



CHAPTER 3

LITERATURE REVIEW: AGRICULTURAL TECHNOLOGY ADOPTION

3.1 Introduction

In this chapter, a review of relevant literature on adoption and diffusion is provided. The chapter will review and compare the various approaches to study adoption and diffusion found in the literature discussing merits and drawbacks of each. The theoretical framework within which the compared approaches are placed is presented in section 3.2. Section 3.3 will compare analytical models used to analyze adoption and diffusion of technologies and section 3.4 reviews empirical studies of relevance to this research. The final section presents analyses of technology adoption and diffusion in Ethiopia.

3.2 Basic concepts and theoretical foundations of adoption analyses

Technologies play an important role in economic development. Adoption and diffusion of technology are two interrelated concepts describing the decision to use or not use and the spread of a given technology among economic units over a period of time. Adoption of any innovation is not a one step process as it takes time for adoption to complete. First time adopters may continue or cease to use the new technology. The duration of adoption of a technology vary among economic units, regions and attributes of the technology itself. Therefore, adequate understanding of the process of technology adoption and its diffusion is necessary for designing effective agricultural research and extension programmes. The following sections define basic concepts of technology adoption and diffusion and provide a theoretical background to adoption and diffusion processes including hypotheses used to explain the S-shaped curve of diffusion. Stages, approaches and sequence of agricultural technology adoption, and benefits from adoption of innovations are also discussed in this section.

Adoption and diffusion are distinct but interrelated concepts. Adoption commonly refers to

the decision to use a new technology or practice by economic units on a regular basis. Diffusion often refers to spatial and temporal spread of the new technology among different economic units. Many researchers belonging to different disciplines have defined the two concepts in relation to their own fields. Among others, the definition given by Rogers (1983) is widely used in several adoption and diffusion studies. Rogers (1983) made a distinction between adoption and diffusion. He defined diffusion (aggregate adoption) as the process by which a technology is communicated through certain channels over time among the members of a social system¹. This definition recognize the following four elements: (1) the technology that represents the new idea, practice, or object being diffused, (2) communication channels which represent the way information about the new technology flows from change agents (extension, technology suppliers) to final users or adopters (e.g., farmers), (3) the time period over which a social system adopts a technology, and (4) the social system. Rogers (1983) then defined adoption as use or non-use of a new technology by a farmer at a given period of time. This definition can be extended to all economic units in the social system.

Feder et al. (1985) distinguished individual adoption (farm level) from aggregate adoption. Individual (farm level) adoption was defined as the degree of use of a new technology (innovation)² in a long-run equilibrium when the farmer has full information about the new technology and its potential. Aggregate adoption (diffusion) was defined as the process of spread of a technology within a region. This definition implies that aggregate adoption is measured by the aggregate level of use of a given technology within a given geographical area. Similarly, Thirtle and Ruttan (1987) defined aggregate adoption as the spread of a new technique within a population. The distinction between adoption and diffusion is

¹ The social system refers to a set of interrelated units that share common problems and are engaged in joint problem solving to accomplish a common goal (Rogers, 1983). A social system encompasses individuals, organizations, or agencies and their adopting strategies (Knudson, 1991).

² A technology is any idea, object or practice that is perceived as new by the members of a social system (Mahajan and Peterson, 1985). Innovations are classified into process and product innovation. A process innovation is an input to a production process, while product innovation is an end product for consumption. The agricultural technologies considered in this study fall in the first category. In this study the terms innovation and technology are interchangeably used.



important for theoretical and empirical analyses of the levels of the two economic phenomena.

The adoption decision also involves the choice of how much resource (i.e. land) to be allocated to the new and the old technologies if the technology is not divisible (e.g. mechanization, irrigation). However, if the technology is divisible (e.g., improved seed, fertilizer and herbicide), the decision process involves area allocations as well as level of use or rate of application (Feder et al., 1985). Thus, the process of adoption decision includes the simultaneous choice of whether to adopt a technology or not and the intensity of its use. Besides, before adoption choices are made a farmer makes a set of several interdependent decisions (Hassan, 1996).

A distinction has to be made between technologies that are divisible and that are not divisible with regard to the measurement of intensity of adoption. The intensity of adoption of divisible technologies can be measured at the individual level in a given period of time by the share of farm area under the new technology or quantity of input used per hectare in relation to the research recommendations (Feder et al., 1985). This measure can also be applied to the aggregate level of adoption in a region. On the other hand, the extent of adoption of non-divisible agricultural technologies such as tractors and combine harvesters at the farm level at a given period of time is dichotomous (use or no use), and the aggregate measure becomes continuous. In the latter case, aggregate adoption of a lumpy technology can be measured by calculating the percentage of farmers using the new technology within a given area.

3.2.1 Adoption, diffusion and abandonment of new technology

The introduction of a new technology consists of two phases. In the first phase, the new technology is introduced to farmers through for instance, demonstrations plots or other means and the new technology will be adopted when found beneficial. The second phase is characterized by declining use of the new technology over time until abandonment (Dinar and Yaron, 1992). Abandonment (discontinue use) of a new technology is a reflection of either a loss of profitability due to increasing costs of inputs, falling yields or the results of



a switch to another more profitable technology. In the case of new improved seeds, abandonment is stopping the use of new variety any more. On the other hand, replacement of the existing improved variety with recently released new one is considered a continuation of use of the improved seed, because the new varieties are substitutes for each other. With this background, technology diffusion is presented next.

The concept of early and late adopters provided the basic hypothesis for explaining the S-shape nature of the adoption path. Studies by Mosher (1979), Rogers (1983), Mahajan and Peterson (1985), and Bera and Kelley (1990) provided explanations related to the process of acquiring information and the time lags that creates in terms of the speed of adoption among various members of the community in question to become adopters. In other words, the S-shaped curve results from the fact that only a few members of the social systems (farmers) adopt a new technology in the early stage of the diffusion process. At the early stages of introduction of a new technology, only few farmers obtain full information about the potential economic benefits of the technology and hence the adoption speed is slow. Moreover, even if they get full information about the potential economic benefits of the technology at the early stage, most farmers fear the possible risks associated with the new technology and hence do not opt to adopt. However, in subsequent time periods potential adopters acquire more information about the benefits of the technology and the degree of riskiness associated with it. Then adoption accelerates until it reaches an inflection point after which it increases gradually at a decreasing rate and begins to level off, ultimately reaching an upper ceiling. Studies by Griliches (1957) and Mansfield (1961) attributed the S-shaped diffusion curve to the spread of information as well as economic factors. Their studies showed that the rate of adoption of a technology is a function of the extent of economic merits (profitability) of the technology, the amount of investment required to adopt the technology and the degree of uncertainty associated with it and availability of the technology. Another study by Gutkind and Zilberman (1985) also revealed that the S-shaped diffusion curve can be explained by the profit maximization behavior, learning by doing and subjective evaluations of decision makers. The Gutkind and Zilberman's (1985) study also indicated that the tendency of large firms to be early adopters of new technologies explains the S-shape curve, based on the assumption that large farmers have advantages over smaller farmers in most of the determining factors listed above, e.g., better

access to information, education, capital and credit.

Theoretical and empirical adoption studies also investigated factors determining the long-run ceilings of the S-shaped diffusion curve. The long-run upper limit or ceiling of the S-shaped curve is determined by the economic characteristics of the new technology in the aggregate adoption. A study by Griliches (1980) showed that aggregate adoption ceiling is a function of economic variables (e.g. profitability) that determine the rate of acceptance of a technology. Differences in profitability of a technology in different regions result in different adoption ceilings.

3.2.2 Speed of technology adoption

Many adoption studies indicated that there is a great variation in the speed of technology diffusion. It has been argued that potential adopters' perceptions of the attributes of the new technology affect the speed with which that technology is adopted. A study by Rogers (1983) identified five characteristics of innovations that have an impact on the speed of adoption. Those characteristics of innovations included: relative advantage, compatibility, complexity, divisibility, and observability. Another study by Supe (1983) added two more attributes that affect the rate of adoption: variations in the cost of adoption and group action requirements of the technology. For example, technologies such as drainage and watershed management require group actions for adoption compared to technologies that are taken up on an entirely individual basis such as improved seed and fertilizer. The later group of technologies are adopted faster than those technologies that require group actions, as all farmers may not be equally interested in these technologies.

Of the technological characteristics mentioned above, relative advantage is regarded as the one with the strongest effect on the rate of adoption. The relative advantage can be subdivided into economic and non-economic categories. The economic categories are related to the profitability of the technology while the non-economic features are a function of variables including saving of time (leisure) and increase in comfort (Ratz, 1995). The higher the relative advantages the higher the rates of adoption. The compatibility of a technology indicates the degree to which that technology is consistent with the existing

social values, cultural norms, experiences and needs of the potential adopters. This attribute also plays a key role in influencing the speed of adoption.

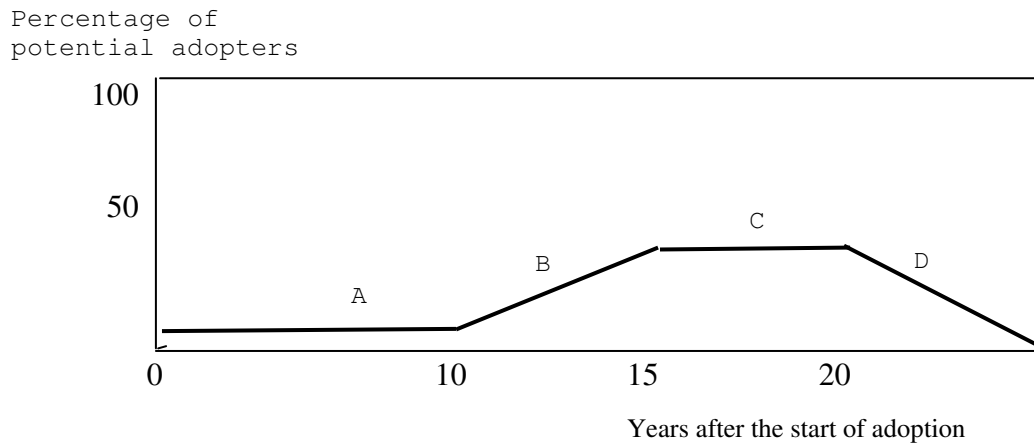
A study by Byerlee and Hesse de Polanco (1986) examined the relationship between rates (speed) of adoption of technologies and various economic factors. Their study showed that the adoption pattern of a particular technology is a function of five characteristics (profitability, riskiness, divisibility or initial capital requirement, complexity, and availability). Their study further indicated that profitability and riskiness of a given technology are a function of agro-climatic and socio-economic environments, such as rainfall and prices. In other words, rainfall and prices indirectly influence the rate of adoption. Interactions between technological components will also affect the rate of adoption. The benefits of using improved seed (hybrid) for instance, are enhanced by fertilizer application especially under favourable environmental conditions, e.g. in high potential areas (Feder, 1982; Byerlee and Hesse de Polanco, 1986; Hassan et al., 1998).

The rate and speed of improved technology adoption depends on the availability of improved technologies, which involve the generation and dissemination of these technologies to users (e.g., farmers). Generation of improved technologies is a time-intensive process and the technologies also depreciate (Alston et al., 1998). More time is also required for adoption to take place i.e. the time that passed from the introduction of the improved technology until the decision is made to use it. Figure 3.1 depicts the time taken to generate and disseminate improved technology and the adoption process. A generic adoption profile includes the technology development lag ending with a release of new technology (A) and the initially increasing adoption rate, which reflects the growing number of farmers in the target area who are using the technology (B). An adoption plateau occurs when most target farmers have been exposed to the technology and have decided whether or not to adopt it (C). Adoption then declines as the technology becomes obsolete (D). Together, these components determine the speed with which adoption of yield increasing technologies have impacts on farmers' production (Mills et al., 1998).

The other important reason for the length of time needed for technology generation, dissemination and adoption is how fast results are achieved as an indicator of the greater

potential economic returns. Benefits received today worth more than those received tomorrow because they can be reinvested sooner to earn additional returns (Alston et al., 1998).

Figure 3.1. Technology generation and adoption profile



Source: Adapted from Mills et al (1998)

3.2.3 Categories of adopters and stages of adoption

Adoption studies also identified and described five categories of adopters in a social system. The categories included innovators, early adopters, early majority, late majority, and laggards (Mosher, 1979; Rogers, 1983). Describing the characteristics of these groups a study by Rogers (1983) indicated that the majority of early adopters are expected to be younger, more educated, venturesome, and willing to take risk. In contrary to this group, the late adopters are expected to be older, less educated, conservative, and not willing to take risks. However, a study by Runquist (1984) noted that the practical aspect of the classification of adopters into five categories is relevant to deliberate or planned introduction of innovation. The usefulness of this categorization is restricted as there is evidence indicating a movement from one category to the other, depending on the technology introduced.

Considerable efforts were made to identify the various stages of the adoption decision

process. Studies by Rogers and Shoemaker (1971) and Rogers (1983) described the innovation adoption decision process, as the mental process from the first knowledge of an innovation to the decision to adopt or reject. The study further indicated that the innovation adoption decision process is different from the diffusion process. The former takes place within the mind of an individual while the latter occurs among the units in a social system or within a region. Based on this theoretical background the study identified five stages in the adoption process. These are (1) awareness or the initial knowledge of the innovation (2) interest and persuasion toward the innovation, (3) evaluation or the decision whether or not adopt the innovation (4) trial and confirmation sought about the decision made, and (5) adoption. These stages in the diffusion process imply a time lag between awareness and adoption. It is usually measured from first knowledge until the decision is made whether to adopt or not. Hence, adoption is not a random behaviour, but is the result of sequence of events passing through these adoption stages (Rogers, 1983).

3.2.4 Mode and sequence of agricultural technology adoption

Attentions have also been given to explaining the mode (approach) and sequence of agricultural technology adoption. Two approaches are common in the agricultural technology adoption literature. The first approach emphasises the adoption of the whole package while the second one stresses step-wise or sequential adoption of components of a package. Technical scientists often recommend the former approach while field practitioners specifically farming system and participatory research groups advance the latter. There is a great tendency in agricultural extension programmes of developing countries to promote technologies as a package and farmers are expected to adopt the whole package.

Opponents of the whole package approach strongly argue that farmers do not adopt technologies as a package, but rather adopt a single component or a few suitable technologies (Mann, 1978; Byerlee and Hesse de Polanco, 1986). Several adoption studies reviewed by Nagy and Sanders (1990) and Leather and Smale (1991) concluded that farmers choose to adopt inputs sequentially. Initially, adopting only one component of the package and subsequently adding components over time, one at a time. The major reasons



often given for sequential adoption of a package of technologies are profitability, riskiness, uncertainty, lumpiness of investment and institutional constraints (Byerlee and Hesse de Polanco, 1986; Leather and Smale, 1991). A farmer first selects the technology that best exhibits these attributes. Another study by Ryan and Subrahmanyam (1975) revealed that farmers might look upon each part of the technological package as a less risky activity than the complete package in terms of what the farmer could lose if crop failure occurs in that season. Their study concluded that sequential adoption of components of technological package is a rational choice for farmers with limited cash. As cash is accumulated from previous adoption of a component of a package, farmers will add another component based on the relative advantage and its compatibility under their condition. This process will continue until the whole package is fully adopted.

A study by Rauniyar and Goode (1996) defined patterns of technology adoption based on the relationship between the technological components adopted. First, the study termed the adoption pattern independent, if the technologies (practices) are independent of one another. Under such conditions the adoption pattern of a farmer will be largely random (Rauniyar and Goode, 1996). This assertion is not in agreement with a study by Rogers (1983), which showed that farmers' adoption decision is not random. Farmers make rational decisions taking into account the environment under which they operate. The probability of adopting a given technology is not conditioned by the adoption of the other technology. Secondly, if farmers adopt technologies in a specific order, the adoption pattern is sequential. This implies that the probability of adopting a technology is conditional on adopting technologies that precede it in the sequence. Thirdly, the adoption pattern becomes simultaneous if more than one technology is adopted as a package and no specific adoption of a technology precedes or follows the adoption of another technology.

3.2.5 Risk and adoption of a new technology

As indicated above adoption decisions depend on farmers' attitude toward risk (risk aversion or risk neutrality) and riskiness of the new technology. The impact of the new technology is not known and farmers have to make subjective judgments about the possible risks they will face. Farmer's risk attitude is analyzed by direct utility elicitation (DUE), observed economic

behaviour and experimental methods (Binswagner, 1980). The Von-Neuman Morgenstern (VNM), the modified NVM and the Ramsey methods are among the DUE methods. However, the Ramsey method is less severely affected by preferences to probabilities and gambling (Anderson, Dillon and Hardaker, 1977).

For instance, the impact of risk on the optimal level of fertilizer use is illustrated in Figure 3.2. The type of risk analyzed here is the uncertainty about possible weather outcomes: “good weather” or “bad weather”. If “good weather” occurs the best crop yield will be obtained and if “bad weather” occurs crop yield will be poor. The total value product (TVP) received in response to applying fertilizer for the “good and bad weather” and farmers’ expected total value product (ETVP), based on the subjective probability of the weather, are represented by TVP1, TVP2 and E(TVP), respectively. A total factor cost (TFC) line shows total production cost associated with an increase in fertilizer use.

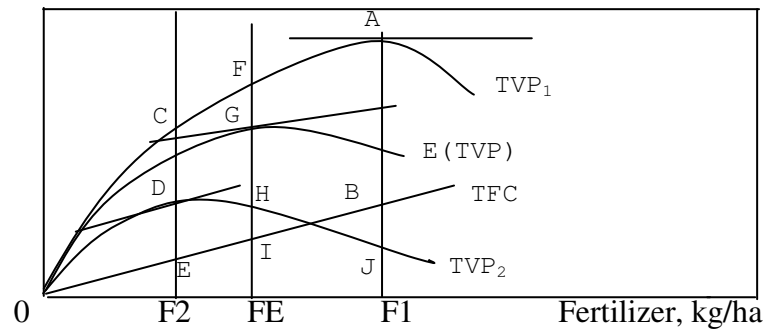
The demand for fertilizer depends on its contribution to the value of output. Two elements determine returns to fertilizer use. The first is its technical relationship between the different levels of fertilizer and the quantity of output produced holding all other factors constant. Second, based on profit maximization assumptions of the theory of the firm, an optimum level of fertilizer is achieved at the point where the value of additional output (TVP) from an extra unit of fertilizer is equal to its cost (price of fertilizer).

For instance, three alternatives fertilizer levels: (F1), (F2) and (FE) were chosen, the rationality of which depend on the risk preferences of farmers. A risk averse farmer is assumed to operate at D on (TVP2), while a risk loving farmer operates at A on (TVP1) and a risk neutral farmer operates at G on E(TVP). An application rate of (F1) represents an efficient allocation if a “good weather” occurs (TVP1), and provides the largest profit of AB. On the other hand, if (F1) is chosen and a “bad weather” occurs (TVP2), a farmer incurs a loss of (BJ). If a “bad weather” occurs, application of (F2) level of fertilizer is efficient on (TVP2). At application level (F2), if it turns out to be a “good weather” a profit of (CE) is obtained. But if it turns out to be a “bad weather” the farmer still makes a profit of (DE) albeit it will be small. Finally, a fertilizer application rate of (FE) represents an optimal level of a balanced assessment of the average outcome of a “good and bad

weather”. A profit of (GI) is obtained if (FE) is chosen, which is less than the largest possible profit (FI) on (TVP1) if it turns out to be a “good weather”. On the other hand, if a “bad weather” occurs there will be a loss of (GH) which is less than the largest possible loss (FH) on (TVP2).

Figure 3.2. Decisions under Production risk.

Total value of
production and
production cost



Source: Ellis, 1993.

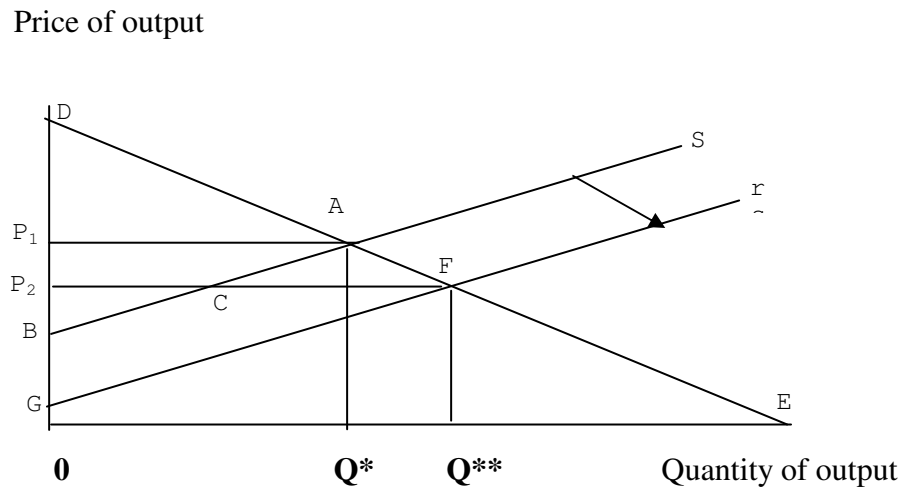
3.2.6 Distribution of benefits obtained from adoption of innovations

Adoption of a new production technology increases production and shifts the supply curve to the right from earlier position (Figure 3.3). This shift shows the effect of adoption on a number of other variables in addition to the quantity produced (example, the price paid by consumers and the price received by producers). For instance, using economic surplus measures (consumer and producer surplus) the shift can be used to measure the distribution of benefits between producers and consumers as well as to identify the effects on industry revenue and to measure total increases in economic efficiency and total social benefits (Alston et al., 1998).

As Figure 3.3 depicts the adoption of new technology results in shifting of the supply curve from s to r , which increases both the consumers and producers surpluses. Consumers receive area (DAP_1) whereas producers receive area (P_1AB) in surplus before adoption of the new technology. After adoptions of the new technology consumers receive area of $(DAFP_2)$ where as producers receive area of (P_2FG) . The supply shift then results in output

price decrease from P_1 to P_2 , which affects both consumer and producer surpluses. The total gain from the adoption of the new technology is represented by area (ABGF).

Figure 3.3. Economic benefits from adoption of new production technology



The impacts of the technology adoption induced supply shift on consumers and producers are complex. As it is clearly depicted, both producers and consumers benefit from the supply shift, but who benefits more depends on the relative elasticity of both demand and supply (Gujarati, 1992). When demand is inelastic than supply, a positive (negative) shift in supply increases (reduces) consumer surplus more than reduction (increase) in producer surplus. With more elastic demand curve, a positive (negative) shift in supply result in smaller increases (reduce) in consumer surpluses than producer surpluses. Similar results are obtained with price inelastic and elastic supply curves, and holding supply price inelastic (elastic).

3.3. Approaches to analysing technology adoption and diffusion

Several analytical frameworks have been developed to analyse adoption and diffusion of agricultural innovations. Some were more suited and applied to adoption decisions while others did model diffusion better. This section provides a review of the various analytical models developed for studying adoption and diffusion of agricultural technologies.

3.3.1. Models explaining technology diffusion

As explained earlier in this chapter, the diffusion process has been commonly modelled to follow an S-shaped curve describing how technology as a new innovation spreads within adopting communities over space and time. Several models (static and dynamic) have been used to analyse this process.

3.3.1.1 Static diffusion model

The logistic function and its variants were commonly used to capture the nature of an S-shaped diffusion curve as discussed below.

3.3.1.1.1 The basic logistic model

A logistic function was specified to model the diffusion process as follows:

$$\partial N_t / \partial t = g_t (N^M - N_t) \quad (1)$$

where $\partial N_t / \partial t$ is the rate of changes in adoption over time t and g_t is the coefficient of diffusion, which measures how fast adoption occurs. N_t is the cumulative frequency of adopters at time t and N^M is the maximum number of adopters in a social system over time. The number of potential adopters not joining at time t is $N^M - N_t$.

Griliches (1957) used the above model to estimate the diffusion of hybrid corn in the United States (U.S.). The percentage area planted to hybrid seed was estimated using the ceiling, the time variable and the rate of growth coefficients. This study also used the logistic function to estimate the relationship between the rate of adoption and profitability variables. Differences in profitability of technology in different regions or districts resulted in different adoption rates. The study showed that the diffusion rate of hybrid seeds in different farming areas was positively related to the increased profit achieved by the farmers introducing the new seed. However, the study did not reveal why producers did not adopt the new technology immediately, even if it was profitable.



Past studies on the path of technology adoption measured diffusion in terms of the distribution of adopters (frequency) over time (Rundquist, 1984; Thirtle and Ruttan, 1987). When the cumulative frequency of adoption is plotted against time, the result approximated an S-shaped (sigmoid) diffusion curve. Although the diffusion pattern of most innovations can be derived in terms of a general S-shaped curve, the exact form of each curve including the slope may vary depending on the analytical models used to describe the adoption-diffusion process (Sahal, 1981). For instance, the logistic function, the Gompertz function, the modified exponential function, the cumulative normal distribution function, and the cumulative log normal distribution function all provide S-shaped curves. The logistic distribution function, which is the simplest to estimate and interpret, is more widely used in most adoption and diffusion studies.

Studies by Gore and Lavaraj (1987), Doessel and Strong (1991) and Knudson (1991) questioned some of the assumptions of the basic logistic model. The studies attempted to improve the relevance of the logistic function by relaxing some of its stringent assumptions. For example, Doessel and Strong (1991) relaxed the assumption of constant population and incorporated population variability (unknown population) in investigating the diffusion of new pharmaceutical drugs. It was assumed that the intercept and diffusion rate are not affected by the size of the population. The modified logistic model produced valid estimates if the members of any size of a population have the same behavioural characteristics.

In the study of semi-dwarf wheat varieties in the U.S. by Knudson (1991), the assumption of a fixed adoption ceiling of the logistic model was relaxed to allow for the possibility of non-adoption and changes in complementary technology. The study by Knudson (1991) applied the modified logistic model on semi-dwarf wheat varieties and showed that the modified logistic model better fitted the data compared to the standard logistic model that is commonly based on the assumption of constant ceilings. Another study by Gore and Lavaraj (1987) also relaxed the assumption of homogeneous population and estimated the standard and modified logistic models to describe diffusion of crossbred goats in a spatially heterogeneous population (within town and outside town) in a village in Pune of west India. The study revealed that diffusion in a village within the town follows the

logistic model while diffusion in a village outside town was a function of information received from adopters within a village. The modified logistic model resulted in a marginal improvement over the standard logistic model.

3.3.1.1.2 The distinction between innovators and imitators in models of diffusion analyses

The basic logistic model was based on imitation theory, which assumes that the adopting population consists of homogeneous imitators (Feder et al., 1985; Knudson, 1991; Weir and Knight, 2000). While this approach clearly describes how innovation diffuses, communication channels are not explicitly modelled. Their effect is implicitly captured in the diffusion coefficient, g_t (equation 1).

The diffusion model that disaggregates adopters into innovators and imitators measures the value of the constant relating the number of new adopters to potential adopters as a function of the specific technology, the social system, the channel and change agents used to diffuse the technology and economic factors (Mahajan and Peterson, 1978; Akinola, 1986). The said constant can also be expressed as a function of previous adopters if higher order terms are dropped. Modifying the basic logistic diffusion model to provide for these concepts yield (Mahajan and Peterson, 1978):

- (1) The coefficient of innovation or the rate of adoption of the proportion of the population whose adoption decision is influenced by exogenous information, and
- (2) The coefficient of imitation or the rate of adoption of the population whose adoption is based on internal interactions.

The coefficient of imitation takes into account the interaction between adopters and non-adopters. This modified model is similar to the new-product growth model (Bass, 1969)³, which was further developed by Mahajan and Peterson (1978).

³Bass (1969) model assumes that the adoption coefficients of imitators and innovators are constant. This assumption is unreasonable as a general case, since socio-economic, institutional, and the supply conditions of the innovation influence these variables.

The theory of imitation on which the standard logistic models were based has been questioned in many diffusion studies. In the standard logistic model the population or social system is assumed to be homogeneous and imitators. Hence, new users imitate adopters. However, adopters do not only influence potential users in the social system as they are also influenced by external information sources such as extension agents and mass media. To estimate such effect, models that account for influences from the internal and external sources of information have been developed. Such models classify the population into two categories, the innovators and imitators. It is assumed that the innovators adopt the new technology independent of others in the social system (Feder and Umali, 1993). Their adoption decision is influenced by external information sources such as extension agents, technology suppliers and mass media. However, the adoption decisions of imitators depend on the number of adopters in the social system. The roles of agricultural extension services and inputs suppliers represent the external information sources while interaction among farmers themselves represents internal information sources (Rogers, 1983).

One problem with the logistic model is that it imposes a symmetric diffusion trend with a maximum diffusion rate occurring when 50% of the potential cumulative adopters have adopted (Thirtle and Rutan, 1987). It is based on the premise that diffusion occurs through interpersonal contacts among a group of homogenous adopters (Mansfield, 1961). But not all diffusion models require symmetry around 50% inflection point. For instance, the Gompertz model (equation 2) imposes an asymmetric trend with the maximum diffusion rate occurring when 37% of the potential cumulative adopters have adopted.

$$\frac{\partial N_t}{\partial t} = g_t \log N^M - N_t \quad (2)$$

The assumption here is that although adopters are homogeneous, early adopters are relatively more cohesive than middle and late adopters and hence they adopt at a faster pace.

Concerning the symmetric nature of the logistic curve, the symmetry of the logistic curve does not always fit observed data. Alternative non-symmetric diffusion models were developed to fill this gap. The inflection point and degree of symmetry of these flexible logistic models are determined by the observed data sets and not imposed *a priori* (Bewley and Fiebig, 1988).

The above static diffusion models work best when the adoption process modelled satisfies certain assumptions. According to Mahjan and Peterson (1985), six basic assumptions underlie static diffusion models:

- 1) The adoption decision is binary (an individual adopts or does not adopt);
- 2) A fixed, finite ceiling exists;
- 3) The coefficient of diffusion is fixed over time;
- 4) The innovation is not modified once introduced, and its diffusion is independent from the diffusion of other innovations;
- 5) One adoption is permitted per adopting unit and this decision cannot be annulled;
and
- 6) Geographical boundaries of a social system stay constant over a diffusion process.

However, for many applications the static diffusion model is open to two objections. First, there will be no rationale *ex ante* for assuming that diffusion follows a particular trend in many cases. Second, in most economic contexts the assumption of a fixed ceiling on the adopting population is unrealistic. For instance, the potential number adopters of a biological innovation will vary depending upon the availability of innovations, which itself is a result of the profit-maximizing efforts of firms. This calls for models that allow more flexibility with regard to inflection and symmetry points (Mahajan and Peterson, 1985; Knudson, 1991).

3.3.1.2 Dynamic diffusion models

Dynamic diffusion models allow the determinants of diffusion to change every time period and, hence, measure the rate of adoption more accurately than the static model. For instance, as the real price of an innovation decreases and stabilizes, an innovation becomes more attractive and is adopted more rapidly. A dynamic model could capture this change whereas a static model could not. Moreover, a dynamic model can include more variables that affect diffusion as a result of its flexible form and hence measure more directly the impact of these factors (Mahajan and Peterson, 1978, 1985, Knudson, 1991).

Studies by Mahajan and Peterson (1978) and Metcalfe and Gibbons (1983) used the dynamic model relaxing some of the assumptions (adoption ceiling, changes in the technology, disadoption) of the static model. Unfortunately, their model, although theoretically appealing, it is difficult to estimate because data required for the profit equations are virtually impossible to obtain.

A model overcoming these data limitations was developed by Knudson (1991) to estimate the diffusion of semi-dwarf wheat varieties across the U.S. In this model, the maximum numbers of adopters were considered to be a function of a wheat supply, wheat prices farmers' received and paid, and the price paid for fertilizers at a given time. All mentioned prices were lagged one year. Two factors accounted for this: First, the model used price variables lagged only for one year because producers' expectations were based on relatively recent experiences used. Second, a common deflator does not deflate the price variables; rather the price variable that would have been the deflector is used as explanatory variable to measure its impact (Tomek and Robinson, 1981). Comparison of results of static and dynamic diffusion models show that the dynamic model provides a better fit to the data as well as offering additional insights into the economic determinants of wheat adoption (Knudson, 1991). In particular, the pattern of adoption of improved varieties was affected by changes in fertilizer prices (Knudson, 1991).

3.3.2 Models analysing adoption of innovations

Generally, it is assumed that farmers' decisions in a given period of time and space are derived from maximization of expected utility or expected profit subject to resources constraints. Therefore, adoption depends on farmers' discrete choice of a new technology from a mix including the traditional technology and a set of components of the new technology (Feder et al., 1985). To answer the question of what determines whether a particular technology is adopted or not and intensity of adoption, most of the adoption of agricultural innovations studies used static rather than dynamic models.



3.3.2.1 Static adoption models

A static model refers to farmers' decisions to adopt an improved technology at a specific place and a specific period of time. This model attempts to answer the question of what determines whether a particular technology is adopted or not and what determines the pattern of adoption at a particular point in time. The results of these studies are often contradictory regarding the importance and influence of certain variables (Ghadim and Pannell, 1999). One limitation of the static model is that it does not account for time in the adoption process nor for the farmers' ability to learn to improve their technical efficiency in growing and marketing the crop. These weaknesses are addressed in dynamic adoption models.

The majority of adoption studies continue to be in the static binary setting of logit or probit models (Jansen, 1992; Shields et al., 1993; Polsen and Spencer, 1991). In these models the adoption decision is merely dichotomous (whether or not to adopt) where a functional relationship between the probability of adoption and a set of explanatory variables is estimated econometrically using logistic distribution for the Logit procedures and the normal distribution for the Probit procedures. The Logit/Probit methods investigate the effects of regressors on the choice to use or not use, but it does not measure the degree or intensity of adoption (Feder et al., 1985). For instance, if a Probit model is used to analyse data on fertilizer adoption, a farmer who adopts the recommended level of fertilizer is treated the same as a farmer who applies one tenth of the recommendation (Ghosh, 1991). But the alternative static econometric procedures such as the Tobit (Tobin, 1958) are used to analyze quantitative adoption decisions when information on the intensity of adoption is available (e.g., data on percentage of area planted to improved varieties, amount of fertilizer/herbicide applied, etc.). However, in working with continuously measured dependent variables such as quantity or area, some of the data points will have a zero value (i.e., for non-users). In this case the dependent variable is censored where information is missing for some range of the sample. If information on the dependent variable is available only if the independent variable is observable, the dependent variable is described as truncated (Kennedy, 1992). The Tobit model provides coefficients that can be further disaggregated to determine the effect of a change in the i^{th} variable on changes in the

probability of adopting the new technology and the expected intensity of use of the technology. However, a study by Dong and Saha (1998) indicated that a Tobit model imposes restrictions that the variables and coefficients determining whether and how much to adopt decisions are identical.

The alternatives to analyse farmers' adoption decisions include the use of double hurdle models, which take into account zero observations (Cragg, 1971; Heckman, 1976). The choice of a model is important because it influences the empirical results obtained (Jones and Yen, 1994). Inappropriate handling of non-users also can result in biased and inconsistent estimates (Amemiya, 1984). For instance, the Tobit model assumes that decisions regarding adoption and intensity of use are related. However, studies by Cragg (1971) on the demand for durable goods and Coady (1995) on fertilizer use indicated that such decisions might not be intimately related. The Heckman (1976) model is the most restrictive of the double hurdle models available because it assumes that none of the zeros for the non-adopters are generated by the adoption decision (i.e., first hurdle dominance) so that standard Tobit censoring is irrelevant (Jones, 1989).

Another study by Saha et al (1994) also modelled adoption as a mixed dichotomous-continuous framework with non-random sample selection, where producers' adoption intensity was conditional on their knowledge about the new technology. They argued that producers' choices are significantly affected by their exposure to information about the new technology. The model is comprised of three equations with correlated errors. The first two are the sample selection and the adoption versus non-adoption equations, both of which have dichotomous dependent variables. The third equation explains adoption intensity, a continuous variable. With this model their study showed that including sample selection and adoption intensity in the model specification yields substantially different results and inferences compared to the traditional dichotomous specification.

A study by Dong and Saha (1998) proposed the more general framework of a double-limit hurdle model that incorporates Tobit and probit models as testable special cases. The study departs from the existing adoption studies in that actual adoption occurs when the innovation is perceived as more profitable, on average, than the traditional technology

(Feder et al, 1985). The study by Dong and Saha (1998) argues that adoption may not occur even when the new technology is expected to be more profitable, because the value of the alternative course of action, waiting and adopting only if one is certain about the return from the new technology, may be higher.

Hassan et al (1998) also used a two-stage decision process to study farmer's adoption of modern maize varieties in Kenya. Both decisions of whether or not to adopt improved maize seed, and whether to plant hybrids or open pollinated varieties (OPVs) were modelled as binary choices. This procedure was selected because only a negligible number of farmers mix maize types and there is no need to investigate area allocated to each. In this model farmers choose between local cultivars and two types of improved seed (hybrid and improved OPVs). Thus, the decision problem is separated into two stages, with each stage represented by a separate equation. One equation models farmers' choice between local and improved maize varieties. The second equation analyses adoption decision about which type of improved variety to use: hybrid or improved OPVs (non-adopters are excluded from the second equation).

Other study by Hassan (1996) showed that a fairly comprehensive range of plating choices made by maize farmers in Kenya, including discrete endogenous variables creating self-selectivity, is modelled and estimated as one system of interrelated decisions. Two-stage and three-stage probit procedures are used to handle the simultaneity and self-selectivity problems. It is common that although some elements of farmers' planting decisions are observed as qualitative endogenous choices (whether or not to double crop) they are usually treated as exogenous variables. Few examples of simultaneous estimation of qualitative adoption decisions are found in the agricultural technology adoption (Smale et al., 1995; Saha et al., 1994).

A study by Workeneh and Parikh (1999) used Probit and ordered Probit to examine both the significance of the impact of farmers' perceptions in adoption decisions of new technology and how perceptions are influenced by the decision to adopt new technology. The Probit approach was used to analyse the adoption decision, while farmers' perception variables were modelled using the ordered Probit methodology since there is an ordering to

the categories associated with the dependent variable. The ordered Probit model assumes that there are cut-off points which define the relationship between the observed and unobserved dependent variables (Pindyck and Rubinfeld, 1981). A simultaneous equations model combining the Probit and ordered Probit approaches provided a useful approach to modelling the two-way relationship between perception and adoption.

For jointly determined dependent variables simultaneous equations systems of discrete and continuous endogenous variables such as Heckman (1978) and Nelson and Olson (1978) were proposed. However, systems estimation by conventional two or three stage least square Generalized Probit model estimates would not eliminate simultaneous equation bias. Therefore, Heckman (1978) used a reduced form of parameter estimates as instruments to overcome the problem of estimating systems of equations with discrete and continuous endogenous variables. These instruments result in consistent parameter estimates and are asymptotically more efficient than the Generalized Probit estimates. Hence, each structural equation can be estimated with the instruments included as one of the explanatory variables with the appropriate discrete or continuous variable estimation procedures.

3.3.2.2 Dynamic adoption models

Dynamic adoption models allow for changes in farmers' adoption decisions as farmers gain skills in growing or marketing the improved seed from year to year. In a dynamic model, at the beginning of each period the type of technology the farmer uses in that period, his allocation of land to different crops, and use of other variables are determined. At the end of each period, the actual yields, revenues and profits/losses realized, information and the experiences accumulated during the period by the farmer, and information from other farmers are used to update decision making in the next period (Ghadim and Pannell, 1999).

A few studies used dynamic models to explain adoption decisions. O'Mara (1971) was among the first to employ a Bayesian approach in explaining the evolution of a decision-makers' perception about a new technology. Linder et al (1979), Stoneman (1980), Linder

and Fischer (1981) followed O'Mara's work where a common theme of these studies is that the producer collects information about actual profits derived by other producers from the innovation and updates *prior* perceptions about the expected return from the new technology.

Studies by Beseley and Case (1993b), and Foster and Rosenzweig (1995) established the importance of learning in the dynamic adoption process. The study by Beseley and Case (1993b) modelled farmers as being uncertain about the profitability of the new seed relative to the old ones. The said study simulated the sub-game perfect number of plots to be planted to the new seed, given that farmers learn about the profitability of the new seeds through experience and compared this with the pattern found in their data. In contrast, Foster and Rosenzweig (1995) modelled the optimum input use as being unknown and stochastic. Farmers learn about the optimal combination through their experience and from the experience of their neighbours.

A study by Carletto et al (1996) modelled adoption and abandonment as combination of two processes which are unfolding over time, but with different origins. The first is the historical time where market and institutional conditions were highly favourable to adoption. The other is the human time, which is composed of two opposite forces (positive and negative). A positive force for adoption and retention is the accumulation of knowledge associated with the passage of time before adoption (learning from others) and years of production after adoption of new technology (learning by doing). A negative force is associated with the passage of time after adoption caused by yield loss. The various time structural factors are unlikely to affect all farmers in equal manner, creating biases capable of offsetting the initial competitiveness of small farmers in growing new technologies over time. This study modeled adoption not as one time behavioral choice within specified time intervals, but as processes of choices of when to adopt and when to abandon using Weibull duration model based on the semi-log functional form.

A study by Cameron (1999) examined the dynamic adoption process of learning using panel data in the adoption of new high-yielding variety. This study used average profit differential between the new and the old seed that has been experienced by the farmer as



the dynamic learning term.

3.4 Empirical studies of technology adoption and diffusion

Adoption is a behavioral choice at a particular time and space while diffusion is the adoption pattern over time. Agricultural technology adoption has long been of interest to social scientist because of its importance in increasing productivity and efficiency. The agricultural sector in developing countries has its own special characteristics (seasonality of production and heavy dependence of production on natural phenomena). Because of these special characteristics of agriculture the following reviews were made only for developing counties.

3.4.1 Adoption studies in developing countries

In developing countries, adoption studies started about four decades ago following the Green Revolution in Asian countries. Since then, several studies have been undertaken in Asia and Latin America to assess the rate, intensity and determinants of adoption. Most of these studies focused on the Asian countries where the Green Revolution took place and was successful.

A review by Ruttan (1977) on several empirical studies on the adoption of Green Revolution technologies revealed the following generalizations:

1. The new High Yielding Varieties (HYVs) of wheat and rice were adopted at a rapid rate in those areas where they were technically and economically superior to local varieties.
2. Farm size and farm tenure have not been serious constraints on the adoption of new HYVs, and were not important sources of differential growth in productivity. This was mainly because productivity of HYVs was approximately the same on small and large farmers' fields.
3. The introduction of the new high yielding wheat and rice technology has resulted in an increase demand for labour.
4. Landowners have gained relatively more than tenants and labourers from the

adoption of high yielding varieties of wheat and rice.

However, the review indicated that there are many exceptions to the generalizations made. These exceptions occurred due to the fact that the technologies have been introduced to environments with different economic, social, institutional, political and agro-climatic settings. A study by Perrin and Winkelman (1976) also summarized adoption studies done by the Centro Internacional de Mejoramiento de Maiz Y Trigo (CIMMYT) on maize and wheat in six countries (Kenya, Tunisia, Colombia, El-Salvador, Mexico, and Turkey). The study concluded that the differences in adoption rates among those countries were explained by differences in information acquired, agro-climatic and physical environments, availability of inputs, differences in market opportunities for the crops, and differences in farm size and farmers' risk aversion characteristics. A comprehensive survey of agricultural technology adoption studies in developing countries by Feder et al. (1985) and Feder and Umali (1993) also found that farm size, risk, human capital, labour availability, access to credit and land tenure systems were the most important factors in influencing farmers' decision of technology adoption.

A study by Jarvis (1981) indicated that the diffusion of fertilized grass-legume pastures in Uruguay followed the logistic path during the first years following its introduction. The study considered the number of ranchers borrowing money from the bank for pasture development each year as a proxy for new adopters of improved pastures. Credit recipients also received good technical assistance from livestock development coordination project. The information on borrowers provides a good estimate of total adopters and the rate of new adopters over time. The adoption of improved pastures by Uruguayan ranchers was estimated by varying the ceiling from 10% to 100% of the total potential adopters. The logistic function with the highest coefficient of determination (R^2) was considered as the best estimates of the ceiling and the rate of diffusion. In this study, the rate of diffusion (hectares planted) was expressed as a function of beef and fertilizer prices. Both the rate and limit of diffusion were found positively related to changes in the profitability of the technology when beef and fertilizer prices were included.

Using panel data, studies by Beseley and Case (1993b), and Foster and Rosenzweig (1995) revealed that learning from own experience and learning from neighbours' experience are

both important determinants of adoption. These findings are in contrast to earlier investigation by McGuirk and Mundlak (1991) that showed that adoption was constrained by insufficient fertilizer and irrigation, not by insufficient information. An other study by Cameron (1999), using panel data confirmed that learning is an important variable in the adoption process, cross-sectional estimates of a dynamic process are biased but the extent of this bias may be small, and illustrated methods to estimate the unobserved household heterogeneity in a dynamic model.

3.4.2 Adoption and diffusion research in Africa

In Africa, new agricultural technologies have been introduced in the mid 1970. The success story achieved in Asia was not duplicated in African countries except for hybrid maize in Kenya (Gerhart, 1975; Blackie, 1989; Roy, 1990; Byerlee, 1994a) and Zimbabwe (Rukuni, 1994), thus the literature on technology adoption in Africa is relatively limited.

Akinola (1986a) applied Bass's (1969) innovator-imitator model in the diffusion of cocoa spraying chemicals among Nigerian cocoa farmers. The model employed includes the internal and external information sources that exist in agricultural technology diffusion process. The result indicated that the Bass (1969) model is only slightly better than the standard logistic model. Another study by Akinola (1986b) relaxed the assumption of constant adoption coefficient of innovators; the coefficient of imitators and the equilibrium number of potential adopters remain constant with time. The said study tested the diffusion patterns of cocoa spraying chemicals in Nigeria and indicated that the data on the diffusion of cocoa spraying chemicals among Nigerian farmers fitted the model fairly well.

Rauniyar and Goode (1996) estimated the interrelationships among technologies already adopted by maize farmers in Swaziland. By applying factor analysis the study showed that farmers adopted the technologies investigated in three independent packages: (1) improved maize variety, basal fertilizer, and tractor ploughing, (2) topdressing fertilizer, and chemicals, and (3) planting date, and plant population (density). However, the empirical findings did not support sequential adoption. The study explained that farmers in Swaziland tend to adopt packages rather than individual technology component or practice.

In contrary to these findings there are a number of empirical studies supporting sequential adoption pattern (Ryan and Sabrahamanyam, 1975; Byerlee and Hesse de Polanco, 1986; and Leather and Smale, 1991).

3.5 Analyses of technology adoption and diffusion in Ethiopia:

Current status and research gaps

This section reviews adoption studies in Ethiopia and presents methodological approaches used, important variables identified by the previous studies, and their limitations.

Since the end of 1960, a number of institutions have been attempting to generate and disseminate improved agricultural technologies to smallholders in Ethiopia. Adoption studies started in the mid 1970. Some of these studies were carried out in areas where integrated rural development projects had been undertaken following the introduction of integrated rural development pilot projects and minimum package programmes in some parts of the country (Tesfai, 1975; Cohen, 1975; Bisrat 1980; Aragay, 1980). These studies focused on evaluating the performance of the pilot projects and on examining the rate of adoption of technologies promoted by these projects. A study by Cohen (1975) did go beyond determining the rate of adoption and assessed the economic and social impacts of the new technologies in the Chilalo Agricultural Development Unit (CADU) area.

Research conducted in the 1980s and onwards in Ethiopia assessed the status of agricultural technology adoption using descriptive statistics and found out that the rate of adoption of improved varieties, fertilizer, herbicide, and other agronomic practices were low (Mulugetta et al., 1992). The amounts of fertilizer and herbicide applied by most farmers in Ethiopia were below the recommended levels (Hailu et al., 1992; Legesse et al., 1992; Legesse, 1992). Some of the research conducted during this period also focused on the impact of centrally planned economic policies (i.e., state farm formation, collectivization, resettlement, villagization, price control and inter regional trade regulations) on the technology adoption process.

Formal adoption studies using econometric models were carried out after the mid 1980.

These studies provided information on the use of improved inputs including seed, fertilizer, herbicides, extent of adoption and factors that limit adoption decisions of smallholders in Ethiopia. Although these studies provided useful information on the rate of adoption and factors influencing adoption, the intensity of adoption was not adequately addressed. In general, the adoption studies had some limitations in their analyses and, thus, did not adequately explain farmers' adoption decisions.

Most of the adoption studies conducted in Ethiopia used conventional static adoption models (e.g., Logit and Probit) for dichotomous dependent variables. In a few cases, the Tobit model was used to study farmers' extent and intensity of adoption of improved technologies. Moreover, some of these studies had methodological limitations (Aragay, 1980; Yohannes et al, 1990), while others have data limitation (Bisrat, 1980). The study by Aragay (1980) had two methodological limitations. First, the study had used a linear regression model to analyze the adoption behaviour of farmers. This model determines the probability that an individual with a given set of attributes makes one choice rather than the alternative (Pindyck and Rubinfeld, 1981). Thus, the study did not include non-adopters in the analysis and therefore creates sample selection bias. Second, to identify factors affecting adoption the study drew conclusions from a correlation analysis, which does not control for the effect of other variables simultaneously.

Most empirical adoption studies in Ethiopia actually examined the relationship between observed explanatory variables and actual decisions made by individual decision makers in acceptance of a technology. However, the study by Yohannes et al (1990) used intended (planned) adoption for some of sample farmers as the dependent variable. The said study considered those farmers who have expressed their intention to adopt the technology in the following years as adopters. Although it is often valuable to obtain farmers' opinions about the feasibility of using a technology and identify its merits and drawbacks, this information cannot be used to assess adoption decisions. Statements about what a farmer would like to do or hopes to do are not substitutes for data on actual technology adoption (CIMMYT, 1993). Those farmers who have a plan to adopt a technology may or may not adopt it.

Using a two-step regression model, a study by Bisrat (1980) investigated patterns and



determinants of fertilizer adoption in the Bako and Jima areas. In the first step, the study estimated the rate of adoption using a Logit model, then regressed rate of acceptance on a number of explanatory variables. The limitation of this study was that the number of observations for each study area was small (only four per area). As a result, the two parameters, (the intercept and slope or rate of adoption) were estimated with only two degrees of freedom.

Some of the studies were conducted more than two decades ago (Cohen, 1975; Tesfai, 1975; Bisrat, 1980; Aragay, 1980) and since then, a number of changes have taken place in the structure of the rural economy of the country. For instance, the landlord-tenant relationship was abolished and extension strategy and policies related to rural development and rural organizational structures have been changed. As a result, the findings of these studies may not reflect critical factors currently underlying adoption patterns. There were also a few adoption studies after the economic reforms in the post-socialist system. Most of these reviewed studies used a component approach neglecting the fact that farmers often choose to adopt components of a technology package sequentially. All of the reviewed adoption studies except Bisrat (1980) and Chilot et al. (1986) did not examine profit, whereas only Yohannes Kebede (1990) and Abinet and Dillon (1992) addressed risk in adoption decisions. Moreover, only Asfaw et al. (1997) and Negatu and Parikh (1999) considered farmers' perception of improved varieties. Surprisingly, none of the adoption studies in Ethiopia considered the value of straw in farmers' adoption decisions.

With regard to analytical models, all reviewed adoption studies except Legesse (1998) used the conventional static models in farmers' adoption decisions. As indicated earlier static models do not capture changes in adoption decisions over time. Studies on the extent and intensity of adoption, which are important for increasing food production and achieving food security, were limited (e.g., Legesse, 1992; Mulugetta et al., 1995; Chilot et al., 1996; Asfaw et al., 1997; AD Alene et al., 2000). In the latter years, there were also improvements in using better models such as discriminate analysis (Getachew et al., 2000, Tesfaye et al., 2001), duration models (Legesse, 1998), and Probit and ordered Probit models (Negatu and Parikh, 1999), double hurdle two-stage models (Berhanau and Swinton, 2003) to explain farmers' adoption decisions. However, none used panel data in

a dynamic adoption process such as learning

The above summary indicates that there are still research gaps that should be addressed in order to explain farmers' adoption decisions adequately. For instance, adoption is a dynamic process, which results from learning about the new technology overtime. To better understand farmers' adoption decisions, one needs to particularly study farmers who have used the new technology over time. Although the dynamic process of adoption is recognized in the theoretical literature (O'Mara, 1971; Linder et al., 1979), almost all the reviewed studies used cross-sectional data due to the scarcity of micro-level data over time. Thus, the studies have been unable to explore the dynamic nature of the process of adoption. However, studies by Besley and Case (1993b), Foster and Rosenzweig (1995) and Cameron (1999) used panel data and established the importance of learning in the adoption process. Information on the importance of learning, extent of adoption, impact of profit and risk, which are key factors in influencing farmers' adoption decisions over time are not available in Ethiopia and not adequate elsewhere. Moreover, all of these reviewed adoption studies except Traxler and Byerlee (1993) had not examined the impact of profit and risk by including the straw yield. Excluding the straw yield of an improved variety underestimates the profit from the adoption of improved seed. This study, therefore, attempted to fill these gaps by providing further evidence on the importance of learning in the dynamic adoption of improved technologies. A component or a package approach was employed to a sub-sample of *tef* and wheat producers who have been using these technologies overtime after exposure. The Xtprobit and Xttobit panel data models were used to examine the dynamic adoption process. The study included the value of *tef* and wheat straw in the estimation of profit and risk from the improved varieties. The information obtained will be useful to researchers and policy makers in the generation and dissemination of new technologies in order to raise agricultural productivity and food security.