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REGULAR ARTICLE

IT IS TOO LATE TO REGRET AND TAKE RISK: FARMERS' ADOPTION DECISION FOR STALL-FEEDING (SF) IN TIGRAY, ETHIOPIA

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ABSTRACT

Research background: Despite a growing interest in the role of time and risk preferences in explaining technology adoption, empirical studies that investigate this behavior are scant. Numerous studies have attempted to identify the determinants of adoption of new technologies. However, those studies failed to capture the duration of time farmers will take to adopt a given technology using a proper model such as duration model.
Purpose of the article: This study developed a technology adoption theoretical model that incorporates time and risk preferences in addition to household level characteristics. Using this model, we tested whether impatience and risk aversion delays or expedites stall-feeding adoption or not.
Methods: Using cross sectional data of 518 sample farmers from Ethiopia, both semi-parametric (Cox PH) and parametric (Weibull PH and Weibull AFT) models have been applied to estimate the conditional probability of SF adoption. This enables us to convey information not only on why a farmer adopted, but also on the timing of the adoption decision.
Findings: As expected, our results indeed show that, the time of stall-feeding adoption increases with discount rate. Individuals who are patient and risk loving adopt stall-feeding sooner than individuals who are impatient and risk averse. Likewise, farmers who are more less-averse adopt SF technology latter compared to farmers who are risk neutral. The estimated results also revealed that economic incentives (i.e. prices) was found to be the most important determinants of the time farmers wait before adopting new technologies. While higher output price significantly accelerates SF adoption, higher input price decelerates the adoption period. The expected milk yield (first moment) had a positive significant effect on the adoption decision, indicating that higher expected mean, on average decreases farmers' time to adopt.
Findings in this study suggest that, land and labor endowment shorten the time to adopt SF. However, market distance delay the adoption of SF. Moreover, access to information, education of household head, breed cow ownership, and location of the farmer, accelerated the likelihood of early SF adoption. To the best knowledge of the authors, this is one of the first adoption studies to have incorporated time and risk preference in its parametric and semi-parametric adoption analysis.

JEL Code: Q1, Q5, O16, Q57
Key words: Stall-Feeding; duration model; hazard rate; time discounting model; Ethiopia

INTRODUCTION

In both theoretical and empirical literature, time preferences is coming to the center stage in explaining technology adoption behaviors. Households with present-biased preferences (impatience) are more likely to have low technology adoption especially in the fields of agriculture and this in turn, will leave them in a cycle of poverty traps **(Banerjee *et al*., 2010; Duflo *et al*., 2011; Le Cotty *et al*., 2014; Tucker, 2006)**. Decision-makers tend to devalue future rewards for which they must wait so that the value of future reward is discounted to equate the present flow benefits (see **Frederick *et al*., 2002; Tucker**, **2006**). The discount rate, hence shows how individuals weigh current versus future rewards which are crucial to understand technology adoption dynamics.
Theory suggests that individuals with higher discount rates are less likely to adopt new technologies with benefits that only occur in the future but that require relatively large up-front investment costs. Farmers may discount seriously the delayed advantages and thereby show that they prefer the immediate gains (traditional technology and input investment) rather than of investing in modern agricultural inputs and harvesting higher yield in the future. Time preference refers, as how a decision-maker subjectively values the tradeoff between the current benefit versus deferred benefit flows **(Duquette *et al*., 2013; Duflo *et al*., 2011; Le Cotty *et al*., 2014: Tanaka *et al*., 2010, Ashraf, 2009)**.

In the past three decades, studies aimed to understand how individual preferences condition agricultural investment decisions have proliferated **(Duflo *et al*., 2011; Le Cotty *et al*., 2014: Tanaka *et al*., 2010, Ashraf, 2009; Liu and Huang, 2013; Ray *et al*., 2018; Kijima, 2019)**. Using a study from Western Kenya **Duflo *et al.* (2011)** found a result which proved present-biased or impatient farmers postpone fertilizer adoption; and **Le Cotty *et al.* (2014)** confirmed that impatience decreases the likelihood of improved grain storage technology adoption in Burkina Faso. Likewise, the work of **Yesuf (2004)** indicated that higher discount rate was correlated with low adoption of soil conservation technology in Ethiopia. Similar result was echoed by **Tucker (2006)** using a study conducted in Madagascar. However, none of the stated studies have touched, how individual risk preference affects farming decisions in the process of technology adoption **(Chavas et al., 2010)**.

Interestingly, several studies **(Feder *et al*., 1985; Liu and Huang, 2013; Ray *et al*., 2018; Kijima, 2019)** have also recognized the importance of capturing the effect of risk and individual preferences on the technology adoption decision. Farmers are expected to select the technology that offers the maximum expected utility, given their level of risk preference **(Foster and Rosenzweig, 2010; Barham *et al*., 2014)**. Findings indicate that risk preference affects farmers' willingness to try new practices **(Greiner *et al*., 2009)**. The state of risk preference, affects the adoption of new technologies in many ways and has been found to reduce the adoption of new technologies/practices **(Ghadim *et al*., 2005)**. Especially if farmers perceived the new agricultural technology as an uncertain proposition, then the individual subjective risk preferences tend to play a major role in technology adoption **(Holden, 2015)**. In line to this, **Ward and Singh (2015**) found that risk averse and loss averse farmers are more likely to switch to new rice seeds in India. Besides, a recent findings by **Liebenehm and Waibel** (2018) proved that a loss averse and impatient farmer is less likely to adopt prophylactic drugs leading to losses of higher and sustainable returns, thereby deteriorates risk management abilities and likely perpetuates poverty.

This paper aims to establish whether individual time and risk preferences play an important role in the adoption of stall-feeding technology in Ethiopia. Though few studies **(Garcia *et al*., 2008; De Cao *et al*., 2013; Klitzing *et al*., 2014; Hadush, 2018)** showed that benefits from modern stall-feeding, if properly implemented, however, its pace of diffusion in practice is slower than anticipated **(Lenaerts, 2013; Bishu, 2014; Hadush, 2018)**. Given the financial constraints **(Cole *et al*., 2013),** state of available information on the benefits **(Gine and Yang, 2009)** and level of social connectivity of the potential adopter **(Conley & Udry, 2010)**, the hypothesis that differences in adoption decisions are explained by individual time and risk preferences need to be tested **(Duflo *et al*., 2011; Le Cotty *et al*., 2014: Tanaka *et al.,* 2010; Liu and Huang, 2013; Ray *et al*., 2018; Kijima, 2019)**. It might be the case that if farmers have a strong preference for immediate rewards, the higher return of stall-feeding may be subjectively discounted, to below the more immediate value of traditional free grazing so that free grazing is preferred and vice versa. Thus, the lag in the benefit realized from the investment may suggest, the potential influence of farmers' time preference to explain their adoption.

Knowing time consistent behavior of our respondents', and using time-consistent discounting model, this paper aims to provide an evidence based explanation in the stall-feeding adoption variation among farmers. We claim that even in cases of, where farmers are not financially constrained and aware of the benefit of stall-feeding, differences in stall-feeding adoption intensity may suggest difference in individual preferences. Therefore, it helps us to establish a causal relationship between the discount rate and stall-feeding adoption in a framework where farmers are time-consistent using a simple protocol to elicit discount rates. Accordingly, individuals are asked to choose between a small immediate reward and a delayed large reward in two-time term frames; which enables to generate an average monthly individual discount factors **(Ashraf *et al*., 2006; Meier and Sprenger, 2010; Bauer *et al*., 2012; Meier and Sprenger, 2013)**.

While a small number of studies attempted to assess the extent to which individual preferences drive individual decisions in saving or borrowing, this study claims to be a pioneer work in providing evidence that time-consistent model of discounting explains the variation of technology (stall-feeding) adoption and expected to contribute to the tiny stall adoption literature. More importantly, in most cases during the introduction of new technology, planners either assume that farmers will assign a discount rate similar to farmers in other parts of the world (bench mark discount rate), or completely ignore time discounting factor at all. Our analysis enables us to provide evidence based policy input in this regard. If our analysis provides us causal relationship between time and risk preferences and adoption, it will be instrumental in helping in predicting how individuals will behave with new technology adoption process and show how discount factor and risk vary in the individual's behavior; which can help explain why low levels of adoption of socially desirable technologies in the future.

In this case, we hypothesized that individuals with high discount rates will be less likely to adopt beneficial technologies and are less likely to favor long-term payoff; implying that as impatience increases it decreases stall-feeding adoption and vice versa. Second, we also hypothesize that stall-feeding adoption decreases with increasing risk aversion behavior. Third, we expect loss adverse individuals have adoption difficulties. We further propose that SF adoption positively and directly respond to output price but negatively respond to input cost of adoption.

The rest of the paper is organized as follows; Section 2 discusses the existing literature on factors that influence household stall feeding adoption decisions with particular emphasis on time and risk preference. The next section explains deeply the relevant theoretical model. Section 4 presents a description of the survey data and experimental design while its sub-section deals on empirical model for estimating stall feeding adoption. Results and discussions are presented in section 6 while section 7 presents conclusions and suggestions.

LITERATURE REVIEW

Livestock farming relies on a number of decisions which includes among other things; feeding rations, breed type selection, and pasture management. For instance, as the decision to adopt stall feeding, entails both short-term costs and long-term benefits in terms of greater livestock productivity and ecological sustainability **(Ghadim *et al*., 2005; Lenaerts, 2013; Bishu, 2014; Hadush 2018)**. A plausible reason for the slow and/ low adoption of some technologies is the timing of benefits and costs associated with new technologies. Risk aversion will be less likely to adopt new technologies with benefits that occur in the future but that require relatively large up-front investment costs **(Duquette *et al*., 2013; Le Cotty *et al*., 2014)**. Following the seminal works of **Fisher (1930)** and **Paul Samuelson (1937)**, many economists have started to a better understanding of time preferences as conditioning factor in individuals 'decision making. **Samuelson** in his constant discounted utility model, noted that individuals with a hyperbolic discount function are more patient in the near future and grow more patient as the delayed rewards get further and further away, which indicates present bias. **Luhmann (2013)** in his work, comparing hyperbolic and exponential discounting models, concluded that, exponential discounting models do not allow for present bias, whereas hyperbolic discounting models do. Few studies which focus on the existence of present bias itself rather than the shape of the discount function which tried to examine the association of present bias with undesirable behaviors, such as procrastination, lack of savings, and a higher probability of quitting job **(Burks *et al*., 2012)**.

Despite the apparent importance of discounting behavior, there is little supporting evidence in its role in the technology adoption of farmers and, more particularly, to stall feeding decisions **(Chavas *et al*., 2010)**. Some directly related studies includes the work of **Duflo *et al*. (2011)** who argued that, those present-biased farmers may procrastinate fertilizer purchases until later periods, and fail to make profitable investments in fertilizer in Western Kenya. **Le Cotty *et al.* (2014)** using hypothetical questions about risk aversion and time discounting in Burkina Faso, showed that impatience decreases grain storage adoption, whereas risk aversion increases storage level. Similarly, **Tucker (2006)** stated that farmers discount future harvests sufficiently and thereby prefer the immediate gains from foraging rather than the delayed advantages of investing additional agricultural inputs using time preference in Madagascar. Another related work in the subject is of **Yesuf (2004)** whose study highlighted the relationship between time preference and adoption of soil conservation technology using elicited discount rates. In his study, higher discount rates were found to be significantly correlated with low adoption in Ethiopia.

Sullivan *et al.* (2010) using survey and field experiment data, from China stated that households with higher discount rates used less labor for applying inputs and spent less on forest inputs in response to forest plot certification. Empirical studies in developing countries have also identified different factors in relation with technology adoption. Accordingly, they found that poor farmers may be credit-constrained **(Cole *et al*., 2013)**, lack information on future benefits of the technology **(Gine and Yang, 2009)**, and may be too risk averse to experiment with new technology **(Liu and Huang, 2013; Conley and Udry, 2010)**. In that **Liu and Huang (2013)** using TCN[1] approach with cotton farmers in China found that more risk-averse and more loss-averse farmers adopt Bt cotton later. Meanwhile, social network facilitates adoption of new technology by enabling farmers to learn about benefits of new technologies from their peers, imitate their peers' decisions, or respond to their peers' experience **(Conley and Udry 2010)**.

However, **Ray *et al.* (2018**) found that risk averse farmers and farmers who overvalue smaller probabilities adopt technology sooner than others. Farmers are expected to be motivated to adopt new technology whenever it promises them higher return i.e. the first moment-predicted mean is positively related to adoption **(Kassie *et al*., 2009; Juma *et al*., 2009; Ogada *et al*., 2014)**. Economic factors relating to output and input prices are important factors to influence the adoption process **(Martínez-García *et al*., 2016)**. A higher input cost delayed SF adoption **(Hadush *et al*., 2019; Martínez-García *et al*., 2016)**. Hence, **Liebenehm and Waibel (2018)** recommended that further research is needed to assess the role of behavioral factors (time preference, loss aversion and risk aversion) on technology adoption.

THEORETICAL MODEL

Why farmers in developing countries who face similar financial constraints and agro-ecological conditions differ in technology adoption such as, fertilizer, recommended agronomic practices and stall-feeding adoption behavior which is the focus of this paper. A hypothesis to be tested is that other things remaining constant, differences in agricultural decisions are explained by individual preferences. If farmers are too impatient, they may be reluctant to use new technologies such as stall-feeding technology.

This section tries to develop a theoretical mode which is used to test that impatience decreases stall-feeding adoption whereas individuals with low discount rate are likely to adopt stall-feeding sooner. Consider a farmer who produces milk or drought power under the inter-temporal decision by dividing the production season into the lean and the harvest season produce h_t, consumes $h_t - c_t \geq 0$ and keeps c_t up to the next lean season. Assuming there is no uncertainty on the milk or milk product price nor on harvest level, the farmers will have a fixed milk price $\underline{p}$ in the harvest period.

The farmers in the lean season decides to feed his/her cow/ox x_t under stall-feeding practice at unit price (k),[2] and consumes the remaining value of his/her harvest, $\bar{p}c_t - kx_t \geq 0$, where $\bar{p}$ is the price of milk or milk product at the lean season. The farmer expects an increase in production under the new investment (improved feeding scenario) and production h_t increases as the number of stall-fed cows increases, x_{t-1}. More precisely, $h_t \equiv h(x_{t-1})$ and $h' > 0$ while $h'' \leq 0$. The model assumes that farmers have no access to credit nor can save any amount of valuable good between the lean season and the next harvest season, implying that the whole harvested amount is supposed to be self-consumed or sold before the next harvest season. In rural farm households, it is logically true that the price of milk or milk product falls from the period of harvest to the lean period. Then we assume that $\bar{p} > \underline{p}$.

Denoting u as the utility function of the farmer (with $\mathrm{u}' > 0$ and $\mathrm{u}'' \leq 0$) and $\sqrt{\rho}$ represents the discounting factor between the two seasons, the discounted sum of the utility of the farmer starting from the harvest season is given by

$$U_t = \sum_{r=1}^{+\infty} \rho^{\frac{r-1}{2}} u\left(\underline{p}(h(x_{r-1}) - c_r)\right) + \rho^{\frac{r-t+1}{2}} u(\bar{p}c_r - kx_r) \tag{1}$$

Farmers maximize their discounted sum of utility by choosing the number of stall feed cows under, x_t, and the stock , c_t, for all t. Following the above expression, the necessary condition for an interior solution ($x_t > 0, c_t > 0, h_t - c_t > 0, \bar{p}c_t - kx_t > 0$) are:

$$-\underline{p}\mathrm{u}'\left(\underline{p}(h(x_{t-1}) - c_t)\right) + \bar{p}\sqrt{\rho}\,\mathrm{u}'(\bar{p}c_t - kx_t) = 0$$

And

$$-k\mathrm{u}'(\bar{p}c_t - kx_t) + \underline{p}h'(x_t)\sqrt{\rho}\,\mathrm{u}'\left(\underline{p}(h(x_t) - c_{t+1})\right) = 0$$

Dealing on the stationary solution i.e., $x_t = x$ and $c_t = c$, the necessary condition for these expressions become:

$$\frac{\mathrm{u}'(\bar{p}c - kx)}{\underline{p}\mathrm{u}'\left(\underline{p}(h(x) - c)\right)} = \frac{1}{\sqrt{\rho}\bar{p}}, \tag{2}$$

and $\frac{\sqrt{\rho}h'(x)}{k} = \frac{\mathrm{u}'(\bar{p}c - kx)}{\underline{p}\mathrm{u}'\left(\underline{p}(h(x) - c)\right)}$

This expression reduces to

$$h'(x) = \frac{k}{\rho\bar{p}} \; or x = h'^{-1}\left(\frac{k}{\rho\bar{p}}\right) \tag{3}$$

From this expression, the model shows that the adoption of stall-feed cows is a decreasing function of the price or the cost of stall feed (k) but an increasing function of the annual discount rate (patience) ρ, price of milk and milk product at the lean season, $\bar{p}$. Furthermore, it does not depend on the utility function i.e. risk aversion and on the price of price of milk and milk product at the harvest season, $\underline{p}$.

In order to take price and harvest uncertainty into account, we further assume that the price of milk in the lean season is unknown in the time of harvest season but it is distributed according to cumulative distribution M. Besides, future harvest is not also certainly known at the time of lean season and assumed to be τh_t, where τ is distributed according to cumulative distributing N. The harvest $\tau h_t(x_{t-1})$ is known at the harvest season of year t, and then the farmer chooses c_t that maximize

$$U_t = \sum_{r=1}^{+\infty} \rho^{\frac{r-1}{2}} u\left(\underline{p}(\tau h(x_{r-1}) - c_r)\right) + \rho^{\frac{r-t+1}{2}} \int u(pc_r - kx_r)\, dM(p)$$

Then the first order condition is given by;

$$-\underline{p}\mathrm{u}'\left(\underline{p}(\tau h(x_{r-1}) - c_r)\right) = \sqrt{\rho} \int \mathrm{u}'(pc_r - kx_r)\, dM(p)$$

Since price is known (p) at the lean season of year t, the farmer chooses x_t that maximize

$$U_t = \sum_{r=1}^{+\infty} \rho^{\frac{r-1}{2}} u(pc_r - kx_r) + \rho^{\frac{r-t+1}{2}} \int u\left(\underline{p}(\tau h(x_r) - c_{r+1})\right) dN(\tau)$$

The first order condition is then given by;

$$k\mathrm{u}'(pc_t - kx_t) = \sqrt{\rho}\underline{p}\, h'(x_t) \int \tau \mathrm{u}'\left(\underline{p}(\tau h(x_t) - c_{t+1})\right) dN(\tau)$$

Rearranging the two first order conditions result in

$$\underline{p} \int \tau \mathrm{u}'\left(\underline{p}(\tau h(x_{t-1}) - c_t)\right) dN(\tau) = E(\tau)\sqrt{\rho} \int \mathrm{pu}'(pc_t - kx_t)\, dM(p)$$

and

$$k \int \mathrm{pu}'(pc_t - kx_t)\, dM(p) = E(p)\sqrt{\rho}\underline{p}\, h'(x_t) \int \tau \mathrm{u}'\left(\underline{p}(\tau h(x_t) - c_{t+1})\right) dN(\tau)$$

or

$$\frac{\underline{p}}{E(\tau)\sqrt{\rho}} = \frac{\int \mathrm{pu}'(pc_t - kx_t)\, dM(p)}{\int \tau \mathrm{u}'\left(\underline{p}(\tau h(x_{t-1}) - c_t)\right) dN(\tau)}$$

and,

$$h'(x_{t-1}) = \frac{k}{E(p)\sqrt{\rho}\underline{p}} \frac{\int \mathrm{pu}'(pc_t - kx_t)dM(p)}{\int \tau \mathrm{u}'\left(\underline{p}(\tau h(x_t) - c_{t+1})\right)dN(\tau)}$$

Focusing only on the stationary solution, the stationary number of stall feed cows are given by;

$x = h'^{-1}\left(\frac{k}{E(\tau)E(p)\rho}\right)$, for all t

In summary, the model presents that the adoption of number of stall feed cows is a decreasing function of the price or the cost of stall-feed (k)but an increasing function of the annual discount rate (patience) ρ, expected price of milk and milk product at the lean season, $E(p)$ and expected yield, $E(\tau)$. Furthermore, as in the case no uncertainty, the adoption of stall fed cows does not depend on the utility function i.e. risk aversion and on the price of price of milk and milk product at the harvest season, $\underline{p}$. This model rules out that adoption of stall feeding is an independent of risk aversion

MATERIALS AND METHODS

Study Area and Survey Design

The study is conducted in the Tigrai region in the northern part of Ethiopia by randomly selecting 632 farm households. The Rural Household Survey dataset collected (cross sectional) in 2018 run by MU research project[3]. To capture the systematic variations among the different agro-climatic zones in terms of, agricultural potential, population density and market access conditions, four communities were selected from each of the four zones and three communities that represent irrigation projects. Likewise, one with low population density and one with high population density were strategically selected from each zone among communities to reflect far distance market **(Hagos, 2003)**.

The study was conducted in five zones (the next lower administration unit to region) covering 11 districts and 21 *Tabias* (lower administrative units to district) so as to yield 632 sample size. A cross-sectional data set for the year 2017/2018 was extracted from the survey since some variables used in this paper were only added in the last wave. The estimation of stall-feeding adoption further reduced the sample size to 518 farmers, including those who only own cattle during the study year. The descriptive statistics of the important variables used in the study are presented in Table1 and are discussed there.

Measuring Time Preferences

In order to test whether heterogeneity in individual time preferences affects stall feeding adoption, we measure individual time preferences using a hypothetical question **(Ashraf *et al*., 2006; Meier and Sprenger, 2010; Bauer *et al*., 2012; Meier and Sprenger, 2013)** to link the state of impatience to stall feeding adoption. In particular, we investigated whether individuals who exhibit present-biased preferences and impatience have higher or lower stall-feeding adoption decision. Individuals under two multiple price lists were asked to make a series of choices between a smaller reward (X) in period t_0 and a larger reward (Y>X) in period t_1 keeping Y constant by varying X in two-time frames. In time frame 1, t_0 represents the present (t = 0) and t_1 is one month (τ =1); and in time frame 2, t_0 is six months from the study date (t_0 = 6) and t_1 is seven months from the study date (t_1 = 7) indicating that the delay length, d, is one month in both time frames. In both frames, the value of X varies from ETB 75 to ETB[4] 40 while Y is held constant to ETB 80.

Employing monetary rewards and multiple price lists as a preference elicitation mechanism enables us to identify differences in patience and present bias between individuals similar to time preference measures derived from other methodologies **(Chabris et al., 2008)**. Time preference measures obtained from price lists at the individual level have been shown to be stable over time (see **Meier and Sprenger, 2010)**. Using information from both price lists allows us to measure individual discount factors (IDF) and present and future bias. Individual discount factor (δ) is measured by taking the point in a given price list, X^* at which individuals switch from opting for the smaller (earlier payment) to opting for the larger (later payment). That is, a discount factor is taken from the last point at which an individual prefers the earlier smaller payment, assuming that $X^* \approx \delta^d \times$Y, where d represents the delay length **(Meier and Sprenger, 2010; Bauer et al., 2012; Meier and Sprenger, 2013)**.

As the delay length, d, is always one month for both time frames, $\delta \approx (X/Y)^{\frac{1}{d}}$. Since our procedure produce two discount measures,$\delta_{0,1}$ and $\delta_{6,7}$, we use the average of these calculated monthly discount factors as the discount factor in the main analysis. Besides we are able to measure present bias and future bias to identify dynamic inconsistency. An individual is present-biased if he is more impatient when presented with a choice with a shorter delay and more patient with longer delays and if the individual is future biased, more patient with a shorter delay and impatient with longer delays **(Bauer et al., 2012)**. We classify an individual as present-biased if $\delta_{0,1}<\delta_{6,7}$, and as future-biased if $\delta_{0,1}>\delta_{6,7}$. For our primary analysis, we use dummy variables Present Bias (=1) and Future Bias (=1).

In order to validate our result cautiously, our elicitation design enables us to reduce the effect of seasonality on time preferences, as the future choice is shifted forward by exactly one month. In the long-term frame, we avoid proposing a choice between an amount now and a higher one a month from now. Instead, the choice is made between six months from now and seven months which involves front-end delay, in the sense that no reward is ever obtained without some minimal delay, allowing us to compare two uncertain choices and to avoid a possible bias toward the present and certain option as proposed by **Frederick et al. (2002**). The format used in this elicitation is presented in appendix A.

Measuring Risk Preferences

Although our intention in this paper is not to estimate risk preference, we include risk preference in order to test the link between risk aversion and patience in our time preference estimation. Exploring people's risk preference through field experiment in developing countries are mostly derived from the types of instruments developed by **Binswanger (1980)** or **Holt and Laury (2002**).While the **Holt and Laury (2002)** approach uses choices from a list of binary lotteries that differ in expected payoffs and variance to infer parameters for risk-aversion, the instrument we employed in this paper instead is similar to the approach of **Noussair *et al*. (2013)** and **Drouvelis and Jamison (2012)** asking respondents to directly compare declining present choices with constant future choices.

A simple hypothetical risk elicitation instrument was presented to our respondents using similar approach of **Noussair *et al.* (2013)** and **Drouvelis Jamison (2012)** who measured risk aversion by counting the number of safe choices made by the individual in five and seven list choices respectively. In order to elicit risk preferences, participants were shown a table with seven rows and asked to choose between a safe option and a lottery option in each row where the safe option is held constant in each row, but the amount in the lottery option increase from row to row. More precisely, in the first-row subjects choose to receive 60 ETB with certainty, or they choose to play the lottery and have a 50 percent chance of receiving 0 ETB and a 50 percent chance of receiving 110 ETB. The amount in the lottery row increases from110 ETB to120, 130, 140, 160, 180, and 200 ETB. Our measure of individual risk aversion is the number of instances in which a respondent chose the certain row. Thus, our *risk aversion* measure ranges from a lowest possible value of 0 to a highest possible value of 7. Then respondents revealed their risk preferences by switching from option 1 to option 2.

A choice of zero safe option, out of seven choices indicates risk preferring individual and a risk neutral individual would make either one or two safe choices, out of the seven choices, and more than two safe choices indicate risk aversion. More safe choices indicate greater risk aversion according to **Noussair *et al*. (2013).** Consulting the work of Drouvelis and Jamison

(2012) as a measure of loss aversion, we used the frequency with which a subject chose the safe option. A detail elicitation table is presented in an Appendix B.

Empirical Model Specifications

To estimate the hazard rate, the time required to adopt SF, duration model was applied. Duration model has its origin in survival analysis, where the duration of interest is the survival of a given subject. While in economics this model is used in labor market studies, where unemployment spells were analyzed **(Verbeek, 2008)**. More recently, **Hannan and McDowell (1984, 1987)** and **Burton *et al.* (2003)** have used it to capture dynamic aspects of adoption processes of agricultural technologies. Since this study intends to estimate the survival, hazard rate and the factors affecting the probability that the farmer adopt SF, in the next short time interval given that it has lasted to that period.

Survival function

Coming to the model specification, T is a non-negative continuous variable representing the duration of stay in a given state measured in years and the probability of a farmer stays in the same state until or beyond time (t) is given by the survival function.

$$S(t) = \Pr(T \geq t) = 1 - F(t) \tag{4}$$

Where t is the age of an enterprise, the survivor function reports the probability of surviving beyond time t.

Hazard function

The hazard function is defined as the limiting value of the probability that T lies between t and t+Δt, conditional on T being greater or equal to t, divided by the interval Δt, as Δt tends to zero.

$$h(t) = \frac{f(t)}{S(t)} = \lim_{dt \to 0} \frac{\Pr\,(t \leq T < t+dt | T \geq t)}{dt} \tag{5}$$

Where $F(t) and f(t) = dF(t)/dt/$ are the corresponding cumulative distribution and probability density function, respectively. In technology adoption study, the hazard function, therefore, represents the probability that a farmer will adopt SF at time t, given that the farmer has not adopted before t. Given a vector of explanatory variables x_ix, the hazard function (Lancaster 1990) may be redefined as,

$$h(t, X_i) = h_0(t)e^{\sum_{i=1}^{N} \beta_i X_i} \tag{6}$$

The hazard function $h(t, X_i)$ h(t) gives the instantaneous potential per unit time for the event to occur, given that the farmer has not adopted SF up to time t given the set of explanatory variables denoted by X_i. Equation (6) the $h(t, X_i)$ represents Cox model at time t- is the product of $h_0(t)$ which is the baseline hazard and the exponential expression e to the linear sum of $\beta_i X_i$.

The two most popular ways of specifying hazard function are the proportional hazard (PH) and the accelerated failure time models (AFT).

The PH Specification

The hazard rate in all proportional hazard models can be written as follows:

$$h(t, X_i) = h_0(t)e^{\sum_{i=1}^{N} \beta_i X_i} = h_0(t)\lambda \tag{7}$$

Where, $h_0(t)$ is the baseline hazard and depends on t but not X_i; indicating the pattern of time dependence that is assumed to be common to all units; $\lambda = e^{\sum_{i=1}^{N} \beta_i X_i}$ on the other hand is a unit-specific (non-negative) function of covariates (which does not depend on t) which scales the baseline hazard function common to all units up or down. Once we recognize the time dependency, the three hazard parameterization models which specify a particular shape for the hazard rate can be specified as follows **(Cleves *et al.*, 2010; Jensen, 2008)**.

i) Exponential Model: assumes a flat hazard which implies the risk of an event occurring is flat with respect to time.

$$h(t,\, X_i) = \lambda_i = e^{\sum_{i=1}^{N} x_i \beta_i} \tag{8}$$

ii) Weibull Model: assumes a monotonic hazard

$$h(t,X) = \lambda p(\lambda t)^{p-1} = \exp(\beta_0 + X_i\beta_i)pti^{p-1} \quad (9)$$

Where $\lambda = e^{Xi\beta i}$ and p is a shape parameter

iii) Gompertz Model: follows monotone hazard rates that either increase or decrease exponentially with time**.**

$$h(t) = \lambda e^{\gamma t} = \exp(\gamma t)\exp(\beta_0 + X_i\beta_i) \quad (10)$$

Where $\lambda = e^{X_i\beta_i}$ and γ is a shape parameter

The AFT Specification

The word "accelerated" is used in describing AFT models, assumed for $T_i = \exp(-X_i\beta_i)t_i$ and $\exp(-X_i\beta_i)$ is called the acceleration parameter **(Cleves *et al.*, 2010)**. Moreover, the AFT model assumes a linear relationship between the log of (latent) survival time T and characteristics of the units X: $\ln(T) = X\beta + z$; where β is a vector of parameters and z is an error term. This may be rewrite as:

$$Y = \mu + \sigma u = Y - \mu/\sigma = u \quad (11)$$

Where $Y = \ln(T)$, $\mu \equiv X\beta$, and $u = z/\sigma$ is an error term with density $f(u)$ and σ is a scale factor which is related to the shape parameter of the hazard function.

Having the above AFT model specification, the distributional assumptions about u determine which sort of AFT model describes the distribution of the random variable T. With this regard, five parametric AFT models (time parameterization models) have been specified; to analyze the risk of an event occurring (SF adoption) over time T and the set of covariates, and thereby the best model was selected using appropriate model selection criteria. The models include; Weibull distribution, Exponential distribution, Log-logistic distribution, Lognormal distribution and Gamma distribution. Accordingly, the AFT models functional form are presented below **(**see **Cleves *et al.*, 2010; Jensen, 2008)**.

i) Exponential Model

$$h(t, X_i) = \lambda_i = e^{\sum_{i=1}^{N} -X_i\beta_i} \quad (12)$$

Thus, the key note is that $\lambda i = e^{X_i\beta_i}$ in the PH format and $\lambda i = e^{-X_i\beta_i}$ in the AFT format (the change in signs).[5]

ii) Weibull Model

From the AFT specification such that:

$$\ln(T) = X\beta + \sigma u \quad (13)$$

The relationship between PH and AFT Weibull metric given as:

$$\beta_{AFT} = \frac{-\beta PH}{p} \quad \text{or} \quad \beta_{PH} = \frac{-\beta AFT}{\sigma} \quad (14)$$

Hence, the AFT Weibull metric is written as:

$$h(t, \lambda i, \gamma) = \gamma\lambda i t^{\gamma-1} \quad (15)$$

Where $\lambda i = e^{-Xi\beta i}$; and the effect of the covariates is to accelerate time by a factor of $\exp(-Xi\beta i)$

iii) Lognormal Regression Model

It assumes a non-monotonic hazard with an inverted U-shaped hazard function. Its hazard function is given as:

$$h(t) = \frac{\frac{1}{t\sigma\sqrt{2\pi}}exp\left[\frac{-1}{2\sigma^2}\{Ln(t)-\mu\}2\right]}{1-\Phi\left\{\frac{Ln(t)-\mu}{\sigma}\right\}} \quad (16)$$

Where Φ is the standard Normal cdf; $\mu = X\beta$ and σ is a shape parameter

iv) Log Logistic Regression Model

This model is appropriate for data with non-monotonic hazard rates and where the error term follows the Log-Logistic Distribution. It has an inverted U-shaped with the following hazard function:

$$h(t,X) = \frac{\lambda\frac{1}{\gamma}t\left[\left(\frac{1}{\gamma}\right)-1\right]}{\gamma\left[1+(\lambda t)^{\left(\frac{1}{\gamma}\right)}\right]} \tag{17}$$

Where$\lambda i = e^{-(Xi\beta i)}$; λ is the location parameter and γ is the shape parameter,

v) Generalized Gamma Regression Model

It has two shape parameters (ρ and κ) and possessing a highly flexible hazard function that allows for many possible shapes. The density of the generalized gamma distribution is:

$$f(t) = \frac{\lambda\rho(\lambda t)^{\rho k-1}e^{-(\lambda t)^{\rho}}}{\Gamma(\kappa)} \tag{18}$$

Where $\lambda i \ = e^{-(Xi\beta i)}$ and includes special cases/ shape parameters:
If κ = 1, then the Weibull distribution is implied
If κ = p = 1, the exponential is implied
If κ = 0, the log-normal is implied
p = 1, the gamma distribution is implied

An important issue in the duration analysis is the issue of duration dependence, thus "true" duration dependence or "state dependence" versus spurious" duration dependence. Following Lancaster (1979), the problem is addressed by introducing a multiplicative random effect in the PH specification shown in equation 3 above.

$$h(t, x_i, v) = h_0(t)e^{\sum_{i=1}^{N}\beta_i X_i}v \tag{19}$$

Where v is a real positive random variable with mean one and varianceθ, and θ is estimated from the data **(Cleves *et al.,* 2010; Lancaster, 1979)**. Therefore, given the different parametric model specification, the Akaike's Information Criterion (AIC) was conducted to pick the right distributional function ('right' shape for the time dependency). The choice of independent variables was guided mainly by our theoretical model and previous studies, economic theory and the characteristics of the practice under consideration.

RESULTS AND DISCUSSIONS

Descriptive Results

The study was conducted in the Tigrai region in the northern part of Ethiopia by randomly selecting 632 farm households. This study used a cross-sectional data from Tigrai Rural Household Survey dataset collected in 2018 run by MU. To control the systematic (if any) variation in agro-climatic conditions, agricultural potential, population density and market access conditions, four communities were selected from each of the four zones and three communities which are considered irrigation potentials. Furthermore, one with low population density and one with high population density were strategically selected from each zone among communities to reflect far distance market **(Hagos, 2003)**. The study was conducted in five zones covering 11 districts and 21 Tabias so as to yield 632 sample size. A cross-sectional data set for the year 2017/2018 was extracted from the survey since some variables used in this paper were only added in the last wave.

Table 1 Descriptive Statistics

VARIABLES	(1) Mean	(2) SD	Description	Prior
Family size	5.873	2.413	Family size in number	+
Age	56.83	15.20	Age of household head in years	?
Discount factor	0.498	0.404	Average individual monthly discount factor	?
Lasttime	4.793	3.277	Average survival /lasting time to adopt stall feeding	?
Risk Aversion	4.411	2.120	Number of safe choices from risk field experiment	?

Loss Aversion	4.622	2.132	Number of safe choices from loss field experiment	?
Log labor time	4.747	1.435	Adult labor allocated to cattle rearing in hours	?
Expected mean	1.160	0.696	First moment derived from milk production	?
Information	0.583	0.494	Information access via radio and mobile (1/0)	?
Location	0.936	0.244	highland =1 if altitude >2500masl	?
Farm size	1.391	1.225	Total cultivated land in hectare	?
Own cow	0.332	0.471	Ownership of milking local cow (1/0)	?
Log Input Exp	5.370	0.521	Log of modern animal input expenditure (ETB)	?
Gender	0.264	0.441	Sex of household head (Male=1)	?
Lndistmkt	5.062	1.677	Log of distance to market in minute	?
Log milk price	2.523	0.564	Village milk price in Ethiopian currency (ETB)	?
Education	0.481	0.500	Household head education (1= literate)	?
Improved	0.334	0.472	Household breed cow ownership (1/0)	?
ADP	0.556	0.497	Seasonal adoption of stall-feeding	?
FADP	0.363	0.481	Full year adoption of stall-feeding	?
Lasttime	4.793	3.277	Average lasting time to adopt stall feeding	?

Source: Own Survey, 2015

The estimation of SF adoption further reduced the sample size to 518 farmers, excluding those who did not own cattle during the study year. Duration analysis treats the length of time to adopt (or adoption spell) as the dependent variable unlike discrete choice models. The start of the duration spell was set either at the year the practice was first introduced in the village or the year the households in the village started farm adoption decision (the potential year of first adoption).

The sample consisted of 518 households: 187 (36.10%) adopted stall feeding in a full year scale; and 331 (63.9%) are those who are non-adopters until the survey period. However, farmers practicing SF at least in single season are 288 (55.6%), whereas those of non-adopters are 230 (44.4%) in the study area. The specific variables hypothesized to influence the speed of adoption are presented in Table 1 and their expected direction of influence are indicated respectively.

Based on the descriptive analysis, the average time to adopt was found to be 3.7 years. The average age of the sampled farmers was 56.8 years and had an average 5.87 family size at the time of the survey, which is common in rural Ethiopia. Likewise, an average individual monthly discount factor, AVIDR[6], is 0.5. This discount factor is low, but consistent with **Meier and Sprenger (2010)** and **Meier and Sprenger (2013)**, whose result reveals an average individual monthly discount factor of 0.84 in Boston using the same experimental design and **(Bauer *et al*., 2012)** in which the average individual monthly discount factor is 0.6 in India using the same design. An average discount factor of 0.5 was also reported by **Yesuf and Bluffstone (2008)** in Ethiopia.

We found average of 4.4 and 4.6 safe choices in risk/loss field experiment, suggesting that farmers in the sample in general are risk and loss averse. The average log labor time allocated to stall feeding is 4.7 hours per day implying this practice takes a large share of farmers' daily time. On the production risks, the average first moment (expected mean) is around 1.16. From the total 518 households, 302 farmers or close to 58% reported to have access to information via radio, TV or mobile, and of these 302, 80% had adopted it. The farmers in this region are having an average land holding of 1.4 hectares and close to 93% households live in the highlands, of which 67% are SF adopters. This is because the highland is attributed to low land holdings due to population pressure which forces farmers to invest in output-increasing or feed -saving practices in the study area.

On average, farmers who owned an improved breed cow and local milking cow are about 33% and 36% respectively with a mean of 1.8 local milking cows. The average log animal input expenditure (including salt, brewery, bi-product and veterinary services) of the farmers is 5.37 ETB (Ethiopian Currency) with an average log milk price value of 2.5 ETB per day. Of the farmers contacted, the proportion of male headed farmers is higher (74%) than female headed farmers which is 26%. Among the sample farmers, 51% have a literacy education, which on average constitutes half of the sample farmers. Similarly, the average log distance to the local market in the sample is found to be 5.06 walking minutes.

Semi-Parametric and Parametric Estimation Results

While estimating the probability of adoption, both fully parametric and semi-parametric duration models are estimated and the models are compared in terms of fit, magnitude, sign and significance of the estimated coefficients. A semi parametric proportional hazard regression, Cox- proportional model is estimated for the sampled farmers. In this model, the relationship between the probability of an event/failure occurrence and various covariates have been analyzed. In this case, no assumptions are necessary to be made about the shape of the baseline hazard rate **(Cleves *et al*., 2010)**. In order to check the robustness of the estimation and compare results across alternative estimates, three hazard parameterization models have been estimated. From the proportional hazard (PH) family models, exponential, Weibull and Gompertz were estimated but Weibull proportional hazard was favored based on the Log likelihood-ratio, AIC and BIC test statistics. Hence, the discussion and analysis is based on mainly the Weibull metric estimated results, which assumes a proportional relationship between the baseline hazard and the influence of respective covariates reported in Table 2. For the brevity, hazard ratios are reported for the Cox PH and PH models rather than coefficients.

A hazard ratio greater (less) than one denotes that the variable has a positive (negative) effect on the likelihood of the spell ending, that is on SF adoption. A unity hazard ratio implies no effect of the variable on adoption. The shape parameter, ρ is 4.79 for seasonal adoption indicating a positive duration dependence. That is, the probability of farmers' adoption increases with time.

AFT models are also alternatively estimated and presented in Table 3, so as to check the robustness of the effect of the specified covariates on SF adoption's waiting time. Thus, the effect of the covariates is to accelerate time by a factor of exp ($-X_i\beta_i$). Standard coefficients are reported for the AFT Weibull model. The parameter estimates for this model is reported in accelerated failure-time metric and represent the effect of an explanatory variable on the conditional probability of adoption at time period t.

A negative coefficient indicates a shorter pre-adoption spell (that is the relevant variable speeds up the adoption process) and increases the probability of adoption, while a positive coefficient reflects longer pre-adoption spell and lower probability of adoption. A positive (negative) coefficient would indicate a factor that would delay (accelerate) adoption; and vice versa. Table 3 presents estimated results of AFT Weibull selected from the five AFT models.

Table 2 Estimates of Proportional Hazard Models

	(Seasonal-SF)		**(Full-SF)**	
VARIABLES	**PH Weibull**	**CoxPH**	**PHWeibull**	**CoxPH**
Average discount factor	0.587***	0.632**	0.656*	0.662*
	(0.111)	(0.117)	(0.142)	(0.141)
Risk Aversion	0.870**	0.884**	0.897**	0.900**
	(0.0491)	(0.0495)	(0.042)	(0.042)
Loss Aversion	0.887**	0.897**	0.924*	0.925*
	(0.046)	(0.046)	(0.041)	(0.040)
Expected Mean	1.370**	1.354*	0.625***	0.663**
	(0.220)	(0.212)	(0.113)	(0.119)
Log Milk price	1.257*	1.194	1.422**	1.344**
	(0.167)	(0.160)	(0.203)	(0.194)
Log Input Expenditure	0.885*	0.880**	0.661***	0.680***
	(0.057)	(0.056)	(0.096)	(0.098)
Farm size	1.071*	1.062	1.081	1.051
	(0.038)	(0.040)	(0.066)	(0.068)
Log Labor Time	1.284***	1.201**	1.183**	1.170**
	(0.100)	(0.095)	(0.089)	(0.088)
Information	1.482***	1.410***	1.437**	1.371**
	(0.193)	(0.183)	(0.230)	(0.218)
own cow	1.536***	1.419**	1.939***	1.694***
	(0.229)	(0.212)	(0.346)	(0.301)
Age	0.998	0.997	1.001	1.002
	(0.004)	(0.004)	(0.006)	(0.005)
Family size	1.034	1.020	1.107***	1.089**
	(0.031)	(0.031)	(0.039)	(0.038)
Gender	0.563**	0.604**	0.609**	0.635**
	(0.142)	(0.153)	(0.139)	(0.144)
Education	1.509**	1.383*	1.415*	1.464*
	(0.290)	(0.263)	(0.281)	(0.292)
Improved	1.344**	1.392**	2.260***	1.837***
	(0.197)	(0.200)	(0.404)	(0.325)
Location	5.144***	3.269***	3.247***	2.155**
	(1.521)	(0.985)	(1.081)	(0.686)
Lndistmkt	0.862*	0.874*	1.445***	1.335***
	(0.066)	(0.065)	(0.126)	(0.113)
Lnp	2.632***		2.249***	
	(0.120)		(0.127)	
Constant	0.001***		0.001***	

	(0.001)		(0.001)	
LR chi2	0.000	0.000	0.000	0.000
AIC	399	2755	624	1948
BIC	480	2827	705	2020
Observations	518	518	518	518

NB: ***, **,*Implies that the estimated parameters are significantly different from zero at 1, 5, and 10% significance level respectively; Figures in parentheses are standard error

Tables 2-3 exhibits consistent results from both estimates. Results showed that, the hypothesized variables such as expected mean of milk, price of milk, farm size and family labor time, access to information, agro-ecology location, literacy rate, ownership of breed and milking local cows significantly and positively influenced SF adoption. However, variables such as log input (bi-product, salt, brewery and vaccination) expenditure, individual monthly discount factor, risk aversion, loss aversion and distance to service road, and female household headship delayed early SF adoption. Against our expectation, age of household head appears to have no influence on the adoption process of seasonal and full model estimates.

The standard economic theory stated that the tendency to adopt new practice is driven by the individual time preferences of the decision makers. It has been argued that a high level of impatience may prevent farmers from making long-term investments **(Duflo *et al*., 2011; Le Cotty *et al*., 2014; Tucker, 2006: Tanaka *et al*., 2010, Ashraf, 2009)**. Our result showed a negative association between SF's hazard rate and individual monthly discount factor; implying that impatient farmers have a lower probability of adoption than those patient counter partners. The AFT model, has also gave similar results, a farmer with a high discount factor increase time to adopt, other variables held constant, by 20% on average. This concurs our prior expectation and earlier findings **(Yesuf, 2004; Le Cotty *et al*., 2014; Duflo *et al*., 2011)**. Inline to this, **Duflo *et al.* (2011)** stated that present-biased or impatient farmers postpone fertilizer adoption in Western Kenya while **Le Cotty *et al.* (2014)** confirmed that impatience decreases grain storage adoption in Burkina Faso. Another related work is of **Yesuf (2004)** whose result indicated that higher discount rate was correlated with low adoption of soil conservation technology in Ethiopia. This is also similar to the behavior of Malagasy farmers; whose loss aversion significantly reduces their rice intensification **(Takahashi, 2013)**.

In many developing countries, rural farm is considered as a risky activity given its dependence on environmental factors that are beyond farmer's control. Farmers will, given their level of risk preference, select the technology that offers the maximum expected utility **(Foster and Rosenzweig, 2010; Barham *et al*., 2014)**. Risk aversion describes observed behavior that demonstrates a fear of variance in outcomes **(Tanaka *et al*., 2010; Brick and Visser, 2015; Di Falco, 2014)**. Farmers perceive any new agricultural technology as an uncertain proposition, which allows individual subjective risk preferences to play a major role in technology adoption **(Holden, 2015)**. In connection to this, **Liu and Huang (2013)** and **Ward and Singh (2015)** are the only pioneer studies that inclusively examine the role of expected utility theory (EUT) and prospect theory (PT) for adoption of BT cotton seeds in China. The finding of **Liu and Huang (2013)** indicated that more risk averse and loss averse farmers adopt the BT cotton seed later, while **Ward and Singh (2015)** found that risk averse and loss averse farmers are more likely to switch to new rice seeds in India. At the same time, **Liebenehm and Waibel (2018)** proved that a loss averse and impatient farmer is less likely to adopt prophylactic drugs in West Africa.

Earlier findings indicate that risk preference affects farmers' willingness to try new practices **(Greiner *et al*., 2009)**. It affects the adoption of new technologies in many ways and has been found to reduce the adoption of new technologies/practices **(Ghadim *et al*., 2005)**. It has been documented that risk averse farmers are expected to adopt practices more slowly than risk-loving farmers to avoid the cost of uncertainty and the cost of learning a new technology **(Sassenrath *et al*., 2008)**. Our result revealed a negative association between SF's hazard rate and risk aversion; implying a farmer with a high-risk aversion, found to have a lower probability of SF adoption than those with risk-loving. The AFT model, has also provided similar results, a farmer with a high-risk aversion, on average, increases time to adopt SF, other variables held constant, by 5.3%. This is consistent with the finding of **(Liu and Huang, 2013; Sassenrath *et al*., 2008; Ghadim *et al*., 2005)**. However, **Ray *et al.* (2018)** found that risk averse farmers and farmers who overvalue smaller probabilities adopt his technology sooner than others.

Another variable which was considered to affect SF's adoption is loss aversion **(Liu and Huang, 2013; Ray *et al*., 2018; Kijima, 2019)**. It is found that loss-averse household adopt SF latter. Higher loss aversion, holding other variables constant, reduces the estimated hazard of SF's adoption to 88.7% of its starting value. The results from the AFT model, revealed that loss aversion, on average, decreased the time to adopt for a SF, other variables held constant, by 4.5%. This is in contrast with most of the literature which finds that loss aversion delays the adoption of new technologies **(Liu and Huang, 2013, 2013; Ray *et al*., 2018; Kijima, 2019).**

Farmers are expected to be motivated to adopt new technology whenever it promises them higher return i.e. the first moment-predicted mean is positively related to adoption **(Kassie *et al*., 2009; Juma *et al*., 2009; Ogada *et al*., 2014)**. The expected milk yield (first moment) had a positive significant effect on the adoption decision, indicating that the higher the expected return, the greater the probability of adopting SF. From the AFT model (Table 3), higher expected mean, on average decreases farmers' time to adopt, other variables held constant, by 12% in the case of seasonal and 21% in the case of Full

year respectively. Economic factors relating to output and input prices are important factors to influence the adoption process **(Martínez-García *et al.*, 2016; Ghadim *et al.*, 2005)**. One possible reason for the relatively slow adoption of the new practice has been probably due to the relative advantage it offers **(Ghadim *et al.*, 2005)**.
Adoption of SF by smallholders is mainly driven by the objective of increased milk production, for both home consumption and sale **(Klitzing *et al.*, 2014; Lenaerts, 2013; De Cao *et al.*, 2013; Hadush, 2018)**. Inline to our expectation, higher milk price induces faster SF adoption. A one unit increase in milk price, holding other variables constant, induced the estimated hazard of SF graduation to 25.7% of its starting value. An addition of similar result was also portrayed by AFT model, where farmers of higher milk adopt SF faster (8.5%) than farmers with less milk output. This agrees with the finding of **Hadush (2018)** and **Dadi *et al.* (2004)** in which milk price was positive and significant factor SF adoption. This result suggests that economic incentives are more important influences on the speed of adoption than any environmental, institutional or personal factors.

Table 3 AFT Models' Estimation

VARIABLES	**(Seasonal) AFT- Weibull**	**(Full) AFT- Weibull**
Average discount factor	0.202***	0.187**
	(0.072)	(0.096)
Risk Aversion	0.0531**	0.048**
	(0.021)	(0.021)
Loss Aversion	0.045**	0.035**
	(0.019)	(0.019)
Expected Mean	-0.120*	0.209***
	(0.061)	(0.079)
Log Milk price	-0.087*	-0.156**
	(0.050)	(0.063)
Log Input Expenditure	0.047*	0.184***
	(0.025)	(0.065)
Farm size	-0.026*	-0.035
	(0.013)	(0.027)
Labor Time	-0.095***	-0.0749**
	(0.029)	(0.034)
Information	-0.150***	-0.161**
	(0.049)	(0.072)
Owncow	-0.163***	-0.295***
	(0.056)	(0.078)
Age	0.001	-0.001
	(0.002)	(0.002)
Family size	-0.013	-0.045***
	(0.011)	(0.015)
Gender	0.218**	0.221**
	(0.096)	(0.102)
Education	-0.156**	-0.154*
	(0.073)	(0.089)
Improved	-0.112**	-0.363***
	(0.056)	(0.077)
Location	-0.622***	-0.524***
	(0.108)	(0.145)
Lndistmkt	0.056*	-0.164***
	(0.029)	(0.038)
ln_p	0.968***	0.810***
	(0.045)	(0.057)
Constant	3.140***	3.316***
	(0.311)	(0.482)
LR chi2	0.000	0.000
AIC	399	624
BIC	480	705
Observations	518	518

NB: ***, **,*Implies that the estimated parameters are significantly different from zero at 1, 5, and 10% significance level respectively; Figures in parentheses are standard error

However, a higher input cost delayed SF adoption. Our result from Table 2 revealed a negative association between SF' hazard rate and input expenditure; implying that farmers with a high input cost, found to have a lower probability of SF adoption than those with low input cost farmers. The AFT model, has also shown similar results, increasing input expenditure increases time to adopt seasonal and full SF, other variables held constant, by 4.7% and 18.4% respectively. This result finds a favor from the findings of **Hadush *et al.* (2019)** and **Martínez-García *et al.* (2016)**, whose result indicate higher expenditure on salt, brewery and veterinary services discourages SF adoption.

Land owned and labor supply are posited to decrease time to adoption **(Newbery and Stiglitz, 1981)**. It is hypothesized that large farm size increases the probability of the adoption of new practices. This makes adoption more feasible since larger farm size is associated with greater wealth, high availability of capital, and high-risk bearing ability to invest in new technology **(Norris and Batie, 1987)**. There is strong evidence, in Table 2, that farmers with more land size labor availability take shorter to adopt seasonal and full SF. The estimated coefficients for land size and labor time in Table 3 suggest that increasing land size and availability of labor decreases the time to adopt SF by 2.6% and 9.5% respectively. As it is expected, farmers with larger farms adopt earlier, and this was borne out by the analysis. This corroborates recent finding of **Murage *et al.* (2011)** where farm size increased the speed of adoption of weed control in Kenya.

As we hypothesized, variables associated with access to information and milking cow ownership, lead to shorter time to SF adoption. Considering the magnitude and significance of the coefficients in both models, information and breed cow had similar influence on adoption of full and seasonal SF. If the farmer had any access to information and milking cows, his/her probability of SF adoption increased its hazard rate by 1.48 and 1.54 times higher. Consistent with this result, the AFT model revealed that a farmer with access to information and milking cow adopted SF 15% and 16% earlier than a farmer without information and cows. This result mirrors results for static adoption analysis of SF in East Africa **(Turinawe *et al.*, 2011; Hadush, 2018** and **Gunte, 2015)** who stated that adopters of improved forages had higher access to a mobile telephone and milking cows. The less important influence on the SF adoption process appear to be age of household head and family size, except that family size shortens the time to full SF adoption by 4.5%.

Contrary to the previous findings of **(Gunte, 2015; Hadush, 2018)** female household head shortens the time to SF adoption. Female head farmers adopted earlier, on average, than male head farmers. This is a fascinating result as it corroborates the past debates in the context **(Kaliba *et al*., 1997)** that female-headed households usually tend to be poor, and thus prefer to have few breed cows under stall feeding practice in Kenya. Of the remaining variables, farmer's literacy and breed cow ownership, appear to be the most important influences on the speed of adoption; their coefficients all have the expected signs and are significant. The hazard increases by 46-51% (SSF and SFSF) if a farmer is literate compared to not having any, *ceteris paribus.* From the AFT model, the farmer's time to adopt SF decreases by almost 15 percent compared to a farmer not having any literacy, which is similar to that in PH models. Consistent with this study, previous studies provide evidence that education is indeed important in the choice and adoption of different practices **(Abdulai and Huffman, 2005; Hadush, 2018)**.

A hazard ratio of 1.34 and1.84 (SSF and FSF) of improved cow ownership indicates that a Farmer with breed cow is 34 and 84 percent more likely to adopt SSF and FSS at time *t* than a farmer without breed cow. Based on the AFT model, a farmer with breed cow adopted SSF and FSF 11% and 36% earlier than a farmer without breed cow. This result was expected and in line with the findings of **Hadush (2018)** who found a positive relationship between a number of breed cattle and adoption of SF. Interestingly, a greater elevation of the farm household has the effect of shortening the time to SSF and FSF adoption. If a farmer is located in the highland, the farmer showed a 5.144- and 2.155-times higher hazard rate than a farmer located in the lowland. Likewise, the AFT models indicated that highland location decreases the log of time to failure (time to adopt) by 0.622 for SSF and 0.524 for FSF. That is, location in a highland decreases the waiting time to adopt SSF and FSF by 62% and 52% respectively. This finding is consistent with **Hadush (2018)** and **Hadush *et al.* (2019)** on the adoption of SF in Ethiopia

The evidence regarding the importance of the distance variable in the adoption decision is reasonably strong. A one walking minute increase in distance from the local market, *ceteris paribus*, reduces the estimated hazard of SSF adoption to 86% of its starting value. The farther the farmer lives from a local market; the more time it takes to adopt SSF. Considering the magnitude and significance of the AFT coefficient, a farmer living a mile farther from the local market increases her time to adopt, other variables held constant, by 9 percent on average which is consistent with our expectation and findings in the literature **Dadi *et al.* (2004) and Hadush (2018)** who showed that distance to market significantly retarded the adoption of fertilizer and SF in rural Ethiopia.

CONCLUSION AND POLICY IMPLICATIONS

A number of studies have dealt on identifying the determinants of adoption of new technologies. However, those studies use probit models to explain why a farmer adopted but fail to capture the farmer's time to adoption using a proper model such as duration model. Moreover, many scholars believe that time preference explain individual decision-making behavior as it captures the patience of individuals, in addition to risk aversion. Despite there is an increasing interest in the role of time and risk preferences in explaining technology adoption, empirical adoption studies that investigate this behavior are scant. In this paper, we develop a simple theoretical technology adoption model that incorporates time and risk preferences to test that impatience and risk aversion delays stall-feeding adoption whereas individuals with low discount factor and risk aversion are likely to adopt stall-feeding sooner.

Using survey data from Ethiopia, Cox PH, Weibull PH, and Weibull AFT models have been estimated. Both parametric and semi-parametric models are applied to estimate the conditional probability of SF adoption, in which the full parametric models include the Weibull PH model and the Weibull AFT model, and the Cox PH model is the semi-parametric model. This enables us to convey information not only on why a farmer adopted, but also on the timing of the adoption decision, using cross sectional data of 518 sample farmers in Ethiopia, which cannot be portrayed by discrete probit models. In this paper, we try improve our understanding of the process of technology adoption over time and enhance our ability to predict the effect of time-varying variables on adoption using duration analysis.

The main conclusion of this study is that it is not only the economic or individual characteristics of the farmer that are important influences in the timing of the adoption decision but factors related to information, location, discount factor, attitudes toward risk and loss. The main findings have shown that indeed the time of stall-feeding adoption increases with increasing discount rate. This is to imply that impatience lengthens the time to adopt stall-feeding whereas patient individuals are likely to adopt stall-feeding sooner. Likewise, farmers who are more risk averse a loss averse adopt this technology latter compared to farmers who are risk neutral/loving and loss-loving. This is one of the first adoption studies to have incorporated time and risk preference in its parametric and semi-parametric adoption analysis.

The estimated models suggest that economic incentives (i.e. prices) are the most important determinants of the time farmers wait before adopting new technologies. While higher milk price significantly induces faster SF adoption, higher input price increases the time to adoption period. The expected milk yield (first moment) had a positive significant effect on the adoption decision, indicating that higher expected mean, on average decreases farmers' time to adopt. Findings in this study suggest that land and labor endowment shorten the time to adopt SF However, market distance and male headship were found to delay the adoption of SF in the study area. In addition, the findings in this study suggest that risk age is not a significant factor. Access to information, education of household head, breed and local cow ownership, and location of the farmer, accelerated the likelihood of early SF adoption. As a result, it can be argued that the decreased time to adoption due to living in highland is related to population pressure and resource scarcity.

The main limitation of this paper is that the measure of time and risk preferences is based on hypothetical experimental design. In this case, it is possible that individuals may tend to be risk–lover than they are in the case of incentivized experimental design. This affects individual decision making in the case of technology adoption. The second point worth that this paper used a cross-section data which does not capture the dynamic nature of the state of adoption. Thus, the authors call for a further study with an incentivized experimental design and panel data in the study area.

Endnotes:

[1]Tanaka, Camerer, and Nguyen (2010) (hereafter TCN) developed a method to measure PT parameters: risk aversion, loss aversion, and nonlinear probability weighting by presenting Vietnamese respondents with 35 pairwise lottery choices, seven of which contain gains as well as losses, and use farmers' choices in these pairs to estimate the three PT parameters. TCN incorporates PT but does not reject EU outright particularly, prospect theory converges to the standard expected utility model when α=1and λ=1. This approach is applicable to our study since its design is simple to less educated respondents.

[2]Assuming that there is a one-to-one correspondence between number of milking cows treated under stall $-$ feeding and the amount of improved inputs used, then k can also be interpreted as the per cow cost under stall-feeding practice.

[3] Mekelle University. This dataset has been initially used by Holden et al. (2011) and Hagos (2003) for their PhD study

[4] ETB refers to Ethiopian currency where 1USD≈24 ETB during the study year, 2015

[5] The change in sign makes sense because the PH format uses covariates to model the hazard rate whereas the AFT format uses covariates to model the survival times. The AFT metric gives a more prominent role to analysis time.

[6] For a similar approach (see Ashraf et al. 2006; Meier & Sprenger 2010; Bauer et al. 2012; Meier & Sprenger 2013), and see the appendix for the full explanation of the field experiment.

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Appendix A. Choice Experiment for Time Preference

Individual discount factor (δ) is measured by taking the point in a given price list, X^{*} at which individuals switch from opting for the smaller (earlier payment) to opting for the larger (later payment) using a hypothetical questions[1]. That is, a discount factor is taken from the last point at which an individual prefers the earlier smaller payment, assuming that $X^{*} \approx \delta^{d}$ ×Y, where d represents the delay length. As the delay length, d, is always one month for both time frames, $\delta \approx (X/Y)^{\frac{1}{d}}$ .Since this procedure produce two discount measures,$\delta_{0,1}$ and $\delta_{6,7}$, the average monthly discount factors is used as the discount factor in the main analysis. The author classify an individual as present-biased if $\delta_{0,1}<\delta_{6,7}$, and as future-biased if $\delta_{0,1}>\delta_{6,7}$ to use in the analysis.

Instruction: Please indicate for each of the following 12 decisions, whether you would prefer the smaller payment in the near future (A) or the bigger payment later (B). Switching from option A to option B is possible at any point.

S/N	**Option A: Today (t_0 = 0)**	**Decision: A or B**	**Option B: 1 Month (t_1 = 1)**
1	ETB 75 guaranteed today		ETB 80 guaranteed in a month
2	ETB 70 guaranteed today		ETB 80 guaranteed in a month
3	ETB 65 guaranteed today		ETB 80 guaranteed in a month
4	ETB 60 guaranteed today		ETB 80 guaranteed in a month
5	ETB 50 guaranteed today		ETB 80 guaranteed in a month
6	ETB 40 guaranteed today		ETB 80 guaranteed in a month
	Option A: six month (t_0 =6)		**Option B: 7 Month (t_1 = 7)**
7	ETB 75 guaranteed in 6 month		ETB 80 guaranteed in 7 month
8	ETB 70 guaranteed in 6 month		ETB 80 guaranteed in 7 month
9	ETB 65 guaranteed in 6 month		ETB 80 guaranteed in 7 month
10	ETB 60 guaranteed in 6 month		ETB 80 guaranteed in 7 month
11	ETB 50 guaranteed in 6 month		ETB 80 guaranteed in 7 month
12	ETB 40 guaranteed in 6 month		ETB 80 guaranteed in 7 month

Appendix B. Hypothetical Risk

A simple hypothetical risk elicitation instrument was presented to the respondents[2] to measure risk aversion by counting the number of safe choices made by the individual in a five and seven list choices respectively. A choice of zero safe option, out of seven choices indicates risk preferring individual and a risk neutral individual would make either one or two safe choices, out of the seven choices, and more than two safe choices indicate risk aversion.

Instruction: choose either option A, which gives you a certain 60 ETB or option B with 50% chance of getting 0 and 50% chance of getting the specified ETB amount. You can switch from option A to option B at any point you want to switch.

Risk				
Option A		A or B	Option B	
1	100 % of 60 ETB		50 % 0 and 50% 110 ETB	
2	100 % of 60 ETB		50 % 0 and 50% 120	
3	100 % of 60 ETB		50 % 0 and 50% 130	
4	100 % of 60 ETB		50 % 0 and 50% 140	
5	100 % of 60 ETB		50 % 0 and 50% 160	
6	100 % of 60 ETB		50 % 0 and 50% 180	
7	100 % of 60 ETB		50 % 0 and 50% 200	

[1] See for more details (Ashraf et al. 2006; Bauer et al. 2012)

[2] See for similar approach (Noussair et al. 2012; Drouvelis et al. 2012; Meier and Sprenger 2013)