BAE
Bio-based and Applied Economics

AIEAA
ASSOCIAZIONE ITALIANA DI ECONOMIA AGRARIA E APPLICATA

OPEN ACCESS

Citation: S. Russo, L. Phali, M. Prosperi (2022). Dealing with endogeneity in risk analysis within the stochastic frontier approach in agricultural economics: a scoping review. *Bio-based and Applied Economics* 11(4): 339-350. doi: 10.36253/bae-13516

Received: August 18, 2022
Accepted: February 12, 2023
Published: May 3, 2023

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Editor: Simone Cerroni.

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Dealing with endogeneity in risk analysis within the stochastic frontier approach in agricultural economics: A scoping review

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Abstract. Literature on farm productivity and efficiency was reviewed using a scoping review methodology, focusing on studies that have included risk and risk management tools within the stochastic frontier analysis in agricultural economics. This study contributes to investigating the methods used to account for endogeneity by using a risk-accommodating stochastic frontier approach when analysing farmers' performance. Despite the increasing methodologies proposed in the literature, only a few studies have treated endogeneity in farm risk-performance evaluations. According to our findings, 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 performances. Endogeneity and risk issues need to be concurrently addressed to make strides in achieving economic and environmental sustainability. Neglecting endogeneity in these analyses may lead to biased estimates and thus inappropriate policy recommendations failing to boost the productivity and technical efficiency of farmers.

Keywords: stochastic frontier analysis, agricultural economics, risk, endogeneity.
JEL codes: C18, Q12, D81.

HIGHLIGHTS

- Scoping review of studies that account for risk in Stochastic Frontier Analysis
- We synthesise methodologies dealing with endogeneity in risk-accommodating SFA
- The lack of risk and endogeneity accommodation in analysis yields biased results
- Literature gap in SFA dealing with risk and endogeneity in agricultural economics
- Risk and endogeneity inclusion may help develop effective agricultural policies

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1. INTRODUCTION

Agriculture is one of the sectors where risk and uncertainty play a decisive role in production decision-making (Ahsan *et al.*, 1982; Moschini and Hennessy, 2001). 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 (Ramaswami, 1992; Cerroni, 2020). While exerting their typical actions, farmers do not aim only to maximize profits but also try to minimize the risk impact on income loss (Just and Pope, 1978, 1979; Antle, 1983; Finger, 2013). The conceptualization of agricultural risk 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 given the stochastic nature of agriculture. Within market risks, there are those associated with price volatility for both input and output prices, as well as those related to asymmetric information, international trade, and liberalization processes. 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 and 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 various reasons to be interested in how risk affects farmers' decision-making and their economic performances. Farm performance evaluations are fundamental for policymakers and producers to enhance 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 their production functions (Antle, 1983). Therefore, risk-averse production decisions differ from risk-neutral ones due to the marginal risk premium, which is the absolute value of the risk effect of input use on output (MacMinn and Holtmann, 1983; 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 a risk-neutral farmer, who employ the profit-maximizing input vector (Nelson and Loehman, 1987; Ramaswami, 1993). As such, the risk aversion due to the uncertainty of outcomes may result in non-profit-maximizing input use, potentially resulting in lower technical efficiency and productivity (Roll, 2019). By ignoring the risk impact on production, Battese *et al.* (1997) conclude that estimates of technical efficiency would be skewed. Consequently, neglecting the interrelation between farm performance and risk-averse deviations from efficient behaviour would lead to incorrect policy implications and recommendations (Just, 2003).

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 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 limitations of the DEA methodology is that it is not possible to consider the effect of risk on efficiency, which could be confused and interpreted as technical inefficiency. Accordingly, it seems that SFA might be more suitable to model productivity and efficiency in 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 regard 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 to realistically account for and predict producers' technical efficiency (Battese *et al.*, 1997).

The primary motivation paving the way for the present study is 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. It is the general definition of endogeneity, which refers to the correlation between explanatory variables and the error terms. However, it is essential to note that endogeneity may occur for several reasons. For instance, farmers may adjust their inputs according to observed shocks, which usually are included in the random error term. Therefore, the correlation between the production inputs and the statistical error term due to the observed shocks would result in endogeneity (Latruffe *et al.*, 2017). In addition, a 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 presence of endogeneity leads to erroneous inferences about the assessment of input elasticities and economies of scale, as well as inaccurate and inconsistent estimates of farm technical efficiency (Karakaplan and Kutlu, 2017). 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 that boost farm performance being left out (Russo *et al.*, 2022). The impact of the inaccuracy and inconsistency of results may be highly relevant when risk analysis is performed (Battese *et al.*, 1997).

Given the motivations listed above, this paper presents a review of literature that covers agricultural productivity and efficiency analysis. The particular focus is on studies that have adopted the SFA method with the inclusion of 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 article 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. It is important to highlight these two issues as when they are not considered in modelling, the biased estimates found after analysis may be used to inform policy. This then leaves room for the ineffectiveness of policy interventions as they would be developed without considerations of the complexity of the agricultural production modelling. The exclusion of the effects of risk and risk-mitigation practices on studies that aim to investigate farmers' decision-making would provide inconsistent and irrelevant production guidelines. This review depicts the gaps that researchers need to fill and methods that can be adopted to ensure valid and consistent results that can be used for policy development aimed at ensuring agricultural productivity and efficiency.

In the following section, the scoping review methodology, eligibility criteria, and selection process of articles are presented. The results section, presents and illustrates insights of the literature analysed. Finally, we discuss the results and provide some conclusions, highlighting the limitations of the study and future research areas.

2. METHODOLOGY

The scoping review method was adopted to conduct the 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 used to develop policy or practical 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 is more 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 into 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 the 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 was identified. The Scopus bibliographic database was used to research the relevant studies, including articles written in English and published in peer-reviewed journals earlier than 30 June 2021. We opted to focus on articles indexed in Scopus since it is one of the two most used bibliographic databases, and it includes most (about 99%) of the journals indexed in Web of Science (Singh *et al.*, 2021), particularly in the social sciences topics (Mongeon and Paul-Hus, 2016).

The search was characterized by a combination of three keyword groups included in the paper abstract, title, or keywords. The following structured query developed using Boolean operators and wildcards was 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 related to the risk, and the third to the agricultural context.

The final set of articles was exported to the Mendeley referencing tool for assessment. For consistency purposes, all the authors screened the initial set of articles. We screened the same publications and discussed our chosen studies for review. To be included in the sample, the eligibility criteria used the following: (i) research topic on agricultural production (ii) inclusion of risk and risk management in farm productivity and efficiency analysis; (iii) the adoption of SFA to model technical efficiency and agricultural productivity.

The selection process followed several steps which gradually reduced the number of studies according to the eligibility criteria, as shown in Figure 1. The search output initially included 162 peer-reviewed articles. In the first screening step, titles and abstracts were examined, where papers focusing on issues related to risk analysis in the agricultural sector using the SFA approach were retained. Then, the full text of the remaining 94 studies were 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 were examined to consider their insights as regarding endogeneity issues. At the end of the screening process, 44 articles were retained. Of the 162 articles, 11 were disqualified because they were not focused on agricultural economics, and 40 for 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 models (Guo *et al.*, 2019; Wang *et al.*, 2020).

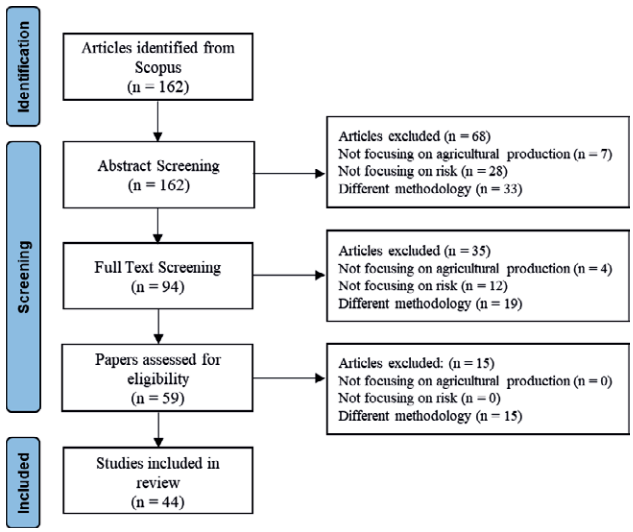

Figure 1. PRISMA-ScR Flow diagram. Source: Own elaboration based on Tricco *et al.* (2018).

3. RESULTS

The results of the analysis showed that there are several approaches adopted in estimating stochastic production frontiers with risk considerations. Figure 2 below presents a histogram of the distribution of the common approaches employed in the retained articles. The most commonly used methods were those of 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[1].

[1] Among them, there are the approaches proposed by Aigner *et al.* (1977), Antle (1983), Blarel *et al.* (1992), Caudill *et al.* (1995), Koop

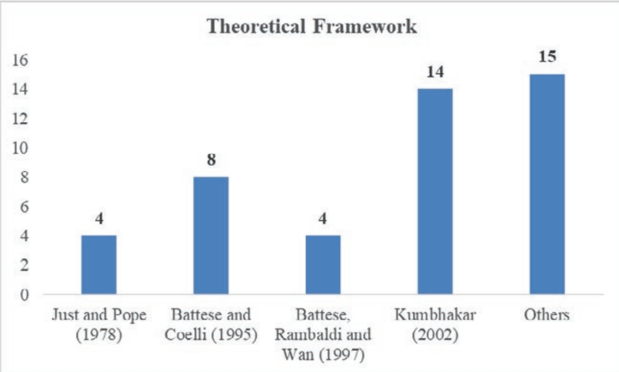

Figure 2. Theoretical and methodological framework to estimate the production frontier. Source: Own elaboration. Note: The sum is 45 because one article compared the Just and Pope and Kumbhakar models.

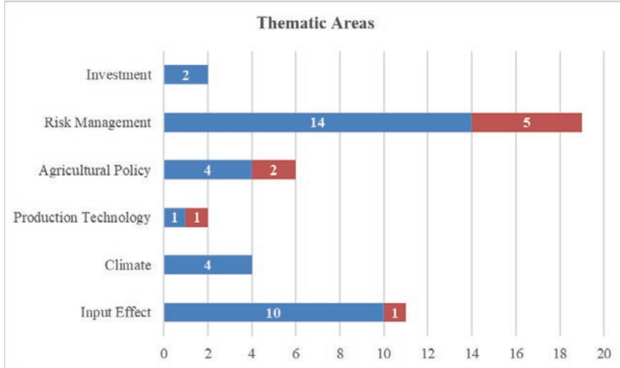

Figure 3. Literature thematic areas accounting for the articles that dealt with endogeneity issues. Source: Own elaboration.

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 were the ones proposed by Just and Pope (1978), Battese *et al.* (1997), and Kumbhakar (2002)[2].

Six different thematic groups were identified within the literature analysed, as shown in Figure 3. 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 technologies, such as intensive or extensive (Nguyen *et al.*, 2020) and organic or conventional production (Tiedemann and 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 3, the articles that dealt with endogeneity and those that did not are differentiated with colour schemes. The colour red represents the articles that dealt with endogeneity. As a result, only nine studies out of 44 (about 20%) 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 one on input effects.

The different methods implemented to account for endogeneity are presented in Table 1. 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, and 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 adopters and non-adopters. 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 observed heterogeneity, obtaining samples of farmers homogenous in terms of socioeconomic characteristics. Then, they estimated a stochastic frontier using the model proposed by Bravo-Ureta *et al.* (2012) to correct for unobserved 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 fron-

et al. (1997), Greene (2003, 2005), Tsionas (2006), Yesuf *et al.* (2008), O'Donnell *et al.* (2010), Power *et al.* (2011), Bravo-Ureta *et al.* (2012), Karagiannis and Tzouvelekas (2012), Kumbhakar *et al.* (2014), and O'Donnell (2016).

[2] 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.

tier following the approach proposed by Karagiannis and Tzouvelekas (2012). The authors addressed the potential selection bias as 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 production shocks 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 conditions. 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 shocks.

In addition to results related to SFA, some other articles which emerged from the search string accounted for 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 of 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

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)	Bravo-Ureta *et al.* (2012)	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 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.

maize varieties on farm productivity, yield variance, and downside risk exposure in Zambian maize-growing farms. The research proposed by Wang *et al.* (2018) studied 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 endogeneity related to the change in the usage of productive inputs under different states of nature according to the productivity shocks. Moreover, they proposed a two-stage instrumental variables approach to correct the endogeneity bias due to self-selection.

4. DISCUSSION

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. The vast majority of the articles using SFA in agricultural production did not consider risk despite its relevance in the field. For example, by omitting the keywords related to risk from the search query, the number of articles increases from 162 to 2595. Given that risk effects on productivity and technical efficiency are unavoidable, the stochastic production frontier must include risk sources to accurately account for and predict the technical efficiency of producers (Battese *et al.*, 1997). However, it was alarming to discover that relatively few articles account for risk by implementing a SFA approach. This may be attributed to the fact that this approach is still in development and the model is rather complex, regarding both the modelling and estimating procedure (Kumbhakar *et al.*, 2015).

It is worth noting that when the effects of risk are included in the model, the endogeneity sources are often ignored, resulting in biased estimates of parameters. Therefore, studies considering risk in the SFA approach seem to fail to represent the complexities of agricultural production modelling, such as accounting for endogeneity issues. Despite the methods of dealing with the endogeneity issues in production frontiers being 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 shocks. In addition, other endogeneity sources may arise with the taking up 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 (Nelson and Loehman, 1987; Ramaswami, 1993). More productive farms, for example, are more likely to have the financial and managerial resources for risk mitigation (Enjolras *et al.*, 2012; Santeramo *et al.*, 2016). In addition, the self-selection problem needs to be addressed to avoid inconsistent estimates of risk mitigation tools on farm results. It is because, 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 such as risk aversion or perceived barriers to adopting risk management tools (Coletta et al., 2018; Di Falco and Veronesi, 2013; Giampietri et al., 2020). 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 (Ramaswami, 1992; Russo *et al.*, 2022). 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 because 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 (Wu and Babcock, 1998). However, among the articles within the risk management thematic area, the few that dealt with endogeneity mainly considered the self-selection bias. None of these treated the endogeneity due to the input correlation with production shocks.

The lack of studies that deal with endogeneity by using the SFA approach in agricultural economics may be explained as follows. 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 (Karakaplan and Kutlu, 2017), which drastically reduces the number of researchers that are able to deal with these problems. Agricultural economists have to push 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.

Our findings show a gap in the literature in identifying a comprehensive approach capable of dealing with either risk and endogeneity concurrently when assessing farm productivity and technical efficiency in the SFA framework. This apparent deficiency in literature in the field may be related to the lack of consolidated knowledge in terms of standardized methodologies. As emerged in the current analysis, the authors applied different production frontier models by using several strategies to deal with both risk and endogeneity issues. The use of several statistical platforms leads to a situation where the routines are available in a fragmented way. For example, only certain softwares may be more appropriate to treat a specific problem. There is not yet a software where all the estimators are available (Kumbhakar *et al.*, 2020). Furthermore, despite its widespread use, only the most basic implementations of the SFA are available across the broad array of statistical platforms. As such, the lack of existing routines requires researchers to be able to program or code (e.g., creating new command or algorithms) to develop a frontier that accounts for all these factors.

5. CONCLUSION

With the increasing availability of data compared to the past and access to appropriate analytical methods/routines and statistical softwares, SFA may represent a useful approach to yield valuable results that can improve the effectiveness of policies in the agricultural sector. This is also imperative for the future development of well-suited policy instruments. To this end, a scoping literature review was conducted to overview the existing knowledge in farm risk analysis within the SFA framework. In particular, this article aimed to investigate the methods proposed in the literature to deal with endogeneity in SFA risk analysis.

The main limitation of this study is related to the inclusion of only peer-reviewed articles published in academic journals. However, this was deemed to be enough to highlight the gap in the literature. Therefore, for future studies of this domain, we suggest the review of grey literature as the approaches proposed in the study are still under development.

The findings of this research highlight the need for more studies that investigate the farm productivity and efficiency which also account for risk and endogeneity issues. This result is quite critical since the researchers' goal is often related to providing policy indications to enhance farm performance without focusing on the accuracy of data analysis. Neglecting risk and endogeneity in benchmarking studies may yield biased estimates and thus lead to incorrect policy recommendations. 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 plausible to conclude that much still needs to be done in order to get a comprehensive approach to represent the complexity of agricultural production modelling.

Despite the relevant implications of risk and risk management tools in agricultural decision-making and economic performances, the SFA literature which focuses on these aspects is still underrepresented. Research should be focused on measuring the impact of the different sources of risk when assessing farm productivity and technical efficiency. This can ensure that policy recommendations are based on more representative results. As such policy formulation can integrate possible mitigation strategies needed to enhance performance.

Researchers should develop more accurate and sophisticated methodologies to take into account the complexity of the agricultural production modelling. Therefore, expert researchers are strongly encouraged to provide more information to ensure the replicability of their findings, for example, providing their own programming codes and guidelines for practitioners and policy analysts.

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