Duration Analysis of Technology Adoption in Bangladeshi Agriculture

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1 Introduction

There is a large body of literature on identifying the determinants of the adoption of new technologies. This literature has focused on technical, organizational, and environmental factors. Most of these studies used cross-sectional data to estimate probit-like models for static analysis of technology choices (Feder *et al*., 1985; Knudson, 1991; Jansen, 1992; Shields *et al*., 1993; Polson and Spencer, 1991; Akinola, 1987; Weir and Knight, 2000 among others). However, technology adoption is a dynamic process, where time plays an important role and the explanatory variables may change during the observation period (Lapple, 2010). Traditional methods employed in a static analysis of technology adoption have limitations in that inference about the stochastic adoption process. The current study uses duration models, which model the length of time to adoption, to investigate the factors that prompt Bangladeshi farmers to adopt integrated pest management (IPM) and to assess the relative importance of these factors in the adoption decision.

The length of time, or “duration”, a farmer waits before adopting a new technology is expected to depend on several variables. Some of these variables vary with time (age of the farmer, input prices, output prices) and some are constant (gender of the farmer, geographical location, education level). This paper investigates the potential determinants of adoption by incorporating a wide range of variables in duration analysis. The paper explains the time a farmer takes to adopt pheromone traps, one of the IPM practices in sweet gourd farming in Bangladesh. The study estimates the probability that a farmer with a given set of characteristics adopts pheromone traps in a particular year, provided adoption has not yet occurred. 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, and sign and significance of the estimated coefficients. This study finds that even though the non-parametric estimate of the hazard function indicated a non-monotonic model such as log-normal or log-logistic, estimating a monotonic model did not perform worse. More importantly, no differences in the sign and significance of the estimated coefficients in different models are found. A second and perhaps more informative finding is that it was not the economic or the personal characteristics of the farmer that influenced the adoption decision, but the factors related to information diffusion such as membership in an association, training, distance of the farmer's house from local and town markets, and farmer's perception about the use of IPM. Neither the farmer's personal characteristics nor any of the economic variables were found to have a significant influence on the technology adoption decision.

A farmer with a source of income other than farm and who is a member of an association/groups in the village is more likely to adopt early. The distance to a center point such as a local market and town market increases the time to adoption. Distance variables may be (positively) related to cost issues (such as transportation costs), but they also affect (negatively) the ability to gain information about a new innovation. Because IPM practices are not capital-intensive compared to traditional pest management practices, increased transportation costs due to distance from a center point is not expected to greatly influence IPM use negatively. The increased time to adoption due to living farther from a center point is more closely related to obtaining information about the innovation than higher transportation costs.

Extension organizations (such as DAE, IPM club, or NGOs) train farmers about new farming techniques. A farmer's participation in training on vegetable farming decreases the time to adoption. Information gained from training sessions can create a positive impression about the new innovations. When farmers perceive that IPM is good for crops, due to the manner with which little or no pesticides are used, increases the likelihood of adoption. Farmers who believe IPM is good for crops adopt earlier than farmers who believe otherwise. Since the farmers' beliefs about the health benefits of IPM use has not been found to be statistically significant, it cannot be argued that it is the farmers' positive beliefs about IPM that affects its adoption. Farmers may believe that less pesticide use in farming will lead to better sales of the crops and more profit which in turn motivates the farmer to adopt. However, investigating this indirect economic factor is beyond the scope of this study. Regardless of the reason, providing information by educating farmers about IPM may be an effective way to increase its adoption.

2 Determinants of adoption of agricultural technologies

Theoretical models on technology adoption center around a range of issues from learning and information acquisition to prior beliefs regarding profitability of the innovation (Lindner *et al*., 1979; Lindner, 1980; Feder and O'Mara, 1982; Jensen, 1982, 1983; Feder and Slade, 1984; Bhattacharya *et al*., 1986; and Fischer *et al*., 1996 among others). Empirical works focus mainly on farmer characteristics such as human capital assets, risk aversion, economic potential and risk associated with alternative technologies, and farm assets that link to factor costs (Feder *et al*., 1985). However, an agent's motives for economic behavior may also relate to factors such as political, religious, and personal attitudes (Colman, 1994, Bultena and Hoiberg, 1983; Beus and Dunlap, 1994; Comer *et al*., 1999). Common motivational factors include producers' concerns about their family's health, concerns about husbandry (e.g., soil degradation, animal welfare), lifestyle choice (ideological, philosophical, religious), perceptions about the usefulness of the technology to their objectives (Pannell *et al*., 2006), and financial considerations (Padel and Lampkin, 1994; Padel, 1994). Non-economic variables can be important for technologies such as

IPM, much as they are for organic farming technologies Rigby *et al*., (2001). Large differences in demographic characteristics, economic situations, and attitudes have been found between organic and non-organic producers. Information, particularly in terms of awareness and evaluation of alternative technologies and of sources of information, are regarded as important to an adoption process (Alcon *et al*., 2011; Burton *et al*., 2003; Nowak, 1987). Membership in a relevant association can be an important factor in adoption as it provides services that contribute to the farmer's business and education about the technology (Sidibe, 2005). Farmer's education appears to have a positive effect on the adoption decision (Foltz, 2003; Yaron, 1990), while age does not show a consistent pattern (Rogers, 2003). If households are not unitary, as Razzaque and Ahsanuzzaman (2009) find for Bangladesh, the farmer's spouse also influences technology adoption. Spousal education is expected to have a positive effect on adoption in most instances. Farm level characteristics such as ownership and farm size have been shown to be important in the adoption decision (Feder *et al*., 1985; Feder, 1980).

3 Conceptual framework and econometric methodology

The concept of duration analysis in agricultural technology adoption is adapted from labor economics (Jenkins, 2005). It is assumed that a farmer has two states: (1) adoption, and (2) non-adoption. To adopt the new technology requires that the farmer has the technology available, and is able to earn a profit (V_1) from the adoption that is more than the profit (V_0) from non-adoption. For a given farmer, the non-adoption exit (to adoption) hazard rate $\varphi(t)$ can be written as the product of the exposure to adoption (availability of innovation) hazard $\xi(t)$ and technology adoption hazard $A(t)$:

$$\varphi(t) = \xi(t)\, A(t). \quad (1)$$

In making the technology adoption choice, the non-adopter makes the decision based on the distribution of profit from adoption V_1. The optimal decision is to adopt if V_1 is greater than the profit from the existing technology V_0, $V_1>V_0$. Therefore,

$$\varphi(\mathrm{t}) = \xi(\mathrm{t})[1 - V(t)] \qquad (2)$$

where $V(t)$ is the cumulative distribution function (cdf) of the profit distribution from adoption. How the hazard of adoption varies with duration depends on: (1) the profit with the duration of non-adoption, and (2) how the hazard of information about the new technology varies with duration. With the negligible influence via ξ, the structural model provides strong restrictions on the hazard rate, but the hazard rate in reduced form can be written as

$$\varphi(\mathrm{t}) = \varphi\ (X(t,s),\ t), \qquad (3)$$

where X is a vector of personal characteristics that may vary with non-adoption duration (t) or with time (s). Some of the factors in X increase hazard duration; others reduce it. Thus, a particular shape should not be pre-imposed on the hazard function.

This paper investigates factors influencing the "time to adoption" (waiting time of the household before adoption). A more precise specification of the model is: $t_a = f$(age of HHH, education of HHH, education of HHH spouse, number of HH dependents, HH has off-farm income source (dummy), farmsize, land ownership, livestock, distance to center of local market and town market, HHH membership in an association (dummy), farmer perceptions about: IPM use is good for the crop quality (dummy), IPM use is good for health (dummy)).

Time to adoption, $t_{a,}$ is defined as the years the household took from initial exposure to the pheromone trap technology to the time when the household started using it. Hazard ratios are estimated using a Weibull distribution, and a log-logistic distribution is assumed for estimating the accelerated failure time (AFT).

The most popular specification of duration models is the proportional hazard (PH) model, which is suitable in cases of exponential, Weibull, and Gompertz distributions (Lapple, 2010; Addison and Portugal, 1998; Jenkins, 2005 among others). In the PH specification, covariates are related multiplicatively with the baseline hazard[1] and the hazards are independent of time:

$$h(t|X,\beta) = h_0(t)\ \varphi(X,\beta) \qquad (4)$$

where $h_0(t)$ is the baseline hazard and depends only on time, t, $\varphi(X,\beta)$ is the hazard that depends on covariates determined by economic theory, and β is the vector of parameters to be estimated. Equation (4) can be estimated using two approaches: semi-parametric and fully parametric. The Cox PH specification estimates (4) without any parametric specification of the baseline hazard, $h_0(t)$, while the alternative PH model specifies the baseline hazard function. The specification of the scale parameter, $\lambda=\exp(X\,\beta)= \varphi(X,\beta)$ is widely used to estimate the Exponential, Weibull, and Gompertz models as no assumptions/restrictions are made on β' to get a positive hazard (Kalbfleisch and Prentice, 2002). An alternative approach to specifying the duration model is to estimate the accelerate failure time (AFT). For AFT type, Exponential, Weibull, log-normal, log-logistic, and Gamma models are considered. While PH type assumes a non-linear relationship between the (latent) survival time T and individual farmer's characteristics X, the AFT type assumes a (log-) linear relationship:

$$\ln(T) = \beta^{*}X + z \qquad (5)$$

where z= $\sigma\varepsilon$ and σ is rescaled from the shape parameter of the Weibull distribution with $\sigma=1/p$, and ε has a specific distribution from the above mentioned distribution family. Under the AFT model, the direct effects of the explanatory variables on the survival time, as opposed to the effects on the relative hazard, are measured. The effect of the covariates is to accelerate/decelerate time by a factor of exp($-\beta^*X$). The parameters relate proportionate change in survival time to a unit change in a given regressor. The vector of covariates, X, is constant in the simplest case, but in more complicated cases, it may vary over time. In more complex cases, time is split following the change in the variables. Within each of these time intervals, however, the variables are assumed to remain constant (Lapple, 2010).

Estimation of the parametric models in duration analysis follows the maximum likelihood procedure, although the estimation is complicated because of right censoring. Let c_i be a censoring indicator where c_i equals 0 if censored (spell not ended or not adopted at the time of the survey) and 1 if otherwise. Assuming we have independently distributed data over individuals i, the log-likelihood function is

$$\ln L\ (\theta) = \sum_{i=1}^{n} c_i \ln f(t_i|\theta) + \sum_{i=1}^{n} (1 - c_i) \ln S(t_i|\theta) \qquad (6)$$

where θ is the parameter to be estimated (Greene, 2008). The first part in the likelihood function, $f(t_i)$, provides the likelihood of the of the completed spells for farmers $i = 1,2,\ldots,n$. The calculated survivor function in the second part, $S(t_i)$, at the censored time t_i and with appropriate covariates provides the likelihoods for censored farmer i.

4 The data

Survey data were collected from of 318 randomly selected farmers in four districts of Bangladesh - Jessore and Magura in the south-west, Comilla in the east, and Bogra in the north- and from 2-3 upazilas (local government unit) in each district.[2] Farmers were asked a range of questions about their demographics, individual farm characteristics, costs of production, where they obtain technical information (department of agricultural extension (DAE), family, friends, NGOs etc.), and perceptions are about IPM use. Table 1 provides summary statistics of the variables.

Table 1: Summary statistics of the variables in the paper.

Variable	Mean	Std. Dev.	Min	Max
Age	42.025	12.559	18	80
Off farm income (1=Yes; 0 otherwise)	0.273	0.446	0	1
HH head's education (years)	6.025	4.010	0	16
Spouse's education (years)	4.983	3.694	0	15
Labor Constraint (Dependent/Working person)	3.612	1.646	1	11
Rental status (1=Renter; 0 otherwise)	0.335	0.473	0	1
Association membership (1=yes; 0 otherwise)	0.459	0.499	0	1
Executive member (1=yes; 0 otherwise)	0.103	0.305	0	1
Total farm size (Acres)	1.571	1.938	0.005	12.240
Awareness index (0-40)	8.343	5.958	0	32.000
Value of Cattle (Taka)	48697	48374	0	368500
Total household accessories (Taka)	227839	594907	2000	7200000
Pest pressure index (0-1)	0.125	0.094	0	0.458
Membership in an MFO (1=Yes; 0 otherwise)	0.285	0.452	0	1
Distance from local market (km)	1.211	0.976	0.100	5
Distance from town market (km)	7.176	5.455	0.100	22
Farmer had training on vegetable farming (1=Yes; 0 otherwise)	0.368	0.483	0	1
Whether farmer believes IPM use improves crops by not touching pesticides (1=Yes; 0=otherwise)	0.438	0.497	0	1
Whether farmer believes IPM use is healthy way of farming (1=Yes; 0=otherwise)	0.43	0.496	0	1
Jessore dummy	0.22	0.414	0	1

[2] In the survey, the household heads have not been targeted, instead those have been targeted who make the decisions about agriculture in the household. But it turns out that most of them are household heads. This may provide another insight that household decision making over adoption follows a unitary model (Bandiera and Rasul, 2006). It should not be, however, taken for granted as households are unitary without a formal investigation as Razzaque and Ahsanuzzaman (2009) find that rural households in Bangladesh are not unitary.

Magura dummy	0.22	0.414	0	1
Comilla dummy	0.29	0.454	0	1
Bogra dummy	0.272	0.446	0	1
N	242			

5 Results

Table 2 gives estimation results from the preferred models for IPM adoption. Likelihood ratio tests for preferred models are significant at the 1% level, indicating that the explanatory variables taken together jointly influence the conditional probability of adopting IPM. The shape parameter, p is 6.11 which indicates positive duration dependence. That is, the probability of IPM adoption increases with time. Estimates of the median time of adoption are 6.56 years, and 3.56 years after all individuals are under observation. Table 2 exhibits consistent results from various models. In particular, labor (number of dependents per working person) in the household, land ownership status, being an executive member in any of the associations in the village, farm size, total value of household accessories, and the membership in the microfinance organizations do not appear to influence the adoption decisions, as they are not present in any model or, if present, not significant. Non-influence of both farm size and land ownership status may be due to most IPM adopters being small farmers along with the fact that average farm size is small in Bangladesh. As a result, both value of household accessories, farm size, and land ownership status are not important.

There are some variables that are consistently statistically significant in all models: spouse's education, membership in a village association, distance variables, farmer's training on vegetable farming, and farmer's perception about IPM use. Hazard ratios are reported for the PH models and the standard coefficients are reported for the AFT approach. A hazard ratio greater (less) than one denotes that the variable has a positive (negative) impact on the likelihood of the spell ending, that is on adoption. A unity hazard ratio implies no impact of the variable on adoption. A positive (negative) coefficient in the AFT implies anacceleration (deceleration) in the time to end adoption.

A farmer's education appears not to influence adoption, but a spouse's education has a surprisingly negative effect. Figure 1 provides plots of the estimated hazard function over time for different values of significant variables in the Weibull model. A static regression might suggest that the higher the spouse's education, the lower the likelihood of adoption at any time. However, the plot of estimated hazard due to different levels of spouse's education suggests that though its impact is negative, it is smaller as the level of education increases. The effect of spouse's education on hazard (risk) of failure (adoption) is prominent until the 8th grade, after which the hazard becomes less over time. Fortunately, the signs of all significant variables are as expected except spouse's education.

None of the personal or economic characteristics of the farmer appear to significantly affect the probability of ending the period of non-adoption. Significant variables are those that relate to information diffusion. Being a member in a village association increases the hazard compared to non-members. A hazard ratio of 1.64 of association membership indicates that a member farmer is 64 percent more likely to adopt IPM at time *t* than a non-member. The plot of the estimated hazard for membership status in Figure 1 indicates that the gap widens as the exposure to IPM time increases. This implies the effect of membership differs over time. As the exposure time passes, the association member farmer becomes more likely to adopt. From the AFT model, a member farmer adopted 11% earlier than a non-member farmer. An index of access to extension services (awareness) increases adoption as expected. A farmer who has more access to extension services, such as an extension agent's visit more frequently or participates in farmers' field days, than other farmers is more likely to adopt IPM. A one point increase in the index of extension services provision increases the hazard rate by 4 percent. Hence, the more and better the extension service is, the shorter time it takes for the farmer to adopt IPM. The plot of the estimated hazard in Figure 1 shows that the effect becomes greater after the extension index exceeds 10, which is to get at least 3 services most frequently. It requires further analysis to identify which of the extension services is most effective in increasing speed of adoption.

The literature on agricultural technology adoption often recognizes the distance of the farmer's house from certain important places, such as local market or a bigger town market, as important factors affecting adoption (Dadi *et al*., 2004). In particular, studies that evaluate impacts of specific technologies include those distance variables as instruments in the two stage least squares approach to remedy endogeneity issues. It is expected that distance has a negative impact on the decision to adopt. Following the literature, two distance variables are included: distance to local market, and distance to a bigger town market. The evidence regarding the importance of the distance variables in the adoption decision is reasonably strong, with the relevant coefficients being negative (hazard <1) and statistically significant at the 1% level in all three models, which is consistent with expectations and findings in the literature (Dadi *et al*., 2004). A one kilometer increase in distance from the local market, holding other variables constant, reduces the estimated hazard of IPM adoption to 56% of its starting value, and to 94% for the distance from a bigger town market. The farther the farmer lives from a center point such as a local market or a town market, the more time it takes to adopt IPM. Signs of distance variables in the AFT model appear positive, which indicates the farther the farmer lives from the local market or town market, the more time it takes to adopt. Considering the magnitude and significance of the coefficients in all three models, local market has more influence on adoption than the town market. The plot of hazard for distance variables in figure 4 shows that the increase in hazard decreases as the distance increases. However, from the figure, the effects of first two miles from a village market and first 10 miles from a town market are stronger than a farther distance as the change in increase in hazards are shown to be less after those thresholds. From the AFT model, a farmer living a mile farther from the local market increases her time to adopt, other variables held constant, by 9 percent on average. The corresponding effect for the distance to a bigger town market is 1.3%. Distance variables may be (positively) related to some cost issues (such as transportation costs), but they also affect (negatively) the ability to gain information about a new innovation. Because IPM is not capital-intensive compared to traditional pest management practices, increased transportation costs due to an increase in distance from a center point is not expected to greatly influence IPM use negatively. As a result, it can be argued that the increased time to adoption due to living farther from a center point is more related to obtaining information about the innovation than to increased transportation costs.

Training farmers about agricultural technologies is one activity of the DAE and other agencies involved in agricultural extension. Hence, a farmer's participation in any training program is expected to positively affect the use of new and improved technologies. Regardless of the model, the coefficient of a dummy variable indicating whether the farmer has received any training on vegetable farming is found to be significant at the 1% level. The hazard increases by 87-90% (depending on the model) if a farmer has any training on vegetable farming compared to not having any, *ceteris paribus.* From the AFT model, the farmer's time to adopt IPM decreases by almost 12 percent compared to a farmer not having any training, which is similar to that in PH models. A Farmer's perception about IPM use is found to significantly affect IPM adoption. If a farmer believes that the use of IPM is good for the crop, as it requires fewer chemical pesticides, she has a 2.83 times higher hazard rate than a farmer who does not believe so. The AFT model reveals that a farmer believing that IPM use is good for the crop decreases the log of time to failure (time to adopt) by 0.121. That is, positive beliefs about IPM decrease the waiting time to IPM adoption by 12%. Since the farmers' beliefs about the health benefits of IPM use is not found to be statistically significant, it cannot be argued that it is the farmers' positive beliefs about IPM that affect its adoption. It may be the case that a farmer believes that less use of pesticides will lead to better sales of the crops and more profit which in turn motivates the farmer to adopt. However, investigating this indirect economic factor is beyond the scope of this study. Regardless of the reason, it appears that providing information by training and educating farmers about IPM is an effective way to increase its adoption. Farmers in Bogra and Comilla adopted earlier, on average, than those in Magura, while farmers in Jessore had mixed results depending on the model. The estimate of the regional hazard rate is consistent with the analysis based on the Kaplan-Meier survival curve mentioned before.

We have discussed the coefficients of variables that are significant in all models. Now we consider the variables that are significant in at least one of the models. Holding all variables equal to zero for a hypothetical farmer, the constant in the AFT model is 1.826 which tells us that the hypothetical farmer's time to adopt IPM increases by 183%. The AFT model shows that a farmer having an off-farm source of income, which is the only economic variable that is significant, decelerates the time to adopt IPM by 9 percent. Having off-farm income makes it more likely the farmer will obtain information about innovation from more and sometime better sources. As a result, significance of off-farm income enhances the importance of information dissemination in explaining speed of adoption.

It has been assumed for the above results that the shape of the Weibull distribution is same for all covariates. To investigate whether suspicious variables such as different locations, sources of income, membership status, and training status show different shape parameters, ancillary parameter, *p*, for each of those variables in the Weibull regression is estimated. No substantial differences in estimated coefficients are found, both in terms of magnitude, sign, and significance, from those mentioned in Table 2. Table 3 presents the estimated ancillary parameters for each of the categories. It shows that even though the shape parameter, *p*, is not exactly the same for each category of each variable, none of them changes the direction of the effect of the variable on hazard.

The above results have been obtained assuming that the functional forms are correct and individual farmers in the sample, after controlling observable differences through including explanatory variables, are homogenous. However, heterogeneity may arise due to two reasons: misspecification of the functional forms or the presence of unobserved differences among individual farmers. Ignoring the heterogeneity, if present, may lead to incorrect inferences regarding duration dependence and the effects of regressors (Kiefer, 1988). A frailty model can be used to check the presence of such heterogeneity. A frailty model is a generalization of a survival regression model in which, in addition to the observed regressors, a latent multiplicative effect on the hazard function is allowed. The effect of the unobserved heterogeneity, or frailty, is not directly estimated from data. Instead, the assumed mean and variance of the frailty, θ, with unity mean and finite variance are estimated. If frailty is greater than unity for any specific heterogeneous group, subjects in the group experience increased hazard (risk) of failure (adoption) and are said to be more frail than their cohorts (Gutierrez, 2002).

Proportional hazard model has difficulty handling left truncated data. The hazard ratios, with gamma or inverse Gaussian distributed frailty, decay over time in favor of the frailty effect. Thus, the hazard ratio in the PH model is actually the hazard ratio only for t=0. The degree of decay depends on θ. For this reason, many researchers prefer fitting frailty models in the AFT metric because the interpretation of regression coefficients is unchanged by the frailty – the factors in question serve to either accelerate or decelerate the survival experience (Gutierrez, 2002). As a result, only the AFT model is employed for the estimation of the conditional probability with heterogeneity removed. A gamma distribution of frailty has been used since in a large class of survival models the distribution of heterogeneity among survivors converges to the gamma distribution (Abbrign and Van Den Berg, 2007). Table 4 reports the AFT estimation with the heterogeneity effect removed. The model in Table 4 performs best compared to all the models mentioned above, as its log-likelihood is -42 which is the highest of all models. AIC and BIC are the lowest among all the models. The null hypothesis that there was no heterogeneity effect is rejected at the 1% level, implying unobserved heterogeneity among individual farmers in the sample. Fortunately, there is no change in the sign of the estimated coefficients from those reported in Table 2. The coefficients in Table 2 are over-estimated. Most importantly, the effect of spouse's education is less with heterogeneity accounted for. Not only its magnitude but also significance changes after individual heterogeneity is captured by the parameter θ. The significance of the coefficient of off farm as a source of income has also improved. Therefore, since the sign and significance of all variables except spouse's education and off farm income have not changed, it is safe to assume that the unexpected result for the coefficient of spouse's education may be due to heterogeneity resulting from omitted variables (such as profitability, attitudes toward risk and ambiguity etc.) rather than from the functional form specification.

6 Conclusion

Numerous studies have focused on identifying the determinants of adoption of new technologies, including technical, organizational, and environmental factors. However, those studies use cross-sectional data to estimate probit-like models that fail to capture the farmer's time to adoption. As a result, the studies are inadequate in explaining the dynamic process of technology adoption. In this paper, duration models are used to capture the dynamic aspects of the IPM technology adoption process in Bangladesh. Using survey data from Bangladesh, Cox PH, Weibull PH, and AFT models have been estimated. Both parametric and semi-parametric models are applied to estimate the conditional probability of IPM adoption, in which the full parametric models include the Weibull PH model and the log-logistic AFT model, and the Cox PH model is the semi-parametric model.

The main conclusion of this study is that it is not the economic or personal characteristics of the farmer that are important influences in the timing of the adoption decision but factors related to information diffusion and perception about IPM use and unobserved heterogeneous behaviors, such as attitudes toward risk and ambiguity.

Sources of off-farm income and being a member in any association in the village increases the likelihood of early adoption. Distance to a center point such as a local market or a town market increases the time to adoption. Distance variables may be (positively) related to some cost issues (such as transportation costs), but they also affect (negatively) the ability to gain information about a new innovation. Because IPM is not capital-intensive compared to traditional pest management practices, increased transportation costs due to an increase in distance from a center point is not expected to greatly influence IPM use negatively. As a result, it can be argued that the increased time to adoption due to living farther from a center point is related to obtaining information about the innovation rather than increased transportation costs. One of the primary services offered by extension agencies (such as DAE, IPM club, or any NGOs) is to train farmers. Farmer's participation in a training session on vegetable farming decreases the time to adoption. If farmers believe that IPM use is good for crops, due to the manner with which little or no pesticides are used, this increases the likelihood of adoption. That is, those farmers who believe IPM is good for crops adopt earlier than farmers who believe otherwise. Since the farmers' beliefs about the health benefits of IPM use is not found to be statistically significant, it cannot be argued that it is the farmers' positive beliefs about IPM that affect its adoption. It may be that farmers believe that less use of pesticides will lead to better sales and profits, which in turn motivates the farmer to adopt. However, investigating this indirect economic factor is beyond the scope of this study. Regardless of the reason, it appears that providing information by training and educating farmers about IPM is an effective way to increase its adoption. If speedy adoption is desired, then policies should encourage more training about the new innovation. This training will not only teach farmers about the technologies but also will affect the subjective probability of the effectiveness of the innovation and thereby influence its use. More effective dissemination should lead to a higher speed of adoption.

Table 2: Estimation of conditional probability of IPM adoption

	PH model (Weibull)		Cox PH model		AFT model (Loglogistic)	
Variables	Haz. Ratio	Std. Err.	Haz. Ratio	Std. Err.	Coef.	Std. Err.
Age	1.004	0.011	1.000	0.002	0.000	0.002
HH head's education (years)	1.028	0.039	1.002	0.008	-0.006	0.007
Spouse's education (years)	0.882***	0.032	0.980***	0.007	0.023***	0.007
Off farm income (1=Yes; 0 otherwise)	1.419	0.399	1.055	0.062	-0.085*	0.049
Labor Constraint (Dependent/Working person)						
Rental status (1=Renter; 0 otherwise)						
Association membership (1=yes; 0 otherwise)	1.644*	0.432	1.112**	0.060	-0.110**	0.047
Executive member (1=yes; 0 otherwise)						
Index of Aawareness (0-40)	1.038*	0.021				
Value of livestocks (Taka)			1.000*	4.35E-07	-6.32E-07*	3.83E-07
Pest pressure index (0-1)			0.821	0.252	0.220	0.260
Membership in an MFO (1=Yes; 0 otherwise)			0.951	0.053		
Distance from local market (km)	0.566***	0.106	0.558***	0.103	0.092***	0.031
Distance from town market (km)	0.944**	0.024	0.934**	0.025	0.013***	0.005
Farmer had training on vegetable farming (1=Yes; 0 otherwise)	1.897***	0.449	1.866***	0.447	-0.121***	0.044
Farmer believes IPM use is good for crops (1=Yes; 0=otherwise)	2.83**	1.27	2.58**	1.07	-0.120*	0.062
Farmer believe IPM use is a healthy way of farming (1=Yes; 0=otherwise)	1.53	0.65	1.58	0.628	-0.103	0.062
Jessore dummy	0.354*	0.203	2.938**	1.473	0.081	0.087
Comilla dummy	4.248***	1.904	4.536***	2.119	-0.241***	0.082
Bogra dummy	4.363***	2.035	4.054***	1.970	-0.220***	0.082
Constant					1.826***	0.136
Ancillary	p=6.11	0.805			γ=0.137	0.016139

Log likelihood	-59.247	-369	-47
AIC	146.4945	769	147.699
BIC	195.33	825	200.03
Median time	6.56 years		
N	242		

Note: For the Cox PH model, Breslow method for ties has been used. Standard errors have been obtained bootstrapping with 10,000 replications. ***, **, and * indicate statistically significant at 1%, 5%, and 1% levels respectively. Coefficients with bold cells have been found to be statistically significant at the indicated level using the standard procedure, whereas the gray shaded cells indicate that those are significant at the indicated level using the standard procedure but found to be non-significant with the bootstrapped SE. However, those have been found to be non-significant using the bootstrapped standard errors. The rest have been found similar statistical significance using both standard errors.

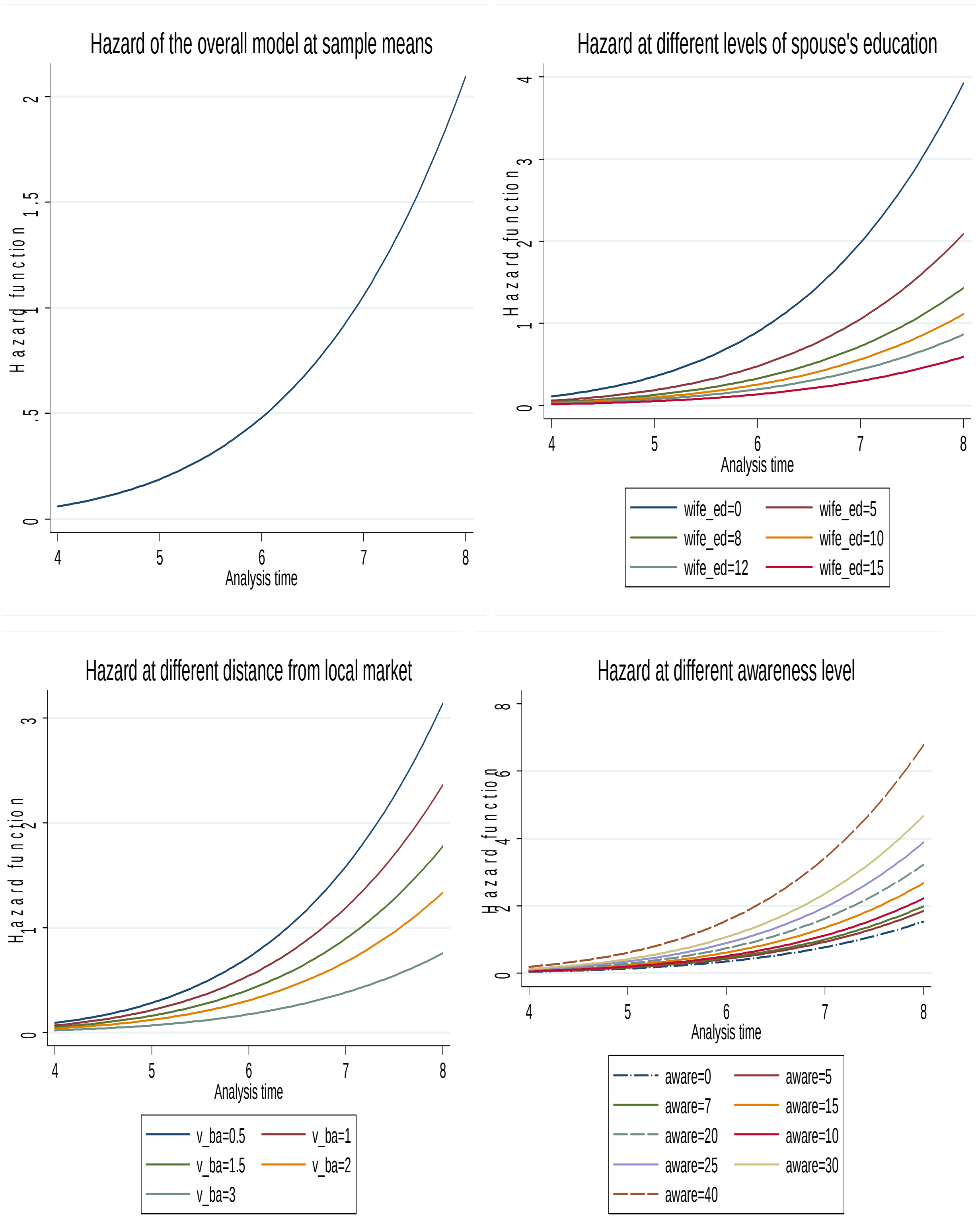
Table 3: Estimation of the ancillary parameter, p, for the Weibull model

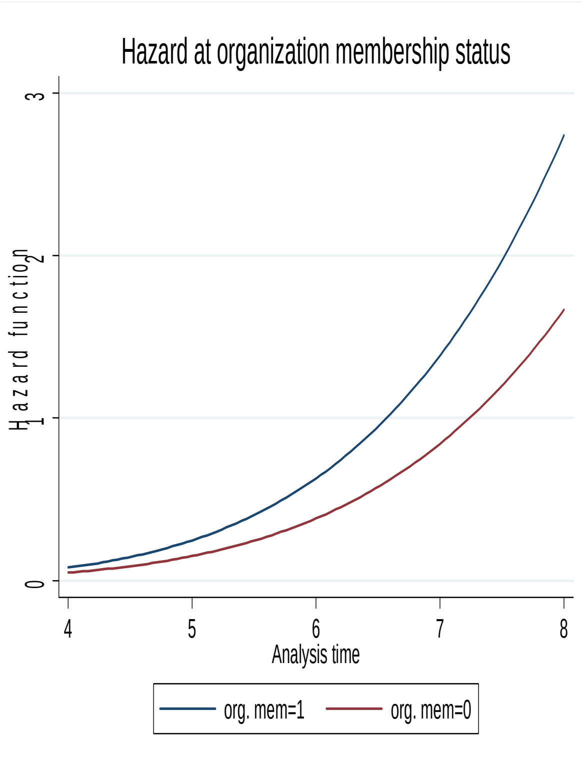
Variables	Coeff.	Std. Err	$\widehat{\ln(p)}$	$\hat{p}$
Magura			1.861	6.430
Jessore	-0.104	0.047	1.757	5.794
Comilla	0.132	0.044	1.993	7.338
Bogra	0.137	0.045	1.998	7.372
Constant	1.861	0.143		
Non-off farm			1.800	6.049
Off farm	0.033	0.027	1.833	6.252
Constant	1.800	0.133		
Not a member in an organization			1.786	5.964
Organization member	0.044	0.025	1.830	6.235
Constant	1.786	0.135		
No training on vegtable farming			1.781	5.934
Has tranining on vegetable farming	0.054	0.023	1.835	6.265
Constant	1.781	0.135		

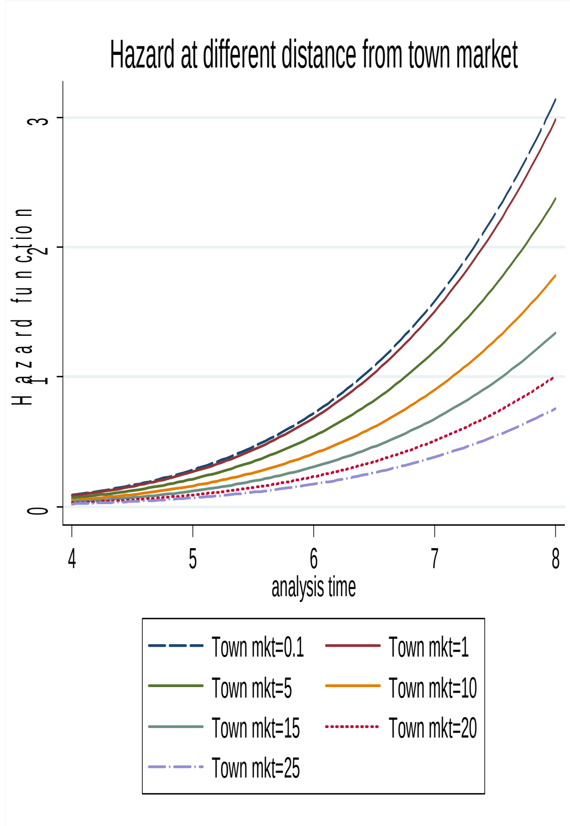
Note: $\widehat{\ln(p)}$ is the fitted ancillary parameter, p, regressing p on the corresponding dummy variables in the table.

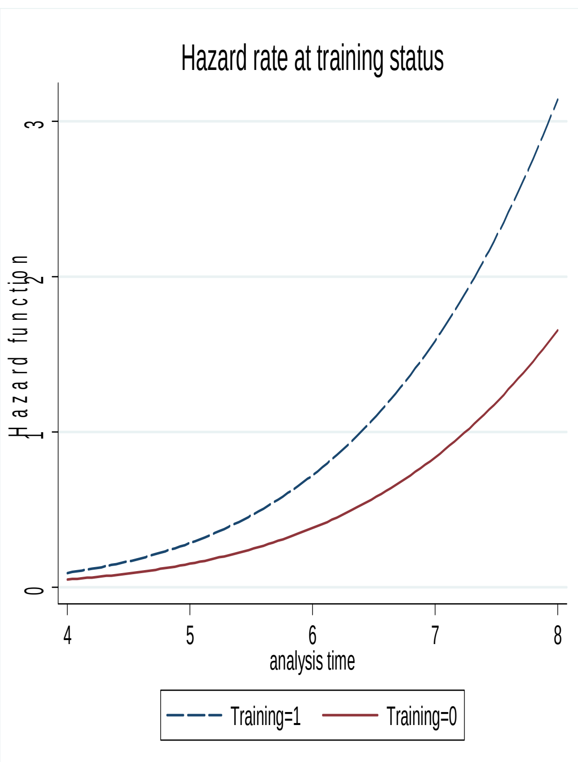
$\hat{p}$=Exp($\widehat{\ln(p)}$) that provides the hazard for the corresponding category.

Figure 1: Weibull estimate of hazard with respect to different variables




Hazard at organization membership status
Hazard function
0
1
2
3
4
5
6
7
8
Analysis time
org. mem=1
org. mem=0


Hazard at different distance from town market
Hazard function
0
1
2
3
4
5
6
7
8
analysis time
Town mkt=0.1
Town mkt=1
Town mkt=5
Town mkt=10
Town mkt=15
Town mkt=20
Town mkt=25


Hazard rate at training status
Hazard function
0
1
2
3
4
5
6
7
8
analysis time
Training=1
Training=0

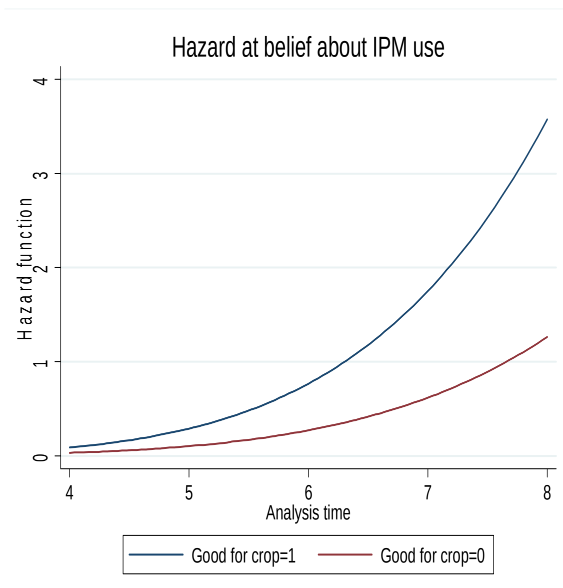

Hazard at belief about IPM use
Hazard function
0
1
2
3
4
4
5
6
7
8
Analysis time
Good for crop=1
Good for crop=0

Table 4: Estimation Results for IPM Adoption: Heterogeneity Effect Removed

Variables	AFT model (Log-logistic) Coef.	Std. Err.
Age	0.000	0.001
HH head's education (years)	0.004	0.004
Spouse's education (Years)	0.009**	0.004
Off farm income (1=Yes; 0 otherwise)	-0.072**	0.029
Association membership (1=yes; 0 otherwise)	-0.072***	0.027
Value of livestocks (Taka)	-1.0E-07	2.1E-07
Pest pressure index (0-1)	0.029	0.190
Distance from local market (km)	0.039**	0.016
Distance from town market (km)	0.010***	0.003
Farmer had training on vegetable farming (1=Yes; 0 otherwise)	-0.107***	0.029
Farmer believes IPM use is good for crop (1=Yes; 0=otherwise)	-0.042	0.041
Farmer believes IPM use is a healthy way of farming (1=Yes; 0=otherwise)	-0.058	0.041
Jessore dummy	-0.081	0.051
Comilla dummy	-0.151***	0.044
Bogra dummy	-0.104***	0.042
Constant	1.698***	0.085
γ (ancillary parameter)	0.048	0.007
θ (heterogeneity capturing parameter)	3.812	0.822
Log-likelihood	-41.92	
LR test for θ=0	χ^2 =10.25	p-val= 0.001
Frailty distribution	Gamma	
AIC	120	
BIC	183	

Note: θ is the estimated frailty effect to capture heterogeneity effect, if any. γ is the ancillary parameter for the log-logistic distribution.

References

Abbring, J.H. and Van Den Berg, G.J. (2007), 'The unobserved heterogeneity distribution in duration analysis', *Biometrika*, **94**(1), 87-99.

Addison, J.T. and Portugal, P. (1998), 'Some specification issues in unemployment duration analysis', *Labor Economics*, **5**, 53-66.

Adesina, A. and Zinnah, M. (1993), 'Technology characteristics, farmers' perceptions and adoption decisions: a Tobit model application in Sierra Leon', *Agricultural Economics*, **9**, 297-311.

Akinola, A.A. (1987), 'An application of Probit Analysis to the adoption of tractor hiring services scheme in Nigeria', *Oxford Agrarian Studies*, **16**, 70-82.

Alcon, F., de Miguel, M.D. and Burton, M. (2011), 'Duration analysis of adoption of drip irrigation technology in southeastern Spain', *Technological Forecasting & Social Change*, **78**, 991-1001.

Beus, E.B. and Dunlap, R.E. (1994), 'Agricultural paradigms and the practice of agriculture', *Rural Sociology*, **59**, 620-635.

Bhattacharya, S.K., Chaterjee, K., and Samuelson, L. (1986), 'Sequential of research and the adoption of innovations', *Oxford Economic Paper*, **38**, 219-243.

Bultena, G.L. and Hoiberg, E.O. (1983), 'Factors affecting Farmers' adoption of conservation tillage', *Journal of Soil and Water Conservation*, **4**, 281-284.

Burton, M., Rigby, D. and Young, T. (2003), 'Modelling the adoption of organic horticultural technology in the UK using Duration Analysis', *The Australian Journal of Agricultural and Resource Economics*, **47**(1), 29-54.

Carletto, C., de Janvry, A. and Sadoulet, E. (1999), 'Sustainability in the diffusion of innovations: smallholder nontraditional agro-exports in Guatemala', *Economic Development and Cultural Change*, **47**, 345-369.

Cleves, M., Gutierrez, R., Gould, W. and Marchenko, Y. *An Introduction to Survival Analysis Using Stata*, 2nd edn. (Texas, USA: Stata press, 2008).

Colman, D. (1994), 'Ethics and externality: agricultural stewardship and other behaviour', *Journal of Agricultural Economics*, **45**, 299-311.

Comer, S., Ekanem, E., Muhammed, S., Singh, S. and Tegegue, F. (1999), 'Sustainable and conventional farmers: a comparison of socio-economic characteristics, attitudes and beliefs', *Journal of Sustainable Agriculture*, **15**, 29-45.

D'Emden, F.H., Llewellyn, R.S. and Burton, M.P. (2006), 'Adoption of conservation tillage in Australian cropping regions: An application of duration analysis', *Technological Forecasting & Social Change*, **73**, 630-646.

Dadi, L., Burton, M. and Ozanne, A. (2004), 'Duration Analysis of Technological Adoption in Ethiopian Agriculture', *Journal of Agricultural Economics*, **55**(3), 613-631.

Dasgupta, S., Meisner, C. and Wheeler, D. (2004), 'Is Environmentally-Friendly Agriculture Less Profitable for Farmers? Evidence on Integrated Pest Management in Bangladesh', Development Research Group, World Bank Policy Research Working Paper 3417.

Davies, S. (1979), *The Diffusion of Process Innovation*, Cambridge University Press, Cambridge.

De Souza Filho, H.M. (1997), *The Adoption of Sustainable Agricultural Technologies: A Case Study in the State of Espirito Santo, Brazil*, Ashgate Publishing, Aldershot, U.K.

D'emden, F.H., Llewellyn, R.S. and Burton, M.P. (2005), 'Adoption of conservation tillage in Australian cropping regions: An application of duration analysis', *Technological Forecasting & Social Change*, **73**, 630-647.

Feder, G. (1980), 'Farm size, risk aversion and the adoption of new technology under uncertainty', *Oxford Economic Papers*, **32**, 263-283.

Feder, G., R., J. and Zilberman, D. (1985), 'Adoption of agricultural innovations in developing countries: a survey', *Economic Development and Cultural Change*, **33**, 255-298.

Feder, G., and Umali, D.L. (1993), 'The adoption of agricultural innovations: a review', *Technological Forecasting and Social Change*, **43**, 215-239.

Feder, G., and Slade, R. (1984), 'The acquisition of information and the adoption of new technology', *American Journal of Agricultural Economics*, **66**, 312-320.

Feder, G., and O'Mara, G.T. (1982), 'On information and innovation diffusion: a Bayesian approach', *American Journal of Agricultural Economics*, **64**, 145-147.

Fischer, A.J., Arnold, A.J. and Gibbs, M. (1996), 'Information and the speed of innovation adoption', *American Journal of Agricultural Economics*, **78**, 1073-1081.

Foltz, J.D. (2003), 'The economics of water-conserving technology adoption in Tunisia: an empirical estimation of farmer technology choice', *Economic Development and Cultural Change*, **51**(2), 359-373.

Fuglie, K.O. and Kascak, C.A. (2001), ‘Adoption and diffusion of natural-resource-conserving agricultural technology’, *Review of Agricultural Economics*, **23**, 386-403.

Greene, W. *Econometric Analysis*, 6th edn. (New Jersey, USA: Prentice Hall, 2008).

Gutierrez, R.G. (2002), ‘Parametric frailty and shared frailty survival models’, *The Stata Journal*, **2**(1), 22-44.

Hannan, T.H. and MacDowell, J.M. (1984), ‘The determinants of technology adoption: The case of banking firm’, *Rand Journal of Economics*, **15**, 328-335.

Hannan, T.H. and MacDowell, J.M. (1987), ‘Rival precedence and dynamics of technology adoption: an empirical analysis’, *Economica*, **54**, 155-171.

Hattam, C. and Holloway, G. (2007), ‘Bayes Estimate of Time to Organic Certification’, Conference paper presented at the Agricultural Economics Society’s 81st Annual Conference, University of Reading, UK.

Hazell, P. and Anderson, J. (1986), ‘Public policy toward technical change in agriculture’, Chapter 8 in P. Hall (ed.) *Technology, Innovation and Economic Policy*, Philip Alan.

Heckman, J.J. and Singer, B. (1984), ‘Econometric Duration Analysis’, *Journal of Econometrics*, **24**, 63-132.

Jansen, H.G.P. (1992), ‘Inter-regional variation in the speed of modern cereal cultivars in India’, *Journal of Agricultural Economics*, **43**, 88-95.

Jenkins, S. *Survival Analysis*, Unpublished manuscript, (Clochester, UK: Institute for Social and Economic Research, University of Essex, 2005. Available at:

https://www.iser.essex.ac.uk/files/teaching/stephenj/ec968/pdfs/ec968lnotesv6.pdf; last accessed August, 19, 2014).

Jensen, R. (1982), 'Adoption and diffusion of an innovation of uncertain profitability', *Journal of Economic Theory*, **27**, 182-193.

Kalbfleisch, J. and Prentice, R. *The Statistical Analysis of Failure Time Data*, 2nd edn. (New Jersey, USA: Wiley-Interscience, 2002).

Kiefer, N.M. (1988), 'Economic Duration Data and Hazard Functions', *Journal of Economic Literature*, **26**, 646-679.

Knudson, M.K. (1991), 'Incorporating technological change in diffusion model', *American Journal of Agricultural Economics*, **73**, 724-733.

Levin, S.G., Levin, S.L. and Meisel, J.B. (1987), 'A dynamic analysis of the adoption of a new technology: the case of optical scanners', *Review of Economics and Statistics*, **86**, 12-17.

Lindner, R.K., Fischer, A. and Pardey, P. (1979), 'The time to adoption', *Economics Letters*, **2**, 187-190.

Lindner, R.K. (1980), 'Farm size and the time lag to adoption of a scale neutral innovation', mimeographed, University of Adelaide, Adelaide, Australia.

Mead, N. and Islam, T (2003), 'Modelling the dependence between the times to international adoption of two related technologies', *Technological Forecasting & Social Change*, **70**(8), 759-778.

Mills, B. F. (2000), 'Job Search, Employment Density, and the Rate of Exit of Unemployment in Nonmetropolitan Labor Markets', *Southern Rural Sociology*, **16**: 148-174.

Mohr, L. 1982, *Explaining Organizational Behavior*, Jossey-Bass, San Francisco, USA.

Nie, X. (2013), 'Information Technology Adoption Based on Survival Analysis', *International Journal of Digital Content Technology and its Applications (JDCTA)* **7**(6), 628-635.

Pannell, D.J., Marshall, G.R., Barr, N., Curtis, A., Vanclay, F. and Wilkinson, R. (2006), 'Understanding and promoting adoption of conservation practices by rural landholders', *Australian Journal of Experimental Economics*, **46**, 1407-1424.

Polson, R.A. and Spencer, S.C. (1991), 'The technology adoption process in subsistence agriculture: The case of cassava in southern Nigeria', *Agricultural Systems*, **36**, 65-78.

Qi, J., (2009), *Comparison of Proportional Hazards and Accelerated Failure Time Models*, Masters Thesis, Department of Mathematics and Statistics, University of Saskatchewan, Saskatoon, Saskatchewan, Canada.

Rahman, S. (2003b), 'Environmental impacts of modern agricultural technology diffusion in Bangladesh: an analysis of farmers' perceptions and their determinants', *Journal of Environmental Management*, **68**: 183-191.

Ricker-Gilbert, J., Norton, G.W., Alwang, J., Miah, M. and Feder, G. (2008), 'Cost-Effectiveness of Alternative Integrated Pest Management Extension Methods: An Example from Bangladesh', *Review of Agricultural Economics*, **30**, 252-269.

Rogers, E.M. (2003), *Diffusion of Innovations*, V ed New York.

Shields, M.L.G., Rauniyar, G.P. and j Goode, F.M. (1993), 'A longitudinal analysis of factors influencing increased technology adoption in Switzerland, 1985-1991', *The Journal of Development Areas*, **27**, 469-483.

Sidibe' (2005), 'Farm-level adoption of soil and water conservation technique in Northern Burkina Faso', *Agricultural Water Management*, **71**(3), 211-224.

Spanos, A. (2011), 'Revisiting the Statistical Foundations of Panel Data Modeling', Unpublished manuscript, Department of Economics, Virginia Tech, Blacksburg, VA, USA.

Thirtle, C.G. and Ruttan, V.W. 1987, *The Role of Demand and Supply in the Generation and Diffusion of Technical Change*, Harwood Academic Publishers, Chur.

Van Den Berg, G.J. (2001), 'Duration Models: Specification, Identification and Multiple Durations', Chapter 55 in *Handbook of Econometrics*, Vol. 5, Edited by J.J. Heckman and E. Leamer, Elsevier Science B.V.

Weir, S. and Knight, J. (2000), 'Education externalities in rural Ethiopia: Evidence from average and stochastic frontier production functions', Oxford: Center for the study of African Economies, mimeo.

Yaron, D.D. (1990), 'Influence of quality and scarcity of inputs on the adoption of modern irrigation technologies', *Western Journal of Agricultural Economics*, **12**(2), 224-233.