured in hectares and refers to the Utilized Agricultural Area (UAA). *Capital* is an aggregate, measured in euro, formed by working capital and real estate, subtracted by the farmland value to avoid the problem of multicollinearity with the variable *Land*. *Intermediate inputs*, measured in euros, refer to expenditures on water, crop certification, fertilizers, pesticide, services, energy (fuel, electricity, and heating), marketing (materials, transport, and intermediation), and other generic expenses. *Labour*[5] refers to the total number of hours worked per year in grape farming.

The expenditures on *crop insurance* were used to investigate the relationship between insurance, production, and efficiency. 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), the intensity of insurance (measured by the amount of insurance premiums paid) was used 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, the value one has been added for not insured farms to obtain the logarithm and not to incur biased results, as indicated 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 1 when the input, insurance, in this case, is not used. If the coefficient of such a dummy is statistically significant, then the intercepts of insured and not insured farms are not equal, and the absence of the dummy variable will provide biased results. In addition, to mitigate the possible omitted variables bias, a set of variables referred to as other risk management tools alternative to insurance has been included, namely irrigation and on-farm agricultural and non-agricultural diversification. *Irrigation* is the percentage of irrigated over the total land. *Non-agricultural diversification* is a dummy variable taking a value one when the farm produces non-agricultural services (e.g., agritourism, educational, etc.) in addition to farming. *Agricultural diversification* is a dummy variable taking the value one when the farm is involved in other crops or livestock in addition to grape, and the value zero otherwise. Accounting for the 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 impact of adopting each adaptation strategy separately (Wu and Babcock, 1998).

In addition, other variables were included to control for additional sources of heterogeneity due to the environmental and economic characteristics of the farm. As for the farm's *location*, there are three dummy variables referred to as *altimetry* (plain, hill, and mountain) and four dummies variables for farms placed in the Southern, Central, North-eastern, and North-western *regions*. *Economic size* is

[5] Missing values were around 27% of observed values. When the information on farm labour was available for at least one year, it was 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 in grape were missing in all years for one farm, it was replaced with an approximation based on year and location (province, region, and altimetry) mean.

defined based on standard output and is divided into five classes: small (less than 25000 euros), medium-small (25000-50000 euros), medium (50000-100000 euros), medium-large (100000-500000 euros), and large farms (over than 500000 euros).

Finally, Table 4 shows the mean and standard deviation values of all variables included in the model separating insured and uninsured farms. As it is possible to find out from the Table, insured farms have a higher production and input use than uninsured farms. They also have a higher percentage of irrigated land. There is no difference in both diversification means. Insurance adoption increase with the growth of economic size and altimetry. Finally, most insured farms are located in the north-eastern regions, while insurance is less diffused in the south.

Table 4. Descriptive Statistics (Insured vs Uninsured Farms)

Variable	No Insurance		Insurance	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**
Output and Inputs				
Production	50024	130627	83761	151990
Land	8.07	16.03	11.98	20.99
Capital	410406	1116236	697727	2256782
Intermediate Inputs	10439	33155	17215	47099
Labour	2146	3462	3399	7025
Risk Management Strategies				
Insurance	0	0	4110	10489
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
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

Source: Own elaboration based on FADN data

6.3. Results

The endogeneity test indicates that insurance is endogenous, and correction is needed (X^2 = 21.25; p < 0.0001). Therefore, the IV panel approach has been implemented as proposed by Karakaplan and Kutlu (2017a). First, the instrument's strength needs to be assessed. 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, the possibility of the inclusion of the dummy variable was checked, which allows for different intercepts for insured and uninsured farms and avoids biased results as proposed by Battese (1997). The z statistic of the coefficient estimated for the dummy is -0.47 (p = 0.635). It indicates that the intercepts of insured and not insured 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 5, while output elasticities with respect to inputs are calculated and reported in Table 6. Estimated output elasticities are statistically significant and positive for all production inputs. The estimated elasticity of the time trend shows that there is a positive and significant technological change during the period under analysis.

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:

$$\epsilon_{ins} = \frac{\partial\, ln\, y_{it}}{\partial\, ln\, ins_{it}} = \beta_{ins} + \beta_{ins^2}\, ln\, ins_{it} + \sum_k \beta_{kins}\, ln\, x_{kit} + \beta_{tins} t \qquad (7)$$

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

The other interest of the present work is to investigate whether insurance affects the use of inputs. More in detail, the intention is to analyse the substitutability between insurance and other inputs, i.e., the ability to substitute insurance for another input without affecting the output level. 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:

$$\frac{\partial \epsilon_{ins}}{\partial\, ln\, x_{kit}} = \beta_{kins} \qquad (8)$$

where k are the inputs land, capital, intermediate inputs, and labour. A negative elasticity indicates a substitute relationship, while a positive elasticity indicates a complementary one. It has been found 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 weak substitute for intermediate inputs. It 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 to capital and intermediate inputs, while capital is a substitute for intermediate inputs. Finally, land and capital usage decreased over time, while the application of intermediate inputs increased. The parameter β_{tins} measures the effect of insurance on technological change. As seen in Table 5, it is found to be positive but not statistically significant, indicating that insurance expenditures have not affected the technological changes. As for 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, following 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 growth of altimetry, and farms located in the South produce more than farms located in the Centre and less than farms located in the North.

Table 5. Production Frontier Estimates

Variable	Parameter	Est.	Std. Err.	z	P > |z|
		Inputs and trend			
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_{1^2}	-0.0560	0.0238	-2.35	0.019
Capital^2	β_{2^2}	-0.0018	0.0087	-0.20	0.838
Int. Inputs^2	β_{3^2}	0.0124	0.0084	1.47	0.140
Labour^2	β_{4^2}	0.0031	0.0057	0.54	0.586
Trend^2	β_{t^2}	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	$\boldsymbol{\beta_{ins}}$	**0.0640**	**0.0260**	**2.46**	**0.014**

Insurance^2	$\boldsymbol{\beta_{ins^2}}$	**0.0076**	**0.0019**	**3.92**	**0.000**
Land * Insurance	$\boldsymbol{\beta_{1ins}}$	**-0.0018**	**0.0034**	**-0.53**	**0.594**
Capital * Insurance	$\boldsymbol{\beta_{2ins}}$	**-0.0006**	**0.0020**	**-0.33**	**0.745**
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

Source: Own elaboration based on FADN data

Note: In bold are shown the coefficients related to insurance expenditure

Table 6. Output Elasticity

Variable	Est.	Std. Err.	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

Source: Own elaboration based on FADN data

The results of the efficiency function are presented in Table 7. Since the inefficiency function is estimated, a negative parameter indicates that the variables have a boosting effect on technical efficiency. Like Roll (2019), the above estimates show that insurance has an enhancing impact on efficiency. Irrigation has a statistically significant and positive effect on efficiency. It 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 in enhancing efficiency. Agricultural and non-agricultural diversifications do not have 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 that reduced 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. The coefficients of the other size classes are not statistically significant. This result can be due to the fact that there is a high presence of small and highly specialized farms in the market (Kim et al., 2012). Farms operating in Southern areas of Italy were found to be more efficient than the farms located in Northern areas likewise to what was previously assessed by Urso et al. (2018). Finally, farms located in hilly are less efficient in comparison with those placed in plain areas. There is no statistical difference between the mountain compared to the lowland areas.

Table 7. Inefficiency Estimates

Variable	Parameter	Est.	Std. Err.	z	P > |z|
Insurance	$\boldsymbol{\delta_{ins}}$	**-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

Source: Own elaboration based on FADN data

Note: In bold is shown the coefficient related to insurance expenditure

6.4. Discussion

This section aims to clarify the effect of crop insurance expenditure on the production, technical efficiency, and input use of commercial grape-growing farms in Italy. Crop insurance might be a relevant 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 results from an economic point of view (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. This study intends to add to this stream of empirical literature. The focus is on the Italian grape growers' sector because it is the cultivation with the highest participation in the crop insurance program in Italy (ISMEA, 2018). Using FADN data, the effect of crop insurance on input use, production, and efficiency was estimated using the endogenous panel stochastic frontier model proposed by Karakaplan and Kutlu (2017a).

Similar to Roll (2019), the results of this thesis show that insurance has a boosting effect on both production and technical efficiency. As for the insurance effect on input use, the findings show that insurance does not have a statistically significant impact on labour, land, and capital while having a statistically 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, just like the quantity of land is fixed in the short-medium term in the case of perennial crops such as grapevines. The insurance impacts 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 significant negative impact of insurance on intermediate inputs indicates that insurance is a substitute for intermediate goods. In the sample of grape growers analysed in this study, most of the expenses in intermediate inputs are tied to the purchase of crop protection chemicals. Hence, the expenditure to purchase intermediate inputs is primarily dominated by crop protection chemicals (i.e., fungicides, pesticides, and herbicides). The results of the present work contribute to the growing literature on the intensive margin relations between 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 the findings of Enjolras and Aubert (2020) in France, in the case of Italian grape production, insurance decreases the intermediate input use while increasing output. The results of this thesis differ from those 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 (positive effect of insurance on pesticides use). It highlights that insurance and pesticide policies need to account not only for the heterogeneity of pesticide typologies, as shown by Möhring et al. (2020a) but also for the heterogeneity due to the specific condition in which each sector operates (Goodwin et al., 2004). Hence, it is not conceivable to provide a policy indication based on the inspection of what happens in a single farming sector (Möhring et al., 2020b).

The causes of the changes found in input use and supply, as explained in paragraph 3.6, can be the risk reduction and moral hazard effects induced by insurance. As for the risk reduction effect, as described in earlier work by Ramaswami (1992), 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. Indeed, crop insurance is often affected by the 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 impact 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 sunk costs related to high investments in land and capital equipment. Considering 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 influence 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 a relevant 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 taken before the beginning of the season, to avoid an opportunistic farmer that adopts insurance after observing the 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. In fact, grape production is characterised by the highest pesticide use per hectare (Aka et al., 2018), mainly fungicides (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 equally in the EU and Italy (ISMEA, 2018). The decline in the use of defence chemicals induced by insurance can help to diminish both 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, due to the increase in insects and insect-borne diseases, the overuse of pesticides might be reasonable. 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 arising from uncertain outcomes. Additionally, insurance may provide farmers 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, thus 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, the findings of this work 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 the model applied in this thesis. Second, the significance of the substitution effect between insurance and intermediate input use shows that the taking up of the translog specification is also necessary. Lastly, the statistical significance of the coefficients of the variables referred to as the risk management tools alternative to insurance underlines the importance of including them to avoid omitted variables bias.

6.5. Conclusions

This chapter analysed how insurance affects the production decisions of commercial grape-growing farmers in Italy by estimating a panel instrumental variable stochastic frontier that accounts for the endogeneity arising from the adoption of crop insurance. More specifically, this study aimed to investigate the relationship of crop insurance with production, technical efficiency, and input use in Italian quality grape-growers farming. Similar to Roll (2019), the findings of the analysis show that insurance has a positive effect on production and efficiency, while reducing the use of intermediate inputs. These results are absolutely consistent with the neoclassic theory and indicate that insurance can play an essential role in scaling down the suboptimal input use arising from the existence of risk in agricultural production. The positive effect of insurance adoption in 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 viewed as a re-optimisation of input use rather than the moral hazard effect. Furthermore, the input use optimisation due to insurance adoption may explain the gain in efficiency. Finally, the results of this work show that controlling for endogeneity in the causal relationship between insurance and production is needed to avoid biased parameter estimates.

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

Another relevant limitation of this study is due to the fact that there is no distinction between the crop insurance schemes adopted by the farmers in FADN data. In fact, the only data available in the dataset are the expenditures on crop insurance without a differentiation regarding the insurance schemes. Therefore, future studies may try to distinguish among the schemes using other data sources to provide well-suited policy indications.

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 for the investigation of the effect of insurance on the use of production input with alternative attributes.

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

These findings have several policy implications. First, these results differ from those previously found in different crops and countries. It 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 allowed to give a policy indication based on what happens in a single crop. 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 while at the same time preventing pest resistance.

7. General Discussion and Conclusions

Despite recent growth in the scientific literature on crop insurance in agricultural economics, only a few studies have concentrated on the effects of crop insurance expenditure on farm outcomes. In particular, the impacts of insurance on productivity (Vigani and Kathage, 2019) and technical efficiency have received scant consideration (Roll, 2019). Analysing the effect of insurance on farm performances and input use is essential for policymakers to enhance producers' economic and environmental sustainability (Farrell, 1957). It is even more relevant due to the increasing investment in the crop insurance policy in European countries. Therefore, this thesis investigates how crop insurance affects the production and technical efficiency of farming and whether insurance changes the utilized input quantities.

For this purpose, Chapter 2 of this work introduces the Italian crop insurance market and the relative legislation. Later, the theoretical literature has been analysed as concerns the estimation of the production frontier. In particular, chapter 3 studies the input use decision under the so-called theory of uncertainty of outcomes, which constitutes the environment that farmers face during their activity (Moschini and Hennessy, 2001; Komarek et al., 2020). Moreover, this chapter investigates the relationship of risk-aversion with the usage of input, which causes a more conservative input use and thus lower results (Nelson and Loehman, 1987; Ramaswami, 1992). Finally, the effect of insurance on production decision-making and farm performance has been reviewed. From a theoretical point of view, crop insurance might be an effective strategy for improving farm performances by lowering the usage of inefficient inputs, therefore impacting economic and environmental farm achievement (Roll, 2019). Contrarily, the adoption of insurance may result in farming practices that are inefficient and driven by moral hazard, which has unfavourable effects (Quiggin et al., 1993). It remains an empirical question how the input utilization and output are affected overall by moral hazard and risk reduction (Ramaswami, 1993). Therefore, a stochastic frontier analysis has been conducted to measure these effects.

In order to develop a proper stochastic frontier model, in chapter 4, a Scoping Review has been conducted to investigate the methods to account for risk and risk-management tools in this framework. The main driving force behind the current study is the realization that, in contrast to its relevance in the agricultural sector, the majority of the scientific literature on farm-level production does not take risk into consideration when implementing a stochastic frontier (Just, 2003). Given that risk effects on technical efficiency are unavoidable, the stochastic production frontier must include risk sources in order to accurately account for and predict the farmers' technical efficiency (Battese et al., 1997). Moreover, the recent literature on the stochastic frontier analysis highlights the requirement to deal with endogeneity issues to estimate unbiased parameters as regards the production frontier and technical efficiency (Amsler et al., 2016; Karakaplan and Kutlu, 2017a, 2017b). Even though the literature emphasizes the importance of these problems, the review of the current work assesses the luck of the study considering risk and risk-management tools in the stochastic frontier framework in agricultural economics. In addition, when the effects of risk are included in the model, the endogeneity sources are often ignored, resulting in biased estimates of parameters. This result is quite worrying because, often, the goal of researchers is to provide policy indications in order to enhance the efficiency of the farms. A comprehensive approach that can cope with risk and endogeneity allows for achieving more precise estimates and policy recommendations by ensuring the augmentation of agricultural productivity and technical efficiency. Yet, the lack of study to address these problems may be related to the fact that this approach is currently being developed, and the model is rather sophisticated in terms of both modelling and estimate in the stochastic frontier approach than in the standard regression models (Kumbhakar et al., 2015), which drastically reduce the number of researchers that are able to deal with these problems. In fact, the best economists in this field are more concentrated on sorting out the issues in sectors different from the agricultural ones. However, agricultural economists have to push the need for the advancement of more sophisticated methodologies to account for these issues since farming production is much more complex than other productive sectors. Indeed, agricultural production studies have to take into account the biological production cycle and environmental conditions, factors that are less relevant in other sectors.

Having noted this literature gap, combined with the lack of studies aiming to investigate the impact of insurance on productivity (Vigani and Kathage, 2019) and technical efficiency (Roll, 2019), a case study has been carried out to measure the relationship between crop insurance, input use and farm performances in the grape farming, following the method proposed by Roll (2019). Additionally, compared to the just mentioned author, has been implemented a methodology to account for the endogeneity of the insurance adoption in Italian grape farming (chapter 5).

The results from the case study examined in chapter 6 demonstrate the necessity of treating insurance endogeneity in order to estimate unbiased parameters. Numerous factors make endogeneity a crucial concept to take into account. First, the endogeneity test provided by Karakaplan and Kutlu (2017b) demonstrates the existence of endogeneity in the model used in this thesis due to self-selection and reverse causality. Second, the importance of the substitution effect between insurance and the use of intermediate inputs demonstrates the necessity of adopting the translog function to avoid model misspecification. Last but not least, the statistical importance of the coefficients of the variables known as the risk management tools alternative to insurance highlights the necessity of including them to prevent omitted variables bias.

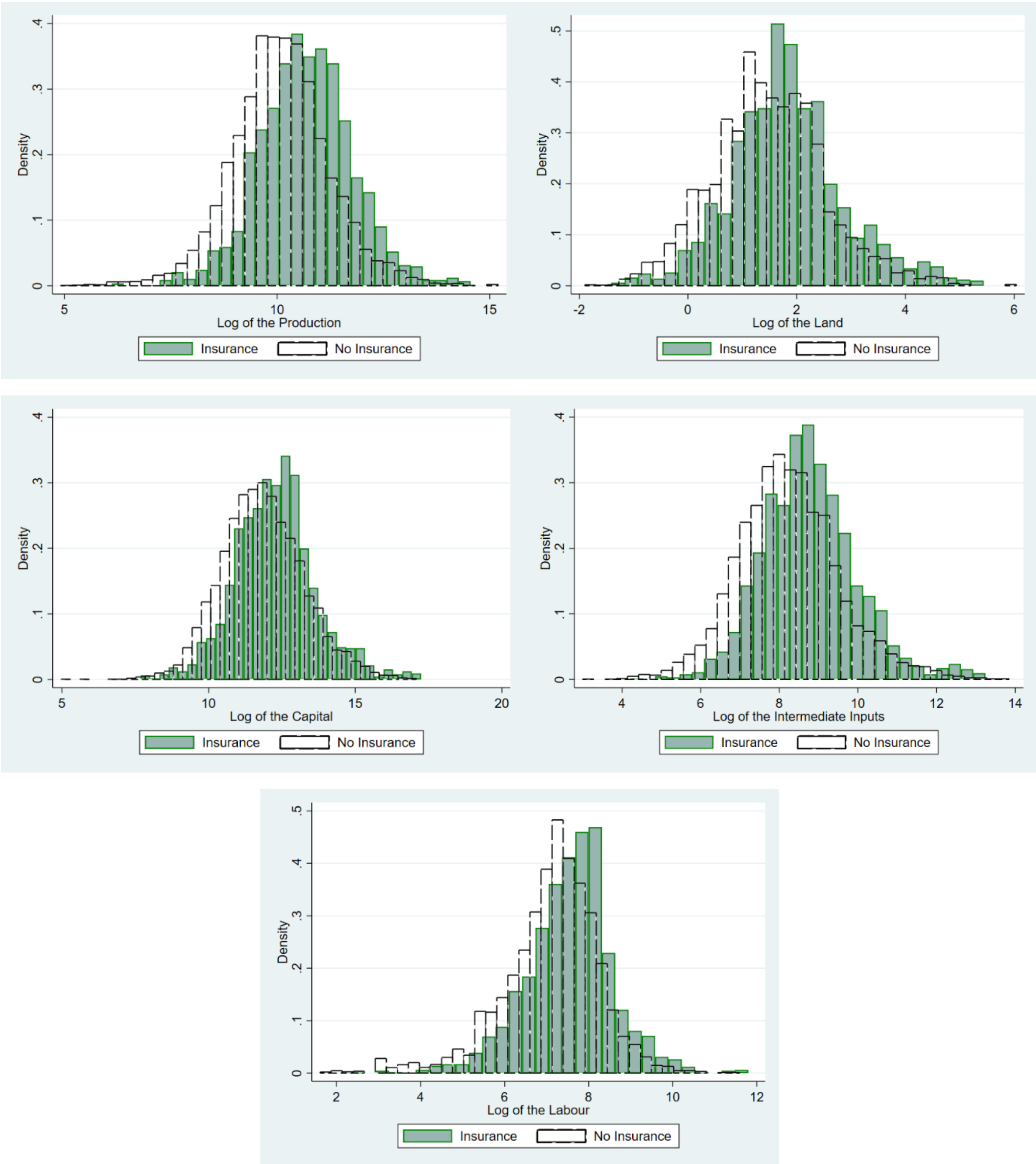
Moreover, the findings of this study indicate that insurance increases farming output and efficiency while decreasing the usage of intermediate inputs. The increase in production and technical efficiency observed in this study implies that the risk reduction impact outweighs the moral hazard effect in the Italian grape cultivation context. In other words, rather than reflecting the impact of moral hazard, the decrease in input use brought about by insurance adoption can be seen as a re-optimization of input use. This outcome is not unexpected because risk-averse farmers will optimize their utility function besides considering the variance and mean effects of input, whereas an insured farmer will only consider profit maximization when optimizing his utility function (Just and Pope, 1978, 1979). While it might make sense for an uninsured farmer to use an efficiency-reducing tool to lower production risk, the insured farmer lacks this motivation because the consequences of an incident are much less severe (Roll, 2019). In other words, insurance adoption mitigates the effects of risk-aversion on production decision-making boosting farming outcomes.

Finally, the fact that insurance has a statistically significant negative impact on intermediate inputs suggests that it can be used to replace intermediate goods. The findings of this study add to the growing body of research on the intensive margin relationships between insurance and input use by demonstrating that insurance increases output while reducing intermediate input use. As explained in section 6.4, most of the intermediate input costs in the sample of grape growers examined in this study are related to the purchases of crop protection chemicals such as fungicides, pesticides, and herbicides. The chemical use reduction caused by insurance in grapevine production in Italy bodes well for the success of the EU Commission's pesticide-reduction agenda. As a result, insurance may have the potential to be a tool for reducing the environmental and health consequences of risk-averse farmers' inefficient input allocation. In addition, these results diverge from those previously found in various crops and EU member countries. It implies that depending on the unique circumstances in which each sector operates, insurance and pesticide policies must take this heterogeneity into consideration. Therefore, it is not possible to base a policy recommendation on what occurs in a single crop.

However, this study is not free of limitations. The main limitation of the empirical application of this study regards the consideration of the intermediate input use as a unique variable. Due to this restriction, it is not possible to investigate how insurance affects the use of production inputs with various risk profiles. Further research is required to determine the relationship between insurance and particular intermediate inputs used in the grape-growing sector, given the different nature of the production inputs included in that variable in this analysis.

Appendix

Figure 18. Distribution of the mean values of the logarithm of output and input levels for insured and uninsured farmers over all the observations from 2008 to 2017.



Source: Own elaboration based on FADN data

Table 8. Insurance Demand Estimates to Correct for Endogeneity

Variable	Parameter	Est.	Std. Err.	z	P > |z|
Provincial Premium per Hectare	$\alpha_{p/UUA}$	**0.0030**	**0.0001**	**22.00**	**0.000**
Land	α_1	0.2114	0. 0867	2.44	0.015
Capital	α_2	-0. 0914	0. 0340	-2.69	0.007
Int. Inputs	α_3	0. 1704	0. 0428	3.98	0.000
Labour	α_4	0. 1775	0. 0312	5.70	0.000
Irrigation	α_{irr}	0. 5682	0. 0845	6.73	0.000
Non-Agr. Diversification	α_{dn}	-0. 2379	0. 0985	-2.41	0.016
Agr. Diversification	α_{da}	0. 3410	0. 0735	4.64	0.000
Trend	α_t	0. 0375	0. 0121	3.08	0.002
Medium-Small	α_{es2}	0. 1565	0. 1215	1.29	0.198
Medium	α_{es3}	0. 4541	0. 1507	3.01	0.003
Medium-Large	α_{es4}	0. 7951	0. 2004	3.97	0.000
Large	α_{es5}	1.3376	0. 3244	4.12	0.000
Hill	α_{alt2}	-0. 1563	0. 0855	-1.83	0.068
Mountain	α_{alt3}	0. 7761	0. 1133	6.85	0.000
Centre	α_{loc2}	0. 7584	0. 1130	6.71	0.000
Northeast	α_{loc3}	0. 3033	0. 1215	2.50	0.013
Northwest	α_{loc4}	0. 0662	0. 1126	0.59	0.557
Constant	α_0	-2.5822	0. 4044	-6.39	0.000

Source: Own elaboration based on FADN data

Note: In bold is shown the coefficient related to the instrumental variable

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