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"If matters get mixed up

then

scrutinize the cause

and

you will know what the effects will be"

Imam Ali (AH)

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Chapter 1

General Introduction

In this thesis, our focus is on to study complementarity. The concept of complementarity is a *priori* rather simple to define and understand. Indeed two factors are complementary if a marginal increase of one factor increases the marginal productivity of the second factor. This leads, more than a half century ago, Samuelson (1947) to declare:

> "In my opinion the problem of complementarity has received more attention than its merited by intrinsic importance"

Yet, a quarter century later, Samuelson (1974) came to assert:

> "The time is ripe for a fresh, modern look at the concept of complementarity. The last word has not yet been said on this ancient preoccupation of literary and mathematical economists. The simplest things are often the most complicated to understand fully"

A recent theoretical and empirical literature gives a confirmation of this assertion by emphasizing the potential importance of interactions and complementarity between different elements of organizational design (Milgrom and Roberts, 1990; Holmstrom and Milgrom, 1994). This stream of research looks at organizations as complex systems, in which resources, activities, processes are highly interdependent characteristics that concur in forming the organizational system (Rivkin and Sigglekow, 2003; Levinthal, 1997). A major finding of this literature is that organizational design practices are "clustered": the adoption of practices is correlated across firms and some "sets" of practices consistently appear together. Economic theory suggests that such clustering might arise if the choice are complements. The analysis of such complementary effects needs both theoretical and empirical tools.

First, because practices are discrete by nature new monotone comparative statics methods are needed that can be conduced without many of the restrictions required by the implicit-function theorem. One advantage with new approach is that derivatives of relevant functions need not to be continuous, and objective functions need not to be concave. It has also the appeal of ease of use relative to the implicit function theorem. But the main advantage is that it works for discrete (as well as infinitisimally) change in a policy or exogenous variable. Similarly, taking serioulsy into account the problem of practices adoption strategies between many players and choice variables make the calculation of a definitive comparative static result tedious if not impossible. Multiple equilibria are also common in many games, making it difficult to apply the implicit-function theorem. Monotone comparative methods are also tractable in this setting. Recent works shows that unambiguous comparative static results can emerge when a game exhibits increasing monotonic best-reply functions, wich occurs when all strategic variables are complementary (Milgrom and Roberts, 1990; Vives, 1999). That is, each player's own choice variables are complementary and all strategic variables across players are strategic complements. A game with this structure is called a supermodular game or a game with strategic complementarities.

Second, new empirical models are needed to test for complementarity. Indeed, most of the recent studies have neither recogneized nor accounted for the potential impact of unobserved variation in the costs and benefits of the organizational practices (Arora and Gambardella, 1990; Ichniowski et al., 1997). Following Athey and Stern (1998) our thesis uses the productivity and adoption approaches to test for complementarity. We more precisely focus on the separable identification of the complementarity parameter and the parameter of joint distribution of unobservables.

In what follows, we first give some motivations for modeling and testing for complementarity (1.1), before presenting the main objectives (1.2) and empirical context of our thesis (1.3). Finally, we present the outline of our thesis dissertation (1.4).

1.1 The need to model and test for complementarity

The first formal formulation of the complementarity framework in the field of management and organization is due to Milgrom and Roberts (1990, 1995) who studied the shifts to modern manufacturing. The declared purposes of their work were to give substance to previously elusive notions such as "fit" or "systems effects" and complementarity between practices, provide some basis for interpreting claims such as the need for strategy and structure to fit one another by clarifying some ambiguities and enrich our understanding concerning directions of causation.

The definition of complementarity adopted by the majority of contributions in this field (and also that will be adopted in the present study) is that of Edgeworth complements: two strategies/activities are complements if doing (more of) anyone of them increases the value to doing (more of) the others (Milgrom and Roberts, 1995). The idea is that of positive mixed-partial derivatives of a payoff function, in which the marginal returns to one variable are increasing in the levels of the other variable. From this point of view, returns of each variable (strategy/activity) are related to that of its complements, and then a variation in the level of one variable is more profitable if the whole system is changed. For an empirical view, whether a combination of strategic choices together can deliver an output greater than the adoption of choices in isolation gives an idea to study the synergistic effects of business strategies on production. More precisely, complementarity can be defined as marginal benefit of acquiring one business strategy increases with the acquisition of relevant strategy. Inversely, substitutability can be defined as marginal benefits of acquiring one strategy decreases with the acquisition of related strategy (Milgrom and Roberts, 1994).

In their contribution, Milgrom and Roberts (1990, 1995) use the lattice theory, together with the supermodularity concept, to provide a mathematical framework able to represent this kind of complementary interactions (positive and negative) among variables with a tractable model (despite the high number of variables to consider). This approach avoids some of the main restrictions typical of economic models (payoff function's continuity and differentiability and domain's convexity) (Moretti and Tamma, 2010).

After this seminal work, two main streams of research emerged: that of theoretical contributions and that of empirical studies. On the theoretical side several contributions have been developed, mainly focusing on well-defined areas of research, dealing with specific economic and managerial instances (Vives, 1990; Holmstrom and Milgrom, 1994). Schaefer (1999) represents the optimal partitioning of product design. Another interesting example of application of the complementarity framework is that of Mayer et al. (2004) who designed a model based on the concepts of complements and substitutes, which examines the idea present in procurement management that sees supply inspections and supplier plant inspections as substitutes. The work of Csorba (2006) applies the complementarity concept to develop a general model to describe and solve the screening problem faced by a monopolist seller of a network commodity. A burgeoning literature tries to test for complementarity using experimental economics. Strategy and organization scholars simulated complementarities among organizational characteristics to study their effect on performance, innovation, complexity and competitive advantages (Levinthal, 1997; Levinthal and Warglien, 1999; Ghemawat and Levinthal, 2000; Gavetti and Levinthal, 2000; Rivkin, 2000; Porter and Sigglekow, 2001; Sigglekow and Levinthal, 2002; Sigglekow, 2002).

The method widely used to test for complementarity is empirical studies. Two approaches are developed in these empirical researches (Athey and Stern, 1998). The first one test for complementarity effects on the firm performance (Whittington et al., 1999; MacDuffie and Krafcik, 1992; Parthasarthy and Sethi, 1993; Ichniowski et al., 1997; Ichniowski and Shaw, 1999; Massini and Pettigrew, 2003). Using mainly OLS models, this approach show that two business strategies or activities are said to interact if the coefficient of the dummy catching the presence of both activities is positive and significant. Similarly, two strategies (activities) can be defined as substitutes if the interaction term is negative. Then we can think of substitutability as a complementarity of negative intensity. The second approach is related to the adoption rate, namely oriented to analyze complementarities identifying the adoption rate of some organizational characteristics (new technologies, practices, innovative strategies, etc.) by a significant group of firms (Arora and Gambardella, 1990; Colombo and Mosconi, 1995; Abernathy et al., 1995; Whittington et al., 1999; Laursen and Mahnke, 2001; Bresnahan et al., 2002). A first study dedicated to inter-organizational complementarity linkages is due to Arora and Gambardella (1990), who studied external linkages between small and medium size biotechnology firms and universities. They demonstrated through an empirical study for a large sample US, European, and Japanese chemical and pharmaceutical producers, that the strategies of external linkage of the large firms with other parties are complementary to one another. Complementarity here is interpreted as a catalyst for inter-organizational relationships directed to a profound innovation process. Another example is the study of Biesebroeck (2007) about different car and light truck models produced in North America. He suggested that producing this increased variety of vehicles is associated with a productivity penalty. He showed that manufacturers can adopt complementary activities to reduce this penalty. Flexible technology to assemble models derived from different "platforms" on the same assembly line, and bringing previously outsourced activities in-house are two identified components that could minimize the penalty. Mothe et al., (2011) and Mohnen and Röller (2003) study synergistic effects of organizational innovation practices on firm performance.

Most of these studies rarely discussed in detail the issue of unobserved heterogeneity that can cause misleading results (Athey and Stern, 1998). There are different components of unobserved heterogeneity which can deteriorate the results. Some of which can be classified as:

(i) choice set considered by individuals can vary across the members of the population, this unobserved choice set process must be explicitly treated in modeling; *(ii)* some attributes are not directly observable in surveys, but which may be used by decision-makers while choosing an alternative from a choice set. Such attributes are usually individual's perceptions of alternatives and their attributes. For example, in business mode choice context, such attributes include "environmental effects", "managers experience", etc.

1.2 Thesis objectives and contributions

The primary objective for this work is to test for complementarity by separating the aspect of *unobserved heterogeneity*. This implies to develop and test models that also account for the *incoherence problem* of models usually used in the adoption approach.

The main contributions of this thesis is methodological as well as empirical with an emphasis on capturing complementarity using the two approaches (productivity and adoption approaches) defined by Athey and Stern (1998). When data available to us contained a performance measure, we were able to test complementarity by productivity approach. To work with this, we have practiced ordinary least square (OLS) regression as a methodology testing for complementarity. We unfold the use of dummy variables in the OLS regression to measure the synergistic effect of practices or activities on payoff. When we have no measure of performance, we have recourse to the indirect approach by regressing discrete adoption choices on observable characteristics of smallholder farmers. Contrary to classical methods in literature, we use a new way to test complementarity that carries out unobserved heterogeneity separately by estimating a multinomial probit model. We apply the discrete choice model for decision protocol complementarity in a business strategy mode choice context with data from French small agricultural cooperatives (2005) and smallholder farmers from Pakistan (2010). For the survey data on smallholder farmers, we test the existence of complementarity between cropping and livestock activities performed by smallholders by using both approaches.

1.3 Empirical Context

To test for complementarity we use two databases. The first one the quality signaling strategies by small French cooperatives. The second is on the farming systems choices by smallholder farmers in the Punjab Pakistan province.

Innovation and quality signals. Innovation is getting ever more importance in the cooperative business environment today as product lifestyles become shorter and technology transformation rate become faster (Gallouj and Weinstein, 1997; Tidd et al., 2005). Due to this, innovation active firms are found to be more productive than less or no innovation active firms (Anastassopoulos and Rama, 2003; Breschi et al., 2000). The produce-and-sell perception of the commodity agribusiness is being replaced by the strategy of first determining what attributes consumer wants in their food products then creating or manufacturing products with those attributes. With the continuous shifting to the global economy, the international agro-food market for value-added products is growing in terms of business innovation (Dorsey and Boland, 2009).

These innovations constitute different portfolio of agro-food products. Major innovations emanate with the quality of product as consumers are directly addressed and firms have to pay attention to consumer satisfaction. The idea of branding and quality labeling is based on the health and safety matters at one hand, and the recognition of the organization at the other hand. Insurgence of these quality signals were highlighted during the bovine spongiform encephalopathy crisis or mad cow disease, Escherichia coli (E. Coli) in Germany in 2011, and meat adulteration scandal in 2013. To account for this backlash, food safety measure were taken in the form of traceability of agro-food products. Traceability mechanism for food security is based on the effect of information about production safety procedure in manufacturing systems (Gellynk et al., 2006; Cheng and Simmons, 1994).

Sustainability of these innovations is also an issue that is concerned with the economic value to the firm (Alfranca et al., 2004). The reasons of failure of great business entities with disruptive changes in technology, strategy and market structure are due to not considering the economic effects of these innovations (Christensen, 1997). A successful business entity achieves the correct balance between innovation and its value creation. Firms that focus primarily on creativity often end up with a loose organizational structure that carries along a high chance of coming up with innovative product ideas. On the other hand, firms that primarily focus on value creation or value addition often get a more hierarchical organizational structure which means innovative product ideas rarely break the surface because of the rigid structure (Brown and Duguid, 2000).

Within the context of both health matters and economic value of branding and quality labeling adoption in agribusiness, a recent thread of literature has emerged concerning implementation of these quality signals into agro-food products, willingness to pay, and their costs and benefits (Auriol and Schilizzi, 2003; Crespi and Marette, 2003; Lence et al., 2007; Bottega et al., 2009; Giraud-Heraud et al., 2013; Boumra-Mechemache and Chaaban, 2010). A question is yet to be addressed in the literature that how different combination of insignia for agro-food products affect the business entities in terms of payoff.

Crop and livestock mixed Farming. Understanding crop-livestock systems is enormously challenging that is an open assignment for researchers. For example, mixed farming systems consist of distinctive but tightly interdependent components or sub-systems which are highly heterogeneous across regions depending on agro-climatic and demographic conditions (McIntire et al., 2002; Williams et al., 1999). Furthermore, these systems have been dynamically evolving. Across the developing regions, agro-pastoralists have to face tremendous socio-economic and environmental challenges *i.e.* population growth and increasing importance of cash economy, though rates of such changes differ across regions/sub-regions (Delgado et al., 1999; Steinfeld et al., 2006). What makes the evolution of mixed systems unpredictable is that smallholder farmers may pursue multiple objectives (*e.g.* food security and income maximization) with multiple system components (*e.g.* plants and animals). Crop-livestock integration, defined as a process by which farmers intensify their activities by integrating components of crop and livestock activities, is expected to be an economically feasible and environmentally sound pathway for poor agro-pastoralists (Powell and Williams, 1994). Otherwise, there should be competition for resources (*e.g.* land and labor) between components with destabilizing effects on resource sustainability. If productivity is to increase because of increasing demand and increasing land pressure, then there are real research needs to enhance the complementarities between crop and livestock production (Thornton and Herrero, 2001). The potential for integrated crop and livestock is perceived to be high while further population growth is expected in the next few decades. Hence the need to study the drivers of interactions contribute for complementarity (Mortimore, 1991; Kristjanson and Thornton, 2004).

This interdependence of crops and livestock in these systems can be viewed within the context of the economies of scale of joint adoption. Cropping and livestock relationship is of interest and worth noting: use of livestock manure in sustaining soil productivity (fertility) for continuous land use; livestock; animals may also be used as a source of farm power (animal traction). Moreover, particularly small ruminants, stand out as an important source of cash economy at the beginning of the growing season for the purchase of crop inputs. And livestock can be used as a food security in times of crop failure and a form of savings for emergency and important occasions.

Crop-livestock farming systems constitute the dominant land use system in developing countries in Southeast Asia, Sub-Saharan Africa, and Latin America. In developing regions, crop-livestock farming systems are of growing importance, not only because existing systems are expanding, but also because formerly specialized cropping and livestock systems are diversifying into mixed farming (Mortimore, 1991; Thornton et al., 2002; Steinfeld et al., 2006). Considering their significance on livelihoods of the poor, proper understanding of the mixed crop-livestock systems is critically important in order to devise appropriate policy recommendations and institutional reforms for poverty alleviation, food security and sustainable resource management (McIntire et al., 1992; Pell, 1999; Thornton and Herrero, 2001; Kristjanson and Thornton, 2004; Herrero et al., 2007). Moreover, the productivity is also an important concern with these farming systems. A number of factors affect the productivity of specialized or mixed farming systems which are to be investigated. Since these farming systems belong to the poor population of rural areas where most of them are smallholder farmers, it is important of all for them to maximize income from these production systems.

1.4 Outline of thesis

This thesis is organized into six chapters. Chapter 1 presents why it is important to study the model and test of complementarity between existing business strategies. The objective of this chapter is to raise several questions about different methodologies adopted by researchers to test for possible complementarity. In response to existed extant approaches and its inability to cope up with the several statistical aspects of modeling, our motivation of reconsidering the model to test about complementarity is a strive to those issues that can deprive a firm from maximum payoffs by using different business strategies. In the empirical context, we introduce some database that have been used in the thesis to test the complementarity empirically.

In addition to the extant literature, we developed different approaches to test for complementarity following formal procedure of monotone comparative statics and theory of supermodularity (Chapter 2). The three chapters that follow provide empirical responses related to our questions. Thus, the third chapter of this thesis provides evidence regarding the micro economic determinants of the adoption of branding and quality labeling strategic choices of French small agricultural cooperatives (Chapter 3). The fourth chapter comprises of empirical evidence to use the developed methodology for testing complementarity (adoption approach). French small agricultural cooperatives data (2005) were used in this chapter (Chapter 4). The fifth chapter addresses the issue of complementarity between cropping and livestock but in a different manner than discussed in the preceding chapter. In this case, we have used productivity approach in addition to adoption approach to testing complementarity (Chapter 5). Finally, Chapter 6 concludes our study.

Chapter 2 is a preliminary chapter that presents an interpretative survey of the existing literature on adoption of different business strategies in terms of complementarity. It also highlights the technical and business organizational literature and the application of such literature to test for complementarity. The main focus is to set the theoretical basis for testing complementarity between two business strategies/activities. The adoption of branding and labeling strategies for agro-food products compliance with an internal logic of production management, but also introduces an implementation that is accompanied by complementarity organizational practices both internally and externally to the firm. Adoption of both insignia clarifies the consumers perception about brand name who think of that as quality of the product. In the first section, we have highlighted the literature about organizational designs along with the scope of complementarity. The aim of this section is to state the organizational settings in the form of technology, human resources, incentives, coalition with other research institutions, etc. and their adoption for profit maximization problems. In the second section, we have provided with the monotone comparative statics which is the basis for testing complementarity along with its logic and examples. In the next section, lattice theory and supermodular game theory have been discussed. Lattice theory deals with adoption of different business strategies in an ordered manner. Supermodular functions evaluates the payoffs of using different business strategies when these are adopted together or not. In the last section, we have devised two methods to test for possible complementarity between two business strategies. Adoption approach allow us to test for complementarity when explicit performance measure of different strategies is not available. We discuss in detail the econometric issues of prevailed model to test for complementarity and its inability to draw conclusions that leads to increase payoffs in real. To account for these issues, we have devised our own methodology and its coherence to test the complementarity by separating unobserved heterogeneity. In productivity approach we regress performance measure on different characteristics of the business.

Chapter 3 of this thesis has the objective of analyzing the cooperative level determinants for the adoption of brand and label insignia by applying a framework of discrete choice models as business strategies adoption are discrete in nature (Milgrom and Roberts, 1990). To begin with, we study the hypothesis that a cooperatives adoption behavior depends on factors related to its internal characteristics, its vertical relationships or the characteristics of its external environment. The idea is to provide a general hypothesis for brand and label adoption that can be tested on French small agricultural cooperatives based on small cooperatives survey (Enquête petites coopératives, SSP, 2005). The survey was carried by the French National Institute of Statistics (Service central des enquêtes et études statistiques (SCEES)). The other objective of this chapter is regarding the management decisions about branding and labeling signalization which are expected to be endogenous to their performance outcomes. Endogeneity has important implications for the statistical analysis of such decisions which means that there are some unobserved factors that also affect the parameter of interest. To do this, we study the hypothesis of endogeneity of turnover that explicitly depends on quality signals.

The first results that matter for the adoption of branding and labeling choices for agro-food products reveals some major stylized facts. On the one hand, the results confirm the links classically observed in the literature between the size, the mode of organization, the supply chain, and signalized product. Moreover, they emphasize the link between the business of the company or the product chain, and the choice of signalization adopted. Finally, they tend to reveal an influence of market innovation strategies in signalization of brand and label through the effect of geographical target market and the role of distribution. We have used dual empirical approach in this chapter in the form of "unordered" and "ordered" discrete business strategies. Apparently, it seems quite absurd to allow 'order' for the branding and labeling strategies, but we have argued its legitimacy and appropriateness for our study. As far as endogeneity is concerned, results suggest that after unobserved factors possibly influencing both phenomena are controlled for, turnover significantly support for increasing quality signals.

Chapter 4 mainly focus on our extensive work of thesis, *i.e.* testing complementarity. More precisely, we evaluate empirically our developed approach to test for the existence of complementarity between branding and labeling adoption strategies in French small agro-food cooperatives. Our main hypothesis is that the joint adoption of brand and label signalization business strategies for agro-food products results in more payoffs than separate adoption. This aspect is rarely studied in agribusiness. The overall objective is to test for the possible complementarity between branding and labeling strategies in a way to decide whether the payoffs of joint adoption is greater than the sum of payoffs of their adoption separately. We further deepen this analysis by focusing on different observable factors that take part in affecting the choice of adoption of innovation strategies. This aspect is also rarely presented in agro-food literature which can be helpful in determining the choice of innovation strategies for agro-food products, ceteris paribus, and payoffs will rise.

The results show that the joint adoption of branding and labeling strategies is significantly not favorable for small cooperatives in terms of payoffs. Unobserved heterogeneity also matters significantly in explaining simultaneous adoption of both innovative strategies. Apart from this, some observable factors that are in favor of adoption of both innovative choices are: number of employees, cooperatives affiliated with some unions, and those dealing in within the boundaries on European Union. Last factor suggests that consumers in EU are more concerned about the quality of the agro-food product in addition to the brand name of the cooperative.

In this chapter, we have used adoption approach as we did not have the performance measure of using branding and labeling strategies explicitly. But, the turnover that includes in the data represents total sales earned by actualizing all the available sources with the cooperative. We discussed in detail the less suitability of bivariate probit model in testing for complementarity which is based on correlation coefficient due to error terms and plagued with incoherence problem. Contrary to this, we have presented error structure of adoption of branding and labeling business strategies and checked its feasibility with multinomial probit model and found no incoherence problem.

Chapter 5 is the second empirical evidence of our developed approach to test for possible complementarity between cropping and livestock farming activities for smallholder farmers in Pakistan. The integration of two farming activities has largely been discussed, specifically in African literature, but their joint economic value in terms of complementarity or substitutability was rarely studied. Our main objective is that those smallholder farmers whose livelihood depend on both activities are economically well-off in contrast to those who adopt specialized farming activity, either cropping or livestock. In other words, we study to test for possible complementarity between cropping and livestock farming activities among smallholder farmers in Pakistan in 2010. In addition to test for complementarity, our focus is to unveil those factors that affect the joint adoption of farming activities. The inclusion of agro-climatic variables in the form of regional diversity to test their effects on adoption choices make this study more valuable as literature rarely focused on this issue.

In this chapter, we have profit to use both productivity (direct) as well as adoption (indirect) approaches as we have had the performance measure of cropping and livestock adoption explicitly. In productivity approach we have used ordinary least square (OLS) regression by including some dummy variables representing the presence/absence of farming activities. These dummies in addition to other observable factors were regressed to account for complementarity.

The results obtained through the productivity approach are favoring to conclude about complementarity for the smallholders. Next to it, some other factors that account for increasing productivity are age, education, herd size, land size, and mix cropping zone etc. Similarly, the adoption approach ends up with the conclusion of complementarity between cropping and livestock. However, unobservable characteristics influence the adoption decisions about complementarity.

Chapter 2

Theory about Complementarity

Complementarity in business strategies have argued largely on inductive and experiential grounds in the form of management of strategy, structure, and managerial process. These components have come within the purview of economic research, and important advances have been made in understanding these using economic theory. For example, the manufacturing firms that adopt strategic management policies about new technologies and methods appear to differ from traditional firms in their product strategies as well. Many firms broadening product lines, and there is a widespread increased emphasis on quality, both through frequent product improvements and new product introductions, and through reductions in defects in manufacturing. A common exercise in economics is to understand how a particular outcome varies qualitatively with a particular parameter, *e.g.* whether income tax increases the investment level in equilibrium or how two business strategies affect jointly on the payoffs. When one can answer such a question, this is often driven by a supermodularity (or complementarity) assumption.

Complementarity in econometrics is pervasive ranging from strategy adoption problems and acquiring technology issues in industrial organizations. At the heart of complementarity is the notion, due to Edgeworth, in terms of payoffs that the marginal benefit of acquiring one strategy/technology increases with the acquisition of related strategy/technology. This is mathematically captured by supermodular payoff functions (Amir, 2005). In terms of constraints, two activities are complementary if doing one activity more does not reduce the possible activity level for the other activity. This is mathematically captured by lattices (Yildiz, 2007). In the maximization problem, the objective reflects a complementarity between an endogenous variable and exogenous parameter, in the sense that having more of one increases the marginal return to having more of the other, then the optimal value of the former will be increasing in the later. In case of multiple exogenous variables, then all of them must also be complements so as to guarantee that their increases are mutually reinforcing.

In the last two decades, the measurement of complementarity has been somewhat contentious topic of study for economic analysis. In the literature, complementarity has a deep connection with strategic situations, and the concept of strategic complementarity is at the center stage of game-theoretic analysis. The modeling of complementarity, including strategic situations has proved challenging. The likely reason is that the perturbations of payoff and complex strategy spaces are naturally the norm rather than exception (Vives, 2005). It would not rather wrong to say that development of theoretical and empirical studies in literature that pose the question of testing complementarity between strategies is going through transitional phase. Another controversy is the multiple equilibria particularly in case of demand and supply functions equilibrium which are typical in the presence of complementarity and policy analysis is left orphan. The genuine difficulty arise because most of the time, testing for complementarity relies on measuring correlations among error terms of equations representing the optimal decision rules of firms. These simplified representation of the optimal decision rules may also include the effect of misspecification and/or missing variables in addition to individual unobserved heterogeneity of firms environments and organizational structure (Mohnen and Rosa, 2002). In this critical situation, the key is how to build coherent models that are useful for policy analysis. To partake in studying the synergistic economic effects of two strategies on payoffs, we use actual data to evaluate whether complementarities among business strategies/activities exist while at the same time controlling for unobserved correlation among strategies/activities that might only be induced by firms' unobserved heterogeneity.

This chapter develops a comprehensive theory relating to supermodular function on a lattice, with a focus on the connection between supermodular functions and complementarity. The theoretical material is a systematic and integrated view that summarizes and refines previously published research, and introduces new results.

2.1 Organizational Designs and Scope of Complementarity

During the last decade, internal organizational design choices (such as adoption of strategies or incentive program) of firms were also considered in addition to focus on labor demand, investment and productivity (Vandenberghe, 2013). Moreover, recent theoretical and empirical literature emphasizes the potential importance of interactions between different elements of organizational designs and their effects of productivity. A major finding of this literature is that organizational design practices are “clustered”: the adoption of practices is correlated across firms, and some sets of practices consistently appear across firms. Economic theory (e.g. monotone comparative statics and supermodularity theory) suggests that such clustering might arise if the choices are complement (Ludwig et al., 1977).

Firms have the option to use different strategies with a set of constraints (managerial expertise, environmental, etc.) to minimize the costs or to maximize their profits. The need is to explore those strategies that can, with the objective function and the constraint set depending on a parameter, have optimal solutions (Topkis, 1978). Lattices and supermodularity theory are the dynamic tools in economic research to explore the collection of strategies that a firm can adopt to achieve optimization.

Manufacturing process through technology, strategy and organization in a flexible multiproduct firm generates comprehensible and consistent response to market conditions. To handle optimization problems in economics, the objective function not necessarily needs to be differentiable nor convex (Milgrom and Roberts, 1990). There exists the solution to optimization problems that replaced the classical theory of productivity and implicit function theorem. The manufacturing firms that adopt these new methods appear to differ from traditional firms in their product strategies as well. For example, ford changed its production pattern and adopted a parallel team approach to design and manufacturing engineering in conjunction with computer aided simulation techniques that cut the development time of new models by one third (Taylor, 1988). Characteristics of modern manufacturing proved to be time and cost effective tools that were analyzed by economic models to achieve optimization through synthesizing those characteristics that respond in terms of complementarity (Milgrom and Roberts, 1994).

Obviously, every firm has the capacity to maximize its output through less costs and they can benefit the use of maximum resources that they have. In spite of all this, they need external linkages with some organizations that can be resulted in optimizing the objective of the firms. In the field of biotechnology, large firms enter into different kinds of linkages with universities and small/medium sized research intensive firms. These external linkages in the form of research can be tested for complementarity through correlation (Arora and Gambardella, 1990).

By joining different strategies, some firms come across multiple equilibria. Now the problem is to measure which solution produce optimum results. Ordered behavior and lattice theory provide the solutions to optimization problems in case of multiple equilibria. Strategic complementarities based on lattice theory characterizes the optimization problems when there are multiple solutions of interaction between strategies (Vives, 1990, 2005; Vives and Gale, 2009). Innovation is a key factor for achieving a better environmental performance of firms, to the extent that helps increasing the material/energy efficiency of production process and reducing emission/effluents associated to outputs (Mazzanti et al., 2008). Input complementarity between structural characteristics of a firm elucidates the innovation oriented industrial relations.

Well designed projects are the key to successful completion. Different characteristics and policies of the firm play an important part in acquiring the innovation. However, there are some obstacles that cause an interruption or barriers to innovation for the firms. Inability of characteristics and policy implications takes the project towards failure or to postpone it. Obstacles that can reduce the innovation process can be excessive perceived economic risk, innovation costs too high, lack of appropriate source of finance, resistance of change in the firm, lack of skilled personnel, and lack of information on technologies and markets (Galia and Legros, 2004). In addition to test complementarities between innovative products and firm management strategies, some firm structure or incentives can also be discussed in the arena of complementarity. For example, organizational team, incentives, training and knowledge management can also be tested to measure and increase the performance of a firm (Galia and Legros, 2005).

In the last two decades, external technology sources have been used for manufacturing firms with the intensity to cope up with new market challenges and to enhance their payoffs. Some researchers studied the effectiveness of these external technology acquisition on the payoffs of the firms. These external sources are tangible as well as intangible that can acquire through licensing agreements (Cassiman and Veugelers, 2007; Freitas et al., 2008; Hou and Mohnen, 2013).

The adoption of R&D from different sources also affect productivity. These sources in connection with competitors, clients, suppliers, universities, and research institutes provides their synergistic affects in terms of complementarity or substitutability. The ideal situation occurs when all the partners joining with R&D respond in boosting up productivity. But, due to some constraints like firm size or specific strategy combinations can restrict their productivity (Belderbos et al., 2006).

Regulated gambling is a multi-billion dollar industry in the United States with greater than 100 percent increases in revenue over the past decade. Along with this rise in gambling popularity and gaming options comes an increased risk of addiction and the associated social costs. Use of alcohol during gambling is a norm rather than exception in US. Male population separated from their families and from different ethnicity cause complementarity between gambling and alcohol (French et al., 2008).

A business value can be measured in terms of using information technology (IT) e-commerce strategies. A US based empirical study on 114 companies in retail industry was established to test complementarity between IT and e-commerce concluded with synergistic effect between front-end e-commerce and back-end IT infrastructure contributes positively to firm performance in terms of sales per employee, inventory turnover, and cost reduction (Zhu, 2004).

These studies are accounted for testing complementarity either in business strategies or technology. However, most of these studies are “incomplete” due to not accounted for potential impact of unobserved heterogeneity (variation) in the costs and benefits of organizational design practices. Moreover, these studies rarely came across the problems of incoherence analyzing the choices discussed by Miravete and Pernias (2010). Our analysis highlights how particular forms of unobserved heterogeneity bias the test statistic in specific directions. Two alternative assumptions about unobserved heterogeneity are possible: the unobserved returns among practiced strategies are affiliated or these are independent. The presence of positive correlation between the unobserved returns to the two different practices yields positive correlation between strategies. On the other hand, complementarity between strategies creates a force towards understanding interaction effects.

Our second aim to formulate the model is to analyze the properties of a structural estimate of parameters, that is, to verify whether these estimates really describe the objectives? And the assumptions on which correlation have been drawn are really coherent. There are several advantages to using such a structural approach in the context of heterogeneity and incoherence problems. First, by accounting for the unobserved heterogeneity, it is possible to obtain consistent estimates of the parameters of organizational design as well as covariance between unobserved returns to different organizational designs practices. Second, our model nests all prior models we are aware of, and so direct comparison can be made between the implicit assumptions associated with previous approaches. Third, by specifying and internally consistent simultaneous equations system, we can impose the cross equation restrictions of the interaction effects.

Firms are not only multi-input, multi-output production units, but also transform resources in nonlinear ways. Techniques for analysis must be flexible enough to represent the complexity of production processes. We propose that an appropriate research strategy must fulfill a requirement for multidimensional mapping *i.e.* apart from testing complementarity, it also accounts for unobserved heterogeneity at the same time. On the line of the methodological discussion made above, it appears that the quantitative tools available from the productivity and efficiency literature offer great opportunities for carrying out explorative analysis on the multidimensional profile of firms. Furthermore, some initial developments of interactive software promise to deliver, within a few years, friendly tools to manage simulated and real multidimensional scenario building on these aspects. These developments are very important for addressing a critical issue in the literature.

2.2 Monotone Comparative Statics

Monotone comparative statics is particularly concerned with scenarios where optimal decisions vary monotonically with different characteristics of the firm. These characteristics may contain policy change, exogenous factor, or parameter. For a collection of optimization problems where the objective function and the constraint set depend on these characteristics, comparative statics is concerned with the dependence of optimal solutions on these characteristics and monotone comparative statics is concerned with optimal solutions varying monotonically with these characteristics. In a non-cooperative game where every player takes decision independently, the characteristics may affect the payoff function of various players, the collection of strategies, and the set of players participating in the game. Monotone comparative statics technique in economics can be determined as a corner stone of economic analysis which enables predictions and understanding of economic effects by comparing equilibria before and after a change in demand/supply, (eco-industrial) policy, exogenous factor, or parameter. This technique is used for different business strategies in economics concerning analyzing changes in equilibrium due to change in different factor(s) in the optimization problems. It identifies that which or how the factor(s) move due to some interventions in the market. Recent work shows that unambiguous comparative statics results can emerge when a game exhibit increasing monotone functions, which occurs when all strategic variables are complementary. That is, each player's own choice variables are complementary and all strategic variables across players are strategic complements. A game with this structure is called supermodular game or game with strategic complementarities.

To illustrate the advantage of modern approach, we highlight the conceptual views of comparative statics. A number of research papers have focused on monotone methods for comparative statics that are crucial for studying complementarity. These includes Topkis (1978, 1998), Milgrom and Shannon (1994), Milgrom and Roberts (1994), Shannon (1995) and Athey (1996).

This analytic theory has very close concern with the game theory in business, we will use the term 'player' for the agent who make a discrete choice from a set of feasible choices X. These choices could be multidimensional, that is, a vector of N component choice variables set $x = (x_1, \ldots, x_N)$. The choice set X can represent utilization of different strategies in business $\{= 1\}$ or not $\{= 0\}$. For every discrete choice $x \in \{0, 1\}$, it is assumed that the player receives a payoff $\pi(x; \theta) = \pi(x_1(\theta), \ldots, x_N(\theta))$ which is also called objective function, utility function, profit function of the firm and in general each firm wants to maximize it by solving

$$\max_{x \in X} \quad \pi(x; \theta)$$

We study the qualitative properties of the optimum (or optimal set) that a player chooses; and how the optimal choices x^* vary with $\theta = (\theta_1, \ldots, \theta_M)$, a vector of exogenous parameters which is not under control of the player. Study of determining such qualitative relationships is the core of economic theory and is of particular interest, however, are the situations when these qualitative relationships are monotone, that is, choice moves monotonically upwards or downwards to an increase in parameter. Sometimes, the mechanism behind the up and down of economic variable is easy when the choice variable and parameter are real numbers or integers. Contrary to this, it becomes merely enigmatic when the relation between choice variables and exogenous parameter gets more complex like changes in technology or institutions. However, the ideal situation is very rare to have enough information about objective functions and choice sets to be able to do this. It is a more reasonable expectation that qualitative conditions are available about the structure of these problems. However, if one may not know the magnitude of the marginal returns to changing a choice variable, one may know that these returns will be greater or smaller if a parameter is higher or lower. And the tools for comparative statics tells us that this is the only sort of information one needs.

It is rather a good idea to build intuition about what drive comparative statics result, we start to consider situations in which there is one choice variable. In notation, player chooses a single variable $x \in \{0, 1\}$ from X. Also, for simplicity suppose that the player is maximizing the objective function (under certain constraints) (Milgrom and Shannon, 1994) that is composed of a benefit minus cost:

$$\pi(x; \theta) = max_{x \in x^*(\theta)} \; B(x; \theta) - C(x)$$

Benefits and costs or anyone of these could be influenced by other parameters. In general, profit or payoff function is comprised of revenues minus cost. But, here we have used benefits in place of revenues because of generality of the term. When the marginal benefit to an activity is increased and there is no change in marginal cost, or marginal cost increases but less than marginal benefit, more of that activity will be undertaken by an optimising player. In above case, the benefit to increase x is (for $x' \geq x$):

$$B\left(x';\theta\right) - B\left(x;\theta\right) = \triangle B\left(\theta\right)$$

is an increasing function. A necessary and sufficient condition for the family $B\left(\cdot;\theta\right)$ to obey increasing differences is that

$$\frac{\partial^2 B\left(x;\theta\right)}{\partial x \partial \theta} \geq 0$$

This implies that an increase in θ increases the marginal benefits of the action of a player. Note that marginal cost $\left(C\left(x'\right) - C\left(x\right)\right)$ do not change as θ changes. So if for any higher θ (*i.e.* $\theta' \geq \theta$), $\Delta B\left(\theta\right)$ has a higher value, then $x^*\left(\theta\right)$ will be monotone non-decreasing. In this case, raising the parameter directly raises the marginal net return to doing x. Hence, after parameter change, doing more of x will result in higher payoffs. For example, a firm wants to increase its payoffs by choosing only one choice variable *i.e.* quality labeling on its products. By introducing this choice strategy, firm will have to pay a little more in the form of costs but they may be able to get more benefit due to this strategic intervention on its products in the form of quality certification. If firms marginal benefits or marginal returns get increased, we say that firm is getting more by the intervention of one choice variable on its products. Hence, after the parameter change, the optimum $x^*\left(\theta\right)$ is achieved. It turns out the some form of complementarity between choices and exogenous variables lies at the heart of any monotone comparative statics conclusion.

The above theorem provides a sufficient condition for monotone comparative statics whereas its extension has proved to be stronger result that non-decreasing differences is the least restrictive assumption we can place to generate monotone comparative statics.

Example 1[1] To illustrate the comparative statics approach, we investigate the comparative statics of a monopoly firm whose goal is to maximize profit with respect to output. Let the firm's inverse demand be $p = a - bq$ where q is output, p is price, and parameters a and b

[1]We have taken this example from "The Neglect of Monotone Comparative Statics Methods", Trembley and Trembley (2010)

are positive. The firms total cost function (TC) is linear and depends on a regulatory policy (R), such that $TC = cq + R$ and $c > 0$. In this example, the government poses a per unit subsidy to encourage monopoly production: $R = -sq$, $s > 0$. Thus, the firms profit equals $\pi = (a - bq - c + s)\,q$. To ensure that profits are non-negative in equilibrium, $a > c - s$. Our goal is to determine how a change in s will affect the firms profit maximizing output. In this simple model, comparative static analysis can be derived directly from the solution to the monopoly problem. The firms first- and second-order conditions are:

$$\frac{\partial \pi}{\partial q} = a - c + s - 2bq = 0$$

$$\frac{\partial^2 \pi}{\partial q^2} = -2bq < 0$$

From the first order condition, the firms profit maximizing output (q^*) is:

$$q^* = \frac{a - c + s}{2b}$$

Thus for a marginal change in s, $\frac{\partial q^*}{\partial s} = \frac{1}{2b} > 0$. For a discrete increase in s from s^1 to s^2, the change in q^* is $\frac{s^2 - s^1}{2b} > 0$. With explicit function, both the sign and magnitude of change can be obtained.

This is the case when only one output is possible. Monotone methods get more complicated when the player choose two[2] variables. With a single choice variable, checking for increasing marginal returns on increasing differences is essentially all that is required to do monotone comparative static analysis. For two choice variables, the analysis by monotone method gets more complicated due to interaction effects. In this case, the monotonicity theorems[3] also require that both choice variables be complementary. For two choice variables with the objective function $\pi(x_1, x_2, \alpha)$, complementarity of choice variables means that $\frac{\partial^2 \pi}{\partial x_1 \partial x_2} \geq 0$. When this condition holds, the objective function is said to be supermodular. Thus, the application of monotone comparative static analysis in case of two choice variables require that one must check for both supermodularity and increasing marginal returns. To avoid the complication of analyzing monotone comparative statics in case of two choice variables, we use lattice theory which better explains the discrete choice variables adoption by the player.

[2]We restrict upto two choice variables because of limitation of our study.

[3]Strict and weak monotonicity theorems.

Concepts related to supermodular functions on a lattice develops a formal step in the economics literature of complementarity. Following section includes general concepts relevant for the present study on supermodularity and complementarity. The theory in this section is used in the applications that follow in chapters 3 and 4.

2.3 Lattices and Supermodularity

Lattice theory is a branch of mathematics concerning partially ordered sets (Birkhoff, 1984). This theory was first applied by Topkis (1978) and then Milgrom and Roerts (1990, 1995) to profit maximization problems. The laid down structure of lattice theory allows for the use of discrete variables in the optimization process, which is not possible with conventional mathematical tools. It is very important that it permits clear comparative statics results for observed changes in discrete choice variables and internal structure of firms as optimizing responses to environmental changes (Milgrom and Roberts, 1995). This is underlying theory for complementarity analysis. To start with this, we need to know first the preliminaries and definitions about lattice theory.

Definition1 Let $\geq$ be a binary relation on a nonempty set X . The pair $(X,\geq)$is a *partially ordered* set consists of a nonempty set X endowed with partial order relation$\geq$, if $\geq$ is reflexive, transitive, and antisymmetric[4]. A partially ordered set $(X,\geq)$ is said to be *completely ordered* if for $x \in X$ and $y \in X$, either $x \geq y$ or $y \geq x$. When there is no ambiguity, we will say for short that X (rather than $(X,\geq)$) is a *poset*, meaning that the partial order relation is understood. In particular, unless differently specified, $\mathbb{R}$ will always be assumed to be endowed with the usual $\geq$ order relation. If X is a *poset*, we say that the elements of the pair $(x,y) \in X$ are *comparable* if $(x \geq y)$ or $(y \geq x)$ (or both). A partially-ordered set is said to be lattice if each doubleton subset has greatest lower bound (*inf*) or $\wedge X$ and smallest upper bound (*sup*) or $\vee X$.

Definition 2 A *partially ordered* set $(X,\geq)$ is said to be lattice *iff* for all $x,y \in X$,

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4

- The reflexive property states that for every real number x, $x \geq x$. For example, the relation $\geq$ on the set of integers $\{0,1\}$ is $\{<0,0>, <0,1>, <1,1>\}$ and it is reflexive because $<1,1>$ are in this relation.
- The antisymmetric property states that for all real numbers x and y, if $x \geq y$ and $y \geq x$, then $x = y$;
- The transitive property states that for all real numbers x, y and z, if $x \geq y$ and $y \geq z$, then $x \geq z$.

$$x \vee y = (max\{x_1, y_1\}, \ldots, max\{x_n, y_n\})$$

$$x \wedge y = (min\{x_1, y_1\}, \ldots, min\{x_n, y_n\})$$

Here, operators $\vee$ and $\wedge$ are called join (or supremum) and meet (or infimum) respectively, and S denotes the discrete business strategies or choice variables that a player has to choose. For our purpose, the nodes of the lattice will represent different business strategies or payoffs due to the adoption of choice variables. A typical business firm could use none, one or both of the business strategies and can result in four possible states: $(x = 0 = y)$ if a particular business uses none of the strategy; $(x = 1, y = 0)$ if it uses first strategy only; $(x = 0, y = 1)$ if it second strategy only; and $(x = 1 = y)$ if it uses both of the given strategies. If the two strategies were complementary, then using both simultaneously would be better than using either one individually and certainly better than using neither. The lattice for this is shown in Fig. 1.1 where vertical height represents profit. Lattice speaks for different profit levels achieved by using different combinations of strategies. From this we can see the optimal path for the business to follow in order to increase profits. In complementarity situation, it would be best to use both strategies simultaneously.

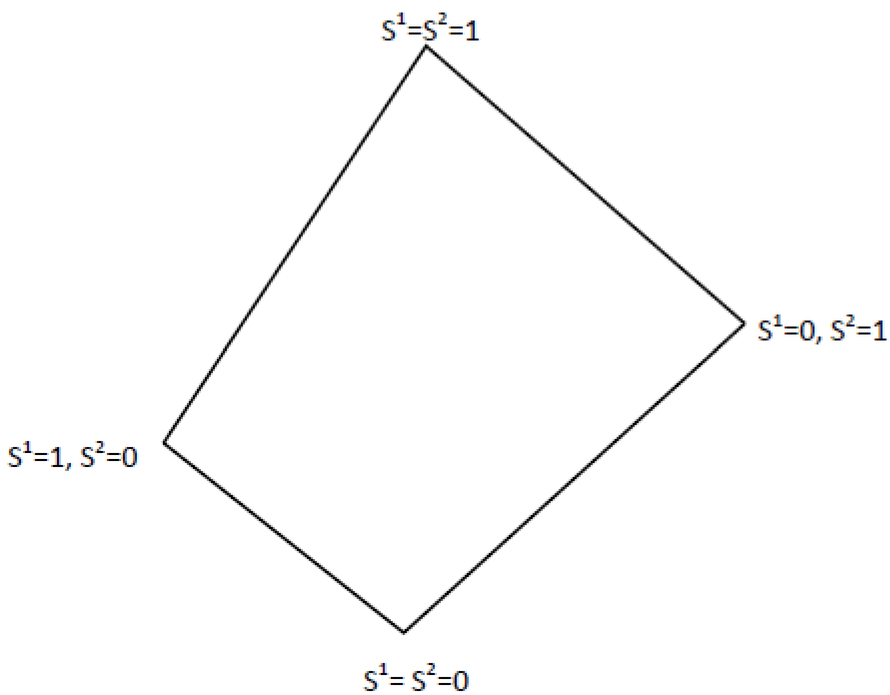

Figure 2.3.1: Lattice

2.3.1 *Supermodularity - a function on lattice*

The step for determining optimal solutions is theory of supermodularity. Milgrom and Roberts (1990) defined a supermodular function when "the sum of the changes in the payoff function when several arguments are increased separately is less than the change resulting for increasing all arguments together". Supermodular function actually exhibits the property of complementarity as increasing or more inputs raises the return to increasing additional strategies.

Theory of supermodularity is the basis for analyzing structural properties of a collection of parametrized problems. Concepts related to supermodular functions on a lattice develops a formal step in the economics literature of complementarity. This theory is based on the use of two business strategies which are discrete in nature and which states that these strategies are adopted by a business $\{=1\}$ or not $\{=0\}$. Supermodularity theory states that the payoffs of two business strategies adopted together is greater than the sum of payoffs of their adoption in isolation, depending on the observable characteristics of the business. For ease to understand, we discuss this theory with the help of lattice. In what follows we present briefly basic elements of the lattice theory.

Given any lattice $(X,\geq)$, a function $f : X \to \mathbb{R}$ is said to be supermodular if for all $x, y \in X$,

$$f(x \vee y) + f(x \wedge y) \geq f(x) + f(y)$$

A *function f* is said to be submodular if *-f* is supermodular. When $X = X_1 \times X_2$, ordered coordinate wise, supermodularity captures the idea of complementarity between $X_1 = (x_1, y_1) = (0,1)$ and $X_2 = (x_2, y_2) = (0,1)$ precisely. Indeed, if we take $x = (x_2, y_1) = (1,0)$ and $y = (x_1, y_2) = (0,1)$, then $(x \vee y) = (x_2, y_2) = (1,1)$ and $(x \wedge y) = (x_1, y_1) = (0,0)$. Then, we can write the inequality in the definition of supermodularity as

$$f(1,1) - f(1,0) \geq f(0,1) - f(0,0)$$

This implies that the marginal contribution of an input is increasing with the other input, capturing the usual meaning of complementarity. One can also write the above inequality as a condition of mixed differences:

$$[f(1,1) - f(1,0)] - [f(0,1) - f(0,0)] \geq 0$$

This condition reduces to a usual restriction on the cross derivatives for smooth functions on $\mathbb{R}^{\nvDash}$:

$$\frac{\partial^2 f}{\partial x_1 \partial x_2} \geq 0$$

A function is supermodular if for every strategic pair of input the function is supermodular in those inputs. The sum of two or more supermodular function is supermodular but the product is not necessarily supermodular (Topkis, 1978). These theorems are important for the decomposition of complex functions such as profit function where there are numerous relationships between subsets supply chain, organizational setup, productivity, and internal costs etc. are involved. These theorems enable the creation of supermodular function to demonstrate the effect of complementarity on output (Topkis, 1978; Milgrom and Roberts, 1990, 1995; Mohnen and Röller, 2005).

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2.4 Complementarity

The standard analytical implementation of the complementarity hypothesis rests upon a cardinal view of the concept: a twice differentiable payoff function $\pi\left(s^1, s^2; X\right)$ is introduced as a function of s^1 and s^2 endogenously determined practices and a vector X of exogenous factors. The necessary and sufficient condition for the practices s^1 and s^2 to be complementary is to find nonnegative mixed partial derivatives:

$$\frac{\partial^2 \pi\left(s^1, s^2; X\right)}{\partial s^1 \partial s^2} \geq 0 \quad \forall \theta \tag{2.4.1}$$

That is, marginal returns on one strategy increases in the level of the other, for any given value of the other arguments of π. It may also possible that given two complementary practices s^1 and s^2, the firm might have no incentive in increasing any of them individually, but still find an advantage in increasing both of them simultaneously.

We suppose that a firm adopt 2 feasible choices s^1 and s^2 from a partially ordered set X feasible choices with the profit maximization principle that the firm has to maximize his own payoffs:

$$max_{s^1,s^2 \subset X} \ \pi(s^1,s^2)$$

where $s^1 \in \{0,1\}$ and $s^2 \in \{0,1\}$ are discrete choices which represents the adoption of choices $\{=1\}$ or not $\{=0\}$. In the context of supermodularity, we simply define that two business activities would be considered as complementary if (*i*) adopting one business strategy does not preclude the adoption of the other; and (*ii*) the total payoffs through joint action is greater than their sum, in isolation. More formally, a firm is free to choose any of the discrete choices or both as $\left(s^1 = s^2 = 1\right)$ or not $\left(s^1 = s^2 = 0\right)$. The ingredients of productivity factor or performance measures which is assumed by adopting each strategy are the payoffs $\left(\pi\left(s^1,s^2\right)\right)$obtained by practicing respective strategy or the percentage of income generated by a strategy. Given that we can only identify payoff differences in discrete choice formulation, consider the payoff difference to positioning on both business activities as:

$$[\pi(1,1) - \pi(0,0)] = [\pi(0,1) - \pi(0,0)] + [\pi(1,0) - \pi(0,0)] + \delta \tag{2.4.2}$$

where δ shows the effect of complementarity. In the principle of complementarity, δ must be positive but it can also be negative if there is substitute relationship between business activities. From above equation, we can easily forsee the connection between complementarity and supermodularity of payoffs of s^1 and s^2 adoption. That is, s^1 and s^2 are complementary *iff*:

$$\delta = \pi(1,1) - \pi(0,1) - \pi(1,0) + \pi(0,0) \geq 0 \tag{2.4.3}$$

This implies that higher payoffs are achieved when the two practices are used together compared to a situation when they are used separately. The definition for substitutability is identical to the definition above except that 'larger' is replaced by 'smaller'.

2.4.1 Testing for Complementarity

First, we use the direct approach to test for complementarity by estimating the "objective function", alternative combinations of s^1 and s^2 adopted by a firm being included as dummy explanatory variables. The direct approach focuses directly on the relation between performance and different combination of these activities. Second, we also use the indirect approach by regressing discrete adoption choices on observable characteristics of the firms.

Contrary to classical methods in literature, we have devised a new way to test complementarity that carries out unobserved heterogeneity separately by estimating a multinomial probit model.

2.4.1.1 *The Direct (Productivity) Approach*

This approach is based directly on the objective function of the business entity which is to maximize the payoffs by utilizing different combination of business activities. The main idea is that the joint implementation of activities should prove to be more valuable in terms of productivity or payoffs than implementing both of them separately. The test of complementarity is thus performed by regressing a measure of performance on a set of dummy variables that represent the adoption of different combination of activities (interpreted as parameters of complementarity), along with observable characteristics on the considered activities. Comparing the impacts of alternative combinations of activities stemming from this estimation allows the detection of complementarity between these activities. One can obtain certain supportive evidence of complementarity (substitutability) when significant and positive (negative) coefficients of the dummy variables are observed. Formally, this approach can be traced back directly to supermodularity (Milgrom and Roberts, 1995; Topkis, 1998) as shown in subsections 1.3. Note that the related definition of supermodularity provided by Milgrom and Roberts (1995) only requires a non-negative (rather than a positive) impact of one practice on the marginal return of another practice. If there are more than two activities to be tested, the intuition is that whatever the activities are complementary, the objective function is supermodular.

Applying this approach, Mohnen and Röller (2005) directly estimated the objective function and investigated whether business decisions are complementary. Lockshin et al. (2008a) studied the complementarity between product, process and organizational innovations and their impact on labor productivity. Ichniowski et al. (1997) also used this approach to test the complementarity between different human resource management practices. However, the factor of unobserved heterogeneity was ignored which may have substantial influence on the association between activities even though complementarity may not exist at all which is the famous endogenous problem. Consequently, direct approach might deliver bias if there are unobserved factors in the error term that are correlated with the adoption of business activities.

The proposed test follow directly from the theoretical development of complementarity/substitutability and establishes the existence of complementarity/substitutability conditional on having unbiased estimates for the explanatory variables. A maintained assumption for this analysis is to provide unbiased estimates is that the drivers of adoption decisions, s^1 and s^2, are uncorrelated with the error term. Our aim is to derive the inequality (2.4.3), by regressing these strategies based on observed characteristics, that can be used in empirical tests to verify whether the inequality is accepted by the data and, hence, whether adoption of s^1 increases the marginal returns of s^2, or *vice versa.* We estimate the following equation through ordinary least squares (OLS) regression:

$$\pi_i\left(s^1,s^2\right)=\left(1-s_i^1\right)\left(1-s_i^2\right)\theta_{00}+s_i^1\left(1-s_i^2\right)\theta_{10}+\left(1-s_i^1\right)s_i^2\theta_{01}+s_i^1s_i^2\theta_{11}+X_i\beta+\varepsilon_i \tag{2.4.4}$$

That is, alternative combinations of different business practices being included as explanatory variables. The performance approach focuses directly on the relation between performance and different practices adopted by firms. This is in order to compare the impact of alternative combinations of adoption choices on the performance of the business. Subscript i refers to the firm i; θ_{11} are the coefficients of productivity on the adoption choice of both activities jointly, the same criteria can be applied to θ_{10}, θ_{01} and θ_{00}. The objective function is supermodular and s^1 and s^2 are complements only if $\theta_{11}-\theta_{01}\geq\theta_{10}-\theta_{00}$. In order to investigate the partial returns from s^1 and s^2, we choose a simplified alternative form to express the objective function. For example, equation (2.4.4) can be rewritten as

$$\pi_i\left(s^1,s^2\right)=\theta_0+s_i^1\cdot\theta^1+s_i^2\cdot\theta^2+s_i^{12}\cdot\delta+\beta X_i+\varepsilon_i \tag{2.4.5}$$

where

$$\theta_0=\theta_{00}$$
$$\theta^1=\theta_{01}-\theta_{00}$$
$$\theta^2=\theta_{10}-\theta_{00}$$
$$\delta=[\theta_{11}-\theta_{01}]-[\theta_{10}-\theta_{00}]$$

θ^1 captures the non-exclusive partial effects of s^1; θ^2 is the non-exclusive returns of s^2; δ tells the returns of adopting both activities s^1 and s^2 together and represents exactly the complementarity coefficient we are trying to test; θ_0 is constant. Hence, the condition for the above production function in a supermodular form can be simplified as (2.4.3):

$$\delta=[\theta_{11}-\theta_{01}]-[\theta_{10}-\theta_{00}]\geq 0 \tag{2.4.6}$$

One important point need to be highlighted here is that the objective function in (2.4.4) is the same as expressed in (2.4.5) but with some transformation, the complementarity can now be reflected by testing inequality (2.4.6). Considering this simplicity, we will adopt above equation in our empirical analysis. Further, it is also worth to note here that equation (2.4.5) clearly shows that the marginal returns to either s^1 or s^2 will not be constant anymore if synergistic effect is present ($\delta \neq 0$).

Athey and Stern (1998) argued that OLS results can be biased due to unobserved heterogeneity in the choice of s^1 and/or s^2. In other words, OLS regression can be estimated the effect of complementarity whilst there is no any complementarity in real, or *vice versa*. We do not have any measure with OLS to correct for this unobserved heterogeneity. To do this, we use adoption approach.

2.4.1.2 *The Indirect (Adoption) Approach*

Since complementarity creates a force in favor of increasing payoffs due to joint adoption of two business activities, if alternative activities are complementary, then we would expect rationally behaving individual firms to exploit this opportunity, investing in these activities at the same time and in the same direction. However, Athey and Stern (1998) noted that we may not be able to test directly for complementarity if we do not have measure of the performance of different activities. In order to take this problem into account, we discuss the prevailed methodology that has been used in literature to test complementarity. This dichotomous approach is not feasible for testing complementarity due to incoherence problem. We first discuss theoretically this incoherence problem and at the second stage, we produce our developed methodology and its feasibility to test for complementarity without having incoherence problem.

Bivariate probit model (Arora and Gambardella, 1990; Arora, 1996) is used to test for the existence of complementarity between two business activities when the performance measure is not available. The model is based on the notion that the individual business derives payoff by choosing a pair of business strategies or activities, and that is postulated to pick those strategies/activities which maximizes the payoffs. More specifically, bivariate probit regresses the non exclusive business activities (cropping and livestock) on the assumed exogenous control variables (X_i), but takes the correlation between them into account explicitly, as in the following model:

$$
s_i^{1^*} = \beta^1 X_i + \varepsilon_i^1, \qquad s_i^{1^*} \begin{cases} = 1 \; if \; s_i^{1^*} > 0 \\ = 0 \; otherwise \end{cases}
$$

$$
s_i^{2^*} = \beta^2 X_i + \varepsilon_i^2, \qquad s_i^{2^*} \begin{cases} = 1 \; if \; s_i^{2^*} > 0 \\ = 0 \; otherwise \end{cases}
$$

where the stochastic errors ε^1 and ε^2 are independent of X_i but not necessarily independent of each other. That is, $E\left(\varepsilon^1\right) = E\left(\varepsilon^2\right) = 0$, $Var\left(\varepsilon^1\right) = Var\left(\varepsilon^2\right) = 1$, $Corr\left(\varepsilon^1, \varepsilon^2\right) = \rho$.

At the first stage, each of the n firms choose whether to adopt each of the two activities. The choice set of each firm consists of the four possible combinations of adoption/non-adoption of the individual activities, denoted $k = \{(0,0), (0,1), (1,0), (1,1)\}$ representing the choices respectively to adopt neither activity, adopt s^1 only, adopt s^2 only, and adopt both activities. After the adoption decisions are made, all firms observe some payoffs as:

$$
\pi_i^{j^*}\left(s_i^1, s_i^2\right) = \left(\theta^{1^*} + \varepsilon^{1^*}\right) \cdot s_i^1 + \left(\theta^{2^*} + \varepsilon^{2^*}\right) \cdot s_i^2 + \delta \cdot s_i^1 \cdot s_i^2 \tag{2.4.7}
$$

where the adoption choice is represented by the two dichotomous variables s^1 and s^2. To catch the complementarity effect, a pairwise interaction term (δ) is introduced. $\left(\theta^1, \theta^2\right)$ represent the observable characteristics whereas $\left(\varepsilon^1, \varepsilon^2\right)$ are unobservable returns to the econometricians. A firm adopt any activity if profitability exceeds some threshold, say, $s_i^{1^*} = \pi\left(1, s_i^2\right) - \pi\left(0, s_i^2\right)$. From the latent[5] profit function (2.4.7), we get

$$
s_i^{1^*} = \theta^1 + \varepsilon^1 + \delta s_i^2 \tag{2.4.8}
$$

Next, we define the adoption indicators as a function of whether a firm earn positive profits if it adopts both business activites:

$$
s_i^j = \begin{cases} 1 \; if \; s_i^{j^*} > 0 \\ 0 \; if \; s_i^{j^*} \leq 0 \end{cases} \quad (j = 1, 2) \tag{2.4.9}
$$

[5]This profit function contains not directly observed characteristics but are rather inferred from original variables.

The main interest is in the structural treatment of error terms because testing of complementarity is based on positive error correlation inducde by unobserved heterogeneity. By substituting (2.4.8) into (2.4.9), we get

$$s_i^1 = \begin{cases} 1 \; if \; \varepsilon_i^1 > -\theta^1 - \delta s_i^2 \\ 0 \; if \; \varepsilon_i^1 \leq -\theta^1 - \delta s_i^2 \end{cases} \qquad and\, similarly \qquad s_i^2 = \begin{cases} 1 \; if \; \varepsilon_i^2 > -\theta^2 - \delta s_i^1 \\ 0 \; if \; \varepsilon_i^2 \leq -\theta^2 - \delta s_i^1 \end{cases}$$

Then, we define

$S_i(1,1) = \left\{ \left(\varepsilon_i^1, \varepsilon_i^2\right) : \pi\left(s_i^1, s_i^2\right) = (1,1) \right\}$ as the set of unobserved characteristics that induce firm i to adopt both activities simultaneously. A firm adopt $\left(s_i^1, s_i^2\right) = (1,1)$ under the profit maximization principle as $\pi(1,1) > \pi(1,0), \pi(1,1) > \pi(0,1)$ and $\pi(1,1) > \pi(0,0)$. That is, we define the set $S_i(1,1)$ of the combination of errors $\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right)$ leading to the joint strategy adoption

$S_i(1,1) = \left\{ \left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta \right\}$

Similarly, we define the following set $S_i(1,0)$ of the combination of errors leading to the adoption of s^1 only

$S_i(1,0) = \left\{ \left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} \leq -\theta^{2^*} - \delta \right\}$

symmetrically, the adoption profile of s^2 only is

$S_i(0,1) = \left\{ \left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} \leq -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta \right\}$

finally the set $S_i(0,0)$ leading to the adoption of none of the considered activities is

$S_i(0,0) = \left\{ \left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} \leq -\theta^{1^*} - \delta, \varepsilon_i^{2^*} \leq -\theta^{2^*} - \delta \right\}$

By drawing these four regions in the Fig. 1.4.1 (for the case of complementarity $(\delta > 0)$) depicts overlapping for the subsets of $S_i(1,1)$ and $S_i(0,0)$. This overlapping intermingles the choies of adoption of both business activities and none of these at an area E^*. This ambiguity leads to the problem of incoherence. This suggest that bivariate probit approach is not the feasible choice to test the notion of complementarity due to unobserved heterogenity across the k alternate choices.

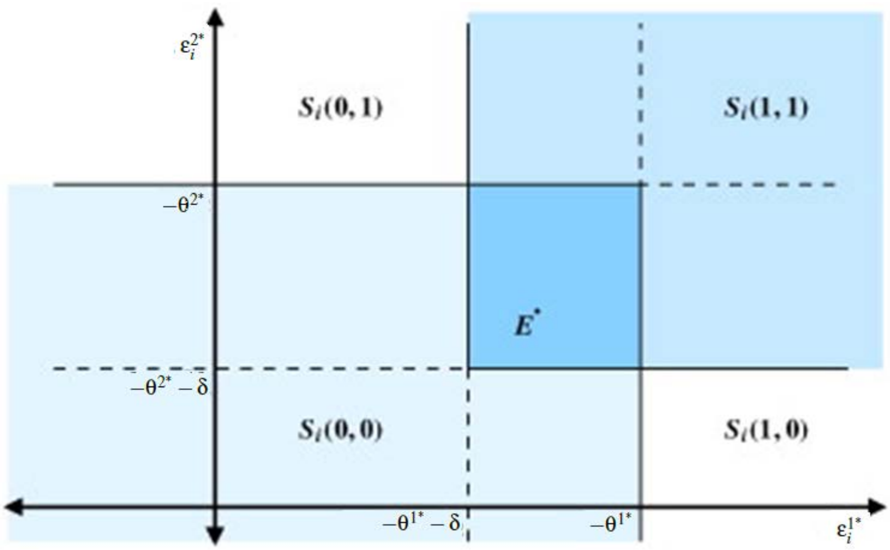


Figure 2.4.1: Adoption of strategies

Multinomial Probit Approach

To solve this incoherence problem, we start with more general pattern of correlation. We suppose that k indicates the exclusive decision of the firm i to adopt business activities. The discrete dependent variable k now takes values as $k = \{0,1,2,3\}$ representing the choices respectively to adopt neither activity, adopt s^1 only, adopt s^2 only, and adopt both activities. The payoffs to firm i from choosing $j \in k$ is:

$$\pi_i^j = \beta^j X_i + \varepsilon_i^j \tag{2.4.10}$$

where X_i is the vector of observed explanatory variables describing firm i and other characteristics important for the determination of choice. The parameter vector β^j are unknown and these are the object of inference. The vector of stochastic errors $\varepsilon_i^j = \left(\varepsilon_i^0, \varepsilon_i^1, \varepsilon_i^2, \varepsilon_i^3\right)'$ represents the unobserved returns of the choices. It is assumed to be distributed as multivariate normal, identically and independently distributed across the n firms, with zero mean and covariance matrix $\sum = \sigma_i^j > 0$, $\forall j$ (positive definite).

Arranging the parameters in (2.4.10) as $\beta = (\beta_0', \beta_1', \beta_2', \beta_3')$ the log-likelihood function to be maximized is:

$$\mathcal{L}\left(\beta, \sum\right) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=0}^{3} y_i^j \ln P_i^j \left(\beta, \sum\right)$$

where the profit indicator π_i^j is latent but we observe the choice $y_i^j = 1$ if a firm i chooses the alternative j and $y_i^j = 0$ otherwise. While $P_i^j = Pr\left(\pi_i^j > \pi_i^l, l \neq j\right)$ represents the probability that the firm i make the choice j under the profit maximization principle. Unfortunately, it is not possible to get a unique maximum likelihood estimate of the parameters $(\beta, \sum)$ in the above model, as they are not identified. The first source of the identification problem is that the observed choices are only informative on the differences of the profits and not on the profits themselves. Then taking differences with respect to the profits associated with $j = 0$, i.e. we take the first alternative as the reference state used to normalize location of the latent variable.

The payoff function π_i^j in (2.4.10) is specified differently for the joint adoption option than for the others. Specifically, the payoff of joint adoption is:

$$\pi_i^{3^*} = \pi_i^{1^*} + \pi_i^{2^*} + \delta$$

where δ captures the effect of complementarity between two business activities. The treatment for joint adoption payoff takes into account its econometric interpretation. However, this specification is convenient given our aim to estimate the effects of observable characteristics of the firms on the complementarity between s^1 and s^2. This approach was proposed by Gentzkow (2007) and Arora et al. (2010). For identification, we have taken differenced payoffs in (2.4.2) because payoff of adopting neither activity is normalized to zero, as is necessary given that only the payoff differences determines the observation's choice. Next,

$$\pi_i^{3^*} = \left(\beta^{1^*} + \beta^{2^*}\right) X_i + \left(\varepsilon_i^{1^*} + \varepsilon_i^{2^*}\right) + \delta$$

states that firm i choose both activities to earn an average payoff $\pi_i^{3^*}$, with the assumption that payoff of joint adoption is greatest of all other strategies i.e. $\pi_i^{3^*} > \pi_i^{0^*}$, $\pi_i^{3^*} > \pi_i^{1^*}$ and $\pi_i^{3^*} > \pi_i^{2^*}$. Let us define $\theta^{j^*} = \beta^{j^*} X_i$, with $\theta^{j^*} = \left(\theta^{1^*}, \theta^{2^*}\right)'$. Rewriting these conditions lead to the following constraints on the errors:

$$\begin{aligned} \varepsilon_i^{1^*} &> -\theta^{1^*} - \delta \\ \varepsilon_i^{2^*} &> -\theta^{2^*} - \delta \\ \varepsilon_i^{1^*} + \varepsilon_i^{2^*} &> -\theta^{1^*} - \theta^{2^*} - \delta \end{aligned} \tag{2.4.11}$$

The structural model that was assumed by Miravete and Pernias (2010) to study complementarity, is:

$$\pi_i^{j^*}\left(s_i^1, s_i^2\right) = \left(\theta^{1^*} + \varepsilon^{1^*}\right)\cdot s_i^1 + \left(\theta^{2^*} + \varepsilon^{2^*}\right)\cdot s_i^2 + \delta \cdot s_i^1 \cdot s_i^2$$

As previously, $\left(\theta^1, \theta^2\right)$ represents the observable characteristics along with $\left(\varepsilon_i^1, \varepsilon_i^2\right)$ as unobservable returns. Identification of these error terms would be resulted in variances σ_1^2 and σ_2^2, and a correlation parameter ρ. A positive value of ρ would indicate that firms that tend to be more profitable in adopting s^1 also tend to be more profitable in adopting s^2, or *vice versa*, even if no profit complementarity exists between the two. Such positive correlation would also capture unobserved heterogeneity among firms in the preference for business activities. Negative correlation, on the other hand, may imply unobserved gains from specialization in one of the activities. The correlation actually presents an identification problem in that correlation between ε_i^1 and ε_i^2 has a similar effect on the payoffs as the complementarity term. Rewriting conditions of assuming maximization principle that are due to joint adoption of business activities, we get the same (1.4.11) set of constraints of multinomial probit (MNP) on the unobserved returns. This suggest that the above structural model can be estimated by MNP. With a MNP, we are able to separate the complementarity effect from that of unobserved heterogeneity, since we can estimate both δ and ρ. We employ the system of constraints (1.4.11), by defining the set S_3 of the combination of errors $\left(\varepsilon_i^1, \varepsilon_i^2\right)$ leading to the joint adoption $(j = 3)$

$$S_3 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta, \varepsilon_i^{1^*} + \varepsilon_i^{2^*} > -\theta^{1^*} - \theta^{2^*} - \delta\right\};$$

Similarly, we define the following set S_1 of the combinations of errors leading to the adoption of cropping only $(j = 1)$

$$S_1 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*}, \varepsilon_i^{2*} < -\theta^{2^*} - \delta, \varepsilon_i^{1^*} - \varepsilon_i^{2^*} > \theta^{2^*} - \theta^{1^*}\right\};$$

symmetrically, the set S_2 of the adoption of livestock only profile $(j = 2)$

$$S_2 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} < -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*}, \varepsilon_i^{2^*} - \varepsilon_i^{1^*} > \theta^{1^*} - \theta^{2^*}\right\};$$

finally, the set S_0 leading to the adoption of none of the aforementioned livelihood activities $(j = 0)$

$$S_0 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} < -\theta^{1^*}, \varepsilon_i^{2^*} < -\theta^{2^*}, \varepsilon_i^{1^*} + \varepsilon_i^{2^*} < -\theta^{1^*} - \theta^{2^*} - \delta\right\}.$$

The purpose of restudying above constraints is to testify our model against the problem of incoherence due to bivariat probit. We show graphically that there is no overlapping between these different sets in either situation of supermodularity $(\delta > 0)$ or submodularity $(\delta < 0)$. Therefore, we can estimate parameters of the model along with the correlation between different adoption choices. That is, it is possible to separate the complementarity between business activities from the unobserved heterogeneity, and thus recover the structural-parameter estimate of complementarity by using multinomial probit (MNP).

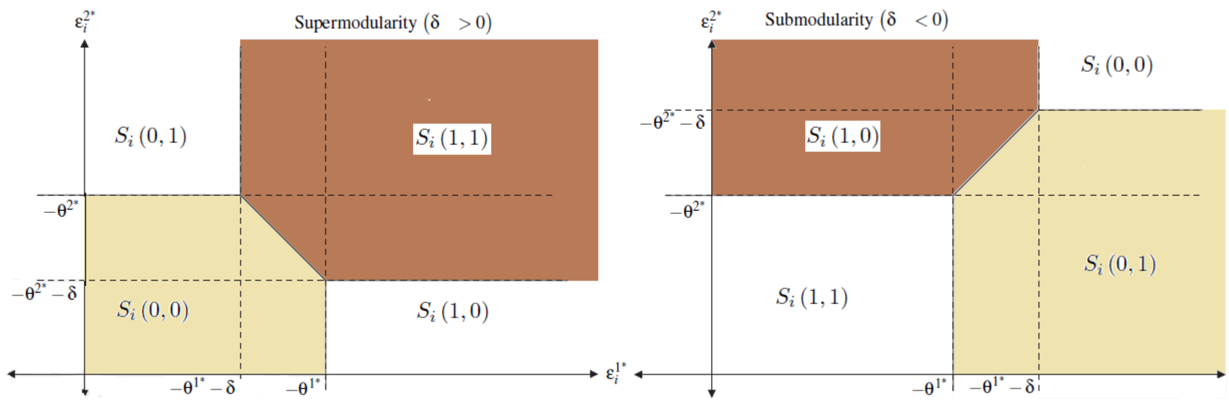


Figure 2.4.2: Profile of adoption of business activities

2.5 Identification

Identification of Multinomial Probit (MNP) model rests on underlying assumptions about the nature of individual decision-making. Statistical methods commonly used to identify models of multinomial choices often impose restrictive assumptions about these choices that render inferences suspect. The first problem is to normalize the location of the latent variable. That is, profits are taken as differenced from others and not the profit itself[6]. We take profits from other sources as the reference for normalization, *i.e.*$\pi_i^*(0,0) = 0$. In this way, profits can explain by how much better or worse a firm would do by adopting either or both activities than would do by adopting other activities than cropping and/or livestock.

The second problem of identification is exclusion restriction. That is, restrictions that certain exogenous variables in the model do not affect the stochastic profits π_i^{k*} of certain alternatives (Keane, 1992). To follow this mechanism data must contain some variables that affect the profit levels of any one activity but not the other.

The third problem is to identify the MNP using estimation techniques. The difficulty with Maximum Likelihood Estimation (MLE) is well known i.e. evaluating integral of multivariate normal densities through MLE is nigh impossible to estimate. When a model consists of higher dimensional alternatives, its identification can be extremely computationally burden-

[6]For details, see Train 2009 for an extensive discussion.

some. Markov Chain Monte Carlo (MCMC) makes the MNP problem much more tractable. The advantage of MCMC over MLE is that for a three or more choice problem it is not difficult to obtain precise estimates of unobserved heterogeneity.

There are other class of multinomial choice models like HEV (Heteroscedastic Extreme Value) but they do not identify the source of unobserved heterogeneity among the profit levels of alternatives and that can also affect complementarity (Gentzkow, 2007). In other words, these models rely on the assumptions of Independence of Irrelevant Alternatives (IIA) and estimate error correlation as zero ($\rho = 0$). Whereas the MNP model can estimate both $\left(\theta^1, \theta^2, \delta^{12}\right)$ which catches complementarity, and $(\rho' s)$ the correlation coefficients between the errors (Gentzkow, 2007).

Chapter 3

Small French Cooperatives quality signaling through Labels and Brands

3.1 Introduction

Despite the general trend of growth in the size of agricultural and agro-industrial cooperatives, small cooperatives, defined as a cooperative with 10 or less full time employees[1], continue to play a significant role in farming activities in France. Indeed, even if the 1 500 small cooperatives represent less than 1% of the processing and marketing activity of agro-food products, they make a total turnover of 3.6 billion euros and are the first intermediary of over 100 000 small farmers. Therefore, they are closely engaged in their production and strategic choices to market access. Since the major factor of survival of these small French farmers is their access to markets, and more particularly to "niche markets" where quality signals may generate some value (Blogowski et al., 2005; Aubert and Perrier-Cornet, 2010), quality signal strategies developed by those small cooperatives are a key factor of rural development in France.

Many quality signals can be used, mainly brands (private signals) and common labels, to foster the development of quality products in the market (Auriol and Schilizzi, 2003; Crespi and Marette, 2003; Lence et al., 2007; Bottega et al., 2009). Previous research has typically focused on either brand or common label efficiency independently, while in many instances

[1] Recall that agricultural cooperative societies form a legal category of society that distinguishes civil and commercial companies. Their operations based on solidarity farmers producers to ensure their supply, processing, marketing, and sale of their products. These cooperatives are exempted from corporation tax provided to operate in accordance with the legal provisions that govern them.

both signals coexist. Agricultural products pairing brand names and certified labels, such as indications of origin, are indeed very common (e.g. Roquefort cheese, Scottish whiskeys and most of the french wines). This chapter aims to understand the different drivers of the quality signal choices made by the small French cooperatives, with a particular focus on the coexistence of both signals[2]. To do this, we use a database from the national survey conducted in 2005 by the ministry of agriculture on the exhaustive sample of 1 500 small French agricultural cooperatives. The four possible quality signal strategies that the cooperative may choose are the following: (i) no quality signal; (ii) common label only (AOC, IGP, AB, ...); (iii) brand only; (iv) mix signal, i.e. both signals (label and brand) are adopted.

To analyze the drivers of these different quality signals, multinomial logit estimations are carried out in our database. The most striking result is the effect of the marketing variables and mainly the export markets. If exporting has a significant and positive effect on adopting a quality signaling, there is a clear differential effects between the specific exporting markets. Exporting outside the EU borders mainly impacts the brand only signal, while exporting inside the EU borders affects the label choice and the mix signal. This result supports the idea that the label only strategy is not relevant outside the domestic market, and outside the EU borders the brand only signal seems to be the more adequate strategy. The second significant result is the impact of the products. For example, branding alone are much more common for fruit and vegetables, as well as for meat, while for beverages products (mainly wine) are mostly common in mix signal (label and brand). Regarding the marketing channel, the most significant variable is the supermarket that impacts mainly the brand strategy (either in a mix signal or in a brand only strategy).

Our results provide also some specific results on the potential complementarity between both signals, i.e. label and brands, by analyzing the drivers of the mix signal. First, among the organizational and governance variables the number of employees (EMP) as well as being member of a union of cooperatives (UNION) and having a subsidiary (SUBSID) have a significant and positive impact. It also appears that this strategy is commonly present in the beverage, as well as in meat and fruits & vegetables, but with less magnitude.

After checking for the robustness of our estimation results in the multinomial logit, we also analyze the possibility of an ordinal ranking among the different quality signals. That is, moving from a no signal strategy then to a common label, a mix signal (label and brand) and then finally to a brand only strategy, may generate a higher profit for the cooperative.

[2]Our database is also original because, in contrast to the previous literature on labels and brands, we analyze the strategic choices done by producers, here the cooperatives of producers, and not by consumers.

We first estimate a simple ordered logit model, whose results show a clear evidence of an ordered choice and bring a confirmation of the different drivers found in the previous multinomial logit model. This simple ordered model makes however the restrictive assumption that the coefficients of the exogenous variables are the same across the quality signal alternatives (parallel regression assumption). To overcome this shortcoming, we have recourse to a generalized ordered model and a sequential logit model. The estimation mainly show some contrasting results, i.e. if the organizational structure and the governance variables are able to explain the adoption of a quality signal (whatever the signal), they have less impact on the choice of a brand (either in a mix signal or a brand only strategy). The increasing impact on brand adoption concerns mainly products such as beverages and meat, and the marketing variables such as exporting outside the EU borders and having recourse to a supermarket marketing channel. That is, it seems that with the move toward a mix signal and a brand only signal the organizational variables becomes less relevant, whereas the impact of marketing drivers seem to increase. The results of the sequential model show clearly that the adoption decision of a quality signal does not follow a sequential process. That is choosing a brand does not necessarily imply that we chose a common label in a first step and a mix signal in a second step. Finally, to deal with the possible endogeneity problem of the turnover variable, we estimate a specific simultaneous equations model where one of the (ordered) dependent variable (quality signal) depends on the second dependent variable (turnover). The results of this bivariate ordered probit model show first that our turnover variable is indeed endogenous and significant and clearly have positive effect on the probability of choosing a higher quality signal. Moreover, we find also the same result than in the generalized ordered model, i.e. the organizational variables have less impact in the choice of a higher quality signal. Our bivariate ordered probit model seems to suggest that this result is due to the fact that the organizational variables have no direct impact on the quality signal choice, but that they have an indirect effect through the increase of the turnover variable.

The remaining sections are organized as follows. In section 3.2 we present and discuss the related literature on quality signaling. Section 3.3 presents our database and the test variables. Section 3.4 presents an ordered choice model and its results. In section 3.5, we consider that the dependent variable may be ordered and estimate ordered and sequential models of choice. We also treat for the endogeneity problem by having recourse to an ordered bivariate probit model. Section 3.6 provides some concluding remarks.

3.2 Related Literature

Quality signaling is widespread in the food and agricultural products, because these products are subject to market failures identified by Stigler (1961) and Akerlof (1970). Since these pioneering contributions, the market failures stemming from information asymmetries have been the object of considerable research. Nelson (1970, 1974) and Darby and Karni (1973) extended Stigler's (1961) economics of information theory by considering how different types of quality or attributes of goods (search, experience, credence)[3] interact with consumer confusion and thus generates more or less severe market failure. This problem of asymmetric information is due to the fact that the producer knows the good attributes that consumers can only determine through search or experience, or cannot determine at all. In the food markets, this problem of asymmetric information impacts negatively on the market: the quality of total supply drops and higher quality goods are driven out of the market, due to adverse selection effect.

In response to the unfair competition from producers who sell lower quality goods at the same price, the producer maintaining the quality of its goods adopts signaling strategies to create a reputation of "high quality producer". In his dynamic models of reputation, Shapiro (1982, 1983) show that in one-shot purchase situations, quality can be better signaled if there exists: (i) reliable quality certification; (ii) informed buyers, such as readership of reviews or consumer reports, that may exert a positive externality on uninformed buyers (Mahenc, 2004). In a repeated purchase setting, when consumers can learn which good provides the desired attribute they buy it, producers can establish a reputation for quality via brands (Klein and Leffler, 1981; Shapiro, 1983; Landes and Posner, 1987, 2003; Grossman and Shapiro, 1988b). Consumers tend indeed to use the quality of products offered by the same brand in the past as an indicator of future levels of quality. Reputation, through brands, embodies expected quality in that individuals extrapolate past behavior to make inferences about quality future behavior. This value judgment develops over time creating an intangible asset. The value of this asset is given by capitalization of future price premia (Belleti, 1999). Even when there is competing brands of the same good, a trademark system can still be more efficient than generic advertising. Crespi and Marette (2002) and Marette and Crespi (2007) show

[3]Search attributes are ones that can be verified prior to purchase through direct inspection or readily available sources. Experience attributes are ones that can be verified only after use of the product (Ford et al., 1990). Credence attributes are ones that are difficult to verify even after use (Darby and Karni, 1973). Products may have one, two, or all three of those types of attributes. For example, in the case of mouthwash, a search attribute would be color, an experience attribute would be taste, and a credence attribute would be plaque reduction.

that high-quality producers do not benefit from generic promotion when the benefits from generic advertising firm increased demand are outweighed by the cost firm lower product differentiation.

If a credible brand system can be an efficient mechanism to signal quality, its cost can be prohibitive for small individual firms and/or small cooperatives in agriculture and food production. This is one of the justifications for specific types of government intervention such as the development of food standards and grades (Gardner, 2003; Lapan and Moschini, 2007). Alternatively, producers, firms and cooperatives can also bundle together to achieve the critical mass required for label certification through a common label. Allowing small producers to collude may indeed improve general welfare by enabling these producers to cover the fixed costs of quality development and certification (Marette et al., 1999; Marette and Crespi, 2003; Zago and Pick, 2004; Lence et al., 2007; Langinier and Babcock, 2008; Mérel, 2009). In many countries in Europe, this common labeling was mainly done with geographically based labels, or geographical indications (GI) such as PGI (Protected Geographical Indications) and PDO (Protected Designation of Origin)[4], where quality attributes are presumed to be linked to the specific geographic origin of the produced goods. This is generally referred to as quality-origin nexus or *terroir*[5]. The collective nature of these common labels as a quality signal means that use of the sign is not limited to a single producer but to all producers within the designation which adhere to code of practice. Product reputation is thus the result of the actions of different agents active in the same area of production and is projected through tradition over a period of time (Marty, 1998). It could be said that GIs are the result of a process whereby collective reputation is institutionalized in order to solve certain problems that arise from information asymmetry and free riding on reputation (Belleti, 1999).

There is a some evidence that common labeling, as an institutionalization of a collective reputation, enable to generate price premium for producers (Thiedig and Sylvander, 2000; Loureiro and McCluskey, 2000). For instance, Loreiro and McCluskey (2000) analyzed the consumer's willingness to pay for GI labels and show that when collective reputation is good, a GI is a powerful tool to promote quality and obtain a price premium[6]. Landon and Smith

[4]In the case of PGI it suffices that one stage of the production process is carried out in the defined area, while in the case of a PDO, all stages of production must take place in this area.

[5]*Terroir*, a French term for "taste of place", refers to a casual relationship between agronomic conditions, craftsmanship and a product's distinct quality (Giovannucci et al., 2009).

[6]Bonnet and Simioni (2001) show in contrast that consumers do not place significant value on the PDO labeled French Camembert and that brand appears to be more relevant in the consumer's evaluation of alternative Products. Gergaud and Livat (2010) find also no significant value on the PDO labeled Bordeaux wine.

(1997, 1998) deepen this analysis and provide an empirical study of the extent to which consumers use both individual and collective reputation current quality indicators when purchasing Bordeaux wine. Two main results emerge. First, there is a huge effect of reputation on price premium. Indeed, the results indicate that the price of Bordeaux wine depends significantly on both expected and current quality, but that marginal impact of expected quality (long-term reputation) on price is approximately 20 times higher than that of current quality. This implies that it take a considerable time for a firm to establish a reputation for high quality that would result in a significant price premium. Second, a collective strategy of reputation building, *e.g.* through GIs, can be more efficient since there can be decreasing marginal cost with reputation building, and positive effect on marginal return. The results suggest that collective reputation indicators play a significant role in price determination, mainly through their impact on expected quality.

But GIs may not necessarily prevent free riding in collective reputation. Winfree and McCluskey (2005) show that with positive collective reputation and no traceability there is an incentive to producers to free ride, i.e. extract rents by producing a lower quality level. And the sustainable level of collective reputation decreases as the number of firms in the production area increases. Chambolle and Giraud-Héraud (1999) and Desquilbet and Monier-Dilhan (2008) also show that a GI can decrease the quality level. Loureiro and McCluskey (2000) show that while the GI label is a powerful tool to promote high quality goods, its use on products that are not of high quality is not an efficient marketing strategy and they suggest that it could impact negatively on the collective reputation. Thus, as shown by Landon and Smith (1997, 1998), it can be efficient to use both collective and individual reputation, by having recourse simultaneously to labels and brands, to solve this problem.

The question that can then be addressed is related to the problem of concurrent use or complementarity between labels (GIs) and brands (trademarks). There is a burgeoning theoretical literature dealing with this issue. Bouamra-Mechemache and Chaaban (2010) investigate whether producers with a quality advantage should collectively choose a GI certification or a private label. Moschini and Menapace (2012) extend the model of Shapiro (1983) to reflect both collective (GIs) and firm-specific (trademarks) reputation in a competitive market. Their main result is that GIs and trademarks turn out to be complementary signals of quality. Indeed, if GIs reveal information regarding the origin of product, it can also reduce costs of building reputation by constraining moral hazard behavior. Therefore, GI certification may improve welfare compared with a situation where only private trademarks would be available for firms. Castinagri et al. (2012), following Tirole (1996) and Winfree and McCluskey

(2005), go one step further and analyze the conditions under which both labels (cooperative reputation) and brands (private reputation) may coexist.

3.3 Data and Description

Our data come from the national survey conducted in 2005 by the ministry of agriculture on the 1 500 small French agricultural cooperatives[7]. This periodical survey aims to study the economic conditions of small agricultural cooperatives processing and marketing excluded from the SCEES[8] annual business survey. From the exhaustive sample of 1500 cooperatives we build a database of 993 individuals after cleaning out missing values, since not the whole cooperatives answered every question.

Although they are small, the size of the cooperatives in our database vary at large since only 10% of these cooperatives realized more than 30% of total sales. Those small cooperatives are also very marked territorially because of the location of their members. That is, more than half are in fact exclusively regional customers, even more than 75% of these make more than 50% of their turnover in the region. Moreover, most of small cooperatives tend to trade with essentially the same type of customers (only 14% do not achieve more than half of their turnover with the same customer). Among the typical customers, other cooperatives occupy a privileged place, indicating the importance of the cooperatives network (Fillipi et Triboulet, 2010). If the majority of small cooperatives develop their activities at the regional level, they realize on average 20% of sales at the national level. 7% of the cooperatives declared exports of their products to other countries and earned 6% of total sales. Exports are mainly oriented to European Union markets and in a lesser extent to out of EU markets. Note that those cooperatives who export are generally the largest small cooperatives, with a median turnover double than those turned exclusively to the domestic market.

3.3.1 Dependent Variables: labels and brands

In the agro-food industry, firms used to adopt two main signals: quality labels and brands. In our database, the different signaling profiles are distributed as follows: *(i)* 30% of small cooperatives use no signal (**NSIG**); *(ii)* 48% of them uses only labels (**LABEL**); *(iii)* 5% uses only brands (**BRAND**); *(iv)* 18% of the cooperatives use a "mix signal" strategy by adopting

[7]Enquête sur les petites coopératives agricoles et forestières, 2005.

[8]Service centrale des enquêtes et des études statistiques (Central office for statistical surveys and studies).

both signals (**LABRAND**).

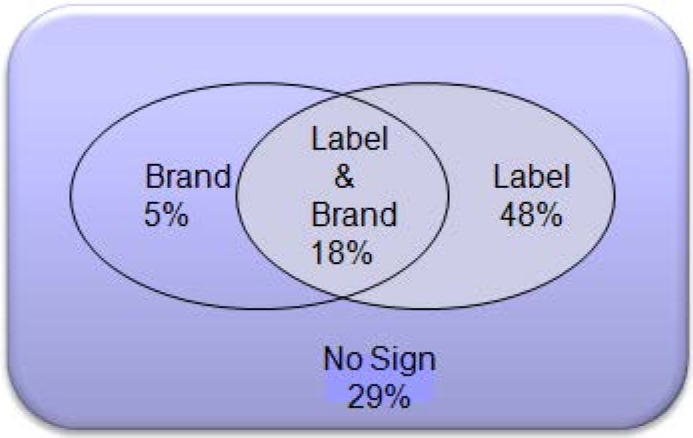


Figure 3.3.1: Distribution of quality signs

First, since the official signs (labels) are widespread in the French agro-food sector, it is not surprising to note that two third of small cooperatives adopt labels. As shown by table 3.1, among the different labels enforced by the French state regulation, there is a large predominance of signs indicating the geographical origin of products (AOC and PGI). Those signs are especially developed for wine and cheese, and more generally 79% of dairy products and 64% of alcoholic beverages are sold by small cooperatives with a label indicating the geographical origin of the product. Other labels hold a significant position with a relatively high organic farming (AB)[9]. The cooperatives may also adopt different labels. Indeed, labels are non-exclusive since different labels can be used to point out different dimensions of quality (The "label rouge" can be chosen to signal organoleptic quality of the product, and the label "AB" to signal its "environmental-friendly" dimension). However, in our database, very few cooperatives among those that use the label strategy adopt more than one label (see table 3.2).

Table 3.1: Dominance of labels

AOC	AB	PGI	CPP	Label	Others
60%	12%	8%	4%	3%	13%

[9]Label Rouge certify that processed and unprocessed food or non-food agricultural products have specific characteristics establishing a level of quality, resulting in particular from their particular conditions of production or manufacture and conform to specifications which distinguish them from similar products and foodstuffs normally sold.

Second, branding is much less common since it concerns less than a quarter of small cooperatives (22%). A notable fact is that brands are primarily associated with a label (18% of the whole sample and 75% of the cooperatives that choose the brand signal), while very few choose to hold only a brand (5% of the whole sample and 25% of those choosing a brand).

Small businesses do not always have the ability to develop their own financial trademarks and many produce on behalf of major brands. This is partly explained by specific institutional features: the wide dissemination of official quality labels. This type of quality labels has the advantage for small cooperatives to collectivize the costs of establishment and implementation of the signal, which allows them to not only assume the economic burden but management of a brand as well.

Table 3.2: Labels owned

no label	35%		
at least one label	65%	Number of labels owned	
		1	85%
		2	12%
		3	2%
		4	1%

3.3.2 Independent Variables

Different variables may explain the choice of quality signals. First, the turn-over realized by the cooperative. The continuous variable **TURN** indicates the log of turnover (millions euros) realized in 2005 by the cooperative. However, to perform their turnover, cooperative structures suffer from lower levels of labor force than capitalist structures. Indeed, a cooperative is defined to be small if it has less than ten employees. We build a variable indicating the number of employees (**EMP**). On average, the cooperatives in our database have less than 4 full-time equivalent employees. But we observe a large variability since some cooperatives have no employees, while others are at the threshold of 10 employees. Due to this limited workforce, farmers, as members of the cooperative, do a large number of jobs mainly in seasonal periods of intense activity for the cooperative. The continuous variable **MEM** indicates the total number of members in log (Table (3.3)).

The other solution to get workforce, equity and new competencies is to join a union of co-operative (Filippi et al. 2006). The membership to a union of cooperatives is indicated by the dummy variable, **UNION**. In our database, nearly 40% of the small cooperatives join an union. These unions take the form of new cooperatives as an umbrella for the associated cooperatives. The consolidation of equity can then carry the heavy equipment that the cooperative base alone cannot achieve. To expand its scope and develop a certain critical size, the cooperative may also hold shares in the capital of other (private) firms. When the holdings reach 50% or more, the firm becomes subsidiary owned by the cooperative. We build a dummy variable **SUBSID** indicating when the cooperative has a subsidiary firm. This organizational model is often seen as a mechanism for the cooperative to market directly its products by creating a marketing firm that sell the products under its own brand (Hendriksen and Bijman, 2002). However, this strategy only refers to 15% of the small cooperatives, mainly those which have the highest turnover.

The second set of variables that may explain the choice of quality signal is related to the nature of the activity and the products of the cooperative, as well as the market structure and the different marketing channels used. There is a clear cut distinction in our database between cooperatives that are just intermediary of exchange (wholesale industries) and co-operatives that industrially processes the products collected from their members. The first category represents 63% of the whole sample and the second 37%. The two categories are very different in their structures. Within the agro-food industry, the wine making activity (60% of the cooperatives) and the dairy industry (25% of the cooperatives) are predominant. As noted previously, these are the two activities where the labels are over-represented. To take into account the effect of the agro-food industry on the signaling strategy, we create a dummy variable **AF** that indicates if the small cooperative processes the farmer's products. In the wholesale trade, there is no dominant activity and the first three sectors are milk, eggs and oil (25%), grain and animal feed (20%) and fruit and vegetables (17%); sectors where labels are less represented. To analyze more precisely the effect of the different types of product, we build five dummy variables representing the five main sectors of production: *(i)* Beverage, mainly wine (**BEV**), *(ii)* cereals and animal feed (**CER**), *(iii)* fruit and vegetables (**FVEG**); *(iv)* meat (**MEAT**); *(v)* milk, eggs and oil (**MILKOIL**).

Small cooperatives are also marked territorially because of the location of their members. This local anchor is often found in the type of market and marketing channel mainly used by small cooperatives. Regarding the type of market, more than half of the cooperatives have regional customers exclusively and three quarters of them make more than 50% of their turnover in the region. We have a dummy variable, (**LT50INREG**), which equals one when the cooperative makes less than 50% of its turnover in the region. Export market represents 3% of total sales on average and essentially turned towards the European Union. But, given their size a significant proportion exported beyond the borders of Europe (5%). Note that the cooperatives that export with a median turnover of around double than the cooperative turned exclusively to the domestic market. We build two continuous variables for the exporting cooperatives: *(i)* percentage of total sales from export in Europe (**EXINEU**); *(ii)* percentage of total sales from export outside EU (**EXOUTEU**). 44% of total sales are being exported with the brand and public label. 8.5% of total sales that is exported in EU are without any public label or brand, and 12% of total sales that export outside EU use brand and label signals.

As for the marketing channel, we notice that most small cooperatives tend to trade with essentially the same type of client (86%). We build a variable that equals one when the cooperative makes less than 50% of its turnover with the same client (**LT50SC**). We control for the different kind of channels, according to the cooperative sells its product to Supermarket (**SUPER**), retailers (**RET**), wholesalers (**WS**), or hotels and restaurants (**OTHER_HOT**).

Table 3.3: Description of variables

Variable	Definition	Mean	S. D.	Min.	Max.
Size and organizational structure					
MEM	Logarithmic value of no. of adherents	3.83	1.26	0.00	8.07
EMP	Number of employees (from 0 to 10)	3.53	3.64	0.00	10.00
UNION	= 1 if coop is affiliated with an Union	0.40	0.49	0.00	1.00
SUBSID	= 1 if coop is subsidizing	0.14	0.34	0.00	1.00
TURN	Logarithmic value of turnover (millions €)	13.7	1.86	0.00	17.26
Activity					
WSI	= 1 if coop is a Wholesale industry	0.30	0.46	0.00	1.00
AF	= 1 if coop is an Agro-food industry	0.69	0.46	0.00	1.00
Products					
MILKOIL	= 1 if coop produces milk & oil (reference)	0.28	0.45	0.00	1.00
BEV	= 1 if coop produces beverages	0.48	0.50	0.00	1.00
CER	= 1 if coop produces cereals	0.06	0.23	0.00	1.00
FVEG	= 1 if coop produces fruits & vegetables	0.07	0.26	0.00	1.00
MEAT	= 1 if coop produces meat	0.05	0.22	0.00	1.00
OTHERS	=1 if coop produces other products	0.05	0.22	0.00	1.00
Export Markets					
EXINEU	% of Turnover by exports within EU	0.35	0.89	-0.47	4.60
EXOUTEU	% of Turnover by exports outside EU	0.06	0.39	0.39	4.60

Variable	Definition	Mean	S. D.	Min.	Max.
Local Market					
LT50INREG	= 1 if less than 50% turnover in the same region	0.21	0.41	0.00	1.00
Marketing Channels					
- cooperative network	= 1 if dealing with a coop network (ref)	0.29	0.45	0.00	1.00
- SUPER	= 1 if dealing with supermarket	0.05	0.21	0.00	1.00
- RET	= 1 if dealing with a retailer	0.10	0.29	0.00	1.00
-WS	=1 if dealing with a wholesaler	0.18	0.18	0.00	1.00
- OTHERS_HOT	= 1 if dealing with hotels & restaurants	0.23	0.42	0.00	1.00
LT50SC	= 1 if less than 50% of turnover with the same customer	0.14	0.35	0.00	1.00

Table 3.4: Descriptive statistics

	All	NSIG	LABEL	LABRAND	BRAND
UNION	40%	30%	46%	40%	48%
SUBSID	14%	11%	14%	22%	14%
TURN (median)	1.28	0.75	1.40	1.74	1.60
MEM (median)	52	60	36	75	112
EMP (median)	3	1	3	5	5
AF	69%	51%	77%	77%	80%
WSI	31%	49%	23%	23%	20%
FVEG	7.5%	8%	6.5%	7.5%	12%
MEAT	28.5%	23%	42%	6%	8%
MILKOIL	5%	5%	4.5%	7%	6%
OTHERS	5%	13%	1%	2%	4%
EXINEU	20%	8.5%	16%	44%	26%
EXOUTEU	5%	2%	3.5%	12%	10%
LT50INREG	21.5%	19%	16%	35%	42%
cooperative network	30%	32.5%	33%	17%	26%
SUPER	5%	3%	4%	8.5%	16%
RET	10%	15%	7%	8.5%	10%
WS	18%	12.5%	19%	24.5%	24%
OTHERS_HOT	23%	28.5%	22%	19%	14%
LT50SC	14%	8.5%	15%	22.5%	10%
Number of observations	993 (100%)	293 (29.5%)	475 (48%)	175 (18%)	50 (5%)

3.4 Unordered Choices

In this section we try to find the drivers of the different quality signal strategies. For this we use the multinomial unordered choice model. We first present the methodology for estimating this type of model (3.4.1) and the results of the estimations (3.4.2). Then we discuss the robustness of our estimates (3.4.3).

3.4.1 The Empirical Model

Considering the four quality signal alternatives, let us denote: *(i)* $m = 1$, if the cooperative chooses no signal; *(ii)* $m = 2$, if the cooperative chooses a common label only; *(iii)* $m = 3$, if the cooperative chooses both signals (label and brand); *(iv)* $m = 4$, chooses brand only.

Choosing the alternative m of a quality signal can be seen as the realization of a latent (unobserved) variable u_m^*. Suppose that the utility derived from this choice depends linearly on a set of exogenous variables $\mathbf{x}$ and an error term ε. The distribution law of the error term defines the model for estimating the probability of occurrence of the alternative considered (probit or logit). The probability of choosing the alternative m is:

$$\Pr(y = m) = \Pr(u_m^* > u_j^*), \forall j \neq m \qquad \text{with } u_m^* = \mathbf{x}\beta + \varepsilon \tag{3.4.1}$$

In the classical case of a choice model with two categories, the estimated probability of occurrence of the alternative considered is a binary probit or logit model. If several alternatives are possible, without predefined order, the probability of each alternative should be jointly estimated with an alternative, taken as a reference. The econometric model required is then a multinomial logit or probit according to the the law of distribution on error terms (Maddala, 1985).

Among the four alternatives, the multinomial model estimates the probabilities of three alternatives and one alternative taken as reference. Therefore we can estimate the probabilities of alternatives 1, 3 and 4 using alternative 2 as a reference. That is,

$$P_m = \Pr(y = m) = \frac{\exp(\mathbf{x}\beta_{m|2})}{P_2} \text{ for } m = 1, 3, 4 \tag{3.4.2}$$

where

$$P_2 = \frac{1}{1 + \sum_{\substack{j=3 \\ j \neq 2}}^{j=4} \exp(\mathbf{x}\beta_{j|2})} \tag{3.4.3}$$

with $\sum_{m=1}^{m=4} P_m = 1, \mathbf{x}$ a vector of k exogenous variables common to the four alternatives and $\beta_{m|2}$ the vector of estimated coefficients for the alternative m, with $m = 1,3,4$, when the alternative 2 is the reference (i.e. $\beta_{m|2} = 0$).

Since the estimated coefficients β of logistic models are not directly interpretable, it is useful to present the results directly in the form of odds; or more precisely, in the form of odds ratio (OR). These allow to observe directly how a marginal effect of the explanatory variable changes the odds ratio considered, by exponentiating the estimated coefficients. As part of binary logistic model, the interpretation of OR is relatively easy because the ratio is equal to the probability of the event on the probability of the opposite event. That is, the odds can be written as follows

$$Odds = \frac{P_1}{(1-P_1)} = \frac{\Pr(y=1\,|\mathbf{x})}{1-\Pr(y=1\,|\mathbf{x})} = \exp(\mathbf{x}\beta)$$

and the odd ratios

$$OR(x_k\,|\mathbf{x}) = \frac{\Pr(y=1\,|x_{k+1},\mathbf{x})/1-\Pr(y=1\,|x_{k+1},\mathbf{x})}{\Pr(y=1\,|x_k,\mathbf{x})/1-\Pr(y=1\,|x_k,\mathbf{x}} = \exp(\beta_k)$$

In a multinomial logit model, the analysis is more complex since several events are considered. Therefore, the odds ratios for each alternative relative to the reference category are not an odd, which is a likelihood ratio of an event on its opposite event. The conditional odds ratios (denoted COR), also referred to as relative risk ratio, is preferred in this case. In a conditional odds ratio, each likelihood ratio is relative to the probability taken as reference (here alternative 2).

$$\text{Conditional Odds}_m\text{ (X)} = \frac{P_m}{P_2} = \frac{\Pr(y=m\,|\mathbf{x})}{1-\Pr(y=2\,|\mathbf{x})} = \exp(\mathbf{x}\beta_{m|2}) \text{ for } m = 1,3,4$$

or

$$COR_{m|2}\,(x_k\,|\mathbf{x}) = \frac{\Pr(y=m\,|x_{k+1},\mathbf{x})/\Pr(y=2\,|x_k+1,\mathbf{x})}{\Pr(y=m\,|x_k,\mathbf{x})/\Pr(y=2\,|x_k,\mathbf{x}} = \exp(\beta_{k,m|2}) \quad \text{for } m = 1,3,4$$

The COR can thus assess whether an explanatory variable increases or decreases the probability of choosing one alternative relative to the alternative taken as reference. For example, in the above equation an increase of one unit of the variable x_k rises by β_k the probability of occurrence of the alternative m, if we take the alternative 2 as the reference.

3.4.2 Results and Interpretations

The results of the multinomial logit model that we estimated are directly presented in the form of exponentiated coefficients (see Table 4) [10]. The interpretation of these results reveals some major stylized facts about the quality signal strategies by small French agricultural cooperatives. Our results exhibit two kinds of drivers of the quality signal strategies: *(i)* the organizational and governance structure variables; *(ii)* the products and market types.

Organizational and governance effects. Our results exhibit an organizational effect since there is a positive correlation between the size of the cooperative and the probability of choosing a signal. Indeed, as the number of members increases, the likelihood of developing a mix signal or a brand only strategy also increases. In other words, the smallest among the cooperatives would be significantly less likely to develop a brand. Similarly, compared to the probability of holding a signal in isolation (common label alone, or brand alone), a higher number of employees increases the probability of choosing a «mix signal» (both signals, label and brand) and to decrease the probability of choosing no signal. As seen previously, the management of a mix signal or a brand is relatively more expensive than a common label or no signaling. Thus, it requires a larger size (Strong et al., 2007). There is also a governance effect since belonging to a network of cooperatives increases the probability of choosing a signal. Indeed, the fact that the cooperative belongs to a Union of cooperatives (UNION), or has a subsidiary firm (SUBSID), reduces by 50% the probability of choosing no signal.

Products and market effects. In the food industry (FI), choosing a single signal (label only or brand only) is more common than in the wholesale trade. Beyond the effect, the type of marketed products has also some impact on the signaling strategy. In dairy products and fats (MILKOIL), it seems that labels are more commonly adopted, whereas this strategy is less developed in Fruit and Vegetables (FEV) or in beverages (BEV), where brands are more commonly used. The table 4 below details the effect of the different products on the probability of choosing a specific quality signal.

Signaling strategy depends also on the type of markets (Lockshin, 2004; Chan Choi and Coughlan, 2006; Hayes et al., 2007). First, it seems that there is an effect of the local mar-

[10] Let us recall that the interpretation of these coefficients is not uniform. It depends on the shape of the explanatory variable (Long 1997). How to interpret these effects depending on whether the explanatory variable is a continuous variable, a dichotomous variable or a polytomous variable with more than two modalities. Indeed, from the estimated coefficients, it is possible to calculate the percentage increase (or decrease) the probability of an alternative over another. Beyond the calculation of these marginal effects, it is interesting to analyze the relative influence of variables on these alternatives.

Table 3.5: Productions and probability of adopting signals

		Products			
		BEV	CER	FVG	MEAT
Alternatives	LABEL	Ref.	Ref.	Ref.	Ref.
	LABRAND	+11	n.s	+4 (*)	+5
	BRAND	+4	n.s	+11(**)	n.s
	NOSIG	+2	+13	+3	n.s

Reading: (*) Compared to the milk and fat, cooperatives in the fruit and vegetables have a chance to own a brand 11 times greater than that of holding an official label alone. (**) The superimposition of a brand to an official label is also more common in this sector than the mere holding of an official label, but to a lesser extent than for the single brand strategy: the probability of reporting quality by both the brand and the official label is four times greater than that of holding an official label.

ket on the signaling strategy. We find that regional market oriented cooperatives are more likely to choose common labels, while those oriented towards the national market are more focused on the brand choice, all things being equal. This can be explained by the territorial anchorage of the smallest among the cooperatives (Filippi and Triboulet, 2006), while those that have access to the national market are also those that have higher turnover, and thus are able to manage more costly quality signals (mix signal and brand) than the common label. Signaling strategies seem also to differ according to the export market. They choose a mix signal strategy for export in EU (EXINEU) and a brand only strategy for export outside the EU (EXOUTEU). Indeed, the probability of choosing a brand rather than a label increases with the share of sales devoted to exports outside the European Union. This can be explained by the difficulty for a common label system to protect its co-owners against fraud outside the EU borders, and the fact that the tradmark system is more able to protect the property rights on the brand than the common labeling system. The other shortcoming is the problem of free-riding that often emerges from common labeling (Chambolle and Giraud-Héraud, 1999; Winfree and McCluskey, 2005; Desquilbet and Monier-Dilhan, 2008; Loureiro and McCluskey, 2000). This may explain why cooperatives exporting in the EU use a mix signal (LABRAND) within the European borders. Indeed, we observe that the export in the European Union instead favors the strategy of a mix signal in relation to a strategy based on a single signal (brand or label). This is also the case in the wine sector where a brand name is often added to the common label indicating the origin of the product (a castel name, e.g

Chateau Latour in the "AOC Pouillac"; or a family name, *e.g.* Taittinger in the "AOC Champagne"). Finally, the marketing channels used by the cooperative (its cooperative network, supermarkets, small retailers, wholesalers, hostels and others) have an impact on the probability of chosing a quality signal. For the no-signal strategy, there is no significant effect of the different channels compared to the reference, *i.e.* the cooperative network. For the two other signals, choosing supermarket (SUPER) increases the probability of holding a brand only or a mix signal. These probabilities are multiplied respectively by 4 and 3, compared to the probability of choosing the reference (common labeling).

Table 3.6: Multinomial logit estimation

Variable Name & Category	LABRAND	BRAND	NSIG
	COR 3/2	COR 4/2	COR 1/2
Size and organizational structure			
MEM	1.23 (1.95)*	2.02 (4.25)***	1.41 (4.24)***
EMP	1.07 (2.43)**	1.05 (1.06)	0.91 (-2.60)***
TURN	0.92 (-0.81)	0.77 (-2.18)**	0.69 (-5.69)***
UNION	0.61 (-2.30)**	0.70 (-1.00)	0.48 (-3.72)***
SUBSID	1.45 (1.42)	0.68 (-0.82)	0.58 (-1.89)*
Sectors			
WSI	Ref.	Ref.	Ref.
AF	0.41 (-2.37)**	1.51 (0.61)	0.44 (-3.11)***
Products			
MILKOIL	Ref.	Ref.	Ref.
BEV	10.91 (6.17)***	3.67 (2.16)**	2.23 (3.38)***
CER	3.09 (1.55)	3.65 (0.99)	12.78 (5.46)***
FVEG	4.20 (2.80)***	11.10 (2.91)***	2.60 (2.64)***
MEAT	5.20 (3.15)***	4.09 (1.55)	1.57 (1.06)
OTHERS	4.32 (1.92)*	8.31 (1.89)*	8.48 (4.25)***
Export Markets			
EXINEU	1.25 (2.18)**	1.13 (0.70)	0.76 (-2.06)**
EXOUTEU	1.32 (1.00)	2.14 (2.36)**	1.67 (2.04)**

Variable Name & Category	LABRAND	BRAND	NSIG
	COR 3/2	COR 4/2	COR 1/2
Local Market			
LT50INREG	1.32 (1.18)	2.29 (2.29)**	1.56 (1.76)*
Marketing Channels			
cooperative network	Ref.	Ref.	Ref.
SUPER	2.60 (2.18)**	3.79 (2.40)**	0.82 (-0.40)
RET	2.04 (1.68)*	1.06 (0.10)	0.88 (-0.38)
WS	1.89 (2.06)**	1.07 (0.15)	0.73 (-1.12)
OTHERS_HOT	1.43 (1.13)	0.59 (-0.98)	1.25 (0.92)
LT50SC	1.92 (2.02)**	0.48 (-1.23)	0.41 (-2.65)***
Constant	-2.61 (-1.91)**	-3.18 (-1.65)*	3.83 (4.20)***
LL		-914.5	
χ_2		493.3***	

* Significant at 10%; ** Significant at 5%; *** Significant at 1% ; t statistic in paranthesis

3.4.3 Robustness of the Estimates

The multinomial logit is a very convenient model for estimating discrete choices, but it has some limitations. An important restriction is the assumption of independence of irrelevant alternatives (IIA), that the odds ratios between the alternatives are independent. The Hausman & McFadden (1984) and the Small & Hsiao (1985) tests are the most usual statistical tests used in the literature to verify the validity of such assumption. In table 3.7, we first report the results of the Hausman & McFadden test. We run three tests: the first two correspond to excluding one of the two non-base categories. The third test (Label only) is computed by re-estimating the model using the largest remaining category as the base category. For the two separate adoption choices of 'brand only' and 'label only', we are unable to estimate the p-values probably due to the negative estimates of chi^2. Hausman & McFadden (1984,

p. 1226) note this possibility and conclude that a negative result is evidence that IIA has not been violated. In spite of that we are inconclusive about acceptance or rejection of null hypothesis.

Table 3.7: Hausman-McFadden test of independence

Omitted	χ^2	df	$p > \chi^2$	evidence
Brand only	-4.323	20	—-	—-
None	2.237	20	1.00	for H_0
Label only	-3.655	20	—-	—-

The second test is the Small & Hsiao one. To perform this test, the sample is divided randomly into two sub samples of about equal sizes. Then the unrestricted multinomial logit model is estimated on both sub samples (the results for which are shown in second column of Table 3.8). Then a restricted sample is created from the second sub sample by eliminating all cases with a chosen value of the dependent variable (the results are presented in third column of Table 3.8). In contrast to the Haussman & McFadden test, the results of the Small & Hsiao test results are conclusive: all the alternative choices are independent of each other.

Table 3.8: Small and Hsiao test of independence

Omitted	lnL(full)	lnL(omit)	χ^2	df	$p > \chi^2$	evidence
Brand only	-206.602	-193.982	25.239	20	0.192	for H_0
None	-73.501	-61.257	24.487	20	0.222	for H_0
Label only	-57.798	-46.700	22.195	20	0.330	for H_0

However, recent literature on the subject shows that both tests do not always generate the right decision. So Long and Freese (2006), who observed that these tests can lead to conflicting results, do not encourage their use. Similarly Cheng and Long (2006) show, from a series of Monte Carlo simulations, that the tests reject the hypothesis of IIA when the alternatives seem distinct and rather do not reject it while alternatives seem a priori close substitutes. It appears preferable to return to first precepts of McFadden (1973) for which verification of this assumption come directly to the user in the choice of alternatives jointly estimated.

Following this advice, our estimates in table 3.6 seem to suggest that the different alternatives (quality signals) are independent. First, because as shown, the common label is more often used in local markets while brands are mainly used for export market, especially outside EU borders. Moreover, the «mix signal» strategy is mainly adopted to solve the «free riding problem» encountered by the common label system. As indicated previously, this strategy is frequently encountered in the wine sector. Since the AOC can only ensure a minimum quality, the high quality producers need to use another strategy to signal the higher quality of their wine (Chambolle and Giraud-Héraud, 2003). Therefore, by targeting a higher market segment, the mix signal strategy can be seen as a close substitute for common label signal.

The Wald test on the alternatives in the multinomial logit seems also to confirm this result, since the drivers for the different alternatives are clearly different (see table 3.9). Only the drivers for the brand alone signal (alternative 4) are not so far from the «mix signal» strategy (alternative 3). To take this into account, we think that it will be interesting to consider another class of models, *i.e.* ordered models.

Table 3.9: Wald test

Alternatives combination *i/j* tested	χ^2	$p > \chi^2$
3/4	25.193	0.154
3/1	139.750	0.000
3/2	101.710	0.000
4/1	64.059	0.000
4/2	52.886	0.000
1/2	162.751	0.000

3.5 Ordered and Sequential Choices

In the previous section we made implicitly the assumption that the different signals are unordered. However, it seems that moving from no-signal strategy to the label and/or brand strategy may generate higher net value for the cooperative. That is, the dependent variable may be ordered, with the following order of the quality signals. In the first step, the cooperative may choose no signal in the market, neither label nor brand. Second, the cooperative may get a higher profit by choosing to signal its products with a common label. With a signal, the cooperative may indeed extract a higher value from the consumers or its customers while the cost of being a co-owner of a label is rather limited since the fixed costs of quality development and certification of the common label is shared among the members of "the club" (Langinier and Babcock, 2008; Mérel, 2009). However, as shown by Winfree and McCluskey (2005), common labeling may not necessarily prevent free riding in collective reputation, which may harm the high quality producers. Therefore, the cooperative may move to a "mix signal", where a private signal (brand) is added to the common label. By using a brand, it can signal its high quality producer status and thus may increase its profit by reducing the negative impact on collective reputation generated by free riders. The cooperative may also move directly to a brand only strategy. This strategy can be more costly since the cooperative has to bear solely the management cost of its brand, but larger cooperative have some economies of scale and have access to high worthy export markets, which may increase dramatically its profit.

If we consider that the quality signal choice is ordered, then using a multinomial model as previously may introduce bias in our results since it ignores the ordinal character of the dependent variable. That is why we have recourse to ordered models, and in this section we propose to test several of these models (Maddala, 1985; Long, 1997; Long and Freese 2006; Green and Hensher, 2008). In what follows, we first estimate a simple ordered logit model and discuss its results. However, this model depends on a restrictive assumption, the proportional odds assumption, where the coefficients of the exogenous variables have to be the same regardless of the alternative considered. Since this assumption is rejected by the two tests conducted, we have recourse to two models that do not impose such restrictive assumption, *i.e.* the generalized ordered model (3.5.2) and the sequential model (3.5.3). Moreover, to deal with the endogeneity problem of the turnover variable, we estimate a simultaneous equations model. To do so, we have recourse to a bivariate ordered probit model (3.5.4).

3.5.1 Simple Ordered Logit Model

Since an ordered model with m alternatives can be written in terms of $m-1$ thresholds, then, among the four signals, a cooperative i chooses a signal s_i if:

$$s_i = \begin{cases} 1 \text{ if } s_i^* < \alpha_1 \\ 2 \text{ if } \alpha_1 \leq s_i^* < \alpha_2 \\ 3 \text{ if } \alpha_2 \leq s_i^* < \alpha_3 \\ 4 \text{ if } s_i^* \geq \alpha_3 \end{cases} \quad \text{with } s_i^* = \mathbf{x}_i\beta + \varepsilon_i$$

where s_i^* is an unobservable latent variable. This model estimates each probability as a linear function of exogenous variables $\mathbf{x}$ and the thresholds α_j

$$\Pr(s = j\,|\mathbf{x}) = \Pr(\alpha_{j-1} \leq s_i^* < \alpha_j\,|\mathbf{x}) = F(\alpha_j - \mathbf{x}\beta) - F(\alpha_{j-1} - \mathbf{x}\beta) \quad \forall j = 1,4 \tag{3.5.1}$$

where F is the distribution function of the logistic part of an ordered logit model.

The estimated coefficients cannot be directly compared to the multinomial model. Indeed, in this latter the effect of an exogenous variable is interpreted by comparing each alternative separately, whereas in the ordered model the alternatives are grouped or ordered. That is with four alternatives, we compare: *(i)* "alternative 1 against the group (2, 3 and 4)" ; *(ii)* " (1, 2) against (3 and 4)"; *(iii)* "(1, 2, 3, 4) against 4". More precisely, we can interpret the results of these comparisons between groups of alternatives as the choice to move, respectively: *(i)* from a no quality signal strategy to a signal strategy (that can be either a common label only, a mix signal, a brand only); *(ii)* to a brand strategy, which consists in a mix signal (label and brand) or a brand only; *(iii)* to a brand strategy only. Note that the constant is supposed to be zero, in order to highlight the effects of the different thresholds separating the different choices.

As previously, for ease of interpretation the coefficients are presented in terms of odds ratio. As was discussed in the previous section, the OR refers to a likelihood ratio that exponentiate coefficients to assess the effect of an incremental change in the exogeneous variable.

$$Odds_{\leq s|>s}(\mathbf{x}) = \Omega_{\leq s|>s}(\mathbf{x}) = \frac{\Pr(y \leq s\,|\mathbf{x})}{1 - \Pr(y > s\,|\mathbf{x})} = \exp(\alpha_s - \mathbf{x}\beta) \text{ for } s = 1, \ldots, 4 \tag{3.5.2}$$

and the odd ratios

$$OR_{\leq s|>s}(x_k\,|\mathbf{x}) = \frac{\Omega_{\leq s|>s}(x_k + 1, \mathbf{x})}{\Omega_{\leq s|>s}(x_k, \mathbf{x})} = \frac{\Pr(y \leq s\,|x_k + 1, \mathbf{x}) / \Pr(y > s\,|x_k + 1, \mathbf{x})}{\Pr(y \leq s\,|x_k, \mathbf{x}) / \Pr(y > s\,|x_k, \mathbf{x}} = \exp(-\beta_k) \tag{3.5.3}$$

Thus, in the model 2.5.3 the odds ratio of the alternative 1 against the other three alternatives is given by:

$$\Omega_{1|2,3,4}(\mathbf{x}) = \frac{\Pr(m \leq 1\,|\mathbf{x})}{\Pr(m > 1\,|\mathbf{x})} = \exp(\alpha_1 - \mathbf{x}\beta)$$

The effect of unit variation of the variable x_k is:

$$OR_{1|2,3,4}(\mathbf{x}) = \frac{\Omega_{1|2,3,4}(x_k+1,\mathbf{x})}{\Omega_{1|2,3,4}(x_k,\mathbf{x})} = \exp(-\beta_k)$$

Similarly, the odds ratio of alternatives 1 and 2 against alternatives 3 are:

$$\Omega_{1,2|3,4}(\mathbf{x}) = \frac{\Pr(s \leq 2\,|\mathbf{x})}{\Pr(s > 2\,|\mathbf{x})} = \exp(\alpha_2 - \mathbf{x}\beta)$$

$$OR_{1,2|3,4}(\mathbf{x}) = \frac{\Omega_{1,2|3,4}(x_k+1,\mathbf{x})}{\Omega_{1,2|3,4}(x_k,\mathbf{x})} = \exp(-\beta_k)$$

The same formula is applied to derive the OR of the alternatives 1,2,3 against the alternative 4. We notice that whatever the comparison of strategies considered, the OR is constant since only one vector of parameters β is estimated. Indeed, a unit increase in the exogenous variable leads to the probability of choosing a strategy relative to other strategies[11] by a factor equal to $\exp(-\beta_k)$.

Our estimation results of the simple ordered model (see table 3.11, model 1) clearly shows that there is some order among the different quality signals. Indeed, the whole cutoff points are significant and positive and their value is increasing. In contrast, the drivers of the decision to move toward a more intensive quality signals seem to be very similar to those found in the previous non-ordered model. First, the organizational and the governance variables have the same effect. Indeed, the turnover, the number of employees on one side and being a member of a union of cooperatives or holding a subsidiary on the other side, have a positive and significant coefficient. That is, the larger the cooperative size, the higher the intensity of the quality signal. Regarding the products and market effects, the drivers of the quality signal intensity are the same than for the brand only strategy in the previous non-ordered model (see table 3.6). In terms of products, compared to milk and oil products, selling beverages and cereals increases the probability of having a higher quality signal. In terms of market, a larger share of export outside the EU borders as well as choosing a supermarket marketing channel and a small number of partners (LT50SC) increases the probability of a change toward a more intensive quality signal.

[11]Or the choice of strategies (1, 2) against strategies (3,4), or the strategies (1,2, 3) against strategy 4.

The proportional odds assumption. If our results give a confirmation of a significant ordinal relationship, they do not highlight differential effects choice in the progression of quality signal. Indeed, in the ordinal model, there is an implicit assumption known as both the *parallel regression assumption* and, for the ordinal logit model, the *proportional odds assumption*. This assumption simply says that the coefficients β are identical across each regression. From (3.5.1) which gives the standard predicted probability

$$\Pr(y = s\,|x) = F(\alpha_s - \mathbf{x}\beta) - F(\alpha_{s-1} - \mathbf{x}\beta) \text{ for } s = 1, ..., J$$

we can derive the estimate from the $J-1$ binary regressions

$$\Pr(y \leq s) = F(\alpha_s - \mathbf{x}\beta) \quad \text{for } s = 1, ..., J-1$$

The proportional odds assumption implies that $\beta_1 = \beta_2 = ... = \beta_{J-1}$. To the degree that the assumption holds, the coefficients $\widehat{\beta}_1 = \widehat{\beta}_2 = ... = \widehat{\beta}_{J-1}$ should be close.

To perform this comparison, we can use two tests. First, the log likelihood ratio test that compares the log likelihood from the ordinal logit model with that obtained from pooling there (i.e. $J-1$) binary models fitted with the logit model. Our results show that the assumption can be rejected at the 1% level. However, this LR procedure tests that the coefficients for all variables are simultaneously equal. That is, it cannot discriminate between coefficients that are identical across the binary equations and those that differ for other variables. The Wald test proposed by Brant (1990) overcome the shortcoming since it tests the assumption for each variable. However, our results in table 3.10 for model 1 (see tables 3.11) show again that the assumption can be rejected at the 1% level[12]. Since this proportional odds regressions assumption seems to be rejected, alternative models that do not impose this constraint should be considered. The first one is the generalized ordered logit and the second is the continuation ratio model, also called sequential logit model.

Table 3.10: Test of parallel regressions

	LR-Test		Brant Test	
	χ^2	P-value	χ^2	P-value
Model 1	198.37	0.000	210.26	0.000

[12]This allows to detect which ones contribute most to the violation of the assumption of parallel regressions. The whole test Brant show that it is mainly the sector dummies that contribute the most, followed by the organizational structure variables and the part of export outside the European Union.

3.5.2 Generalized Ordered Logit

The generalized ordered logit model, discussed by Clogg and Shihadeh (1994) and Fahrmeir and Tutz (1994), allows β to differ for each of the $J-1$ comparisons. That is,

$$\Omega_{\leq s|>s}(\mathbf{x}) = \frac{\Pr(y \leq s\,|\mathbf{x})}{\Pr(y > s\,|\mathbf{x})} = \exp(\alpha_s - \mathbf{x}\beta_s) \text{ for } s = 1 \text{ to } J-1$$

In our regressions, the predicted probabilities are computed as

$$\begin{aligned}
\Pr(y &= 1\,|\mathbf{x}) = \frac{\exp(\alpha_1 - \mathbf{x}\beta_1)}{1+\exp(\alpha_1 - \mathbf{x}\beta_1)} \\
\Pr(y &= j\,|\mathbf{x}) = \frac{\exp(\alpha_j - \mathbf{x}\beta_j)}{1+\exp(\alpha_j - \mathbf{x}\beta_j)} - \frac{\exp(\alpha_{j-1} - \mathbf{x}\beta_{j-1})}{1+\exp(\alpha_1 - \mathbf{x}\beta_{j-1})} \\
\Pr(y &= 4\,|\mathbf{x}) = 1 - \frac{\exp(\alpha_3 - \mathbf{x}\beta_3)}{1+\exp(\alpha_3 - \mathbf{x}\beta_3)}
\end{aligned}$$

Once predicted probabilities are computed, all the approaches used to interpret the OR results can be applied. That is, the three columns of coefficients reported in Table 3.11 (model 2) match well with the following OR:

$$OR_{>1|\leq 1}(x_k\,|\mathbf{x}) = \frac{\Omega_{>1|\leq 1}(x_k+1,\mathbf{x})}{\Omega_{>1|\leq 1}(x_k,\mathbf{x})} = \frac{\Pr(y>1\,|x_k+1,\mathbf{x})/\Pr(y\leq 1\,|x_k+1,\mathbf{x})}{\Pr(y>1\,|x_k,\mathbf{x})/\Pr(y\leq 1\,|x_k,\mathbf{x}} = \exp(\beta_{1,k})$$

$$OR_{>2|\leq 2}(x_k\,|\mathbf{x}) = \frac{\Omega_{>2|\leq 2}(x_k+1,\mathbf{x})}{\Omega_{>2|\leq 2}(x_k,\mathbf{x})} = \frac{\Pr(y>2\,|x_k+1,\mathbf{x})/\Pr(y\leq 2\,|x_k+1,\mathbf{x})}{\Pr(y>2\,|x_k,\mathbf{x})/\Pr(y\leq 2\,|x_k,\mathbf{x}} = \exp(\beta_{2,k})$$

$$OR_{>3|\leq 3}(x_k\,|\mathbf{x}) = \frac{\Omega_{>3|\leq 3}(x_k+1,\mathbf{x})}{\Omega_{>3|\leq 3}(x_k,\mathbf{x})} = \frac{\Pr(y>3\,|x_k+1,\mathbf{x})/\Pr(y\leq 3\,|x_k+1,\mathbf{x})}{\Pr(y>3\,|x_k,\mathbf{x})/\Pr(y\leq 3\,|x_k,\mathbf{x}} = \exp(\beta_{3,k})$$

The results of the generalized ordered logit estimation are given by table 3.11 (model 2). The interest of this empirical model is to highlight the differential effects of moving from one strategy to another as explained above.

We first focus on the drivers of the strategy that consists to moving from a no-signal quality strategy (alternative 1) to a quality signal, whatever this signal either label, brand or both (alternatives 2, 3 and 4). Our results show that the organizational and governance variables have the same effect than in the simple ordered model, except for the variables members of the cooperative which have now a significant and positive effect and in contrast the fact of owning a subsidiary has no more effect. The market variables are also quite similar since a larger share of export outside the EU borders as well as having a higher number of partners and mainly transacting with wholesalers, compared to the cooperative network channel, continue to have a positive effect on the probability of choosing a signal. There are however two differences. First, the supermarket marketing channel is no more significant, which suggests that this channel is likely to be more specific to a particular signal, *i.e.* brand, as noted earlier. Similarly, compared to milk & oil products, cooperatives marketing cereals products and fruit & vegetables are more prone to adopt a signal. In contrast, selling beverages has no more a significant impact, which suggests as previously that such products are more associated to a specific signal strategy.

The second strategy consists in moving from a no-brand signal (alternatives 1 and 2) to a signal that includes a brand (alternative 3, *i.e.* label and brand, and alternative 4, *i.e.* brand only). The drivers of this strategy are now quite different. First, among the organizational and governance variables, only number of members and employees have now a significant and positive effect on moving to a strategy that includes a brand. Among the product variables, selling beverages and meat also impacts positively the choice of such strategy, confirming the previous results on the effects of such variables on brand signal. There are some other changes in the significant marketing channel variables since, besides the previous variables that had effect on the signaling strategy, we note that the supermarket channel is now significant when we analyze the strategy of moving to a brand signaling.

The third strategy consists in moving to a brand only strategy (alternative 4 against others alternatives, *i.e.* 1, 2, 3). The drivers are more contrasted than in the second strategy. Now, in the organizational and governance variables only the number of members have a significant and positive effect on the change toward a brand only signal. Similarly, in the marketing channel variables only selling to a supermarket have a positive effect. Only the impact of the product variables remains the same. These results suggest that the adoption decision of a brand only strategy depends less on organizational structure of the cooperative than on marketing variables, that is, both specific products (*e.g.* beverages and meat) and marketing channels (*e.g.* supermarkets).

3.5.3 The Sequential Logit Model

The continuation ratio model was initially proposed by Feinberg (1980). Although there are versions of this model based on binary models (*e.g.* probit), here we consider the logit version, also called the sequential logit model. This model was designed for ordinal outcomes in which the categories represent three progression of events or stages in some process through which an individual can advance. For example, as noted earlier, a cooperative with a mix signal (label and brand), had a no signal strategy at the first stage, then a label strategy at the second stage.

If $\Pr(y = s\,|\mathbf{x})$ is the probability of being in stage s given $\mathbf{x}$ and $\Pr(y > s\,|\mathbf{x})$ is the probability of being in a stage later than s, the continuation ratio model for the odds is

$$\frac{\Pr(y = s\,|\mathbf{x})}{\Pr(y > s\,|\mathbf{x})} = \exp(\alpha_s - \mathbf{x}\beta) \;\; \text{for } s = 1,2,3$$

where the βs are constrained to be equal across outcome categories, where the constant term differs by stage. Accordingly, $\exp(\beta_k)$ can be interpreted as the effect of a unit increase in x_k on the odds of being in s with being in a higher category given that an individual is in category s or higher, holding all other variables constant.

The results of this sequential logit estimation are given by table 3.11 (model 3). The first point to note is that the cutoff points between the different stages are not significant. This suggests that there is no clear evidence of sequentiality in the adoption process of quality signals. That is, if the cooperative chooses a brand only strategy this does not imply that it has chosen a label signal in a first stage and a mix signal in a second stage. The drivers of a higher quality signal are more or less similar to those found in the simple ordered model. First, in the organizational and governance variables the number of employees and the turnover continue to a significant and positive impact. However, the governance variables (SUBSID and UNION) are no more significant. In contrast, regarding the products sold, more products (MEAT and OTHERS) have a significant impact as in the generalized model. Similarly, regarding the marketing channels, we get the same significant variables than in the simple ordered model. That is, the larger the share of export outside the EU borders, the higher the probability that the adoption process of quality signals follows sequential stages. Moreover, regarding the marketing channels, choosing a supermarket or a wholesaler channel as well as having a higher number of partners are significant drivers of the staged quality signals choice.

Table 3.11: Simple, generalized and sequential ordered logit models estimations

	Model 1	**Model 2**			**Model 3**
Variable Name	Simple Ordered	Generalized Ordered Logit			Sequential Ordered
& Category	Logit				Logit
	OR	$OR_{\{2,3,4\|1\}}$	$OR_{\{3,4\|1,2\}}$	$OR_{\{4\|1,2,3\}}$	OR
Organizational structure					
MEM	0.91 (-1.44)	0.78 (0.20)***	1.23 (2.15)**	1.54 (2.76)***	1.004 (0.08)
EMP	1.08 (3.96)***	1.13 (3.49)***	1.08 (2.94)***	1.02 (0.60)	1.06 (3.41)***
TURN	1.30 (5.30)***	1.37 (5.76)***	1.002 (0.03)	0.90 (-0.73)	1.21 (4.65)***
UNION	1.21 (1.37)**	1.75 (3.08)***	0.92 (-0.47)	0.91 (-0.27)	1.13 (1.04)
SUBSID	1.47 (2.15)**	1.99 (2.50)	1.36 (1.31)	0.82 (-0.46)	1.23 (1.33)
Sectors					
WSI	Ref.	Ref.	Ref.	Ref.	Ref.
AF	1.52 (2.13)**	1.84 (2.51)**	1.02 (0.07)	5.16 (2.29)**	1.40 (1.94)
Products					
MILKOIL	Ref.	Ref.	Ref.	Ref.	Ref.
BEV	1.60 (2.66)***	0.70 (-1.53)	6.75 (6.11)***	3.96 (2.33)**	1.49 (2.6)***
CER	0.16 (4.83)***	0.09 (-5.89)***	1.04 (0.06)	6.83 (1.39)	0.22 (-4.7)***
FVEG	1.08 (0.28)	0.52 (-1.95)*	6.13 (4.07)***	16.53 (3.15)***	1.29 (1.06)
MEAT	1.66 (1.56)	0.91 (-0.23)	6.37 (3.91)***	11.72 (2.77)***	1.57 (1.66)*
OTHERS	0.27 (-3.22)	0.15 (-4.32)	1.97 (1.13)	5.14 (1.48)	0.38 (-2.89)**
Export Markets					
EXINEU	0.95 (-0.30)	0.76 (-1.38)	1.08 (0.7)	1.40 (2.14)**	0.38 (-0.06)
EXOUTEU	1.30 (3.36)***	1.32 (2.46)**	1.39 (3.45)***	1.05 (0.29)	0.99 (3.50)***

	Model 1	Model 2			Model 3
Variable Name	Simple Ordered	Generalized Ordered Logit			Sequential Ordered
& Category	Logit				Logit
	OR	$OR_{\{2,3,4\|1\}}$	$OR_{\{3,4\|1,2\}}$	$OR_{\{4\|1,2,3\}}$	OR
Local Market					
LT50INREG	1.02 (0.14)	0.73 (-1.34)	1.26 (1.14)	1.55 (1.24)	1.12 (0.82)
Marketing Channels					
cooperative network	Ref.	Ref.	Ref.	Ref.	Ref.
SUPER	2.35 (2.71)***	1.83 (1.39)	2.78 (2.83)***	3.83 (2.47)**	2.14 (2.92)***
RET	1.43 (1.39)	1.40 (1.13)	1.78 (1.68)*	1.08 (0.13)	1.31 (1.24)
WS	1.64 (2.51)**	1.69 (2.02)**	1.82 (2.26)**	1.19 (0.35)	1.45 (2.21)**
OTHERS_HOT	0.97 (-0.18)	0.88 (-0.57)	1.16 (0.53)	0.54 (-1.04)	0.90 (-0.67)
LT50SC	1.79 (2.75)***	3.11 (3.50)***	1.82 (2.07)**	0.44 (-1.33)	1.39 (1.83)*
Cut Points					
Cut point 1	3.36 (4.83)***				2.55 (0.59)
Cut point 2	5.97 (8.35)***				4.69 (0.61)
Cut point 3	7.86 (10.78)***				5.60 (0.64)
Constant		-3.30 (-4.26)***	-4.43 (-5.1)***	-6.23 (-2.94)***	
N	993		993		1918
L1	-1014.8		-918.8		
Chi2	292.7***		448.6***		253.90***
Pseudo-R2	0.12		0.21		0.11

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

3.5.4 Bivariate Ordered Probit Model

In our previous univariate models, we made the implicit assumption that the turnover variable was exogenous. However, the cooperative a priori makes a joint decision, *i.e.* it chooses its turnover level as well as its quality signal strategy. Therefore, the turnover variable may be seen as more endogenous than exogenous. Since the different results of our estimates have shown a significant effect of this variable on the quality signal choice, this potential endogeneity problem can become cumbersome since it may biases our estimates.

To take into account the joint nature of the decision making on quality signal and turnover and to deal with the problem of endogeneity, *i.e.* the fact that one dependent variable (turnover) is endogenous for the other dependent variable (quality signal), Green and Hensher (2008) proposed a bivariate ordered probit model where one of the dependent variables is endogenous for the other. The underlying model consists of a simultaneous model of two equations relating the latent strategies of quality signaling (S) and Turnover (T) to individual characteristics of the cooperatives $\mathbf{x}_i$

$$t_i^* = \mathbf{x}'_{1i}\beta_1 + \varepsilon_{1i} \tag{3.5.4}$$

$$s_i^* = \gamma T_i + \mathbf{x}'_{2i}\beta_2 + \varepsilon_{2i} \tag{3.5.5}$$

where t_i^* and s_i^* are two latent variables that can be broadly defined as measures of profitability associated with the two simultaneous decisions, *i.e.* the turnover level and the quality signal; $\mathbf{x}_{1i}$ and $\mathbf{x}_{2i}$ are vectors of exogenous variables that may have some common components, β_1 and β_2 are the vectors that include the coefficients to be estimated, ε_{1i} and ε_{2i} are error terms for corresponding equations and these error terms are assumed to have a bivariate standard normal distribution with correlation ρ; γ_i is a scalar representing the effect that the turnover (T_i) of a cooperative i has on the quality signal (S_i) chosen by the latter.

Estimation of this simultaneous equations model (3.5.4-3.5.5) can be performed with discrete variables as dependent variables instead of t_i^* and s_i^*, and corresponding to ordered changes in turnover and quality signal. These variables can be defined as follows. The dependent variable quality signal S_i is defined as previously, that is:

$$S_i = \begin{cases} \text{1-no signal if } s_i^* < \alpha_1 \\ \text{2-label only if } \alpha_1 \leq s_i^* < \alpha_2 \\ \text{3- label and brand if } \alpha_2 \leq s_i^* < \alpha_3 \\ \text{4- brand only if } s_i^* \geq \alpha_3 \end{cases}$$

For the dependent variable turnover, we create a polytomic variable T_i corresponding to 4 classes:

$$T_i = \begin{cases} \text{1-less than 5 if } t_i^* < \delta_1 \\ \text{2- between 6 and 10 if } \delta_1 \leq t_i^* < \delta_2 \\ \text{3- between 11 and 15.42 if } \delta_2 \leq t_i^* < \delta_3 \\ \text{4- more than 15.42 if } t_i^* \geq \delta_3 \end{cases}$$

where the α_j and δ_j values represent the unknown cutoff parameters to be estimated with β_1 and β_2. The cutoffs satisfy the condition that $\alpha_1 < \alpha_2 < \alpha_3$ and $\delta_1 < \delta_2 < \delta_3$. We have taken the cutoff value for ln(Turnover) as 15.42 which corresponds to the cooperative turnover at 5 million euros. The reason to choose this particular value is that it is the threshold above which the small cooperatives are considered to be wholesalers. Parameters in the system (3.5.4-3.5.5) are identified only if exclusion restrictions are imposed, namely, at least one variable $\mathbf{x}'_{1i}$ in should be excluded from $\mathbf{x}'_{2i}$. An interesting candidate in the determination of change in turnover that is not correlated with quality signal change is others products (OTHERS). Indeed, while these kind of products seem to have an impact on turnover, while having no clear coherence in terms of quality signal since they are miscellaneous.

Following Kaminski and Thomas (2011), we estimate the above bivariate ordered probit model using the Full-Information Maximum Likelihood. We use two specifications. In the first specification, the system is estimated as seemingly unrelated regressions where all explanatory variables are assumed exogenous and a correlation coefficient between random terms in both equations is estimated (FIML I). In the second specification the system is jointly estimated by explicitly accounting for the endogeneity of the other ordered variable on the right hand side of equation (3.5.5) (FIML II). To address the endogeneity problem, we compute a Wald test under the null assumption of exogeneity of the dependent variable turnover

($\gamma = 0$) in the second equation of the system, using this second specification.

The bivariate ordered probit regression results are presented in tables 3.12. Let us first turn to specification tests on the model, addressing the issue of endogeneity and correlation across equations. Our results confirm also the endogeneity effect, since the coefficient γ is positive and significant in the second equation of the system. To address the endogeneity issue, we compute the Wald test statistic under the null assumption of exogeneity of the change in turnover variable in the bivariate-ordered equations (FIML I). The exogeneity test statistic allow us to reject the null assumption of exogeneity of the change in turnover. Hence, our prediction of an endogenous change in turnover is supported by the data, meaning that the turnover level effectively impacts the quality signal. As can be seen in Tables 3.12, correlation among residuals of the two equations of the system is negative and significant ($\rho = -0.45$), which gives support to the bivariate specification and to the simultaneous nature of data-generating processes. Moreover, cut-off values also indicate the preference of ordered discrete specification to the binary discrete choice as more than two cut-off values are significant in each case. We therefore concentrate on the estimates of the bivariate ordered probit specification with the turnover level as an endogenous variable in the quality signal strategy.

Let us now analyze the main drivers of both dependent variables of the system, *i.e.* turnover and quality signal intensity. Regarding the turnover variable, the mains drivers are the organizational and governance variables. Indeed, the number of members and employees, as well belonging to a union of cooperative increases the probability of getting a higher turnover. In contrast, the variables of products and marketing channels seem to decrease the probability of having a higher turnover. Indeed, compared to milk & oil products selling beverages or others products, transacting with a retailer and having different partners (LT50SC) are significant drivers of a lower probability of getting higher turnover. Regarding the quality signal intensity dependent variable, its main drivers have the opposite effect than in the turnover case. The organizational and governance variables are non-significant or have a negative effect, *e.g.* the number of members. In contrast, the products and market variables increases the probability of getting a higher quality signal. Compared to milk and oil products, selling beverages, exporting outside the borders of EU, transacting with a retailer and a larger number of partners increases the probability of getting a higher quality signal.

This contrasted result can be explained by the indirect and positive effect of the turnover variable on the quality signal dependent variable. Indeed, it seems that the positive effect of the organizational and governance variables on quality signal intensity found in univariate ordered models (see table 3.11) is only indirect. Indeed, it is only because these variables increases the turnover that they also raises the probability of adopting a quality signal more intensive, since the turnover has a positive effect on this dependent variable. The direct effect of these variables is then at best non significant and at worst negative. This implies that the only direct drivers of choosing a more intensive quality signal strategy are variables related to the nature of the products or the market structure.

Table 3.12: Bivariate Ordered Probit estimates

Variable Name	**FIML I**	**FIML II**	**FIML I**	**FIML II**
	Turnover		*Quality Signal*	
Organizational Structure				
MEM	0.17 (0.04)***	0.17 (0.05)***	0.02 (0.03)	-0.09 (0.05)*
EMP	0.10 (0.02)***	0.10 (0.02)*	0.006 (0.01)***	-0.01 (0.02)
UNION	0.24 (0.12)**	0.24 (0.12)**	0.14 (0.08)*	-0.02 (0.11)
SUBSID	0.08 (0.16)***	0.08 (0.16)	0.21 (0.10)**	0.14 (0.13)
Sector				
WSI	Ref.	Ref.	Ref.	Ref.
AF	-1.34 (0.19)***	-1.35 (0.19)***	0.14 (0.11)	0.97 (0.19)***
Products				
MILKOIL	Ref.	Ref.	Ref.	Ref.
BEV	-0.31 (0.15)**	-0.31 (0.15)**	0.14 (0.09)	0.32 (0.12)***
CER	-0.25 (0.25)	-0.25 (0.25)	-1.09 (0.20)***	-0.83 (0.23)***
FVEG	-0.13 (0.23)	-0.13 (0.23)	0.002 (0.16)	0.08 (0.19)
MEAT	0.11 (0.24)	0.11 (0.24)	0.23 (0.18)	0.13 (0.22)
OTHERS	-1.23 (0.27)***	-1.23 (0.27)***	-0.85 (0.21)	/////

Variable Name	FIML I	FIML II	FIML I	FIML II
	Turnover		*Quality Signal*	
Export Markets				
EXINEU	0.17 (0.14)	0.17 (0.14)	0.01 (0.09)	-0.10 (0.12)
EXOUTEU	-0.03 (0.06)	-0.03 (0.06)	0.17 (0.04)***	0.17 (0.05)***
Local Market				
LT50INREG	-0.16 (0.15)	-0.16 (0.15)	0.01 (0.09)	0.11 (0.12)
Marketing Channels				
cooperative network	Ref.	Ref.	Ref.	Ref.
SUPER	0.30 (0.28)	0.30 (0.28)	0.51 (0.17)***	0.28 (0.24)
RET	-1.07 (0.19)***	-1.07 (0.19)***	-0.02 (0.14)	0.65 (0.23)***
WS	0.05 (0.18)	0.05 (0.18)	0.25(0.11)**	0.19 (0.15)
OTHERS_HOT	-0.07 (0.16)	-0.07 (0.16)	-0.06 (0.10)	-0.01 (0.13)
LT50SC	-0.55 (0.18)**	-0.55 (0.18)**	0.18 (0.12)	0.51 (0.16)***

Variable Name	FIML I	FIML II
γ	/////	0.62 (0.14)***
Cut Points		
α_1	-3.37 (0.30)***	-3.37 (0.30)***
α_2	-2.20 (0.26)***	-2.20 (0.26)***
α_3	1.90 (0.25)***	1.90 (0.25)***
δ_1	0.01 (0.16)	0.01 (0.14)
δ_2	1.50 (0.16)***	1.36 (0.21)***
δ_3	2.49 (0.18)***	2.26 (0.28)***
Wald χ_2	167.25***	167.25***
ρ	0.19 (0.06)**	-0.45 (0.16)**
Log likelihood	-1372.54	-1372.54
N	993	993

3.6 Conclusion

This chapter aims to understand the different drivers of the quality signal choices made by the small French cooperatives, with a particular focus on the coexistence of both signals. To do this, we use a database from the national survey conducted in 2005 by the ministry of agriculture on the exhaustive sample of 1 500 small French agricultural cooperatives. The four possible quality signal strategies that the cooperative may choose are the following: *(i)* no quality signal; *(ii)* common label only (AOC, IGP, AB, ...); *(iii)* brand only; *(iv)* mix signal, *i.e.* both signals (label and brand) are adopted.

To analyze the drivers of these different quality signals, multinomial logit estimations are carried out on our database. The most striking result is the effect of the marketing variables and mainly the export markets. If exporting has a significant and positive effect on adopting a quality signaling, there is a clear differential effects between the specific exporting markets.

Exporting outside the EU borders mainly impacts the brand only signal, while exporting inside the EU borders affects the label choice and the mix signal. This result supports the idea that the label only strategy is not relevant outside the domestic market, and outside the EU borders the brand only signal seems to be the more adequate strategy. The second significant result is the impact of the products and the marketing channel variables on both the mix signal and the brand only strategy.

Our results provide also some specific results on the coexistence of the two signals, *i.e.* labels and brands, by analyzing the drivers of the mixed signal. First, among the organizational and governance variables the number of employees (EMP) as well as being member of a union of cooperatives (UNION) and having a subsidiary (SUBSID) have a significant and positive impact. It also appears that this strategy is commonly present in the beverage, as well as in meat and fruits & vegetables, but with less magnitude.

After checking for the robustness of our estimation results in the multinomial logit, we also analyze the possibility of an ordinal ranking among the different quality signals. That is, moving from a no signal strategy then to a common label, a mix signal (label and brand) and then finally to a brand only strategy, may generate a higher profit for the cooperative. We first estimate a simple ordered logit model, whose results show a clear evidence of an ordered choice and bring a confirmation of the different drivers found in the previous multinomial logit model. This simple ordered model makes however the restrictive assumption that the coefficients of the exogenous variables are the same across the quality signal alternatives (parallel regression assumption). To overcome this shortcoming, we have recourse to a generalized ordered model and a sequential logit model. The estimation mainly show some contrasting results, *i.e.* if the organizational structure and the governance variables are able to explain the adoption of a quality signal (whatever the signal), they have less impact on the choice of a brand (either in a mix signal or a brand only strategy). The increasing impact on brand adoption concerns mainly products such as beverages and meat, and the marketing variables such as exporting outside the EU borders and having recourse to a supermarket marketing channel. That is, it seems that with the move toward a mix signal and a brand only signal the organizational variables becomes less relevant, whereas the impact of marketing drivers seem to increase. The results of the sequential model show clearly that the adoption decision of a quality signal does not follow a sequential process. That is choosing a brand does not necessarily imply that we chose a common label in a first step and a mix signal in a second step. Finally, to deal with the possible endogeneity problem of the turnover variable, we estimate a specific simultaneous equations model where one of the (ordered) dependent variable (quality signal) depends on the second dependent variable (turnover). The results of this bivariate ordered probit model show first that our turnover variable is indeed endogenous and significant and clearly positive effect on the probability of choosing a higher quality signal. Moreover, we find also the same result than in the generalized ordered model, *i.e.* the organizational variables have less impact in the choice of a higher quality signal. Our bivariate ordered probit model seems to suggest that this result is due to the fact that the organizational variables have no direct impact on the quality signal choice, but that they have an indirect effect through the increase of the turnover variable.

This chapter mainly focuses on the drivers of the different quality signals. Regarding the coexistence of the signals (mixed signals) issue, the results of our estimates are contrasted. Indeed, if there are some specific drivers for the mixed signal strategy (label and brand are jointly chosen) which can suggest a complementarity effect between both signals, label and brand strategies seem to target different markets: the domestic or the EU market for the label only strategy and the outside EU borders market for the brand only signal. Our results are mixed because we did not define a clear-cut test for complementarity. Test convincingly for the complementarity effect implies having recourse to specific econometric models of complementarity (Arora, 1996; Cassiman and Veuglers, 2006; Gentzkow, 2007). Implementing these models is the next step in our agenda of research.

Chapter 4

Is there some Complementarity between Labels and Brands? Evidence from French Small Cooperatives

4.1 Introduction

Consumers demand for quality food has been increasingly drawing attention throughout the world particularly in industrialized countries (Braham, 2003; Vanhonacker et al., 2010; Hu et al., 2011). Many quality signals can be used, both private and common, to foster the development in the market of such quality food, mainly brands and common labels (Auriol and Schilizzi, 2003; Crespi and Marette, 2003; Lence et al., 2007; Bottega et al., 2009). Previous research has typically focused on either brand or common label efficiency independently, while in many instances both signals coexist. Agricultural products pairing brand names and certified labels, such as indications of origin, are indeed very common (*e.g.* Roquefort cheese, Scottish whiskeys and most of the french wines). The objective of this chapter is to explain this coexistence by empirically analyzing the complementarity/substitutability that may exist between labels and brands. To do so, we develop an empirical model of complementarity that we test on a database of the quality signaling strategies from 993 French small cooperatives.

Quality signaling is widespread in the food and agricultural products, because these products are subject to market failures identified by Stigler (1961) and Akerlof (1970). Since these pioneering contributions, the market failures stemming from information asymmetries have been the object of considerable research. Nelson (1970, 1974) and Darby and Karni (1973) extended Stigler's (1961) economics of information theory by considering how different types of quality or attributes of goods (search, experience, credence)[1] interact with consumer confusion and thus generates more or less severe market failure. This problem of asymmetric information is due to the fact that the producer knows the good attributes that consumers can only determine through search or experience, or cannot determine at all. In the food markets, this problem of asymmetric information impacts negatively on the market: the quality of total supply drops and higher quality goods are driven out of the market, due to adverse selection effect.

In response to the unfair competition from producers who sell lower quality goods at the same price, the producer maintaining the quality of its goods adopts signaling strategies to create a reputation of "high quality producer". In his dynamic models of reputation, Shapiro (1982, 1983) show that in one-shot purchase situations, quality can be better signaled if there exists: *(i)* reliable quality certification; *(ii)* informed buyers, such as readership of reviews or consumer reports, that may exert a positive externality on uninformed buyers (Mahenc, 2004). In a repeated purchase setting, when consumers can learn which good provides the desired attribute they buy it, producers can establish a reputation for quality via brands (Klein and Leffler, 1981; Shapiro, 1983; Landes and Posner, 1987, 2003; Grossman and Shapiro, 1988b). Consumers tend indeed to use the quality of products offered by the same brand in the past as an indicator of future levels of quality. Reputation, through brands, embodies expected quality in that individuals extrapolate past behavior to make inferences about quality future behavior. This value judgment develops over time creating an intangible asset. The value of this asset is given by capitalization of future price premia (Belleti, 1999). Even when there is competing brands of the same good, a trademark system can still be more efficient than generic advertising. Crespi and Marette (2002) and Marette and Crespi (2007) show that high-quality producers do not benefit from generic promotion when the benefits from generic advertising firm increased demand are outweighed by the cost firm lower product differentiation.

If a credible brand system can be an efficient mechanism to signal quality, its cost can be prohibitive for small individual firms and/or small cooperatives in agriculture and food production. This is one of the justifications for specific types of government intervention such as the development of food standards and grades (Gardner, 2003; Lapan and Moschini, 2007).

[1] Search attributes are ones that can be verified prior to purchase through direct inspection or readily available sources. Experience attributes are ones that can be verified only after use of the product (Ford et al., 1990). Credence attributes are ones that are difficult to verify even after use (Darby and Karni, 1973). Products may have one, two, or all three of those types of attributes. For example, in the case of mouthwash, a search attribute would be color, an experience attribute would be taste, and a credence attribute would be plaque reduction.

Alternatively, producers, firms and cooperatives can also bundle together to achieve the critical mass required for label certification through a common label. Allowing small producers to collude may indeed improve general welfare by enabling these producers to cover the fixed costs of quality development and certification (Marette et al., 1999; Marette and Crespi, 2003; Zago and Pick, 2004; Lence et al., 2007; Langinier and Babcock, 2008; Mérel, 2009). In many European countries, this common labeling was mainly done with geographically based labels, or geographical indications (GI) such as PGI (Protected Geographical Indications) and PDO (Protected Designation of Origin)[2], where quality attributes are presumed to be linked to the specific geographic origin of the good produced. This is generally referred to as quality-origin nexus or *terroir*[3]. The collective nature of these common labels as a quality signal means that use of the sign is not limited to a single producer but to all producers within the designation which adhere to code of practice. Product reputation is thus the result of the actions of different agents active in the same area of production and is projected through tradition over a period of time (Marty, 1998). It could be said that GIs are the result of a process whereby collective reputation is institutionalized in order to solve certain problems that arise from information asymmetry and free riding on reputation (Belleti, 1999).

There is some evidence that common labeling, as an institutionalization of a collective reputation, enable to generate price premium for producers (Thiedig and Sylvander, 2000; Loureiro and McCluskey, 2000). For instance, Loreiro and McCluskey (2000) analyzed the consumer's willingness to pay for GI labels and show that when collective reputation is good, a GI is a powerful tool to promote quality and obtain a price premium[4]. Landon and Smith (1997, 1998) deepen this analysis and provide an empirical study of the extent to which consumers use both individual and collective reputation current quality indicators when purchasing Bordeaux wine. Two main results emerge. First, there is a huge effect of reputation on price premium. Indeed, the results indicate that the price of Bordeaux wine depends significantly on both expected and current quality, but that marginal impact of expected quality (long-term reputation) on price is approximately 20 times higher than that of current quality. This implies that it take a considerable time for a firm to establish a reputation for high quality that

[2]In the case of PGI it suffices that one stage of the production process is carried out in the defined area, while in the case of a PDO, all stages of production must take place in this area.

[3]*Terroir*, a French term for "taste of place", refers to a casual relationship between agronomic conditions, craftmanship and a product's distinct quality (Giovannucci et al., 2009).

[4]Bonnet and Simioni (2001) show in contrast that consumers do not place significant value on the PDO labeled French Camembert and that brand appears to be more relevant in the consumer's evaluation of alternative Products. Gergaud and Livat (2010) find also no significant value on the PDO labeled Bordeaux wine.

would result in a significant price premium. Second, a collective strategy of reputation building, *e.g.* through GIs, can be more efficient since there can be decreasing marginal cost with reputation building, and positive effect on marginal return. The results suggest that collective reputation indicators play a significant role in price determination, mainly through their impact on expected quality.

But GIs may not necessarily prevent free riding in collective reputation. Winfree and McCluskey (2005) show that with positive collective reputation and no traceability there is an incentive to producers to free ride, *i.e.* extract rents by producing a lower quality level. And the sustainable level of collective reputation decreases as the number of firms in the production area increases. Chambolle and Giraud-Héraud (1999) and Desquilbet and Monier-Dilhan (2008) also show that a GI can decrease the quality level. Loureiro and McCluskey (2000) show that while the GI label is a powerful tool to promote high quality goods, its use on products that are not of high quality is not an efficient marketing strategy and they suggest that it could impact negatively on the collective reputation. Thus, as shown by Landon and Smith (1997, 1998), it can be efficient to use both collective and individual reputation, by having recourse simultaneously to labels and brands, to solve this problem.

The question that can then be addressed is related to the problem of concurrent use or complementarity between labels (GIs) and brands (trademarks). There is a burgeoning theoretical literature dealing with this issue. Bouamara-Mechemache and Chaaban (2010) investigate whether producers with a quality advantage should collectively choose a GI certification or a private label. Moschini and Menapace (2012) extend the model of Shapiro (1983) to reflect both collective (GIs) and firm-specific (trademarks) reputation in a competitive market. Their main result is that GIs and trademarks turn out to be complementary signals of quality. Indeed, if GIs reveal information regarding the origin of product, it can also reduce costs of building reputation by constraining moral hazard behavior. Therefore, GI certification may improve welfare compared with a situation where only private trademarks would be available for firms. Castinagri et al. (2012), following Tirole (1996) and Winfree and McCluskey (2005), go one step further and analyze the conditions under which both labels (cooperative reputation) and brands (private reputation) may coexist.

This chapter offers the first attempt to empirically test for this coexistence by estimating the complementarity effect that may exist between labels and brands. First, we develop empirical models used to test for complementarity effects between different both signals. Since Arora (1996), it is usually considered that the complementarity effect between different practices can be estimated using a bivariate probit. But taking into account the Miravette and Pernias (2010) criticism on the incoherence problem encountered when using such a model, we show that a multinomial probit model can overcome this problem. With a multinomial probit model, it is indeed possible to separate what is due to complementarity and what is due to unobservable heterogeneity.

Second, to estimate both models we use an exhaustive sample of 993 small French cooperatives. The cooperatives may choose between 4 strategies of quality signaling: no sign, label only, brand only, label and brand (mix signal). The question we address is then if the mix signal is due to a complementarity effect, *i.e.* the simultaneous choice of two signals (label and brand) is due to the net gain generated by this combination of signals, or to unobservable heterogeneity between cooperatives. Note that in contrast to the previous literature on labels and brands, our focus is on the strategic choices done by producers, here the cooperatives of producers, and not on the choices done by consumers.

Third, our estimation results show that the evidence of a complementary effect depends on the empirical model used. When we first regress the mix signal variable on the explanatory variables using a bivariate probit, the results exhibit a complementary effect (the correlation term between errors is positive). While the signs seem to have been chosen for different markets (national European market for labels and outside of EU for brands). But as shown by Miravette and Pernias (2010), the bivariate probit model is incoherent when the endogenous variables are discrete since it cannot separate what is due to complementarity and what is due to unobserved heterogeneity. To overcome this shortcoming, we use a multinomial probit that allows to make such separation. The results are clear cut: we get a significant but negative interaction between label and brand variables. That is, both signals are more substitute than complementary.

The remaining sections are organized as follows. In section 4.2 we present and discuss the complementarity effect and the empirical models to test for this effect (a bivariate probit model, and a multinomial probit model). In section 4.3, we present the database and the different variables used in the test. In section 4.4, we discuss and comment the results of the two empirical models and we conclude on the presence of complementarity or substitutability between labels and brands. Section 4.5 bring some concluding remarks.

4.2 Testing for Complementarity

4.2.1 Some Theory

In order to test for complementarity of labels and brands we apply an empirical strategy that is based on the theory of supermodularity. This theory of supermodularity was mathematically developed by Topkis (1978)[5], and first introduced in industrial economics by Vives (1990) and Milgrom and Roberts (1990, 1995) to explain innovation adoption in firms. In the context of supermodularity, two signals are complementary if: *(i)* adopting one signal does not preclude adopting the other; *(ii)* whenever it is possible to implement each signal separately, the sum of the profit to do just one or the other is not greater than the profit of doing both together. Condition *(ii)* can also be understood as follows: the incremental return to implementing any one of the signals is greater if the other has already been implemented. More formally, suppose that there are two quality signals s^1 (label) and s^2 (brand). Each signal can be adopted by the cooperative ($s^1 = s^2 = 1$) or not ($s^1 = s^2 = 0$). The payoff function $\pi(s^1, s^2)$ is supermodular and s^1 and s^2 are complements if

$$\pi(1,1) - \pi(0,1) \geq \pi(1,0) - \pi(0,0)$$

That is adding a signal while the other signal is already adopted has a higher incremental effect on performance (π) than adding the signal in isolation.

4.2.2 The Empirical Models

Athey and Stern (1998) show that the problem of testing for complementarity can be tackled according to two approaches. The first one is the direct approach. It consists in using a production function to determine the effects of choosing particular combinations of innovation strategies on a firm's innovative performance (Belderbos et al., 2006; Cassiman and Veugelers, 2006; Mohnen and Röller, 2005). Using this approach allows for a direct test of the complementarity constraints, by testing multiple inequality constraints simultaneously (Mohnen and Röller, 2005). Two methods are used to test for these inequality constraints. First, for each possible combination of strategies, a corresponding dummy variable is included to capture whether or not the firm is involved in that particular combination of strategies. These dummy variables are then included in a regression analysis and based on the estimates following from the regression analysis, a number of inequality restrictions can be tested. The second

[5] See Topkis (1998) for an extensive treatment of the concept with economic illustrations.

method consists in using pairwise interaction terms to assess complementarity (Bresnahan et al., 2002; Caroli and Van Reenen, 2001; Ichionowski et al., 1997; Carree et al., 2011). Using interaction terms allows for the estimation of the amount of interaction between two or more practices, whereas using a production function with dummies only provides an insight in particular combinations but remains silent on the magnitude of the increasing gains of using the one while already performing the other.

The direct approach requires however a measure of the innovation performance, which is not always available. When we do not have such a measure, we must use an indirect approach: the adoption approach. It tests for a positive correlation between different practices conditional on a vector of exogenous variables X. More precisely, it consists in examining firm simultaneous decision in a bivariate model and analyze cross-equation correlation in the error terms, conditioned on firm characteristics (Arora and Gambardella, 1990). Testing for correlation to infer complementarity derives from the theoretical approach on complementarity presented above. Let us show this. Suppose that our previous payoff function $\pi(.)$ depends also on a vector of exogenous variables (X), and assume that $\pi(s^1, s^2, X)$ is supermodular in (s^1, s^2)[6].

Then the optimal configuration of signals $S^*(s^1(X), s^2(X))$ is monotone non-decreasing in X. Arora (1996) shows that this implies that if a pair of signals (s^1, s^2) is complementary, then they will be correlated when there is heterogeneity in X across firms (cross-sectional study). A bivariate probit regresses the non-exclusive signals s^1 and s^2 on assumed exogenous variables (X) but takes the correlation between them explicitly into account. This model can

[6] A function $f : \mathbb{R}^k \to \mathbb{R}$ is supermodular if

$$f(x \bigvee y) + f(x \bigwedge y) \geqslant f(x) + f(y)$$

for all $x, y \in \mathbb{R}^k$, where $x \bigvee y$ denotes the component-wise maximum and $x \bigwedge y$ the componentwise minimum of x and y. If f is a twice continuously differentiable payoff function defined over actions x and y, then supermodularity is equivalent to the condition

$$\frac{\partial^2 f}{\partial x \partial y} \geqslant 0$$

That is, the marginal payoff ($\partial f / \partial x$) of action x is non-decreasing in y .

be written as follows:

$$
\begin{aligned}
s_i^{1^*} &= \beta^1 X_i + \varepsilon_i^1, \qquad s_i^{1^*} \begin{cases} = 1 \text{ if } s_i^{1^*} > 0 \\ = 0 \text{ otherwise} \end{cases} \\
s_i^{2^*} &= \beta^2 X_i + \varepsilon_i^2, \qquad s_i^{2^*} \begin{cases} = 1 \text{ if } s_i^{2^*} > 0 \\ = 0 \text{ otherwise} \end{cases}
\end{aligned}
$$

where $s_i^{j^*}$, $j = 1,2$, is a latent variable. The errors are such that

$$
\begin{aligned}
E(\varepsilon^1) &= E(\varepsilon^2) = 0 \\
V(\varepsilon^1) &= V(\varepsilon^2) = 1 \\
Cov(\varepsilon^1, \varepsilon^2) &= \rho
\end{aligned}
$$

The main intuition of the bivariate probit model is the following: in the presence of complementarity, a variable that affects only one of the signal directly, say s^1, show up significant in both regressions, since complementarity induces an indirect effect from this variable on the adoption of s^2. That is, the indirect approach gives an indication of complementarity based on the assumption that the actual choice of the chosen practice(s) maps the firm's optimal decision. As explained before, it has the advantage that it can be used if performance effects of the chosen signals cannot be observed.

This indirect approach encounters however two difficulties. First, unobserved heterogeneity between different firms could bias the estimation results and leads either to accepting the hypothesis of complementarity while non complementarity exists, or to rejecting the complementarity hypothesis when activities are in fact complementary. In order to account for this unobserved heterogeneity, it is recommended to use an exclusion restriction that directly impacts one of the practices, but not the other. Note that this "reduced-form test" for complementarity (Athey and Stern, 1998) is only useful if there are not more than two practices to be tested, as far more options a strong indirect effect might outweigh a substitution effect of the pair of practices. We implement this test as a multinomial logit model for the mutually exclusive signals: label, brand, both and none.

Second, this reduced-form approach suppose that the innovations strategies are continuous variables, whereas decisions on innovations are discrete in most common situations (Milgrom and Roberts, 1990, 1995). The extension to the case of binary variables by using a bivariate probit (Cassiman and Veuglers, 2006) make the discrete response model incoherent (Miravette and Pernias, 2010).

Following Arora et al. (2010) and Gentzkow (2007), we mainly show that a multinomial probit approach can overcome both difficulties even when the strategies are dichotomous. That is, we can separate the complementarity between the innovation strategies from the unobserved heterogeneity, by estimating both the parameter of complementarity and the correlation coefficients in the error terms. This result holds because the MNP model is not incoherent. Indeed, we show that there is no overlapping between different sets of combinations of error terms, and therefore it is possible to associate any combination of error terms with a unique combination of innovation strategies without excluding any complementarity effect.

4.2.3 The Multinomial Probit Approach

4.2.3.1 The Model

We consider a situation where n firms in a market decide to adopt (or not) some innovations. More precisely, we analyze the decision of a firm i, $i = 1, \ldots, n$, to adopt two types of innovation[7]. We denote s_i^1 and s_i^2 these innovations, where $s_i^1 = 1$ if the firm i adopts the first type of innovation and 0 otherwise; similarly, $s_i^2 = 1$ if the same firm i adopts the second type of innovation and 0 otherwise. Let the choice j indicate the simultaneous decision of the firm i to adopt these innovations. Then, the firm can make one of four possible choices: $j = 0$ when it neither adopts s_i^1 nor s_i^2 ($s_i^1 = 0$, $s_i^2 = 0$); $j = 1$ when it adopts s_i^1 but does not adopt s_i^2 ($s_i^1 = 1$, $s_i^2 = 0$); $j = 2$ when it does not adopt s_i^1 but adopts s_i^2 ($s_i^1 = 0$, $s_i^2 = 1$); and $j = 3$ when it adopts both ($s_i^1 = 1$, $s_i^2 = 1$).

Each firm i is supposed to make a choice j that maximizes its own profit $\pi_{ij}\left(s_i^1, s_i^2\right)$. The profit maximization theoretical framework results in the following empirical discrete choice model for the latent profit indicator the firm i derives from making the choice j:

$$\pi_{ij} = \beta_j z_i + \varepsilon_{ij} \tag{4.2.1}$$

where the profit associated to each choice has components that are observable and unobservable to the econometrician. That is, z_{ij} is the vector of observed explanatory variables describing individual and alternative specific characteristics which are supposed to be important for the determination of the choice. The parameter vectors β_j are unknown and they are the object of inference. The vector of stochastic terms $\varepsilon_{ij} = \left(\varepsilon_{i0}, \varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}\right)'$ represents

[7]Much of the intuition presented here extends to cases of three or more innovations; however, the analysis becomes far more cumbersome.

the unobserved returns of the choices. It is assumed to be distributed as a multi-variate normal, identically and independently across the n firms, with zero mean and covariance matrix $\sum = \sigma_{ij} > 0, \forall j$ (positive definiteness).

Arranging the parameters in (4.2.1) as $\beta = (\beta_0', \beta_1', \beta_2', \beta_3')$ the log-likelihood function to be maximized is:

$$\mathcal{L}\left(\beta, \sum\right) = \frac{1}{n}\sum_{i=0}^{3}\sum_{j=0}^{3} y_{ij} \ln P_{ij}\left(\beta, \sum\right)$$

where the profit indicator π_{ij} is latent but we observe the choice $y_{ij} = 1$ if the firm i chooses the alternative j and $y_{ij} = 0$ otherwise. While $P_{ij} = Pr\left(\pi_{ij} > \pi_{ik}, k \neq j\right)$ represents the probability that the firm i make the choice j if it gets the greatest profit from this alternative. Unfortunately, it is not possible to get a unique maximum likelihood estimates of the parameters $(\beta, \sum)$ in the above model, as they are not identified. The first source of the identification problem is that the observed choices are only informative on the differences of the profits and not on the profits themselves. Then taking differences with respect to the profits associated with $j = 0$, *i.e.* we take the first alternative as the reference state used to normalize location of the latent variable, leads to

$$\pi_{il}^* = \pi_{il} - \pi_{i0} = \beta_l^* z_i + \varepsilon_{il}^*$$

where $\beta_l^* = \beta_l - \beta_0$ and $\varepsilon_{il}^* = \varepsilon_{il} - \varepsilon_{i0}$ for $l = 1, 2, 3$. The normalized profits for the different alternatives are then

$$\begin{aligned} \pi_{i0}^* &= 0 \\ \pi_{i1}^* &= \beta_1^* z_i + \varepsilon_{i1}^* \\ \pi_{i2}^* &= \beta_2^* z_i + \varepsilon_{i2}^* \\ \pi_{i3}^* &= \beta_3^* z_i + \varepsilon_{i3}^* \end{aligned}$$

This implies that the profit to adopting neither innovation is fixed at zero ($\pi_{i0}^* = 0$). One should then interpret the profits of the other options as differences from the non-adoption option. We measure profit complementarity by how much better or worse the firm would do by adopting both strategies than would two identically firms each specializing by adopting one strategy. We denote the profit complementarity by δ and define it as:

$$\delta = \pi_{i3}^* - (\pi_{i1}^* + \pi_{i2}^*) \tag{4.2.2}$$

One should not infer from the use of the term complementarity any restriction that δ be positive. The case of negative profit complementarity is certainly plausible in many contexts, especially if the two innovation types are substitutes. Rewriting (4.2.2) we get

$$\begin{aligned}\pi_{i3}^{*} &= (\pi_{i1}^{*}+\pi_{i2}^{*})+\delta \\ &= (\beta_{1}^{*}+\beta_{2}^{*})z_i+(\varepsilon_{i1}^{*}+\varepsilon_{i2}^{*})+\delta\end{aligned}$$

The both strategies innovation profile is chosen, *i.e.* the choice $j=3$ is observed, if we have: $\pi_{i3}^{*}>\pi_{i2}^{*}$, $\pi_{i3}^{*}>\pi_{i1}^{*}$, and $\pi_{i3}^{*}>\pi_{i0}^{*}$. Let us define $\theta_{j}^{*}=\beta_{j}^{*}z_i$, with $\theta_{j}^{*}=(\theta_{1}^{*},\theta_{2}^{*})'$. Rewriting these conditions lead to the following constraints on the errors:

$$\begin{aligned}\varepsilon_{i1}^{*} &> -\delta-\theta_{1}^{*} \\ \varepsilon_{i2}^{*} &> -\delta-\theta_{2}^{*} \\ \varepsilon_{i1}^{*}+\varepsilon_{i2}^{*} &> -\delta-(\theta_{1}^{*}+\theta_{2}^{*})\end{aligned} \tag{4.2.3}$$

Now we want to compare these constraints to those generated by the structural model. Following Miravette and Pernias (2010), we define the profit function as follows:

$$\pi_i\left(s_i^1,s_i^2\right)=(\theta_1+\varepsilon_1^{*})\,s_i^1+(\theta_2+\varepsilon_2^{*})\,s_i^2+\delta s_i^1 s_i^2$$

where the innovation choice is represented by the two dichotomous variables s_i^1 and s_i^2. To catch the complementarity effect, a pairwise interaction term (δ) among the two strategies is introduced. As previously, (θ_1,θ_2) represents the observable characteristics of the firm and $\left(\varepsilon_{i1},\varepsilon_{i2}\right)$ returns unobservable to the econometrician. If we observe $\left(s_i^1,s_i^2\right)=(1,1)$ this is because the profit function satisfies the following conditions: $\pi_i(1,1)>\pi_i(0,1)$, $\pi_i(1,1)>\pi_i(1,0)$, and $\pi_i(1,1)>\pi_i(0,0)$. Rewriting these conditions, we get the MNP system of constraints (4.2.3) on the unobserved returns[8].

Since the MNP generates the same set of constraints than the structural model, the structural-parameter estimate of complementarity can be recovered with this model. The intuition of this result is the following. Recall that if the firm adopts the two innovations simultaneously, this can be due to the existence of complementarity or to the existence of these unobservable returns. With a MNP, we are able to separate the complementarity between the strategies from the unobserved heterogeneity, since we can estimate both δ, which catches complementarity, and ρs the correlation coefficients between the errors. Indeed, in contrast to the bivariate approach (Miravette and Pernias, 2010), the MNP model generates no incoherence problem. That is, it is possible to associate each combination of the errors $(\varepsilon_{i1}^{*},\varepsilon_{i2}^{*})$ to one and only one

[8]The only difference is that the estimated parameter in the MNP are normalized.

strategy profile without imposing the restrictive condition $\delta = 0$. Otherwise, we can estimate only the coefficients of correlation between the errors.

To show this, let us rewrite the system of constraints [3.2.5, 3.2.6, 3.2.7] by defining the set S_3 of the combinations of the errors $(\varepsilon^*_{i1}, \varepsilon^*_{i2})$ leading to the joint strategies adoption $(j = 3)$

$$S_3 = \{(\varepsilon^*_{i1}, \varepsilon^*_{i2}) : \varepsilon^*_{i1} > -\delta - \theta^*_1, \varepsilon^*_{i2} > -\delta - \theta^*_2, \varepsilon^*_{i1} + \varepsilon^*_{i2} > -\delta - (\theta^*_1 + \theta^*_2)\}$$

Similarly, we define the following set S_1 of the combinations of the errors leading to the adoption of strategy 1 $(j = 1)$

$$S_1 = \{(\varepsilon^*_{i1}, \varepsilon^*_{i2}) : \varepsilon^*_{i1} > -\theta^*_1, \varepsilon^*_{i2} < -\delta - \theta^*_2, \varepsilon^*_{i2} - \varepsilon^*_{i1} > \theta^*_2 - \theta^*_1\}$$

symmetrically, the set S_2 of the innovation profile 2 $(j = 2)$ is

$$S_2 = \{(\varepsilon^*_{i1}, \varepsilon^*_{i2}) : \varepsilon^*_{i1} < -\delta - \theta^*_1, \varepsilon^*_{i2} > -\theta^*_2, \varepsilon^*_{i2} - \varepsilon^*_{i1} > \theta^*_1 - \theta^*_2\}$$

finally the set S_0 leading to the adoption of neither innovation is

$$S_0 = \{(\varepsilon^*_{i1}, \varepsilon^*_{i2}) : \varepsilon^*_{i1} < -\theta^*_1, \varepsilon^*_{i2} < -\theta^*_2, \varepsilon^*_{i2} + \varepsilon^*_{i1} < -\delta - \theta^*_1 - \theta^*_2\}$$

We show graphically that there is no overlapping between these different sets either when $\delta < 0$ (see Fig.2.1) or when $\delta > 0$ (see Fig.2.2). This implies that a multinomial probit estimation generates no incoherence problem. Therefore, we can estimate both δ, which catches complementarity, and ρs the correlation coefficients between the errors. That is, it is possible to separate the complementarity between the strategies from the unobserved heterogeneity, and thus recover the structural-parameter estimate of complementarity.

Figure 2.1: Regions of the different strategies when $\delta < 0$

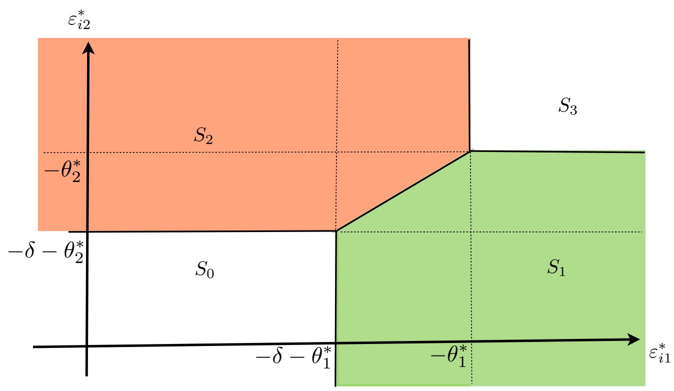
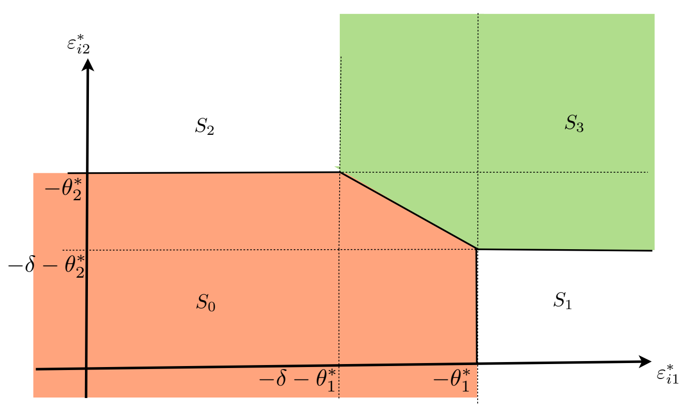


Figure 2.2: Regions of the different strategies when $\delta > 0$



4.2.3.2 Discussion

The problem of normalization is not the only difficulty encountered when we try to estimate a MNP model. A study performed by Keane (1992) shows that even if formal identification of the MNP models does not require exclusion restriction, the parameter identification of the models can be extremely tenuous in the absence of such restrictions[9]. This problem can be solved when the regressors of the stochastic profits π^*_{ij} include an alternative-specific attribute. This means that data must contain some variables - observed for all individuals - which should enter the profit associated with only one alternative and not the others. Such alternative-specific variables are usually available in studies concerning transportation choice (Greene, 2003), where, for example, the price or a quality indicator faced by the individual in each alternative can be observed. Without such a structure of data, the multinomial probit can still be identified if: *(i)* we can find variables that directly impact the choice of one signal strategy but not the other; *(ii)* we impose some additional constraints on the variance-covariance matrix[10].

If other class of multinomial models are easier to estimate, they are less suitable to test for complementarity. This is the case of the standard multinomial model or the HEV (Heteroscedastic Extreme Value) model since the key assumption in this class of models is the "independence" of the extreme value of distribution. This assumption implies that the unobserved portion of profit for one alternative is supposed to be independent of the unobserved portion of profit for other alternatives (Independence of Irrelevant Alternatives Assumption). In other words, the errors among alternatives are supposed to be uncorrelated and thus the correlation coefficients are zero ($\rho = 0$). Therefore, since only δ can be estimated by using such class of models, it is not possible to separate complementarity from unobserved heterogeneity (Augereau et al., 2006)[11]. Whereas the MNP model can estimate both δ which catches complementarity, and ρs the correlation coefficients between the errors (Gentzkow, 2007).

Another solution is to examine firm simultaneous decisions in a bivariate model with an endogenous dummy variable. This model would explicitly test whether the adoption of the first type of innovation is a function of the use of the second type of innovation, and *vice*

[9]Identification of a model is *tenuous* or *fragile* when even if formally identified, this model exhibit very small variation in the objective function from its maximum over a wide range of parameter values (Keane, 1992; p. 193).

[10]See Train (2009) for an extensive discussion.

[11]Note that we have the symmetric case in the bivariate probit model, when $\delta = 0$ and only the correlation coefficients can be estimated due to the incoherence problem.

versa. However, this kind of model is also plagued by the incoherence problem encountered in the classic bivariate model (Heckman, 1978; Tamer, 2003).

4.3 Data and Variables

Our data come from the national survey conducted in 2005 by the ministry of agriculture on the 1,500 small French agricultural cooperatives[12]. This periodical survey aims to study the economic conditions of small agricultural cooperatives processing and marketing excluded from the SCEES[13] annual business survey. From the exhaustive sample of 1500 cooperatives we build a database of 993 individuals after cleaning out missing values, since not the whole cooperatives answered every question.

A small cooperative[14] is defined in this survey as a cooperative that has 10 or less full time employees. By achieving a total turnover of 3.6 billion euros, these small cooperatives represent less than 1% of the processing and marketing activity of agro-food products. But they are the first intermediary of over 100 000 farmers and thus are closely engaged in their production and strategic choices to market access. And although they are small cooperatives, their size vary at large since only 10% of these cooperatives realized more than 30% of total sales.

Those small cooperatives are also very marked territorially because of the location of their members. That is, more than half are in fact exclusively regional customers, even more than 3/4 of these make more than 50% of their turnover in the region. Moreover, most of small cooperatives tend to trade with essentially the same type of customers (only 14% do not achieve more than half of their turnover with the same customer). Among the typical customers, other cooperatives occupy a privileged place, indicating the importance of the cooperatives network (Fillipi et Triboulet, 2010). If the majority of small cooperatives develop their activities at the regional level, they realize on average 20% of sales at the national level. 7% of the cooperatives declared exports of their products to other countries and earned 6% of total sales. Exports are mainly oriented to European Union markets and in a less extend to out of EU markets. Note that those cooperatives who export are generally the largest small

[12] Enquête sur les petites coopératives agricoles et forestières, 2005.

[13] Service centrale des enquêtes et des études statistiques (Central office for statistical surveys and studies).

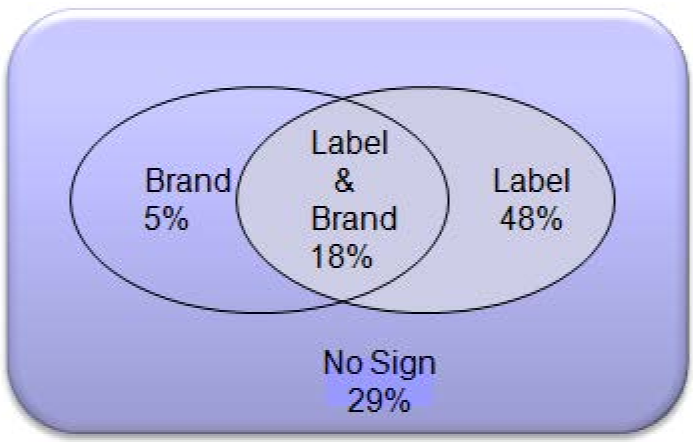
[14] Recall that agricultural cooperative societies form a legal category of society that distinguishes civil and commercial companies. Their operations based on solidarity farmers producers to ensure their supply, processing, marketing, and sale of their products. These cooperatives are exempted from corporation tax provided to operate in accordance with the legal provisions that govern them.

cooperatives, with a median turnover double than those turned exclusively to the domestic market.

4.3.1 Dependent Variables: labels and brands

In the agro-food industry, firms used to choose two main signals: quality labels and brands. In our database, the different signaling profiles are distributed as follows: *(i)* 30% of small cooperatives use no signal (**NSIG**); *(ii)* 48% of them uses only labels (**LABEL**); *(iii)* 5% uses only brands (**BRAND**); *(iv)* 18% of the cooperatives use a "mix signal" strategy by adopting both signals (**LABRAND**).

Figure 4.3.1: Distribution of quality signs



First, since the official signs (labels) are widespread in the French agro-food sector, it is not surprising to note that two third of small cooperatives adopt labels. As shown by table 1, among the different labels enforced by the French state regulation, there is a large predominance of signs indicating the geographical origin of products (AOC and PGI). Those signs are especially developed for wine and cheese, and more generally 79% of dairy products and 64% of alcoholic beverages are sold by small cooperatives with a label indicating the geographical origin of the product. Other labels hold a significant position with a relatively high organic farming (AB)[15]. The cooperatives may also adopt different labels. Indeed, labels are non-exclusive since different labels can be used to point out different dimensions of quality (The "label rouge" can be chosen to signal organoleptic quality of the product, and the label

[15]Label Rouge certify that processed and unprocessed food or non-food agricultural products have specific characteristics establishing a level of quality, resulting in particular from their particular conditions of production or manufacture and conform to specifications which distinguish them from similar products and foodstuffs normally sold.

"AB" to signal its "environmental-friendly" dimension). However, in our database, very few cooperatives among those that use the label strategy adopt more than one label (see table 1).

Table 4.1: Labels owned

no label	35%		
at least one label	65%	Number of labels owned	
		1	85%
		2	12%
		3	2%
		4	1%

Second, branding is much less common since it concerns less than a quarter of small cooperatives (22%). A notable fact is that brands are primarily associated with a label (18% of the whole sample and 75% of the cooperatives that choose the brand signal), while very few choose to hold only a brand (5% of the whole sample and 25% of those choosing a brand).

Small businesses do not always have the ability to develop their own financial trademarks and many produce on behalf of major brands. This is partly explained by specific institutional features: the wide dissemination of official quality labels. This type of quality labels has the advantage for small cooperatives to collectivize the costs of establishment and implementation of the signal, which allows them to not only assume the economic burden but management of a brand as well.

4.3.2 Independent Variables

Different variables may explain the choice of quality signals. First, the turn-over realized by the cooperative. The continuous variable **LN(TURN)** indicates the turnover (millions euros) realized in 2005 by the cooperative. However, to perform their turnover, cooperative structures suffer from lower levels of labor force than capitalist structures. Indeed, a cooperative is defined to be small if it has less than ten employees. We build a variable indicating the number of employees (**EMP**). On average, the cooperatives in our database have less than 4 full-time equivalent employees. But we observe a large variability since some cooperatives have no employees, while others are at the threshold of 10 employees. Due to this limited workforce, farmers, as members of the cooperative, do a large number of jobs mainly in seasonal periods of intense activity for the cooperative. The continuous variable **MEM** indicates the total number of members (Table (4.2)).

The other solution to get workforce, equity and new competencies is to join a union of cooperative (Filippi et al. 2006). The membership to a union of cooperatives is indicated by the dummy variable, **UNION**. In our database, nearly 40% of the small cooperatives join an union. These unions take the form of new cooperatives as an umbrella for the associated cooperatives. The consolidation of equity can then carry the heavy equipment that the cooperative base alone cannot achieve. To expand its scope and develop a certain critical size, the cooperative may also hold shares in the capital of other (private) firms. When the holdings reach 50% or more, the firm becomes subsidiary owned by the cooperative. We build a dummy variable **SUBSID** indicating when the cooperative has a subsidiary firm. This organizational model is often seen as a mechanism for the cooperative to market directly its products by creating a marketing firm that sell the products under its own brand (Hendrikse and Bijman, 2004). However, this strategy only refers to 15% of the small cooperatives, mainly those which have the highest turnover.

The second set of variables that may explain the choice of quality signal is related to the nature of the activity and the products of the cooperative, as well as the market structure and the different marketing channels used. There is a clear cut distinction in our database between cooperatives that are just intermediary of exchange (wholesale industries) and cooperatives that industrially processes the products collected from their members. The first category represents 63% of the whole sample and the second 37%. The two categories are very different in their structures. Within the agro-food industry, the wine making activity (60% of the cooperatives) and the dairy industry (25% of the cooperatives) are predominant. As noted previously, these are the two activities where the labels are over-represented. To take into account the effect of the agro-food industry on the signaling strategy, we create a dummy variable **AF** that indicates if the small cooperative processes the farmer's products. In the wholesale trade, there is no dominant activity and the first three sectors are milk, eggs & oil (25%), grain & animal feed (20%) and fruit and vegetables (17%); sectors where labels are less represented. To analyze more precisely the effect of the different types of product, we build five dummy variables representing the five main sectors of production: *(i)* Beverages, mainly wine (**BEV**), *(ii)* cereals & feed (**CER**), *(iii)* fruit & vegetables (**FVEG**); *(iv)* meat (**MEAT**); *(v)* milk, eggs & oil (**MILKOIL**).

Small cooperatives are also marked territorially because of the location of their members.

This local anchor is often found in the type of market and marketing channel mainly used by small cooperatives. Regarding the type of market, more than half of the cooperatives have regional customers exclusively and three quarters of them make more than 50% of their turnover in the region. We have a dummy variable, (**LT50INREG**), which equals one when the cooperative makes less than 50% of its turnover in the region. Export market represents 3% of total sales on average and essentially turned towards the European Union. But, given their size a significant proportion exported beyond the borders of Europe (5%). Note that the cooperatives that export with a median turnover of around double than the cooperative turned exclusively to the domestic market. We build two continuous variables for the exporting cooperatives: *(i)* percentage of total sales from export in Europe (**EXINEU**); *(ii)* percentage of total sales from export outside EU (**EXOUTEU**). 44% of total sales are being exported with the brand and public label. 8.5% of total sales that is exported in EU are without any public label or brand, and 12% of total sales that export outside EU use brand and label signals.

As for the marketing channel, we notice that most small cooperatives tend to trade with essentially the same type of client (86%). We build a variable that equals one when the cooperative makes less than 50% of its turnover with the same client (**LT50SC**). We control for the different kind of channels, according to the cooperative sells its product to Supermarket (**SUPER**), retailers (**RET**), wholesalers (**WS**), or hotels and restaurants (**OTHER_HOT**).

Table 4.2: Description of variables

Variable	Definition	Mean	S. D.	Min.	Max.
Size and organizational structure					
MEM	Logarithmic value of no. of adherents	3.83	1.26	0.00	8.07
EMP	Number of employees (from 0 to 10)	3.53	3.64	0.00	10.00
UNION	= 1 if coop is affiliated with an Union	0.40	0.49	0.00	1.00
SUBSID	= 1 if coop is subsidizing	0.14	0.34	0.00	1.00
TURN	Logarithmic value of turnover (millions €)	13.7	1.86	0.00	17.26
Activity					
WSI	= 1 if coop is a Wholesale industry	0.30	0.46	0.00	1.00
AF	= 1 if coop is an Agro-food industry	0.69	0.46	0.00	1.00
Products					
MILKOIL	= 1 if coop produces milk & oil (reference)	0.28	0.45	0.00	1.00
BEV	= 1 if coop produces beverages	0.48	0.50	0.00	1.00
CER	= 1 if coop produces cereals	0.06	0.23	0.00	1.00
FVEG	= 1 if coop produces fruits & vegetables	0.07	0.26	0.00	1.00
MEAT	= 1 if coop produces meat	0.05	0.22	0.00	1.00
OTHERS	=1 if coop produces other products	0.05	0.22	0.00	1.00
Export Markets					
EXINEU	% of Turnover by exports within EU	0.35	0.89	-0.47	4.60
EXOUTEU	% of Turnover by exports outside EU	0.06	0.39	0.39	4.60

Variable	Definition	Mean	S. D.	Min.	Max.
Local Market					
LT50INREG	= 1 if less than 50% turnover in the same region	0.21	0.41	0.00	1.00
Marketing Channels					
- cooperative network	= 1 if dealing with a coop network (ref)	0.29	0.45	0.00	1.00
- SUPER	= 1 if dealing with supermarket	0.05	0.21	0.00	1.00
- RET	= 1 if dealing with a retailer	0.10	0.29	0.00	1.00
-WS	=1 if dealing with a wholesaler	0.18	0.18	0.00	1.00
- OTHERS_HOT	= 1 if dealing with hotels & restaurants	0.23	0.42	0.00	1.00
LT50SC	= 1 if less than 50% of turnover with the same customer	0.14	0.35	0.00	1.00

4.4 Results and Interpretations

We regress the endogenous quality signal variables on the independent variables, using the empirical models presented in section 2. In what follows, we first present the estimation results of the bivariate probit (4.4.1) as well as those of the multinomial logit (Table 4.4.2). Then, we will give the results of the multinomial probit estimation and conclude on the evidence of complementary/substitution effect (Table 4.4.3).

4.4.1 The Bivariate Probit

With the estimation of the bivariate probit model, we start with an investigation of the correlation between both quality signals (label and brand) conditional on intra-organizational and environmental characteristics of the cooperative. Label and brand are defined as non-exclusive quality signals, *i.e.* it is possible that the cooperatives may use both.

The results for the bivariate probit estimations, with the two methods of maximum likelihood (MML) and simulated maximum likelihood (SML), are presented in Table (4.3). The first important finding is that there is a significant positive relationship between label and brand signals as indicated by the positive and significant correlation coefficient ρ. This finding suggests that label and brand signals are likely to occur in combination and hence is a first indication of complementarity. To explain this possible complementary effect between labels and brands, we need to analyze the different variables that have significant effect on the adoption of label and brand signals. Concerning the size and organizational structure variables, the small coops that have a higher number of employees (EMP) and turnover (LnTurn) and, at the same time are members (Union) of a larger cooperative, choose preferably a label. In contrast, the small cooperatives that have both higher employees and members (MEM) choose a brand strategy. This may suggest a strong contrast between: *(i)* small cooperatives that have a "cooperative" strategy of growth by developing their relationships and organizational proximities with bigger cooperatives and thus choose a "cooperative" signal like a label; *(ii)* cooperatives that have more "individualistic" strategy of growth with more employees and members and that choose an "individualistic" signal like brand. We observe the same contrast for the different sectors of activity. If, compared to the reference MILKOIL, the cooperatives of the other sectors have less recourse to labels, those in the fruits & vegetables sector (FVEG) are more prone to adopt a brand. This contrasting result holds also for export markets and marketing channels. Indeed, if exporting to European markets (EXINEU) increases the adoption of both signals, the cooperatives that export outside European

Union (EXOUTEU) are less prone to choose a label. For marketing channels, compared to the cooperatives network (reference), transacting with a reduced number of big partners like supermarket and wholesalers increases the probability of adopting a brand. In contrast, having a larger number of small partners (LT50SC, *i.e.* less than 50% of turn-over with the same client) increases the probability of adopting a label.

This contrast in drivers that affect the choice of labels and brands may be explained by the fact that the label and brand signals are not mutually exclusive in the bivariate probit model. That is, observing the label choice can be the result either of choosing a label strategy or of choosing the mix signal (label and brand). To analyze the different drivers of all the combination of signal strategies, we need to estimate a multinomial logit.

4.4.2 The Multinomial Logit

We estimate a multinomial logit model, examining the drivers for the combinations of all signal strategies (NOSIG, LABEL, BRAND, LABRAND). This can be done if the number of categories is not too large and there is sufficient variation in each category. We estimate the following model of quality signal choice:

$$\Pr(Y = j) = \frac{e^{X_i \beta}}{\sum_{i=1}^{4} e^{X_i \beta}}$$

with $j \in \{LABEL, BRAND, LABRAND, NOSIG\}$ and X_i a vector of characteristics of cooperative i. cooperatives choosing no signal (NOSIG) serve as the reference case.

Compared to the bivariate probit model, the multinomial logit model is less restrictive on the effects that exogenous control variables can have on the different choices, allowing coefficients to vary across exclusive combinations of quality signals. The bivariate probit restricts the coefficients to be the same for all LABEL (BRAND) decisions. The multinomial logit model, therefore reveals drivers of exclusive combinations of the different quality signals. That is, the alternatives are exclusive now, *i.e.* each cooperative can only belong to one of the four groups. This allow us to apply the indirect test for complementarity. Recall that this test relies on an exclusion restriction that affects the use of one of the quality signal in isolation as well as the combined use of both signals while not the use of the other signal in isolation. That is, the marginal return from one signal is increased by the other. But, first we are interested in the drivers that affect the stand alone signals (LABEL and BRAND).

In the multinomial logit regression results (table (4.4)), the drivers for the stand alone signals are as contrasted as in the bivariate probit estimation. This may suggest more substitution effect than complementary one between signals. For the label only choice, we get exactly the same significant drivers than in the bivariate probit. For the brand only strategy, the only differences with the bivariate probit regression is that some variables are no more significant. This is the case for the MEAT and Beverage variables, and also for the marketing channels variables. If the supermarket variable still increases the probability of choosing a brand, it is no more the case of the wholesalers.

Second, to apply the indirect test for complementarity between signals we need some theoretical predictions. The literature on supermarkets (Liesbeth et al., 2004) provides us with a theoretical argument from an instrument variable, with a focus on brand, to test indirectly for complementarity. Compared to the other marketing channels, quality signals are widespread and more diverse in supermarkets. On one hand, the suppliers have incentives to develop their own brand strategy to get a larger share of the price premium paid by consumers. Supermarkets may also get some profits from this strategy since a brand signal is a credible commitment that the suppliers will provide a quality good. This could help to sustain the supermarket reputation as a third party guarantor of quality (Bigaiser, 1991; Biglaiser and Friedman, 1994). On the other hand, the development of brands when transacting with supermarkets may also have an indirect effect by increasing the return of a labeling strategy. The suppliers have indeed some incentives to use other signals to escape from the brands competition with supermarkets that recently developed their own (retailer) brands (Hassan and Monier-Dilhan, 2006; Berges et al., 2007; Berges and Bouamra, 2012). Another exclusion restriction is used in brand choice. Hayes et al. (2007) show indeed that brand is the more common signal in the fruit & vegetables sector. The fruit & vegetables market is very atomized, and thus less prone to the development of labels, with very few cooperatives able to ensure a collective action on common labeling adoption and diffusion. But this strategy can also have an indirect effect in the probability of adopting a label signal, since small producers are more and more prone to adopt common signal with the development of the organic label (AB) in the fruit and vegetables short supply chains (Torre and Traversac, 2011).

Two further restrictions are used that center around labels. We expect that the label choice depend on some specific governance of the cooperatives (Sykuta and Cook, 2001). That is, the more a cooperative is a member of a union of cooperatives (UNION), the more it will adopt the common labeling first (Fillipi and Triboulet, 2010). This can be explained by the fact the cooperatives subsidiary usually do not have the full decision rights on its marketing strategies (Bijman and Hendriksen, 2004). But the higher the "small" cooperative turnover, the higher its decision rights, and thus its negotiation power, inside the union to develop (or maintain) its own brand signal strategy. For such cooperatives, it can indeed be worthy to increase differentiation by using a mix signal. That is to say, adding a private signal on common labeling.

The estimation results show that some of our exclusion restrictions for the indirect test work. The supermarket variable impacts the choice of brand in isolation as well as the joint use of label and brand (LABRAND), while there is no impact on the choice of label only signal. Hence, we can conclude that choosing the supermarket as a marketing channel increases the expected marginal returns from brand in the presence of labels (mix signal). We find no significant effect of the other exclusion restriction on fruit and vegetables sector. The second set of exclusion restrictions, that builds on the governance of the cooperatives, also show that the level of the turnover and the subsidiary ownership by the cooperative are important for the label signal, and that the marginal gains from this signal are higher if brands are in place. The results further show that exporting in European countries (EXINEU) and making less than 50% of its turnover with the same customer also increase the marginal gains. But if the retailers (RET) and wholesalers (WS) variables significantly affect the probability of the mix signal (LABRAND), they do not significantly affect stand-alone signals (LABEL and BRAND).

Therefore, the multinomial logit results suggest two comments. It seems that the drivers for the label and brand stand alone signals are very contrasted, which may suggest that both signals are more substitutable than complementary. The indirect test of complementarity show an opposite result, *i.e.* that there is some evidence of complementarity. We find indeed some drivers that affect the use of one of the quality signals in isolation as well as the combined use of both signals (LABRAND) while not the use of the other signal in isolation. In the following section, we will estimate a multinomial probit model that will provide clear-cut result on the presence of a complementarity effect between quality signals.

Table 4.3: Bivariate probit estimation

Variables	MLE		SML	
	BRAND	**LABEL**	**BRAND**	**LABEL**
Constant	-2.79 (0.54)***	-1.99 (0.46)***	-2.79 (0.54)***	-1.99 (0.46)***
Size and organizational structure				
MEM	0.12 (0.05)**	-0.20 (0.04)**	0.12 (0.05)**	-0.20 (0.04)**
EMP	0.05 (0.01)***	0.04 (0.02)**	0.05 (0.01)***	0.04 (0.02)**
UNION	-0.13 (0.11)	0.29 (0.10)***	-0.14 (0.11)	0.29 (0.10)***
SUBSID	0.20 (0.14)	0.36 (0.14)**	0.21 (0.14)	0.36 (0.14)**
TURN	0.03 (0.04)	0.21 (0.03)***	0.03 (0.04)	0.21 (0.03)***
Domain of activity				
WSI	Ref.	Ref.	Ref.	Ref.
AF	-0.11 (0.17)	0.34 (0.14)**	-0.13 (0.17)	0.34 (0.14)**
Activity sector				
MILKOIL	Ref.	Ref.	Ref.	Ref.
BEV	0.97 (0.16)***	-0.28 (0.13)**	0.98 (0.16)***	-0.28 (0.13)**
CER	-0.16 (0.31)	-1.35 (0.24)***	-0.17 (0.31)	-1.35 (0.24)***
FVEG	0.75 (0.23)***	-0.52 (0.19)***	0.72 (0.23)***	-0.53 (0.19)***
MEAT	0.78 (0.25)***	-0.13 (0.22)	0.77 (0.25)***	-0.13 (0.22)
OTHERS	0.20 (0.30)	-1.08 (0.25)***	0.19 (0.30)	-1.08 (0.25)***
Export markets				
EXINEU	0.17 (0.05)***	0.15 (0.06)**	0.17 (0.05)***	0.15 (0.06)**
EXOUTEU	0.11 (0.12)	-0.28 (0.12)*	0.11 (0.12)	-0.28 (0.12)*

Variables	MLE		SML	
	BRAND	**LABEL**	**BRAND**	**LABEL**
Local market				
LT50INREG	0.16 (0.12)	-0.23 (0.12)*	0.15 (0.12)	-0.23 (0.12)**
Marketing channels				
COOP	Ref.	Ref.	Ref.	Ref.
SUPER	0.62 (0.22)***	-0.07 (0.21)	0.62 (0.22)***	-0.06 (0.22)
RET	0.32 (0.20)	0.11 (0.17)	0.30 (0.20)	0.11 (0.17)
WS	0.33 (0.15)**	0.19 (0.14)	0.33 (0.15)**	0.19 (0.14)
OTHERS_HOT	-0.02 (0.15)	-0.04 (0.13)	-0.02 (0.15)	-0.04 (0.13)
LT50SC	0.31 (0.16)*	0.58 (0.17)***	0.30 (0.16)*	0.58 (0.17)***
ρ	0.22 (0.06)***		0.19 (0.06)***	

* Significant at 10%; ** Significant at 5%; *** Significant at 1%.

Table 4.4: Multinomial logit estimation

Variables	Both	Brand	Label
Constant	-6.44 (1.35)***	-7.01 (1.85)***	-3.83 (0.91)***
Size and organizational structure			
MEM	-0.13 (0.11)	0.36 (0.16)**	-0.34 (0.08)***
EMP	0.17 (0.04)***	0.14 (0.05)***	0.09 (0.04)***
UNION	0.25 (0.25)*	0.39 (0.36)	0.74 (0.20)***
SUBSID	0.91 (0.33)***	0.16 (0.50)	0.54 (0.19)
TURN	0.30 (0.10)***	0.11 (0.11)	0.38 (0.06)***
Domain of activity			
WSI	Ref.	Ref.	Ref.
AF	-0.07 (0.39)	1.22 (0.68)*	0.81 (0.26)***
Activity sector			
MILKOIL	Ref.	Ref.	Ref.
BEV	1.55 (0.42)***	0.46 (0.62)	-0.84 (0.24)***
CER	-1.42 (0.71)**	-1.25 (1.28)	-2.54 (0.47)***
FVEG	0.48 (0.55)	1.45 (0.84)*	-0.95 (0.36)***
MEAT	1.19 (0.58)**	0.95 (0.93)	-0.45 (0.42)
OTHERS	-0.67 (0.71)	-0.02 (1.08)	-2.13 (0.50)***
Export markets			
EXINEU	0.49 (0.13)***	0.39 (0.19)**	0.27 (0.13)**
EXOUTEU	-0.23 (0.28)	0.25 (0.30)	-0.51 (0.25)**

Variables	Both	Brand	Label
Local market			
LT50INREG	-0.16 (0.28)	0.39 (0.39)	-0.44 (0.25)
Marketing channels			
COOP	Ref.	Ref.	Ref.
SUPER	1.15 (0.54)**	1.53 (0.63)***	0.19 (0.49)
RET	0.84 (0.44)*	0.19 (0.64)	0.13 (0.37)
WS	0.94 (0.35)***	0.38 (0.50)	0.31 (0.28)
OTHERS_HOT	0.14 (0.34)	-0.75 (0.55)	-0.22 (0.24)
LT50SC	1.55 (0.40)***	0.15 (0.64)	0.89 (0.34)***

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

4.4.3 The Multinomial Probit

As the multinomial logit model, and in contrast to the bivariate probit, the multinomial probit model is less restrictive on the effects that exogenous control variables can have on the different choices, allowing coefficients to vary across exclusive combinations of quality signals. The difference is that for the mix signal (LABRAND), the only explicative variable is the constant, which catches the complementarity effect. Like the bivariate probit model, and in contrast to the multinomial logit, it is possible to estimate a coefficient of correlation between the error terms, which catches the unobserved heterogeneity. Therefore, as explained in section 4.2, with a multinomial probit we are able to separate the complementarity between the strategies from the unobserved heterogeneity, since we can estimate both: *(i)* the parameter δ (the constant term in the regression), which catches complementarity; *(ii)* the parameter ρ (the correlation coefficients between the errors), which catches the unobserved heterogeneity between cooperatives. This separation cannot be done with the previous two models, bivariate and multinomial logit models.

The results in table (4.5) indicate that there is complementarity between quality signals, since the intercept coefficient is significant for the mix signal (LABRAND) choice. This complementarity effect here is a substitutability effect since the sign of the coefficient is negative

(-3.16). Then, this result show that the positive sign in the coefficient correlation found in the previous bivariate probit regression does not catch a complementarity effect, but only some unobserved heterogeneity between cooperatives that explain the mix signal choice. Indeed, the coefficient of correlation in the multinomial probit ($\rho = 0.63$) is positive and significant.

The drivers of both stand alone signals (LABEL and BRAND) exhibit this substitutability effect. Indeed, while exporting inside EU (EXINEU) increases the probability of adopting a label, exporting out the European Union (EXOUTEU) reduces this probability. This result magnified by the regional effect and the origin of the product. Indeed, making less than 50% in the region (LT50INREG) reduces the probability of choosing a label. In contrast, exporting out the EU increases the probability of adopting a brand since the positive sign of the coefficient turns to be significant in the multinomial probit, which was not the case in the previous regressions. This mainly shows that brand signal is made for export outside Europe Union and labels are profitable inside the European Union market. This is coherent with the idea that labels, mainly GIs and PDOs, have an access to an institutional recognition and protection from the European Union that make them profitable. Outside the borders of the EU markets, this protection is less effective and thus the trademark system, and thus brands, is more efficient.

Table 4.5: Multinomial probit estimation

Variables	Both	Brand	Label
Constant	-3.16 (1.01)***	-5.39 (2.68)***	-2.28 (0.87)***
Size and organizational structure			
MEM		0.28 (0.24)**	-0.23 (0.07)***
EMP		0.06 (0.0)**	0.03 (0.03)
UNION		0.26 (0.34)	0.54 (0.17)***
SUBSID		-0.03 (0.39)	0.36 (0.27)*
TURN		0.06 (0.11)	0.25 (0.07)***
Domain of activity			
WSI		Ref.	Ref.
AF		1.01 (0.82)**	0.61 (0.25)***
Activity sector			
MILKOIL		Ref.	Ref.
BEV		0.54 (0.88)	-0.86 (0.28)***
CER		///////	-1.71 (0.46)***
FVEG		1.31 (1.36)*	-0.85 (0.31)***
MEAT		0.87 (1.19)	0.51 (0.29)*
OTHERS		0.35 (1.18)	-1.54 (0.44)***
Export markets			
EXINEU		0.18 (0.12)	0.09 (0.09)*
EXOUTEU		0.16 (0.21)*	-0.29 (0.18)**

Variables	Both	Brand	Label
Local market			
LT50INREG		0.25 (0.27)	-0.03 (0.16)**
Marketing channels			
COOP		Ref.	Ref.
SUPER		1.09 (0.67)***	-0.003 (0.32)
RET		0.14 (0.42)	0.03 (0.22)
WS		0.20 (0.32)	0.12 (0.20)
OTHERS_HOT		-0.38 (0.31)*	-0.15 (0.17)
LT50SC		-0.12 (0.50)	0.62 (0.37)**
Error components			
ρ (Label, Both)		-0.07 (1.01)	
ρ (Brand, Both)		0.46 (0.88)	
ρ (Label, Brand)		0.63 (0.76)***	
σ (Label)		0.98 (1.35)***	
σ (Brand)		1.80 (4.54)***	

* Significant at 10%; ** Significant at 5%; *** Significant at 1%

4.5 Conclusion

Many quality signals have been developed to foster the development of food quality in the agro-food markets, mainly brands and common labels. Previous research has typically focused on either brand or common label efficiency independently, while in many instances both signals coexist. Agricultural products pairing brand names and certified labels, such as indications of origin, are indeed very common (*e.g.* Roquefort cheese, Scottish whiskeys and most of the French wines). The objective of this chapter is to take into account this coexistence by empirically analyzing the complementarity/substitutability that may exist between labels and brands. To do so, we develop a multinomial probit model of complementarity that we test on a database of the quality signaling strategies from 993 French small cooperatives. Our main result is that there is a clear interaction effect between brand and label signal strategies but it is more a substituability effect than a complementary one. The positive correlation that can be observed between both signals is only due to the unobserved heterogeneity between cooperatives.

Given the lack of previous empirical work on this topic of coexistence of quality signals, the first results generated by this research provide some interesting suggestions for further theoretical work which treats the complementarity between quality signals. But, more empirical work is needed to improve the predictive power and the significance levels, and check the robustness of the estimates. Introducing new questions in the survey, and thus new variables in the database, on contracting and governance mechanisms of the cooperatives may help to control for the unobserved heterogeneity. A panel data set on the different surveys on cooperatives signal choices would allow also us to control for unobserved specific effects.

Chapter 5

Crop-Livestock Complementarity and Income Maximization: Policy Implications for Developing Countries

5.1 Introduction

As in many less developed countries, Pakistan is an agriculture based country where either directly or indirectly more than 60% of the population is dependent on agriculture for their livelihoods. A large share of agricultural production comes from the smallholder farmers owning less acreage of agricultural land and having recourse to different farming systems: cropping system alone, livestock system alone, or a mixed cropping and livestock system. According to Edwards et al. (1988), the synergistic interactions of the components of this mix farming system may have a significant and positive economic effect greater than the sum of their individual effects. The fact that smallholder farmers adopt cropping and livestock simultaneously may suggest that these activities are complementary, that is the marginal return to one activity increases as the intensity of the other increases. In this chapter, our study interest is to test for the possible complementarity effect between cropping and livestock activities of the smallholder farmers in the province of Punjab in Pakistan.

Most studies on rural household market participation focus either on crop or livestock markets separately (Lapar et al., 2003; Jaleta and Gardebroek, 2010; Negassa and Jabbar, 2008). Therefore, in explaining smallholder participation in crop markets, livestock usually enters the crop market participation equation as a draught power, risk assurance indicator or as alternative income source to crop sales, assuming that smallholder decision in livestock markets is given. Thus, in mixed crop and livestock farming systems in the Pakistan Punjab, where diverse types of animals are kept and diverse types of crops are produced, the choice of one activity is likely to be influenced by the other. Though, several empirical studies have investigated the integration of crop and livestock activities (Bell et al., 2013; Tarawali et al., 2011; Udo et al., 2011), we did not find any research testing for this possible complementarity effect.

To test for complementarity we have recourse to different empirical models of complementarity. The theoretical framework of complementarity is based on the theory of supermodularity that was first discussed in detail by Topkis (1978). This latter shows that when a function is supermodular it exhibits a complementarity effect. That is, the payoff of jointly adopted strategies is higher than the sum of payoffs of these strategies taken separately. In order to test for this complementarity effect, two approaches are usually used in the literature (Athey and Stern, 1998). Direct approach (also called production approach) is concerned when a performance measure in terms of profit or income generated by the different strategies is available. In this case, we use ordinary least squares (OLS) estimation and regress profit or income on exogeneous variables and dummies representing the different strategies. A complementarity test is run on the coefficient associated to these dummies to see if the marginal return to one activity increases as the intensity of the other increases. If performance measure is not available in the data, we are obliged to use an indirect approach (also called adoption approach) which is based on the analysis of correlation conditional on a common set of exogenous variables.

In both approaches, besides the evidence of a potential complementary effect, we also analyze the different drivers of the smallholder farmer's decision to adopt any activity. These drivers can be: *(i)* the socio-demographics variables of the family's head (age, educational status); *(ii)* variables characterizing the whole family (family size, type of family system, family assets such as land ownership and income generated by the different activities); *(iii)* the different agro-climatic regions in the Punjab Province. Data used in this study were collected from the different agro-climatic regions in Pakistan Punjab. The initial data were collected by the enumerators using survey methods and some variables were collected on households demographic, income and expenditure sources, land resources and livestock inventory, and economic activities they were involved in. The data set used in this study includes 360 household observations.

Results from the production approach provide evidence of a complementarity effect from the mixed farming system. We also obtain interesting insights about contextual variables that affect whether or not such activities may explain this complementary effect. We identify that regional diversity is an important factor in determining economic gains for smallholders because of differences in socio-economic and environmental context and smallholders preferences about adoption of farming activities. Next to it, some other factors that account for increasing productivity are education, herd size, and land size. The adoption approach confirms the result of complementarity even after controlling for unobserved heterogeneity. For this, we use first a bivariate probit to estimate the coefficient of correlation between cropping and livestock. The positive sign of the correlation coefficient is however plagued by an incoherence problem. To resolve this issue of incoherence, we adopt a multinomial probit model that also allows to estimate separately of what is due to complementarity and what is due to unobserved heterogeneity. The result confirms the complentarity effect in the mixed farming system.

This chapter is organized as follows. Section 5.2 reviews the related literature on mixed farming and adoption of cropping or livestock activities. In section 5.3, we discuss the theory of complementarity and the two approaches to test for complementarity (direct approach and indirect approach). Section 5.4 presents the database and the variables. Results are presented in Section 5.5 adjoining to discussion. Section 5.6 concludes.

5.2 Related Literature

The importance of mixed farming system in providing crop and livestock products is not new and for at least two decades, research and development strategies have explored the potential of such systems to address developing countries food needs and mitigate poverty (Lenné and Thomas, 2006; Williams et al., 2004; Parthasarathy and Birthal, 2008). The innumerable benefits of the crop and livestock integration can be agronomic, through the recuperation and maintenance of the soil productive capacity (Ngambeki et al., 1992), and ecological, through the reduction of crop pests and consequently less pesticide use as well as erosion control (Delve et al., 2001). There are also some economic benefits of these systems since they can better manage risk through diversification and may also provide product quality and food security (Devendra and Thomas, 2002).

First, Seo (2010) and Dinar et al. (2008) show that farmers in Africa that turn towards mixed farming system against specialized farming, are more resilient to climatic shocks. However, to get more involvement with the climate, they need to choose some special types of crops and some special species of animals as it is not completely unrestricted due to difference of climatic zones and precipitation. In spring season, they avoid livestock while summer precipitations are the most favourable season to adopt both activities. More generally, since climatic risk management tools in less developed countries are imperfect or completely missing, the adjusted measures taken to control the distribution of risk variables are diversification on the farm (Walker and Ryan, 1990) and risk controling inputs (Just and Pope, 1979). Kurosaki (1995) has shown the importance of livestock as a consumption smoothing measure for income and price risks. He has also found that the rise in the share of livestock subsector in agricultural value added in Pakistan should have improved welfare positions of poorer households in rural areas. Mishra (2007) also highlights the role of livestock in cropping as a risk management tool and an evidence of rural insurance mechanism through livestock. This insurance mechanism plays mainly through revenue diversification (Perry, 1982; Lockwood, 1982). Income from milk and milk products was estimated as 27% of the household income and the sale of animals on the religious festival "Eid-ul-Azha" is considered as one of the best returns of livestock.

Second, mixed farming systems can also provide quality products and food security. Gonzàlez-Garcia et al. (2010) showed that mixed farming production in the Caribbean gives a wide availability and quality of authentic primary products. Their crop residues, agro industrial by-products and other non-conventional feeds are useful to be used in integrated feeding systems. They find that increasing pressure on land is a key factor of the development of mixed farming, which at the same time could mean positive and economic benefits in the promotion of a sustainable and environmental friendly agriculture. However, even if this mixed farming system is more socially efficient than the specialized system, the smallholder farmer adopt crop and livestock activities jointly if the profit generated is higher than with each activity taken in isolation (Lemaire et al., 2013). That is, if the mixed farming system generates complementary effect.

5.3 Testing for Complementarity: theory and empirical models

In order to test for complementarity, two approaches are usually used in the literature. The first one is based on testing the contribution of different combinations of practices, along with observable characteristics, directly on the performance measure (also called productivity approach). If performance measure is not available, the prevailed indirect approach (also called adoption approach) is adopted which is based on the analysis of correlation between discrete decisions on activity, conditional on a common set of exogenous variables.

This complementarity approach traces back to a mathematical theory of lattices and supermodularity functions (5.3.1). From this theoretical framwork, we can derive predictions on the complementarity between strategies chosen by an agent (5.3.2). We test these predictions using the two empirical approaches, productivity approach and adoption approach, highlighted by Athey and Stern (1998) (5.3.3). Identification problems of our empirical models are discussed briefly in subsection 5.3.4.

5.3.1 Lattice and Supermodularity

5.3.1.1 *Lattice*

Lattice theory is a branch of mathematics concerning partially ordered sets[1] (Birkhoff, 1984). This theory was first applied by Topkis (1978) and then Milgrom and Roberts (1990, 1995) and Topkis (1995) to monotone optimization problems in Economics. In what follows we present briefly basic elements of the lattice theory.

Definition: A partially ordered set X is said to be lattice *iff* for all x, y $\in$ S

$$x \bigvee y = (max\{x_1, y_1\}, \ldots, max\{x_n, y_n\})$$

$$x \bigwedge y = (min\{x_1, y_1\}, \ldots, min\{x_n, y_n\})$$

Here, operators $\bigvee$ and $\bigwedge$ are called join (or supremum) and meet (or infimum) respectively.

For our purpose, the nodes of the lattices will represent different farming strategies (see Figure 5.3.1). As in our case the two livelihood activities are cropping and livestock farming adopted by smallholder farmers in Pakistan. A typical smallholder could use none, one or both of these activities resulting four possible states: $\left(s^1 = s^2 = 0\right)$ if the smallholder farmer is involved in none of the given farming activities; $\left(s^1 = 1, s^2 = 0\right)$ if farmer is involved in cropping but not in livestock; $\left(s^1 = 0, s^2 = 1\right)$ if farmer is involved in livestock but not in cropping; and $\left(s^1 = s^2 = 1\right)$ if the farmer is associated with both of the given livelihood activities. If the two farming activities were complementary, then using both simultaneously

[1] A partially ordered set $(X, \geq)$ is said to be completely ordered if for $x \in X$ and $y \in X$, either $x \geq y$ or $y \geq x$. When there is no ambiguity, we will say for short that X (rather than $(X, \geq)$) is a *poset*, meaning that the partial order relation is understood. In particular, unless differently specified, $\mathbb{R}$ will always be assumed to be endowed with the usual $\geq$ order relation.

would be better in marginal gains than using either one individually and certainly better than using neither. The lattice for this is shown in Fig. 5.3.1 where vertical height represents profit. Lattice speaks for different profit levels achieved by using different combinations of farming activites. s^1 and s^2 can also be reversible and can represent either activities. From this we can see the optimal path for a smallholder to follow in order to increase profits. In complementarity situation, it would be best to use both activities simultaneously. The step for determining optimal solutions is given by the theory of supermodularity.

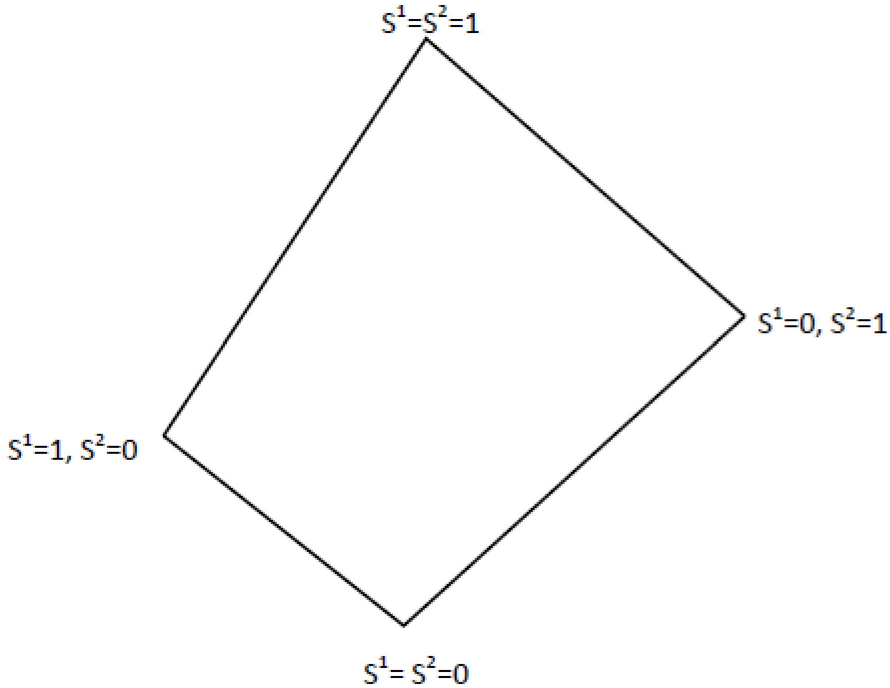


Figure 5.3.1: Lattice

5.3.1.2 *Supermodularity - a function on lattice*

A function is said to be supermodular when the sum of the changes in the payoff function, when several arguments are increased separately, is less than the change resulting for increasing all arguments together (Milgrom and Roberts (1990)). More formally, given any lattice $(X, \geq)$, a function $f : X \to \mathbb{R}$ is said to be supermodular if for all $x, y \in X$,

$$f(x \bigvee y) + f\left(x \bigwedge y\right) \geq f(x) + f(y)$$

A *function f* is said to be submodular if -*f* is supermodular. Moreover, a function is supermodular if, for every strategic pair of input the payoff function, is supermodular in those inputs; and the sum of two or more supermodular function is supermodular but the product is not necessarily supermodular (Topkis, 1978).

5.3.2 Complementarity

A smallholder farmer is supposed to make $S = (s^1, s^2)$ feasible choices, from a partially ordered set X $(S \subset X)$, to maximize his supermodular profit function

$$max_{s^1, s^2 \in S \subset X} \ \pi(s^1, s^2)$$

where s^1 and s^2 are discrete choices $s^1 \in \{0,1\}$ and $s^2 \in \{0,1\}$, which represent the adoption of activities $\left\{s^1 = s^2 = 1\right\}$ or not $\left\{s^1 = s^2 = 0\right\}$. The function $\pi\left(s^1, s^2\right)$ is supermodular, and s^1 and s^2 are complements only if

$$\pi(1,1) - \pi(0,1) \geq \pi(1,0) - \pi(0,0)$$

that is, adding an activity while the other activity is already being performed has a higher incremental effect on profit than adding the activity in isolation. This condition can be rewritten as follows

$$[\pi(1,1) - \pi(0,1)] - [\pi(1,0) - \pi(0,0)] \geq 0$$

If this inequality is always strict, then π has strictly increasing differences in $\left(s^1, s^2\right)$. This inequality states that there is always increasing differences from not making any choice to make both choices. The interpretation can also be: returns are higher if smallholder adopts s^1 choice when he already adopted s^2 choice, and *vice versa.*

Two interesting empirical predictions follow from this theory (Arora, 1996; Athey and Stern, 1998).

1. **(Correlation):** Assume that $\pi\left(s^1, s^2, X\right)$ is supermodular in s^1, s^2 and X, where X is vector of exogenous variables. Then $S^*(X) = \left(s^{1^*}(X), s^{2^*}(X)\right)$, the optimal choice of activities is monotone non decreasing in X. In a cross sectional study, $s^1(X)$ and $s^2(X)$ will be positively correlated.

2. **(Excluded Variable):** Suppose that an increase in X_k increases only activity s^1 directly. But because of complementarity between activities s^1 and s^2, X_k will indirectly

increases activity s^2. Therefore, s^{2^*} will be non decreasing in X_k in the presence of complementarity.

The first result states that two complementary activities will be positively correlated. Positive correlation, however, is neither necessary nor sufficient for complementarity if the conditions specified above do not hold (Arora, 1996). The main problem is that unobserved heterogeneity between different observations could bias the estimation results and lead either to accepting the hypothesis of complementarity while no complementarity exist at all, or to rejecting the hypothesis of complementarity when activities, in fact, are complementary (Athey and Stern, 1998).

The second empirical prediction allows for a less noisy empirical assessment of complementarity. Suppose that cropping and livestock are complementary activities and that an exogenous variable (*e.g.* herdsize) affects only the likelihood of choosing livestock only. Then, as the second empirical prediction states, in addition to positive direct effect on livestock, the exogenous variable will also increase the probability of choosing a cropping activity due to complementarity effect.

5.3.3 Testing for Complementarity

To test for complementarity, we use both approaches. First, we use the direct approach by estimating the profit function, where alternative combinations of business livelihood activities adopted by smallholder farmers being included as dummy explanatory variables. Thus, the direct approach focuses directly on the relation between performance and different combinations of farming activities. The OLS regression used is unfortunelty biased by unobserved heterogeneity. To overcome this probleme, we have recourse to the indirect approach by regressing discrete adoption choices on observable characteristics of smallholder farmers. Contrary to classical methods in literature, we use a new way to test complementarity that carries out unobserved heterogeneity separately by estimating a multinomial probit model.

5.3.3.1 *The direct approach: performance analysis*

This approach is based directly on the objective function of the farmer, who maximizes his profit by using different combinations of farming activities. The main idea is that the joint implementation of activities should prove to be more valuable in terms of profit than the implementation of both of them in isolation. The test of complementarity is thus performed by regressing a measure of performance on a set of dummy variables that represent the adoption of different combinations of activities, along with observable characteristics on the considered activities. One can obtain certain supportive evidence of complementarity (substitutability) when significant and positive (negative) coefficients of the joint activities dummy variables are observed.

Applying this approach, Mohnen and Röller (2005) directly estimate the objective function and investigate whether R&D make-buy choices are complementary. Lockshin et al. (2008a) studied the complementarity between product, process and organizational innovations and their impact on labour productivity. Ichniowski et al. (1997) also used this approach to test for complementarity between different human resource management practices. However, the problem of unobserved heterogeneity was ignored which may have substantial influence on the association between activities, even though complementarity may not exist at all. Consequently, direct approach might deliver bias if there are unobserved factors in the error term that are correlated with the adoption of livelihood activities.

In our context, we simply define that crop and livestock activities are complementary if: (a) a smallholder farmer can choose any one, or both activities at the same time; (b) the total payoffs through joint action is greater than their sum in isolation. More formally, for $j = 1,2$, smallholders are free to choose: *(i)* one of the two activities $\left(s^j = 1, s^{-j} = 0\right)$, *(ii)* both activities $\left(s^j = 1\right)$; *(iii)* none activity $\left(s^j = 0\right)$. The performance measure is the profit $\left(\pi\left(s^1, s^2\right)\right)$. The test for complementarity between two activities is defined by the following inequality

$$\pi(1,1) - \pi(0,1) \geq \pi(1,0) - \pi(0,0)$$

That is, there is evidence of a complementary effect when using together the two activities, compared to a situation where they are used separately, generates a higher profit. The definition for substitutability is identical to the definition above except that "$\geq$" is replaced by "$\leq$".

To test for complementarity, we first estimate the following equation through ordinary least squares (OLS) regression

$$\pi_i^k\left(s^1, s^2\right) = \left(1 - s_i^1\right)\left(1 - s_i^2\right)\theta_{00} + s_i^1\left(1 - s_i^2\right)\theta_{10} + \left(1 - s_i^1\right)s_i^2\theta_{01} + s_i^1 s_i^2\theta_{11} + X_i\beta + \varepsilon_i \tag{5.3.1}$$

where alternative combinations of different farming activities being included as explanatory variables through dummies. θ_{11} is the productivity coefficient of adopting both activities, θ_{01}

the coefficient for cropping, θ_{01} for livestock and θ_{00} for none agricultural activity. X_i is the vector of exogenous variables, β_i the vector of coefficients and ε_i the error terms (unobserved characteristics) distributed as multivariate normal, identically and independently across the n farmers, with zero mean and covariance matrix $\Sigma = \sigma_i > 0$.

The objective function is supermodular and s^1 and s^2 are complements only if $\theta_{11} - \theta_{01} \geq \theta_{10} - \theta_{00}$. In order to investigate the partial returns from cropping and livestock, we rewrite equation (5.3.1) as follows

$$\pi_i^k \left(s^1, s^2\right) = \theta_0 + s_i^1 \theta^C + s_i^2 \theta^L + s_i^{12} \theta^{CL} + X_i \beta + \varepsilon_i \tag{5.3.2}$$

where $\theta_0 = \theta_{00}$; $\theta^C = \theta_{01} - \theta_{00}$; $\theta^L = \theta_{10} - \theta_{00}$; $\theta^{CL} = [\theta_{11} - \theta_{01}] - [\theta_{10} - \theta_{00}]$. That is, θ_0 is the constant, θ^C captures the non-exclusive partial returns of cropping, θ^L is the non-exclusive partial returns of livestock and θ^{CL} the returns of adopting both activities together. This latter represents exactly the complementarity parameter we are trying to test. Hence, the condition for the above production function to be supermodular can be simplified as

$$\theta^{CL} = [\theta_{11} - \theta_{01}] - [\theta_{10} - \theta_{00}] > 0 \tag{5.3.3}$$

However, Athey and Stern (1998) argued that OLS results can be biased due to unobserved heterogeneity. That is, OLS regression can exhibit complementarity effect while there is no complementarity in real or *vice versa*. To correct for this unobserved heterogeneity, we use the adoption approach.

5.3.3.2 *The indirect approach: adoption analysis*

In the adoption approach, we test for complementarity on the basis of a positive correlation between error terms using a bivariate probit model (Arora and Gambardella, 1990; Arora, 1996). The bivariate probit regresses the non-exclusive farming activities (cropping and livestock) on the assumed exogenous control variables (X_i), but takes the correlation between them into account explicitly. Formally, the model is as follows

$$
\begin{aligned}
s_i^{1^*} &= \beta^1 X_i + \varepsilon_i^1, \qquad s_i^{1^*} \begin{cases} = 1 \; if \; s_i^{1^*} > 0 \\ = 0 \; otherwise \end{cases} \\
s_i^{2^*} &= \beta^2 X_i + \varepsilon_i^2, \qquad s_i^{2^*} \begin{cases} = 1 \; if \; s_i^{2^*} > 0 \\ = 0 \; otherwise \end{cases}
\end{aligned}
$$

where the stochastic errors ε^1 and ε^2 are independent of X_i but not necessarily independent of each other. That is, $E\left(\varepsilon^1\right) = E\left(\varepsilon^2\right) = 0$, $Var\left(\varepsilon^1\right) = Var\left(\varepsilon^2\right) = 1$, $Corr\left(\varepsilon^1, \varepsilon^2\right) = \rho$. But, in this reduced-form approach the strategic choices are discrete ones, while Arora and Gambardella (1990) assumed continuous variables. Extending their approach to the case of discrete choices results in incoherence problem, as show by Miravette and Pernias (2010).

To see this, consider the structural model with exclusive activity choices. If smallholder i chooses to adopt cropping (livestock) activity, four different combinations of these activities can be found as: (i) adoption of cropping only $\left(s^1 = 1, s^2 = 0\right)$; ($ii$) adoption of livestock only $\left(s^1 = 0, s^2 = 1\right)$; ($iii$) adoption of both activities $\left(s^1 = 1 = s^2\right)$; ($iv$) adoption of none of cropping and/or livestock $\left(s^1 = s^2 = 0\right)$. The latent profit function of the smallholder is as follows

$$
\pi_i^*\left(s_i^1, s_i^2\right) = \left(\theta^{1^*} + \varepsilon^{1^*}\right) s_i^1 + \left(\theta^{2^*} + \varepsilon^{2^*}\right) s_i^2 + \delta s_i^1 s_i^2 \tag{5.3.4}
$$

To catch the complementarity effect between the two activities s^1 and s^2, a pairwise interaction term (δ) is introduced. $\left(\theta^1, \theta^2\right)$ represent the observable characteristics whereas $\left(\varepsilon^1, \varepsilon^2\right)$ are, as previously, unobservable returns to the econometricians. A smallholder adopt any activity $s_i^{j^*}$ if profitability exceeds some threshold, say, $s_i^{j^*} = \pi\left(1, s_i^k\right) - \pi\left(0, s_i^k\right) > 0$ for $j = 1, 2$ and $j \neq k$. From the latent profit function (5.3.4), we get

$$
s_i^{1^*} = \theta^1 + \varepsilon^1 + \delta s_i^2 \tag{5.3.5}
$$

Next, we define the adoption indicators as a function of whether smallholders earn positive profits if they adopt one of the farming activity

$$
s_i^j = \begin{cases} 1 \; if \; s_i^{j^*} > 0 \\ 0 \; if \; s_i^{j^*} \leq 0 \end{cases} \quad j = 1, 2 \tag{5.3.6}
$$

By substituting (5.3.5) into (5.3.6), we get

$$s_i^1 = \begin{cases} 1 \textit{ if } \varepsilon_i^1 > -\theta^1 - \delta s_i^2 \\ 0 \textit{ if } \varepsilon_i^1 \leq -\theta^1 - \delta s_i^2 \end{cases}$$

and similarly

$$s_i^2 = \begin{cases} 1 \textit{ if } \varepsilon_i^2 > -\theta^2 - \delta s_i^1 \\ 0 \textit{ if } \varepsilon_i^2 \leq -\theta^2 - \delta s_i^1 \end{cases}$$

Then, we define $S_i(1,1) = \left\{\left(\varepsilon_i^1, \varepsilon_i^2\right) : \pi\left(s_i^1, s_i^2\right) = (1,1)\right\}$ as the set of unobserved characteristics that induce smallholder i to adopt both activities simultaneously. A smallholder adopt $\left(s_i^1, s_i^2\right) = (1,1)$ if $\pi(1,1) > \pi(1,0), \pi(1,1) > \pi(0,1)$ and $\pi(1,1) > \pi(0,0)$. That is, we define the set $S_i(1,1)$ of the combination of errors $\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right)$ leading to the joint strategy adoption

$S_i(1,1) = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta\right\}$

Similarly, we define the following set $S_i(1,0)$ of the combination of errors leading to the adoption of cropping only activity

$S_i(1,0) = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} \leq -\theta^{2^*} - \delta\right\}$

Symmetrically, the adoption profile of livestock only activity is

$S_i(0,1) = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} \leq -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta\right\}$

finally the set $S_i(0,0)$ leading to the adoption of none of the farming activities is

$S_i(0,0) = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} \leq -\theta^{1^*} - \delta, \varepsilon_i^{2^*} \leq -\theta^{2^*} - \delta\right\}$

By drawing these four regions in the fig. 5.3.2 (for the case of complementarity $(\delta > 0)$) depicts overlapping for the subsets of $S_i(1,1)$ and $S_i(0,0)$. This overlapping intermingles the choices of adoption of both farming activities and none of these at an area E^*. This ambiguity leads to the problem of incoherence. This suggests that bivariate probit approach is not the feasible choice to test the notion of complementarity due to unobserved heterogenity across the alternate choices.

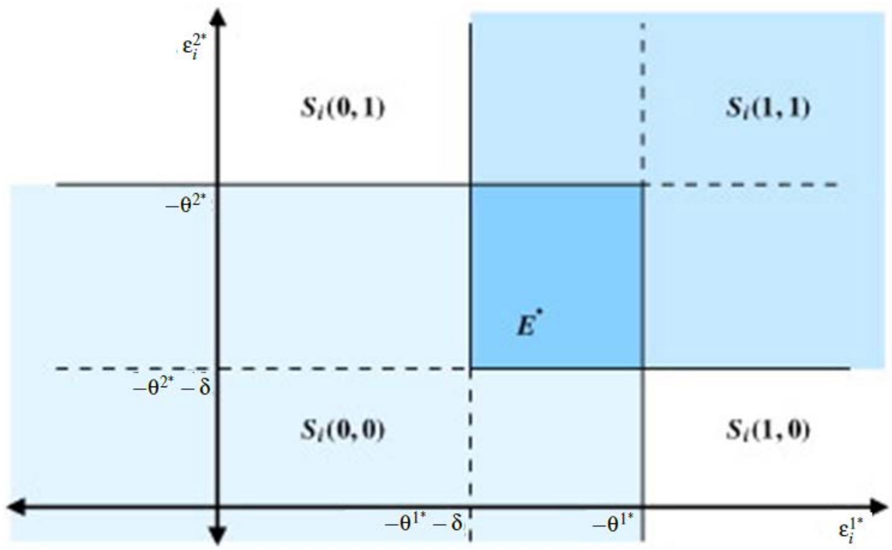


Figure 5.3.2: Incoherent adoption of strategies

Multinomial Probit Approach

To solve this incoherence problem, we start with more general pattern of correlation. We suppose that k indicates the exclusive decision of the farmer i to adopt farming activities. The discrete dependent variable k now takes values as $k = \{0,1,2,3\}$ representing the choices respectively to adopt neither activity, adopt cropping only, adopt livestock only, and adopt both activities. The payoffs to smallholder i from choosing $j \in k$ is:

$$\pi_i^j = \beta^j X_i + \varepsilon_i^j \tag{5.3.7}$$

where X_i is the vector of observed explanatory variables describing smallholder i and other characteristics important for the determination of choice. The parameter vector β^j are unknown and these are the object of inference. The vector of stochastic errors $\varepsilon_i^j = \left(\varepsilon_i^0, \varepsilon_i^1, \varepsilon_i^2, \varepsilon_i^3\right)'$ represents the unobserved returns of the choices. It is assumed to be distributed as multivariate normal, identically and independently distributed across the n smallholders, with zero mean and covariance matrix $\sum = \sigma_i^j > 0$, $\forall j$ (positive definite).

Arranging the parameters in (5.3.7) as $\beta = (\beta_0', \beta_1', \beta_2', \beta_3')$ the log-likelihood function to be maximized is:

$$\mathcal{L}\left(\beta, \sum\right) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=0}^{3} y_i^j \ln P_i^j\left(\beta, \sum\right)$$

where the profit indicator π_i^j is latent but we observe the choice $y_i^j = 1$ if the smallholder i chooses the alternative j and $y_i^j = 0$ otherwise. While $P_i^j = Pr\left(\pi_i^j > \pi_i^l, l \neq j\right)$ represents the probability that the smallholder i make the choice j under the profit maximization principle. Unfortunately, it is not possible to get a unique maximum likelihood estimate of the parameters $(\beta, \sum)$ in the above model, as they are not identified. The first source of the identification problem is that the observed choices are only informative on the differences of the profits and not on the profits themselves. Then taking differences with respect to the profits associated with $j = 0$, *i.e.* we take the first alternative as the reference state used to normalize location of the latent variable.

The payoff function π_i^j in (5.3.7) is specified differently for the joint adoption option than for the others. Specifically, the payoff of joint adoption is:

$$\pi_i^{3^*} = \pi_i^{1^*} + \pi_i^{2^*} + \delta$$

where δ captures the effect of complementarity between farming activities. The treatment for joint adoption payoff takes into account its econometric interpretation. However, this specification is convenient given our aim to estimate the effects of observable characteristics of smallholders on the complementarity between cropping and livestock. This approach was proposed by Gentzkow (2007) and Arora et al. (2010). For identification, we have taken differenced payoffs in (5.3.7) because payoff of adopting neither farming activity is normalized to zero, as is necessary given that only the payoff differences determines the observation's choice.

$$\pi_i^{3^*} = \left(\beta^{1^*} + \beta^{2^*}\right) X_i + \left(\varepsilon_i^{1^*} + \varepsilon_i^{2^*}\right) + \delta$$

states that smallholder i choose both activities to earn an average payoff $\pi_i^{3^*}$, with the assumption that payoff of joint adoption is greatest of all other strategies *i.e.* $\pi_i^{3^*} > \pi_i^{0^*}$, $\pi_i^{3^*} > \pi_i^{1^*}$ and $\pi_i^{3^*} > \pi_i^{2^*}$. Let us define $\theta^{j^*} = \beta^{j^*} X_i$, with $\theta^{j^*} = \left(\theta^{1^*}, \theta^{2^*}\right)'$. Rewriting these conditions lead to the following constraints on the errors

$$\begin{aligned} \varepsilon_i^{1^*} &> -\theta^{1^*} - \delta \\ \varepsilon_i^{2^*} &> -\theta^{2^*} - \delta \\ \varepsilon_i^{1^*} + \varepsilon_i^{2^*} &> -\theta^{1^*} - \theta^{2^*} - \delta \end{aligned} \tag{5.3.8}$$

The structural model that was assumed by Miravete and Pernias (2010) to study complementarity, is:

$$\pi_i^{j^*}\left(s_i^1, s_i^2\right) = \left(\theta^{1^*} + \varepsilon^{1^*}\right)\cdot s_i^1 + \left(\theta^{2^*} + \varepsilon^{2^*}\right)\cdot s_i^2 + \delta\cdot s_i^1\cdot s_i^2$$

As previously, $\left(\theta^1, \theta^2\right)$ represents the observable characteristics along with $\left(\varepsilon_i^1, \varepsilon_i^2\right)$ as unobservable returns. Identification of these error terms would be resulted in variances σ_1^2 and σ_2^2, and a correlation parameter ρ. A positive value of ρ would indicate that smallholders that tend to be more profitable in adopting cropping also tend to be more profitable in adopting livestock, or *vice versa*, even if no profit complementarity exists between the two. Such positive correlation would also capture unobserved heterogeneity among smallholders in the preference for farming activities. Negative correlation, on the other hand, may imply unobserved gains from specialization in one of the activities. The correlation actually presents an identification problem in that correlation between ε_i^1 and ε_i^2 has a similar effect on the payoffs as the complementarity term. Rewriting conditions of assuming maximization principle that are due to joint adoption of farming activities, we get the same (4.3.11) set of constraints of multinomial probit (MNP) on the unobserved returns. This suggest that the above structural model can be estimated by MNP. With a MNP, we are able to separate the complementarity effect from that of unobserved heterogeneity, since we can estimate both δ and ρ. We employ the system of constraints (), by defining the set S_3 of the combination of errors $\left(\varepsilon_i^1, \varepsilon_i^2\right)$ leading to the joint adoption $(j = 3)$

$$S_3 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*} - \delta, \varepsilon_i^{1^*} + \varepsilon_i^{2^*} > -\theta^{1^*} - \theta^{2^*} - \delta\right\}$$

Similarly, we define the following set S_1 of the combinations of errors leading to the adoption of cropping only $(j = 1)$

$S = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} > -\theta^{1^*}, \varepsilon_i^{2*} < -\theta^{2^*} - \delta, \varepsilon_i^{1^*} - \varepsilon_i^{2^*} > \theta^{2^*} - \theta^{1^*}\right\}$;

symmetrically, the set S_2 of the adoption of livestock only profile $(j = 2)$

$S_2 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} < -\theta^{1^*} - \delta, \varepsilon_i^{2^*} > -\theta^{2^*}, \varepsilon_i^{2^*} - \varepsilon_i^{1^*} > \theta^{1^*} - \theta^{2^*}\right\}$;

finally, the set S_0 leading to the adoption of none of the aforementioned livelihood activities $(j = 0)$

$S_0 = \left\{\left(\varepsilon_i^{1^*}, \varepsilon_i^{2^*}\right) : \varepsilon_i^{1^*} < -\theta^{1^*}, \varepsilon_i^{2^*} < -\theta^{2^*}, \varepsilon_i^{1^*} + \varepsilon_i^{2^*} < -\theta^{1^*} - \theta^{2^*} - \delta\right\}$.

The purpose of restudying above constraints is to testify our model against the problem of incoherence due to bivariat probit. We show graphically that there is no overlapping between these different sets in either situation of supermodularity or submodularity. Therefore, we can estimate parameters of the model along with the correlation between different adoption choices. That is, it is possible to separate complementarity between farming activities from the unobserved heterogeneity, and thus recover the structural-parameter estimate of complementarity by using multinomial probit (MNP).

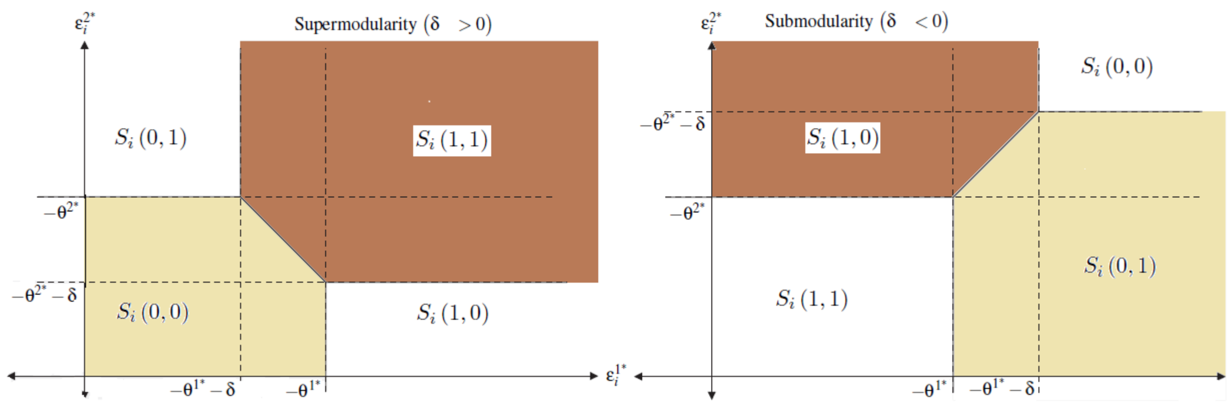


Figure 5.3.3: Adoption of farming activities

5.3.4 Identification

Identification of Multinomial Probit (MNP) model rests on underlying assumptions about the nature of individual decision-making. Statistical methods commonly used to identify models of multinomial choices often impose restrictive assumptions about these choices that render inferences suspect. The first problem is the normalization of the latent variable. We take profits from other activities than cropping and livestock as the reference for normalization, *i.e.* $\pi_i^*(0,0) = 0$. In this way, we can see by how much the smallholder farmer would be better or worse by adopting either one or both activities than adopting others. The second problem of identification is exclusion restriction. That is, restrictions that certain exogenous variables in the model do not affect the stochastic profits π_i^* of some alternatives (Keane, 1992). To follow this mechanism data must contain some variables that affect the profit levels of any one activity but not the other. The third problem is to identify the MNP using a tractable estimation method. The difficulty with Maximum Likelihood Estimation (MLE) is well known, *i.e.* evaluating integral of multivariate normal densities in a three or more choices problem through MLE can be computationally burdensome. Markov Chain Monte Carlo (MCMC) makes the MNP problem much more tractable since it is less difficult to obtain precise estimates.

There are other class of multinomial choice models like HEV (Heteroscedastic Extreme Value), but these models rely on the assumptions of Independence of Irrelevant Alternatives (IIA) and thus estimate error correlation as zero ($\rho = 0$). This implies that such models cannot catch the unobserved heterogeneity, and thus we cannot separate what is due to complementarity and what is the due to unobserved heterogeneity (Gentzkow, 2007). In contrast, the MNP model can estimate both the parameter δ, which catches complementarity, and the ρs, which catches the unobserved heterogeneity.

5.4 Data and Variables

The data for this study come from household survey by the ministry of Planning and Development (P&D), Government of Punjab, Pakistan. The Punjab province is the largest one by rural population and by its share in agriculture (crop and livestock production). Based on the varying cropping pattern, irrigation facilities, soil type, underground water table and rainfall pattern in its different parts, the province is divided into five agro-climatic zones. These zones are named as rice/wheat Punjab, mixed cropping Punjab, cotton/wheat Punjab, low-intensity Punjab, and rain-fed (barani) Punjab (Amjad et al., 2008). The rural household survey was conducted on twelve communities from April to August 2010 in the five previous agro-climatic zones[2]. Equal number of surveys were administered from every zone. A total of 360 surveys were collected. This survey was aimed at estimating the economic conditions of rural households in these zones. Data collection process comprised of making field visits in the selected villages. The targeted families were interviewed at their homes, where the questionnaire was filled in. The objective of the survey was to better know the economic conditions of households in the different agro-climatic zones.

The main sources of earning of these rural households are farming activities, *i.e.* cropping and livestock. In the province, more than half of the households are engaged in both cropping and livestock. While, a very small number of households are engaged in only cropping or only livestock. One third of the sample is involved in economic activities other than farming. In this case, the rural households are involved in Government or military jobs, or they run their own business.

[2] The concept of these surveys as such is not new. More than three decades ago the use of village studies was promoted as an empirically-based alternative to other economic analyses of rural situations (Dasgupta, 1978; Lipton and Moore, 1972; Scoones, 2009; Erenstein and Thorpe, 2011).

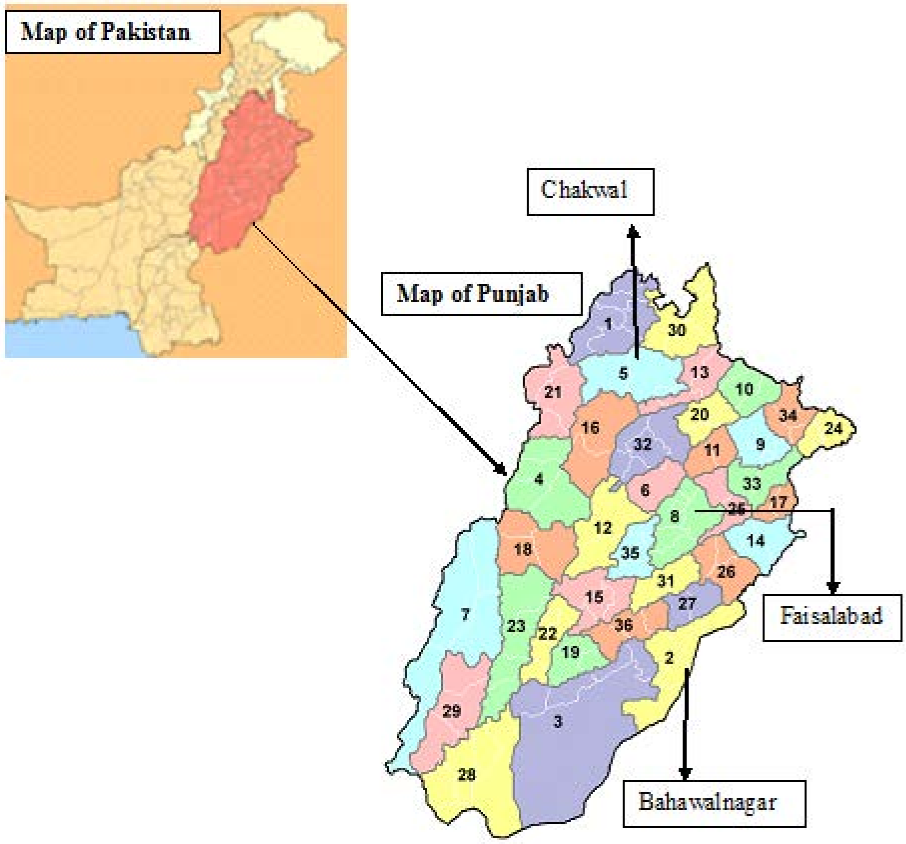


Figure 5.4.1: Studied districts of Punjab, Pakistan

5.4.1 Dependent Variables

Testing for complementarity using the direct approach implies to define a measure of the performance. As a proxy of the performance, we use the income **(INCOME)** variable. This income variable is the net revenue derived from the different activities: *(i)* cropping only activitiy; *(ii)* livestock only activity; *(iii)* mixed farming (crop and livestock) activity; *(iv)* other activities. Other activities include the sources of livelihood other than cropping and/or livestock, such as military services, government jobs, and private business, foreign remittances etc. The Income variable is used as the dependent variable in the linear regression model, to analyze to what extent observable characteristics of smallholder farmers along with activity dummies help explain the income level.

When we test for complementarity using the adoption approach, we analyze the adoption of household activities. On the one hand, households may choose farming activities: cropping **(Crpng)** or livestock **(Livestk)**. They can also choose mixed farming by making both activities simultaneously **(CropLive)**. Apart from above agricultural farming activities, households may also choose other activities **(Others)** such as military services, government jobs, and private business, foreign remittances etc. In our database, these activities are distributed as follows: *(i)* 5% of households were engaged in cropping; *(ii)* 7% were involved in livestock; *(iii)* 53% were involved in both cropping and livestock; *(iv)* remaining 35% were doing their own business or serving Government, military or private sectors. The choice of activities vary in different agro-climatic zones and households are not free at all to choose any farming or other activity disregarding agro-climatic effects. Like in Chakwal which is situated in Potohar plateau, mountainous and rocky region, covered with scrub forest, interspaced with flat lying plains, they choose to adopt either livestock or other activity because it is a rain fed zone where agriculture is mostly dependent on the rainfall and the land is unleveled (Nosheen et al., 2011). In this area, the reliance of households on agriculture farming is minimal. Similarly, the cotton/wheat zone still largely depends for employment on the agricultural sector while this dependency is very low in the rain fed zone, which has good opportunity to seek job opportunities for its labor force in the armed services and government departments (Amjad et al., 2008).

5.4.2 Independent Variables

Different exogenous variables may affect the choice of the dependent variable. First, the socio-demographic variables of the household. The first variable is the age of the household head. In our sample, his average age **(AGE)** is 46 years. Most of the farmers, in Punjab, are illiterate or have poor education, and illiterate or less educated smallholder are more prone to adopt farming as primary occupation. Average number of schooling years **(EDU)** is only 3 years and 36% of the surveyed respondents are illiterate. Therefore, illiteracy and poor education prevail in this sector even if it is evident that literacy is a tool to achieve optimum level of yield and can be a source to enhance income (Tarawali et al., 2011).

Other exogenous variables are related to the structure of the household. First, in rural areas of Punjab, a general culture of living under joint family system **(FmlySys)** is prevailing. More than half of our respondents are living under this type of familial system. About two decades ago, joint family system or large family size was considered as more contributive in terms of farming (joint utilization family labor, cost of production sharing, farm inputs etc.). But, increased variation within and inter families due to change in educational and social status lead members to run their own farming activities privately. This leads to a reduction of the average family size **(FmlySize)**, which is of 5.37 persons in our sample. Most of the families are engaged in a single profession as the whole family profession. For example, if the household head is engaged in cropping activity, the whole family members are there to help them. Only a small number of households were studied whose members were undertaking more than one economic activity. But, only the principle activity was considered in the survey and income earned from principle activity is taken into account. More than one family in the same residence is considered as one household.

In spite of knowing the fact that agricultural farm machinery have substantial place in performing activities and can result in higher productivity, poverty in this sector deprives a large number of smallholders to purchase and use these equipments. However, a small part of surveyed households use some machinery **(FMachinery)** like tractor, planters, threshers, harvesters, and livestock feeders *etc.* They usually do not buy them but rather rent the machines depending on its availability.

We have used two variables to explain the effect of agricultural land. Land size **(LandSize)** owned by the rural households determine their extent of reliance on farming as a source of livelihood. Land size is the number of hectares possessed by a household. While land ownership **(LandOwn)** is a binary variable defining the status of the the farmer, owner of the land used or just a tenant. 80% of the households in our sample are owner of their land. In case of tenancy, we know if the land is under a sharecropping contract **(CropShare)** or a tenancy contract.

Livestock farming is the function of large and small ruminants. The animals mostly domesticated by the rural people were, buffalo, cattle (cow), goat, and sheep. Each household is caracterized by its livestock population **(HerdSize)**. A larger herd size, as well as Landsize, may lead to economies of scale and thus to the choice of one activity, either livestock or cropping, alone.

The purpose of including the regional diversity variables in our analysis is to see that under a vast and an apparently homogeneous region (Punjab) how different contextual or sub-regional (districts) realities influence our dependent variable (along with the other independent variables). Erenstein and Thorpe (2011) have confirmed in a study in five contiguous states in Indo-Gangetic Plains (IGP) region of India that the apparent homogeneity of vast irrigated plains masked the significant diversity in rural assets, livelihood strategies, and livelihood outcomes. Hence the inclusion of region variables in the analysis is to investigate the presence (or absence) of regional effects. Table 5.1 provides some differences between these zones in terms of fammily size, illteracy, ... **Rain-fed zone**, **mixed-cropping zone**, and **cotton/wheat zone** (among five zones) were selected for our sample to be taken, as the data were available only from these three zones.

Another regional effect is the distance from the village to the main market in the district capital in the region. To catch this effect, we build a variable **Proximity**, which gives for every village its distance from the district capital.

Table 5.1: Socio-economic characteristics of agro climatic zones in Punjab

Indices	**Rice/Wheat**	**Mixed**	**Cotton/Wheat**	**Low-intensity**	**Rain-fed**
Family Size	7.90	7.80	8.00	8.40	6.90
Dependency Ratio	0.93	0.94	0.99	1.14	0.79
Illiterate (%)	40.40	47.80	54.80	60.80	31.4
Avg. urban pop (%)	32.27	26.88	20.76	15.16	28.60
% of rural employees in agro-industry (including forestry and fishing)	45.90	54.40	58.90	58.70	31.80

Source: Amjad et al. 2008

Table 5.2: Descriptive statistics of variables

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
INCOME	Logarithmic value of income (in Pak Rupees)	360	12.01	0.733	9.548	14.73
AGE	Age of head of household *1 if 20-29 years; 2 if 30-39 years; 3 if 40-49 years; 4 if 50-59 years; 5 if 60-69 years; 6 if 70+ years*	360	3.272	1.141	1.00	6.00
EDU	Education of head of household *1=Illiterate; 2=Primary ; 3=Middle; 4= Secondary; 5=Higher secondary; 6=Above higher secondary*	360	2.516	1.451	1.00	6.00
FmlySize	Size of a household	360	5.366	1.743	1.00	11.00
HerdSize	Number of animals kept by a household *1 if 1-10 animals; 2 if 11-20 animals; 3 if 21-30 animals; 4 if 31-40 animals; 5 if 40+ animals*	360	1.172	0.498	1.00	5.00
FmlySys	equals to 1 if household has joint family; 0 otherwise	360	0.542	0.499	0.00	1.00
LandSize	Land owned by a household (in hecatres)	360	2.116	3.199	0.00	25.30
LandOwn	equal to 1 if household is the owner; 0 otherwise	360	0.800	0.400	0.00	1.00
Rain-fed Zone	equals to 1 is household live in rain-fed zone; 0 otherwise	360	0.333	0.472	0.00	1.00
Mix-crop Zone	equals to 1 if household live in mix-crop zone; 0 otherwise	360	0.333	0.472	0.00	1.00

Variable	Description	Obs.	Mean	Std. Dev.	Min.	Max.
FMachinery	No. of farm machine accessories used by households	360	0.311	0.946	0.00	6.00
CropShare	equals to 1 if household is sharecropper; 0 otherwise	360	0.144	0.352	0.00	1.00
Proximity	Distance of village from district capital city *1 if distnace is $\leq$ 24 km; 2 if $\leq$ 18 km; 3 if $\leq$ 12 km; 4 if $\leq$ 6 km*	360	2.5	1.119	1.00	4.00
Crpng	equals to 1 household is involved in cropping; 0 otherwise	360	0.586	0.493	0.00	1.00
Livestk	equals to 1 if household is involved in livestock; 0 otherwise	360	0.600	0.490	0.00	1.00
CropLive	equals to 1 if household is involved in cropping and livestock; 0 otherwise	360	0.533	0.499	0.00	1.00
Others	equals to 1 if household is involved in other activities than cropping and/or livestock; 0 otherwise	360	0.347	0.477	0.00	1.00

5.5 Results and Interpretations

Our methodology to examine the complementarity versus substitutability relationship between cropping and livestock activities consists of two steps. First, we directly test for complementarity/substitutablity using the direct approach. Second, we have recourse to the indirect approach. We estimate a bivariate probit model to estimate crop only and livestock only activity in search of complementarity. In a third step, we perform the multinomial logit analysis in search of the variables that affect the choice between different activities. Finally, we perform multinomial probit model on the same drivers to conclude for possible complementarity.

5.5.1 Direct Approach

First, in search for evidence of complementarity in mixed farming, we analyze how the different activities affects the income (performance) that the smallholder farmer gets. Therefore, we regress income on different observable characteristics and activity dummies that may affect the performance of the adoption process. The results of the OLS regression are given in Table 5.3. Our results suggest that choosing cropping (**Crpng**) only activity has no significant effect on the income, while livestock (**Livestk**) only strategy decreases the level of income obtained. In contrast, choosing both activities (**CropLive**) generate a significant increase in the level of income obtained. This is a first evidence of a possible complementarity between crop and livestock activities. To confirm this result, we perform the direct test of complementarity, *i.e.* as defined in (5.3.3) we test for the inequality $(\theta_{11} - \theta_{01}) \geq (\theta_{10} - \theta_{00}) > 0$. The test run does not reject the hypothesis at 1% level of significance. This is a clear evidence of a complementarity effect between cropping and livestock activity.

Second, we analyze other drivers, than activity choice, to explain the income level. First, socio-demographic variables characterizing the farmer have a significant and positive impact on his income. This is the case of age and level of education, since the higher socio-demographic levels, the higher the farmer's productivity and ability to manage the activities of the farm (Feder et al., 1985). Herd size and land size are also showing more effects likely because of economies of scale. Mixed-crop zone is situated at the hub of agro-food processing industry region and whereas returns are high as compared to other agro-climatic zones. So family labour in this mix-crop zone increases the level of income. Farm machinery though has least significant positive effect towards increasing income levels, but its importance can never be ignored in farming activities (Boz et al., 2005). However, machinery costs and technical know-how in handling farm machinery are the main hurdles for smallholders in increasing the output. Least distance from the main cities also results in increasing income levels. Transportation costs and access to new local markets is easy as compared to smallholders far away from main cities.

Table 5.3: Performance regression (dependent variable: Income)

Variables	**Estimate (S.E.)**
Constant	10.540 (0.199)***
AGE	0.065 (0.030)**
EDU	0.075 (0.018)***
FmlySize	0.005 (0.020)
HerdSize	0.248 (0.056)***
FmlySys	0.016 (0.056)
LandSize	0.079 (0.009)***
LandPos	0.052 (0.086)
Cotton/Wheat Zone	Ref.
Rain-Fed Zone	0.001 (0.097)
Mix-Crop Zone	0.523 (0.719)***
FMachinery	0.065 (0.038)*
ShareCrop	0.018 (0.077)
Proximity	0.091 (0.025)***
Crpng	-0.056 (0.124)
Livestk	-0.469 (0.168)***
CropLive	0.791 (0.207)***
	N = 360
	OLS (Huber-White sandwich estimator)
Complementarity test $\theta_{11} - \theta_{10} \geq \theta_{01} - \theta_{00}$	F(1, 346) = 10.15***
Model	F(15, 344) = 24.18***
R^2	0.5120

** Significant at 10%; ** Significant at 5%; *** Significant at 1%*

5.5.2 Indirect Approach

5.5.2.1 Bivariate Probit Results

In search of complementerity between cropping and livestock activities through bivariate probit, activities are defined as non-exclusive, *i.e.* it is possible that a smallholder is benefitting from both activities at the same time. Most important result of bivariate probit analysis is that there is significant positive relationship between crop and livestock as indicated by the positive and significant correlation coefficient (ρ). This finding may suggest that cropping and livestock activities are likely to occur in combination and is hence an indication of complementarity. But, as seen previously this is not necessary nor sufficient condition to test for the existence of complementarity (Athey and Stern, 1998).

To unravel this indication of complementarity, we need to interpret variables that have significant effect on the adoption of farming activities. In our analysis, smallholders who owns some agricultural land ($LandOwn$), who acquire land on crop sharing basis ($CropShare$), and lives near main cities ($Proximity$) choose preferably cropping. On the other hand, smallhoders who have a larger herd size ($HerdSize$), owing some agricultural land ($LandOwn$) , dwellers of mix-crop zone ($Mix-CropZone$), and sharecroppers ($CropShare$) prefer to choose livestock. It indicates a strong agreement of adopting both activities among the smallholder farmers who are owners of agricultural land and acquire more land on crop sharing basis to administer their bigger livestock and to maximize the use of family labour. Contrary to this, regional diversity and joint familial system are less prone to adopt one or the other activity. Smallholder farmers in mix-crop zone invest in livestock with the fact that (s)he is the sole earner from the livestock but not from cropping. But, in spite of crop sharing, smallholder has to take interest in choosing both activities because of two reasons: (i) (s)he can not give up cropping as land was acquired for cropping purpose; (ii) (s)he has a larger herd size and (s)he needs more land to perform livestock activities.

Keeping in view the criticism of Scoones (2009) about the neglect of socio-demographic variables in the study of crop-livestock systems, we included family size ($FmlySize$) and family system ($FmlySys$) as explanatory variables. Higher financial needs of a larger family and the cost of family labour influence negatively the adoption of cropping and livestock.

When cotton/wheat zone is taken as reference, smallholders in rain-fed zones have negative effect on the adoption of cropping and livestock but have a contrasted effect on livestock in mix-crop zone. This may suggest that regional diversity is the main source of some contrasts in the estimated results that affect the choice of cropping and livestock activities.

Table 5.4: Bivariate probit estimation of 360 smallholder farmers

Variables	**Cropping**	**Livestock**
Constant	0.274 (0.478)	0.122 (0.532)
AGE	0.106 (0.078)	0.033 (0.075)
EDU	-0.021 (0.056)	-0.001 (0.056)
FmlySize	-0.081 (0.050)	-0.147 (0.051)***
HerdSize	-0.383 (0.169)**	0.915 (0.261)***
FmlySys	-0.478 (0.163)***	-0.500 (0.165)***
LandSize	0.021 (0.026)	0.023 (0.028)
LandPos	1.039 (0.232)***	0.459 (0.218)**
Cotton/Wheat Zone	Ref.	Ref.
Rain-Fed Zone	-1.559 (0.230)***	-1.273 (0.219)***
Mix-Crop Zone	0.180 (0.217)	0.609 (0.222)***
FMachinery	0.005 (0.081)	0.018 (0.089)
CropShare	1.067 (0.260)***	0.517 (0.238)**
Proximity	0.115 (0.070)*	-0.052 (0.071)
ρ (S.E.)	0.979 (0.013)***	
Wald χ^2 (24)	134.04***	
LR ρ	181.486***	

** Significant at 10%; ** Significant at 5%; *** Significant at 1%; SE in paranthesis*

5.5.2.2 Multinomial Logit Results

Compared to the bivariate probit model, the multinomial logit model is less restrictive on the effects that exogenous control variables can have on different choices, allowing coefficients to vary across exclusive combinations of different activities. Therefore, exclusive choices are not restricted to have same coefficients. In other words, multinomial logit model is also interpretable if every alternate choice has different sets of observed characteristics. To be more clear on this issue, we prefer to take characteristics, for an exclusive choice, that may affect the particular choice and exclude one or more characteristics from any other alternate choice if it may have no affect on that particular choice. Selection criteria of observed characteristics for each strategic choice in terms of exclusion restriction is also a prerequisite to test for complementarity based on adoption approach. But, first we are interested in contextual variables affecting the stand alone activities.

In order to do so we apply the indirect structural test for complementarity that we described in the previous section. Under the assumption that smallholder farmers make the best choice in terms of farming or not we estimate a multinomial logit model for their actual choices: cropping, livestock, both and Others.

$$\Pr(Y = k) = \frac{e^{X_i\beta}}{\sum_{i=1}^{N} e^{X_i\beta}}$$

with $k \in \{Crpng, Livestk, CropLive, Others\}$ and X_i a vector of smallholder farmers characteristics. In search to understand the variables that affect smallholder farmer strategy choices, we ameliorate our search for complementarity. We reveal variables that are relevant for specifying the structural cropping and livestock decisions and that are needed for testing the existence of complementarity. We have taken other than farming activities ($Others$) as reference. The bivariate probit restricts the coefficients to be the same for all cropping (livestock) decisions. Contrary to this, multinomial logit model reveals contextual variables as exclusive combinations of the different farming adoption choices. That is, the alternatives are exclusive now, *i.e.* each smallholder can only belong to one of the four groups.

Sharecropping is a pro poor approach widely used in less developed agricultural countries. The literature on sharecropping contracts (Ayele and Mamo, 2004) provides us with a theoretical argument that smallholders having larger family size and larger number of livestock require additional land. They acquire extra land through sharecropping contracts from those who have excess land. This argument indirectly test for complementarity. Sharecropping uplifts the income on dual side. On one hand, the land owner paid off in the form of crops and on the other hand, smallholders also benefit from this contract by engaging their family labour and to handle bigger livestock. In addition to this, economies of scale are also one important factor for smallholder farmers. Hence, sharecropping contracts may also have an indirect effect of increasing marginal returns from livestock when cropping is already adopted. Apart from sharecropping, crop farming is also associated positively with the ownership of land.

Some studies show that smallholders who own their own agricultural land are likely to get higher income than others who acquire agricultural land on contract or tenure basis (Chand and Yala, 2009; Smith, 2004; Carter and Olinto, 2003). Land owners who invest on livestock also have increasing effect on mixed farming strategy. Farm machinery is another driver to test for complementarity indirectly. Although there are a least number of smallholder farmers who use farm machinery for cropping and livestock, but its importance and utilisation to improve the production level cannot be ignored. As in our case, farm machinery is positive significant to livestock and mixed farming acitivties that also explicate its importance in performing these activities and to increase income by their joint adoption. Larger herd size is likewise more prone to livestock and both activities as in the case of farm machinery. As we stated that larger herd size is needed to be managed in the bigger agricultural land, these two can be considered as substantial parts for each other. It also suggest increasing marginal returns by adopting both activities at the same time and the adoption of livestock activity in isolation, thus, indirectly superimpose cropping over livestock. In these circumstances, we deduce that adequate number of herds and secured land ownership status reinforce the complementary relation between cropping and livestock activities. These are the four main characteristics that indirectly force the adoption of livestock and hence to be tested for complementarity, indirectly.

There are some further comments that center around reducing the likelihood of adoption of farming activities. Regional variations restrict the adoption of farming activities under the agro-climatic conditions. That is, smallholders are not free at all to grow any crops or engage in livestock activity without considering climatic conditions (Garcia et al., 2007). Mixed farming activities in rain-fed zone are clearly not preferred due to climatic restrictions. High diversity in agro-climatic zones do matter and affect the adoption choices of smallholders (Olesen et al., 2011; Jagtap and Amissah-Arther, 1999).

Population growth can make the cost of land relative to labour increase. As this cost increases, people often change the methods of managing cropping and livestock (Templeton, 1999; Binswanger and Deininger, 1997). Increased family turns only increase in labour due to lack of education in this sector. Halting population growth might not capable of improving productivity in the farming activities, thus remain less likely towards these activities.

The estimation resutls show that a significant number of contextual variables for the indirect test work. Sharecropping and land ownership status impacts the choice of cropping in isolation as well as the joint adoption of mixed farming. On the other hand, increasing herd size and increasing farm machinery affect positively on livestock adoption and mixed farming as well. As a result, we can conclude that these contextual variables are the cause to increase marginal returns as having positive impact on either activity in isolation as well as affect positively the other activity, indirectly. Other variables in our empirical analysis are either not significant or show decreasing marginal returns in case of adopting both activities simultaneously as in rain-fed zone, family system and family size.

Like bivariate probit analysis results, multinomial logit resutls are also favourable for joint activity adoption choices. It seems that the contextual variables for adoption of cropping and livestock stand alone activities are feasible, which may result in both activities as complementary than substitute. We find indeed some contextual variables that show the increasing marginal returns for either activity in isolation or for both, but not the other activity. In the following section, we estimate a multinomial probit model that will provide coherent result on the presence of complementarity effect between farming activities.

Table 5.5: Multinomial logit estimation for 360 smallholder farmers

Variables	**Cropping**	**Livestock**	**Mixed**
Constant	8.549 (11.049)	-1.224 (1.674)	-0.364 (1.001)
AGE	0.191 (0.268)	-0.089 (0.338)	0.179 (0.150)
EDU	-0.206 (0.217)	-0.076 (0.260)	-0.020 (0.111)
FmlySize	0.093 (0.201)	-0.615 (0.244)**	-0.245 (0.101)**
HerdSize	-13.93 (10.938)	4.340 (0.833)***	0.915 (0.541)*
FmlySys	-1.421 (0.648)**	-2.269 (0.775)***	-0.994 (0.329)***
LandSize	0.030 (0.116)	0.053 (0.109)	0.052 (0.055)
LandPos	2.425 (0.900)***	-1.922 (0.913)**	1.798 (0.475)***
Cotton/Wheat Zone	Ref.	Ref.	Ref.
Rain-Fed Zone	-3.066 (0.845)***	-0.248 (0.957)	-3.233 (0.490)***
Mix-Crop Zone	-2.896 (1.218)**	-0.220 (1.013)	0.132 (0.432)
FMachinery	0.288 (0.383)	0.531 (0.285)*	0.118 (0.067)*
CropShare	2.002 (0.836)**	-4.267 (5.219)	1.903 (0.532)***
Proximity	-0.202 (0.290)***	-0.202 (0.290)	0.185 (0.147)
LR χ^2 (36)		267.66***	
Pseudo R^2		0.3580	

** Significant at 10%; ** Significant at 5%; *** Significant at 1%; SE in paranthesis*

5.5.2.3 Multinomial Probit Results

The Table 5.6 below presents the multinomial probit results estimated by Gibbs sampling approach (Albert and Chib, 1993). Our primary interest of the study is to investigate whether there is complementarity between cropping and livestock activities. For this, we are firm with the believe that smallholder farmers make the best choice in terms of different strategies we estimate multinomial probit model for their actual choices: $k = 0$ if smallholder farmer chooses other livelihood activities than cropping and livestock; $k = 1$ if the choice is cropping only; $k = 2$ if the choice is livestock only; $k = 3$ if both farming activities adopted. Likewise multinomial logit model and to ease the interpretation of estimates, smallholders with other activities ($Others$) serves as benchmark.

We have estimated the coefficients for both stand alone farming activities as well as the constant terms for all three adoption choices. These constant terms also include a pairwise interaction term between cropping and livestock (δ) that test for complementarity. In addition to this, we have also estimated the coefficients of correlation (ρ) between error terms that catches the unobserved heterogeneity among smallholder farmers. This unobserved heterogeneity measure allows the econometricians to test that how profit levels of smallholders with same observable characteristics are different. The former estimate indicate that marginal returns of cropping on livestock (or *vice versa*) are increasing since the payoff function is supermodular ($\delta = 0.205$) and ends up with the conclusion that cropping and livestock activities have more of a complementary effect than of a substitution effect. The latter test determines that the estimated residual correlation coefficient between cropping and livestock ($\rho = 0.641$) provides the evidence of unobserved heterogeneity among smallholder farmers choosing different strategies with the same apparent characteristics. Despite the fact that unobserved factors affect the choice of adoption, we obtain the effect of complementarity between cropping and livestock.

In our results, we observe that the motivation for smallholder farmers for cropping and livestock is the propritery rights of agricultural land than its size. It states that ownership status is necessary to increase the productivity through joint adoption. The lesser the distance from main city, the adoption of cropping is higher. Farm machinery in livestock is a source to increase its adoption among smallholder farmers as these accessories are very helpful in administering a comparatively bigger flock of animals. Obviously, increasing herd size is showing more profitable characteristic that can add some economic fuel in terms of livestock adoption. A bigger flock of animals that is being used for livestock activity will have lower transaction cost. A number of studies pointed out the livestock utility in the integration of crop-livestock activities in terms of agronomic and ecological vantage. Herd size also assures draught power, the risk assurance and a source of immediate income generation.

Diversity in the agro-climatic zones affects the farming choice adoption because of the geographical, environmental and other factors. Rain-fed zone is less prone to cropping and livestock mainly because of land physiography and its fertility issues. Looking at socio-demographic variables, the effect of joint family and family size stir up on adoption of cropping and livestock due to different family issues and unequal family labour for each family. Moreover, larger population is another hindrance to adopt these activities that do not fulfil their economic needs as they do not own very bigger land sizes and larger number of animals. They are to search other sources of livelihoods for their larger families.

The nature of using bivariate models are distinct from the multinomial choice models in that for the former, the focus is upon the modeling of two decisions, with each decision involving two alternatives, whereas in the latter case there is a single decision among two or more alternatives (Greene, 1993; p. 913). Bivariate probit model has been estimated by using maximum likelihood estimation (MLE) method while we have estimated the multinomial probit model using Gibbs sampling method under Markov Chain Monte Carlo (MCMC) to identify all parameters of our model. The main difference in the estimated results by MCMC is that posterior mean and standard deviation are significantly smaller than the MLE, due to the strong left skewness of the marginal posterior distribution (Albert and Chib, 1993).

Table 5.6: Multinomial probit estimation for 360 smallholder farmers

Variables	Cropping	Livestock	Mixed Farming
Constant	-0.834 (0.912)	-0.095 (0.456)*	0.205 (0.565)**
AGE	-0.350 (0.424)	-0.010 (0.089)	
EDU	-0.365 (0.400)	0.008 (0.060)	
FmlySize	-0.260 (0.352)	-0.090 (0.074)**	
HerdSize	-1.061 (1.000)	0.946 (0.311)**	
FmlySys	-1.120 (0.630)**	-0.347 (0.259)**	
LandSize	0.052 (0.184)	/////	
LandPos	0.475 (0.713)***	0.064 (0.240)*	
Cotton/Wheat Zone	Ref.	Ref.	
Rain-Fed Zone	-1.250 (0.774)*	-0.493 (0.395)*	
Mix-Crop Zone	-0.874 (0.831)**	0.287 (0.306)	
FMachinery	0.011 (0.428)	0.110 (0.081)**	
CropShare	0.749 (0.741)**	0.060 (0.339)	
Proximity	0.685 (0.395)***	-0.011 (0.095)	
Error Components			
	$\rho(Crpng, Livestk)$	0.641 (1.568)***	
	$\rho(Crpng, Mixed)$	0.789 (1.709)***	
	$\rho(Livestk, Mixed)$	0.656 (0.403)	
	$\sigma(Crpng)$	10.539 (21.587)	
	$\sigma(Livestk)$	0.819 (0.337)***	

** Significant at 10%; ** Significant at 5%; *** Significant at 1%; SD in paranthesis*

5.6 Conclusion

In this study, we take a closer look at the relationship between farming activities, that is, cropping and livestock. We distinguish two types of farming decisions of smallholder farmers. Using the methodology developed by Athey and Stern (1998), we systematically examine the complementarity vs substitute relationship between these two farming business activities. Going beyond the mere identification of the relationship, the analysis also focuses on the contextual variables affecting this perceived relationship. In addition to this, bivariate probit analysis was also performed to see the relationship between farming activities on the basis of unobserved factors. We use direct as well as indirect approach to test for the nature and the drivers of the relationship between the two farming activities.

In direct approach, we deduce from OLS regression estimates that cropping and livestock activities have supermodular relation and hence are complementary. On ther other hand, multinomial probit model also suggest the supermodular relation between cropping and livestock through indirect approach.

This study provides a root to explore the multidisciplinary factors that affects the farming activities. First, the results on our small sample nevertheless provide an interesting suggestion for further research. Secondly, more empirical work using the same methodology needs to be done to improve the predictive power, significance levels and check the robustness of results on larger samples. It is suggested that adoption of scientific knowledge and technical assistance can enhance the payoffs upto a maximum level. Besides, a panel dataset would allow us to further control for unobserved heterogeneity effects.

Chapter 6

General Conclusion

In this chapter we summarize the key conclusions from the thesis (6.1), their potential public policy implications (6.2) and suggest avenues for future research (6.3).

6.1 Summary

The challenge set up at the beginning of this thesis was to develop and test empirical models of complementarity. Following Athey and Stern (1998), we had recourse to the productivity and adoption approaches. The models derived from these approaches have been tested using two database: *(i)* a database on quality signal strategies of Small French cooperatives; and *(ii)* a database on farming systems choices by smallholders in the Pakistan Punjab. Our main contributions were: *(a)* estimating a multinomial probit that allows us to separate what is due to complementarity and what is due to unobservable heterogeneity, and thus solving the incoherence problem of the first model of the adoption approach; *(b)* testing for complementarity using both approaches on the same data in order to see if their results are convergent. In what follows, we detail a little bit more the different results obtained in the chapters of the thesis.

In Chapter 2, we presented a survey on the methodology of complementarity. After a brief review of the theory of supermodularity and the monotone comparative statics approach, we show how this theory is able to provide empirical propositions to test for complementarity between different economic activities. Then, we discuss in detail the two approaches suggested by Athey and Stern (1998) and mainly investigated in the literature. More precisely, we focus on the incoherence problem encountered by the bivariate probit model used to test for complementarity in the adoption approach. We show that estimating a multinomial probit is able to solve this problem by estimating two parameters, one that catches the complementarity effect (constant term) and the other that catches the unobserved heterogeneity (correlation coefficient).

Chapter 3 aimed at determining those drivers of branding and labeling strategies that mainly focus on coexistence of both strategies. To do this, multinomial logit estimation were carried out on our database. The most striking result is the effect of marketing variables and mainly the export markets. Exporting outside European Union borders impact branding strategy positively while exporting inside EU mainly affect labeling and mixed signal. This supports the evidence that branding only strategy is more adequately observed outside EU. However, there are some drivers in the marketing channels sector that returns higher probability of choosing both strategies. These drivers are helpful in testing for complementarity/substitutability between branding and labeling strategies that can affect payoffs of the firms and that is the next step in our agenda of research. At the second stage, we also analyzed the ordinal ranking among different quality signaling strategies, *i.e.* starting from no signal strategy to a common label, a mix signal (both labeling and branding) and then finally to a branding only strategy. In addition to classic analysis of ordered choices, we further investigated to control for endogeneity problem of turnover variable on the choice of quality signals. We estimated a specific simultaneous equations model where one of the (ordered) dependent variable (quality signal) depends on the second dependent variable (turnover). The main result of this bivariate ordered probit model is that turnover variable is indeed endogeneous and significant and have clearly positive effect on the probability of choosing a higher ranking quality signal. That is, turnover which is based on the investment level can influence the choice of strategies as well.

In chapter 4, to reveal out the econometric impact of these drivers, we tested the model of complementarity/substitutability between the joint adoption of branding and labeling strategies emprically. Indirect test of complementarity was conducted on our database because of lack of performance measure that exclusively explain the payoffs observed by adopting branding and labeling strategies. Multinomial probit model was used to test for possible complementarity because of its capability to separate of what is due to complementarity from what is due to unobserved heterogeneity. Our estimation resutls show that there is a clear interaction effect between branding and labeling strategies in the form of substitutability (because of inverse interaction effect). The positive correlation that can be observed between both signals is only due to the unobserved heterogeneity among cooperatives.

To further probe into the complementarity theory empirically, we studied one more database in which different strategies of farming activities were adopted by smallholder farmers in Pakistan. In this chapter 5, we benfitted both approaches to test for complementarity, that is, direct and indirect approach. Cropping and livestock activities are confirmed as complement to each other. We identify that regional diversity in an imporatnt factor in determining economic gains for smallholder farmers. Mix crop zone certainly show income growing with the household activities whereas rain fed zone is a weaker area in terms of growing income through agricultural resources. Apart from testing merely the complementarity, we also figured out drivers or contextual variables through multinomial logit model, and which are important to testing complementarity.

6.2 Policy Implications

The results exihibited in this thesis can have some policy implications. First, our substituability results on the quality signals suggest a strong limitation of the common label strategy outside of the EU markets, and this mainly for the smallest cooperatives. This may question the european commission in its strategy and negociation with WTO on the status of common labels and GIs (Geographical Indications) in the international trade. These common quality signals must be secured by a system of property rights, like the trademark system for brands. Our empirical work is one stone in the burgeoning literature, mainly theoretical, that work on the possible coexistence of brands and GIs (Moschini and Menapace, 2012). Second, our results on the mixed farming systems show that these systems are not only social efficient since they can provide some systemic services in the agricultural production, but also because they can increase the income of the smallholders. From our data in the Punjab Pakistan, we show that jointly adopting crop and livestock systems allow to increase the famer income more than the adoption of cropping activities only or livestock activities only. In our knowledge, this is the first time that such a clear result on the economic efficiency of mixed farming is provided. This work open the door to the analysis of mixed farming systems in developed countries in order to this whether mixed systems in those countries also exhibit complementary effect. If such results are obtained, this can give some credit to the new incentive program developed by the Ministry of Agriculture for the adoption of such systems (Agroecology Plan).

6.3 Future research

This Ph.D. thesis has endeavored to advance on the empirical models of testing complementarity effects. Even if we get some very interesting results, our work has some shortcomings.

First, we tried to solve with the problem of incoherence encountered by the bivariate probit model with unobserved heterogeneity bias, by estimating a second parameter using a multinomial probit model. That is, in so doing we separate what is due to unobserved heterogeneity (catched by the correlation coefficient) and what is due to a “real” complementarity effect (the constant term). But the best method to control for unobserved heterogneity is to use panel data. That is, what we aim to do by collecting additional data.

Second, we do not deal with the endogeneity issue in our empirical models of complementarity. If we try to take this into account sucessfully in our ordered model of quality signal choices (see chapter 3) by using an ordered bivariate probit model, we ignored this problem in the more specific models of complementarity in chapters 4 and 5. We have some hope that it can be solved in the bivariate probit model, provided that we find relevant instruments. But estimating a multinomial probit that can catch complementarity effect with endogenous regressor, e.g. income, can be a little bit more difficult.

Third, in the future we would like to apply to other objects the different empirical models of complementarity that we tested. For example, it would be interesting to analyze the efficiency of the adoption of different combinations of innovative cropping practices, e.g. agroecological practices. Indeed, Altieri (1995) show that agroecology is driven by the principle of functional complementarity between different organisms (biological diversity). We would like to know if this principle can also be applied for the different practices of the farming systems. More precisely, we would like to know if some practices are jointly adopted by the farmer because they generate some complementarity effect.

Fourth, we have not yet derived the conditions under which complementarities may also influence the buyer behavior. For example, a new business strategy not only impact the producers capacity but consumer behavior also may vary with the change. To account for consumers behavior, switching costs may play a significant role that can affect the payoffs of respective business strategies. By controlling switching costs sizable complementarities can be existed (Arora et al., 2010). Further, even under the assumption of existence of complementarity, we have only partially addressed the issue of model identification under the umbrella of exclusion restriction assumption. Our models for complementarity are in lack of panel data structure adoption which states the issue of heterogeneity.

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Essais sur la Complémentarité:

changements organisationels et de marché en agriculture

Cette thèse vise à tester pour l'existence d'effet de complémentarités entre différentes activités économiques dans le secteur agricole. Pour cela, nous mobilisons les deux approches que propose la littérature, à savoir l'approche par la productivité et l'approche par l'adoption. Nous commençons par une revue de la littérature sur l'économie de la complémentarité, en nous focalisant sur ces deux approches de la complémentarité et ses modèles empiriques. Nous proposons ensuite trois analyses empiriques permettant de tester ces modèles. La première explore les déterminants du choix de marque et/ou de signes des qualité par les petites coopératives agricoles françaises, avec un focus particulier sur la coexistence de ces deux signes. La seconde fournit un test direct de complémentarité entre labels et marques en recourant à l'approche par l'adoption. En estimant un probit multinomial, il est en effet possible de séparer l'effet de complémentarité de celui de l'hétérogénéité inobservable. La troisième introduit l'approche par la productivité, en sus de l'approche par l'adoption, pour tester de cet effet de complémentarité dans les systèmes de polyculture élevage adoptés par les petits exploitants de la province du Pendjab au Pakistan.

Mots-clés: complémentarité, signes de qualité, polyculture élevage, modèles de choix discrets.

Essays on Complementarity:

organizational and market changes in agriculture

The main objective of this thesis is to test for complementarity between different economic activities in agriculture. To do this, we have recourse to the two approaches proposed by the literature, i.e. the productivité approach and the adoption approach. First, we review the economics of complementarity and analyze the different empirical models to test for complementarity. Then, we propose three empirical analyses testing these models. The first examine closely the drivers of the branding and labeling strategies from French small agricultural co-operatives, with a focus on the coexistence of both quality signals. The second directly test for complementarity between branding and labeling using the adoption approach, by estimating a multinomal probit. This allow us to separate what is really due to complementarity and what is caused by unobserved heterogeneity. Third, in addition to adoption approach, we test for complementarity using a productivity approach in the mixed farming systems adopted by smallholder farmers in Punjab, Pakistan.

Keywords: Complementarity; quality signals; mixed farming systems; discrete choice models.