Original Scientific paper
10.7251/AGRENG2101096I
UDC 634.8:551.583(83)

HOW DO ADAPTATION OPTIONS TO CLIMATE CHANGE, RISK PREFERENCES AND SOCIAL CAPITAL AFFECT TECHNICAL EFFICIENCY OF SMALL VINEYARD FARMERS IN CENTRAL CHILE?

Enrique Ernesto Alvarado IRÍAS[1], Bernhard BRÜMMER[1], Marcela IBÁÑEZ[2]

[1]Department of Agricultural Economics and Rural Development, Georg-August-University Göttingen, Germany
[2]Research Centre, Equity, Poverty and Growth, Georg-August-University Göttingen, Germany
*Corresponding author: ealvarado79@gmail.com

ABSTRACT

Climate change can be seen as a shock that decreases the value of economic activities and production functions. Therefore, this study estimates technical efficiency as an integrated approach with risk preferences and social capital for small vineyard farmers who have adapted to climate change, because empirical evidence shows the key role of adaptation, risk preferences and social capital related to technical efficiency on a one-to-one basis, but not as overarching analysis. This study took place in the O'Higgins and Maule regions of central Chile, data were collected through a field experiment and an exit survey from September to December 2016. Specifically, we conducted an artefactual field experiment to elicit risk preferences from 175 small vineyard farmers; we used the midpoint method to estimate the Cumulative Prospect Theory (CPT) parameters, which indicate vineyard farmers are risk averse, sensitive to losses, and tend to distort probabilities. Then we applied a stochastic frontier analysis on the main variety area of vineyards. Results showed that the influence of capital (0.55) and number of vines (0.32) is higher enough; whereas, labor (0.13) and intermediate inputs (0.11) are also important but relatively low. The scale elasticity is 1.11, showing a Constant Returns to Scale (CRS). On average, technical efficiency was 0.73, which means that farmers could improve their performance by 27%. Additionally, results suggest that experience and education positively influence the technical efficiency, contrary to age, gender, region and density; whereas, access to extension services and irrigation increases efficiency. Also, general trust and membership in farmer organizations increases efficiency; and, as we expected, risk aversion and probability weighting decreases efficiency. In this regard, it is necessary to design policies and strategies focused on facilitate accessibility to exchangeable inputs; in the promotion of extension services with greater action area; facilitate access to irrigation through subsidies and credits; improve trust in programs and networks; develop cooperative enterprises or local and horizontal organizations to share information and services from farmer to farmer; and also generate action plans to promote a better risk and loss behavior in order to seize technological and economic opportunities and not overestimate extreme events.

Keywords: *Technical Efficiency, Stochastic Frontier Analysis, Cumulative Prospect Theory, Risk preferences, Social Capital, Adaptation to Climate Change, and Vineyard farmers.*

INTRODUCTION

Climate change is an alteration of weather conditions over a period of time, normally more than two decades, and has a negative or positive effect on human societies or natural ecosystems. In the case of negative effects, changes in weather patterns (e.g., as a result of changes in temperature or rainfall) can stimulate an increase of pests and disease pressure, droughts or flooding, among other events that could lead to damage on infrastructure and production systems. Climate change means an immediate technological shock that decreases the value of economic activities over time (Kelly et al., 2005); and indeed, climate change can affect the deterministic and stochastic parts of a production function (Alpizar et al., 2011; Kelly et al., 2005). Thus, one process to face climate change effects is adaptation. Several studies point out that implementing relevant adaptation options increases productivity or technical efficiency of crops by reducing negative effects from climate change (Wossen et al., 2015; Roco et al., 2017; Khanal et al., 2018). Accordingly, it is necessary to integrate the effect of adaptation options into technical efficiency analysis. Also, to improve the analysis of technical efficiency in the face of climate change, it is important to include farmers´ risk preferences.

We contribute to the literature in three key aspects: 1) we apply Cumulative Prospect Theory determining risk aversion, loss aversion, and the probability weighting function to understand their effect in technical efficiency; 2) we extend the analysis of the role of social capital by including trust and social norms in addition to social network; 3) we incorporate in the analysis the effect of anticipatory and reactive adaptation options. This study was implemented in the O’Higgins and Maule regions of central Chile, home to 80% of the total grape production in the country, where around 60% of the farmers are small. We conducted an artefactual field experiment to elicit risk preferences from 175 small vineyard farmers. We used the midpoint method to estimate the risk preference parameters. We apply a stochastic frontier analysis on the main variety of grape produced in the vineyard, which allows us the opportunity of appraisal of individual farmer capacities in comparison to a frontier.

MATERIALS AND METHODS

Area of study

This research took place in the two most important regions for the cultivation of vineyards in Chile: Region VI of O´Higgins and Region VII of Maule. For instance, Region VI of O'Higgins contains 34.44% (47,382.07 ha) of the total area in Chile under grape cultivation, while Region VII of Maule contains 38.88% (53,496.51 ha).

Data

Sample data

In general, the data for this study were collected through a field experiment and an exit survey with vineyard farmers of central Chile. We selected farmers based on a database from the University of Talca, Chile. This original database was collected from November 2014 through February 2015 and consisted of 452 vineyard farmers from the Region VI of O'Higgins and Region VII of Maule and it is a cross-sectional data with socioeconomic, irrigation systems, production and social capital variables.

From this database, we randomly selected 204 small vineyard farmers from the regions mentioned above because of their importance for vineyard cultivation. Afterwards, we contacted these farmers by phone to find out their willingness to participate in the research. From these 204 vineyard farmers, 22 were excluded because they no longer cultivate vineyards, and another 7 also were excluded because we identified inconsistencies in the data. In the end, the sample size for this study was 175 small vineyard farmers distributed throughout the regions of O'Higgins and Maule in a total of 16 communities.

Stochastic frontier specification and variable selection

Small vineyard farmers from Region VI of O´Higgins and Region VII of Maule (central Chile) show different proportions of area allocated to vines, a large range of vine varieties, different technologies, management, and market orientation, which means different scales of the vineyards' production. In this regard, the stochastic frontier analysis (SFA) allows us the opportunity of appraisal of individual farmer capacities in comparison to a frontier (Meeusen and van Den Broeck 1977), where deviations from the frontier are explained by the composed error term: the statistical error term or random noise (v_i) distributed as N (0; σ^2_v), and the inefficiency error term (u_i) distributed as N^+ (0; σ^2_u) (Aigner et al., 1977), as we explained in section 2 of the theoretical framework. Nevertheless, as we used a production function based on cross sectional data where farms vary in size, among other factors, we can expect that the inefficiency error term (u_i) is heteroscedastic (Caudill and Ford 1993; Caudill et al., 1995: Wang and Schmidt 2002) and can be dependent on a group of covariates (Wang and Schmidt 2002). Basically, we considered the effect of a vector of variables on the variance of the inefficiency error term distribution, as we can see in equation (15) N^+ (0; σ^2_u) where $\sigma_u = \exp(z\delta)$, this condition is called the scaling property and explains if the models adjust to the data (Simar et al., 1994; Caudill et al., 1995: Wang and Schmidt 2002). However, not all models have this condition. For instance, authors such as Kumbhakar et al. (1991), Huang and Liu (1994), and Battese and Coelli (1995) take into account the effect of a vector of variables on the mean of the inefficiency error term distribution, in this case, $N^+(\mu; \sigma^2_u)$, where $\mu = f(z\delta)$; thus, a higher μ means a higher inefficiency.

In this research, we applied the model developed by Wang and Schmidt (2002) taking into account the scaling property, because, as we mentioned before, due to the differences in area for vines, vine varieties, technologies, management, and market orientation, we anticipated variation at the efficiency level. We were sure about this model after the procedure of estimation and analysis of technical efficiency because we identified the effects of covariates in the model. For the production frontier, we have chosen the Cobb-Douglas function form and tested it against the more flexible translog form. The likelihood Ratio Test (LRT) confirms the selection of the Cobb-Douglas form at a 1% significance level. We also performed the LRT for the selection of the input variables, to avoid omitted or overestimated variable bias.

The Cobb-Douglas production function as an empirical model has an easy interpretation and also assumes equal production elasticities, scale elasticities and unitary elasticities of substitution for firms (Coelli and Sanders, 2013; Greene, 2008), and in general, the coefficients can be interpreted as output elasticities. Fundamentally, the general model is:

$$\ln y_i = \beta_0 + \beta_1 \ln K_i + \beta_2 \ln L_i + \beta_3 \ln IM_i + \beta_4 \ln NV_i + \beta_5 PA_i + (v_i - u_i) \quad (1)$$
$$v \approx N(0, \sigma_v^2)$$
$$u \approx N^+(0, \sigma_u^2) \quad \sigma_u = \exp(z\delta)$$

Where the output (y_i) is the value of the total production of grapes in tons per main variety area, the inputs are capital stock (k_i) explained by the value of vineyards in the main variety area plus one-time investments such as irrigation and training system and labor (L_i) is the total labor days per year to apply agrochemical (fertilizer, acaricide, herbicide, insecticide, and fungicide) and carry out management activities (pruning, harvesting, disbudding, and toping). Intermediate inputs (IM_i) is defined as the total value or cost of agrochemicals (fertilizer, acaricide, herbicide, insecticide, and fungicide) and water rights, the number of vines (NV_i) per area of the main variety, and the plantation age (PA_i). In addition, we included variables that might shift the production frontier: a dummy variable for variety quality (low or high), and training system (parrón or espaldera). All these variables were selected in order to generate a constant flow of services across the farmers, and also to avoid multicollinearity. Furthermore, these variables were scaled by their mean and then we took logarithms in order to have a better convergence of the function. Then, we analyzed the determinants of technical efficiency to explain deviations from the frontier accordingly to Wang and Schmidt (2002) and the scaling function defined as: $(z_i,) = \exp(z')$:

$$\sigma(z_i, \delta) = \exp(\delta_1 + \delta_2 Ex_i + \delta_3 Ag_i + \delta_4 Ed_i + \delta_5 Ge_i + \ldots + \delta_9 Ad_i + \delta_{10} Ir_i + \delta_{11} Pp_i + \delta_{12} \ldots + \delta_{15} Md_i + \delta_{16} In_i + \delta_{17} Tr_i + \delta_{18} Pd_i + \delta_{13} Ma_i + \delta_{14} Hs_i + \ldots Nt_i + \delta_{19} Nr_i + \delta_{20} Mi + \delta_{21} Ra_i + \delta_{22} La_i + \delta_{23} Pw_i) \quad (2)$$

Where Ex_i is experience in vineyards (years), Ag_i is age of farmers (years), Ed_i is level of education (years), Ge_i is gender (male), Ti_i is distance to market (minutes), De_i is density (number of vines per ha), Ad_i is advisor, Ir_i is type of irrigation (drip or furrow), Pp_i is prevention of pests through pheromone diffusers (yes or no), Pd_i is prevention of diseases (yes or no), Ma_i is management (conservation practices), Hs_i is mitigation of frost (heating systems), Md_i is mitigation of diseases (chemical), In_i is insurance (yes or no), Tr_i is general trust (yes or no), Nt_i is network (number of farmers who adopted technologies), Nr_i is norm of reciprocity (organization of agricultural events to improve knowledge), M_i is membership in agricultural organizations (yes or no), Ra_i is risk aversion, La_i is loss aversion, and Pw_i is probability weighting (distortion or not of probabilities). Finally, we use Battese and Coelli (1988) for the estimation of technical efficiency (*TEi*) of each farmer, as it shows in Kumbhakar and Lovell (2000):

$$TE_i = E[e^{-u_i} \mid \varepsilon_i] \tag{3}$$

RESULTS AND DISCUSSION

Risk preferences parameters

From the total farmers of the sample (175), we estimate the Cumulative Prospective Theory (CPT) risk preferences parameters (σ, λ and γ) (Table 1). Our estimations are consistent with estimations in the literature (see section 2.2). For instance, $\sigma = 0.84$ which indicates risk aversion among the farmers. Regarding loss aversion, $\lambda = 2.98$, we can assume that vineyard farmers are three times more sensitive to losses than to gains. Finally, the value of probability weighting is $\gamma = 0.75$ which means that vineyard farmers tend to overestimate small probabilities.

Table 1. Risk preference parameters using the midpoint method (inequalities).

Parameter	Value	Std. Err.	$\beta_0 = 1$
Curvature of value function (Risk aversion) (σ)	0.84***	0.034	0.000
Loss Aversion (λ)	2.98***	0.286	0.000
Probability weighting ([illegible]	0.75***	0.013	0.000
Observations	175		
Clusters	0		

Source: own calculation.

Note: *p < 0.1, ** p < 0.05, *** p < 0.01.

To estimate the parameters of risk aversion, probability weighting and loss aversion for each observation (each individual farmer), we follow the midpoint method established by Tanaka et al., (2010) and applied by Liu (2013); Bocquého et al., (2014); and Ward and Singh (2015).

Functional form: parameters of the production function and determinants

As we stated before, this research took place in Region VI of O´Higgins and Region VII of Maule, central Chile. In these regions, the vineyard production is well explained by a Cobb –Douglas Stochastic Frontier production function, we choose this functional form after testing it against the translog production function. In general, we performed the Likelihood Ratio Test (LRT) to confirm our selection at a 1% significance level (p-value=0.055). This is consistent with the literature, for example, Moreira et al (2011) analyzed the technical efficiency of Chilean grape farmers in central Chile through a Cobb –Douglas production function. In our production model, capital, number of vines per main variety, labor and intermediate inputs are the most important inputs. The coefficients of this group of inputs are all significant, positive and were estimated through the Maximum Likelihood (ML) approach. Other studies in grape vine production indicate that the most influential inputs are block size (an area with one variety and a certain management), labor and machinery (Moreira et al., 2011), and also that land, labor, and agrochemicals (pesticide, herbicide and fertilizer) are the most imperative inputs (Piesse et al., 2018). To a certain extent, these results are similar, as we included the land value in capital and we used number of vines per main variety instead of area in order to avoid multicollinearity among the variables. In addition, our model includes intermediate inputs such as agrochemicals (pesticide, herbicide and fertilizer), but including water rights.

According to the literature, the influence of capital (0.55) and number of vines (0.32) is high enough, whereas, labor (0.13) and intermediate inputs (0.11) are also important but relatively low (Table 2). Finally, the sum of these exchangeable inputs or the scale elasticity is 1.11, showing a Constant Returns to Scale (CRS), we confirm this condition by the Wald-test (p=0.8507). This Constant Returns to Scale (CRS) means that output increases by the same proportional change as all inputs change. Regarding the variables that might shift the production frontier, age of vines is negative, as we expected, but not significant. Whereas, variety quality is negative and significant, which makes sense because generally, the higher the quality the less production. The training system ("parrón") is positive and significant, which means this trellising system helps to improve production.

Table 2. Estimated coefficients for the stochastic production frontier.

Parameter	**Value**	**Std. Err.**
Intercept	0.29***	0.091
Capital	0.55***	0.164
Labor	0.13**	0.073
Intermediate inputs	0.11**	0.058
Number of vines	0.32***	0.087
Age of vines	-0.004	0.002
Variety quality	-0.44***	0.104
Training system	0.50***	0.133
Observations	175	
Chi2	441.41	
P	0.0000	

Source: own calculation.

Note: *p < 0.1, ** p < 0.05, *** p < 0.01.

The mean Technical Efficiency index is 0.73 (73%) with a standard deviation of 0.17, which indicates that farms could improve their performance by 27%.

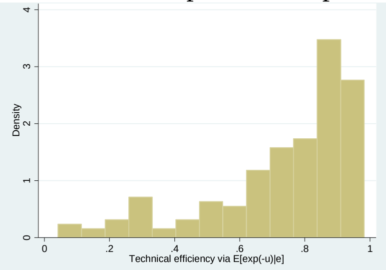

Figure 1. Technical efficiency of vineyard farmers in central Chile.

Source: own calculation.

Deviations from the frontier could be explained by socioeconomic, technological, social capital and behavioral determinants, as we can see in Table 3. As we mentioned in the theoretical framework and methodology, the inefficiency model has a half-normal distribution. In general terms, it is possible to see and understand the effect of socioeconomic variables, adaptation options, social capital forms and risk preference parameters in technical efficiency of small vineyard farmers of central Chile.

Table 3. Determinants of technical efficiency.

Variable	Coefficient	Std. Err.	Effect on TE	ME
Experience	-0.04***	0.015	+	-0.004
Age	0.04**	0.020	-	0.002
Education	-0.08	0.057	+	-0.544
Gender	1.91**	0.812	-	0.015
Time to market	0.02	0.019	-	0.004
Region	2.01***	0.752	-	0.013
Density	0.001***	0.001	-	0.002
Advisor	-1.27**	0.560	+	-0.001
Irrigation	-0.99**	0.530	+	-0.003
Prevention of pests (pheromone diffuser)	-0.06	0.662	+	0.004
Prevention of diseases	-0.98	0.808	+	0.015
Management	1.90***	0.664	-	0.016
Mitigation of frost	-0.67	0.513	+	-0.007
Mitigation of diseases	-0.10	0.468	+	0.015
Weather insurance	-0.58	0.765	+	0.005
General trust	-0.60**	0.254	+	-0.003
Network with adaptation	0.43	0.568	-	0.005

Norm of reciprocity (events)	0.34*	0.198	-	0.046
Membership	-0.90*	0.533	+	-0.002
Risk aversion	0.76**	0.454	-	0.003
Loss aversion	0.25	0.413	-	0.003
Probability weighting	2.88*	1.628	-	0.019
Observations	175			
Chi2	441.41			
P	0.0000			

Source: own calculation.
Note: *p < 0.1, ** p < 0.05, *** p < 0.01.

As we expected, experience in vineyard production has a positive effect on technical efficiency (-0.04) at a significance level of 1%, because more experience can lead to better decision making when farmers face production problems. In the case of age, this determinant decreases efficiency (0.04) and is significant at a 5% level, which is, in some cases, an expected result because we can assume that old farmers are not interested in change or improving their production system. On the contrary, young farmers could show more willingness to participate in extension services programs, adopt new technologies, improve or make changes to their systems in order to have better revenues, etc. Gender (=1 if male) also has a negative effect (1.34) on efficiency at a significance level of 5%, this could be interpreted as female farmers being generally better decision-makers. The distance to the closest market in minutes also has a negative effect on technical efficiency (0.02), this could be interpreted as: the farther from the market the less efficient, because more distance implies more logistics and costs to deliver the grapes, also those farmers that are further away from the market have less access to information and services (prices, technologies, extension services, credits, insurance, etc.). In the case of region, we identified that this variable decreases efficiency (2.01) with a significance level of 1%, which indicates that farmers from Region VII of Maule are less productive than farmers from Region VI of O´Higgins. To confirm this, we compared yields of each region. It turns out that farmers from Region VII of Maule has an average yield of 11.95 tons per ha, whereas farmers from Region VI of O´Higgins has an average yield of 15.37 tons per ha. This may be due to the proximity of Region VI of O´Higgins to the metropolitan region of the country, what means better access to markets, information and services. An interesting determinant is density (vines per ha) because this decreases efficiency (0.01) and is significant at a 1% level. Nevertheless, this could be interpreted as: the small vineyard farmers are more interested in high quality levels of grapevines which implies less vines per ha.

Regarding access to extension services, we identified that this has a positive effect on technical efficiency (-1.27) at a significance level of 5%, which could be interpreted as: the extension services from the government and ministries are well structured with enough quality to solve problems. In the case of irrigation (furrow), this increases efficiency (-0.99) and is significant at a 5% level. This could lead us to believe that farmers do not have problems with water access, of course they paid for water rights but once they have access there are no problems with the amount, this could explain why so few adopt modern irrigation. Moreover, management decreases efficiency (1.90) at a significance level of 1%. This could be due an overuse of cultural practices such as pruning, disbudding, and topping. It would be interesting to analyze the effectiveness and costs of each activity. In relation to other technologies or adaptation options that help to face the negative effects of climate change (prevention of pests, prevention of diseases, mitigation of frost, mitigation of diseases), we found that these could have a positive effect on technical efficiency but they are not significant. Regarding social capital forms, as we mentioned before, empirical studies have showed that social capital plays a key role in understanding sources of inefficiency – efficiency (Binam et al 2004; Muange (2015)). Concretely, we found that general trust makes farmers more efficient or increases efficiency (-0.60) at a significance level of 1%: maybe farmers are more willing to cooperate or engage in productive interactions, they are able to learn from others and also from extension services. In general, more trusting farmers may be more open to receive and share information and services.

In the case of the norm of reciprocity, it has a negative effect on technical efficiency (0.34), this is significant at a 10% level. This result could be explained as such: more time invested in the organization of events to share knowledge could lead to having less time to make decisions about production or to be involved in key production activities on the farm, or perhaps the effect of these agricultural events is not as expected. Membership (-0.90) increases efficiency at a significance level of 1%, this could be explained by farmers being more exposed to information, services, shared experience and having access to technologies or adaptations options. Muange (2015) reports similar findings; he analyzed the effect of social network and membership as mechanisms to access finance, information, and other benefits. Binam et al., (2004) emphasize the role of social capital on technical efficiency; basically, they analyzed the relationship between membership and inefficiency, highlighting how social capital provides incentives for efficient production. They explained that member farmers of an association can share information about technologies and production activities, and they can increase their access to extension services. All of these effects improve market access and incomes.

Regarding risk preferences, in agriculture, risk plays an essential role for production decision making (Bocquého et al., 2014). Moreover, it has an important effect on decisions concerning inputs and also outputs (Kumbhakar 2002). However, thus far, risk preferences, estimated under cumulative prospect theory (CPT), have not been included in the combined analysis of technical efficiency, social capital and adaptation. For these reasons, we included the risk averse, loss averse and probability weighting variables in order to understand their effect on efficiency. In this case, we use these parameters as dummy variables because as Liu (2013) stated, these parameters show some grade of correlation that could lead to a misinterpretation of the results. In this context, under cumulative prospect theory (CPT), farmers exhibit risk averse behavior (0.76), which is significant at a 5% level. Basically, this variable has a negative effect on technical efficiency, as risk averse farmers tend to avoid changes in technologies or practices, even more when these activities are expensive. Finally, the probability weighting variable (2.88) decreases efficiency at a significance level of 1%. This is because farmers who distort probabilities try to avoid changes in production systems.

CONCLUSIONS

This study estimates technical efficiency as an integrated approach including risk preferences and social capital for small vineyard farmers who have adapted to climate change. Empirical evidence shows the key role of adaptation options, risk preferences and social capital related to technical efficiency of productive systems on a one-to-one basis, however up to this point there has been no overarching analysis. This study focuses on Stochastic Frontier Analysis, in order to estimate technical efficiency and its determinants, which are: adaptation options to face climate shocks, risk preferences (risk aversion, loss aversion and probability weighting) and social capital forms (trust, network, and social norms). We also control for socioeconomics variables and physical characteristics of the farm. It is important to highlight that we estimate risk preference parameters under cumulative prospect theory (CPT) (curvature of the function as a measure of risk aversion, loss aversion and probability weighting) because to date, the majority of literature regarding the analysis of risk and technical efficiency has been based on expected utility theory (EUT), which cannot capture how farmers make decisions based on the possibility of gains or losses and how farmers distort probabilities. We used a Cobb – Douglas production function with a sample of 175 small vineyard farmers. Results showed that the influence of capital (0.55) and number of vines (0.32) is relatively high. Whereas, labor (0.13) and intermediate inputs (0.11) are also important but on a relatively low level. The scale elasticity is approximately 1.11, showing a Constant Returns to Scale (CRS), in other words, output increases by the same proportional change as all inputs change.

On average, technical efficiency was 0.73, which means that farmers could improve their performance by 27%. Results suggest that experience and education positively influence the technical efficiency of vineyard systems, as opposed to age, gender, region and density. Access to extension services and irrigation increases technical efficiency. Additionally, general trust and membership in farmer organizations increases technical efficiency. Finally, as we expected, risk aversion and probability weighting (distortion of objective probabilities) negatively influence the technical efficiency. In light of our findings, it is necessary to design policies that facilitate small farmers’ access to a wide range of exchangeable inputs, in order to take advantage of the Constant Returns to Scale. In addition, it is necessary to promote strategies and policies with an emphasis on more extension services with greater action area, facilitating access to irrigation through subsidies and credits and improving trust in programs, projects, and networks. It is also necessary to develop cooperative enterprises or local and horizontal organizations to share information and services from farmer to farmer and also to generate action plans to promote a better risk and loss behavior in order to seize technological and economic opportunities and not overestimate extreme events.

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