Dynamics of Wheat Variety Adoption on Farms in Pakistan:
A Duration Model

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I. Introduction

The irrigated areas of the Province of Punjab, Pakistan are the historical locus of the Green Revolution in wheat. Known in the narrowest sense by the swift diffusion of short-statured, higher-yielding wheat varieties during the 1960s, Pakistan's Green Revolution also entailed public investments in irrigation canals and tubewells, fertilizers, and market development. Technical change generated welfare benefits for farmers and consumers beyond adopting farmers in high-productivity environments like those of Punjab (Renkow 2000). The wheat economy and rural society were transformed; the specter of famine receded (Djurfeldt 2005; Hazell 2010; Larson and Otsuka 2012). Despite such acclaimed progress, large numbers of Pakistanis continue to live in poverty, suffering from malnutrition and micronutrient deficiencies.

Zinc deficiency illustrates this problem. According to the National Nutrition Survey (2011), the average prevalence of zinc deficiency is relatively high in Pakistan, and is more severe among women and children. Nearly 41.6 percent of non-pregnant women, 48.3 percent of pregnant women, and 36.5 percent of children are zinc-deficient. Zinc plays a crucial role in resistance to disease, diabetes control, wound healing, digestion, reproduction, and physical growth.

One way to reduce zinc deficiency is to introduce higher zinc content into wheat, which is still the most important starchy staple in the Pakistani diet. Wheat is grown by a majority of farmers and consumed by almost all rural and urban households. The average Pakistani household spends nearly 15 percent of monthly income on wheat and wheat products (GOPa 2011). To reach poorer people in remote rural areas who do not have access to zinc-enriched food or zinc supplements, scientists have proposed the fortification of popular wheat varieties.

To design effective programs for introducing zinc-fortified varieties, the Government of Pakistan needs to understand the process of wheat variety adoption and diffusion today. Decades after the Green Revolution, most farmers already grow high-yielding wheat varieties. In today's Pakistan, "adoption" refers specifically to a farmer's replacement of one high-yielding variety with a more recently released high-yielding variety, rather than to the replacement of tall-statured varieties or farmers' landraces with newer types, as was the case in the Green Revolution.

Previous research has documented that the slow rate of variety replacement by farmers has posed a major challenge in promoting new wheat varieties in Pakistan (e.g., Heisey, 1990; Farooq and Iqbal, 2001; Khan et al., 2002). One consequence has been the concentration of wheat area in a few popular varieties, which depresses yield potential and aggravates the crop's vulnerability to plant disease, including endemic strains of wheat rust (Heisey et al. 1997). For example, in 1997, six years after its release, Inqilab was sown to an estimated 4.22 mill ha in Pakistan alone (Smale et al. 2002). Inqilab remained the most popular wheat variety until the release of Seher in 2006. A recent stochastic frontier analysis by Battese et al. (2014) confirms that slower variety replacement reduces the technical efficiency of wheat production in the Punjab of Pakistan.

Several salient features in the scholarly discourse about the Green Revolution are potentially relevant to the analysis of variety adoption (replacement) in today's Pakistan. One is the role that transfer of seed and variety information from one farmer to another played in diffusion of the first generation of semi-dwarf wheat varieties and in their replacement by newer, improved releases (e.g, Hussain, Byerlee, and Heisey, 1994). Although investment in public extension services was fundamental for delivering new seed and related information, widespread diffusion depended on informal, socially-mediated exchange. A second is the way that farm size shapes the process of seed-based technical change. A large body of theoretical and empirical research has explored the association of farm size with endowments of various types of capital (human, physical, social, political), and via these endowments, access to market infrastructure, including sources of information (e.g., Feder, Just and Zilberman 1985; Feder and O'Mara 1984; Lipton and Longhurst1989). Battese et al. (2014) also found that the large-scale farmers are more productive and more efficient than smaller-scale farmers. A third was recognition of the importance to some farmers of variety attributes other than grain yield, such as fodder production (e.g., Renkow and Traxler 1994).

In this analysis, we revisit these questions with the goal of contributing to the design of programs to introduce zinc-fortified wheat varieties in Pakistan. Data were collected through interviews with 1116 farmers during October-November 2011 in twenty three districts of irrigated Punjab, representing 3 zones (rice-wheat, cotton-wheat, and mixed zones). Farmers are adopt new wheat varieties more rapidly in irrigated Punjab than in other wheat agro-ecologies of Pakistan, making it a 'laboratory' for observing the dynamics of variety change.

Our conceptual approach is a trait-based model of seed (variety) choice derived from the theoretical framework of the agricultural household, which also recognizes the importance of variety information sources as farmers learn about variety attributes (Hintze et al. 2003; Edmeades and Smale 2006). We apply the conceptual approach with a duration model, which enables us to model explicitly the timing of the adoption event as a function of variety traits, farmer, and market characteristics. Duration analysis includes both time-varying and time-invariant parameters in order to combine insights from cross-sectional and time- series data and account for potential biases caused by unobserved lengths of time in 'spells' or states, such as unemployment (Kiefer 1988). Widely applied by economists to a range of topics (Van den Berg

2001), the approach has been used relatively infrequently to model adoption of agricultural innovations. Examples include studies of resource-conserving technologies by Fuglie and Kascak (2001), organic horticultural practices by Burton et al. (2003), adoption of cross-bred cows by Abdulai and Huffman (2005), and crop technology adoption in developing countries by Dadi et al. (2004) and Matuschke and Qaim (2008).

2. Conceptual framework

a. Hypotheses from earlier adoption literature

The Green Revolution in the Asian subcontinent stimulated a vast literature about the adoption of agricultural innovations in developing economies, which built particularly on the seminal research conducted in the US by Griliches (1960) and Rogers (1962). Exhaustive reviews of the first few decades of this literature were conducted by Feder, Just and Zilberman (1985) and Feder and Umali (1992). Given the role of farmer knowledge and complementary inputs (fertilizer, adequate moisture) in the optimal performance of the first short-statured, high-yielding varieties, early empirical studies focused on the characteristics of farmers (education), access to credit, irrigation, and land. A major theoretical paradigm of this period was farmer decision-making under risk, depicting a farmer's land allocation between "modern" and "traditional" as a portfolio decision determined by risk aversion and the stochastic structure of relative yields (Just and Zilberman 1983). Safety-first and other motivations related to risk were also proposed (e.g., Roumasset, Boussard and Singh 1979). Learning models were another hallmark of this early literature, in which farmers resolved uncertainty by accumulating knowledge about higher-yielding varieties through experimentation and experience, often portrayed as a Bayesian process (e.g., Hiebert 1974; O'Mara 1971; Feder and Slade 1984; Leathers and Smale 1991). Lindner et al. (1979) applied this framework in analyzing the time to adoption.

Variety choice models of this type are less relevant in today's Pakistan because the adoption decision no longer involves the technology shift from a "traditional" (tall-statured, higher-yielding variety or heterogeneous, wheat landrace) to a "modern" (short-statured, fertilizer-responsive variety. Especially in the irrigated areas of Punjab, Pakistan, wheat farmers have now experienced many generations of "modern," higher-yielding varieties. Adoption of wheat varieties in today's Punjab Province is about replacing one modern variety with another, based on whether it performs better than the current modern variety given a farmer's particular growing conditions and objectives. Farmers are more educated and have more access to public information; capital investments are not needed to shift from one higher-yielding variety to another.

On the other hand, the decision to grow a newly released wheat variety is still a process that depends on how individual farmers seek and acquire information. Farmers "learn by doing" and they learn from others (Feder and Slade 1984; Foster and Rosensweig 1994). A major paradigm in recent adoption literature articulates the influence of social learning, social networks, and social capital in the choices made by individual farmers (Besley and Case 1997; Conley and Udry 2003; Munshi 2004; Bandiera and Rasul 2006). A principle in this literature is that costs, and access to information about a new technology, are related to capital endowments, such as farm size. In Punjab, Pakistan, public extension agents are more likely to work with larger-scale growers.

Further, each new release has a unique configuration of traits. A segment the variety choice literature demonstrated empirically that early utility-based models of decision-making omitted variety traits, which are relevant factors in the decision-making for semi-subsistence farmers. Because of a focus on higher yields and yield stability, these models often ignored the role of traits such as grain and storage quality or fodder yield in farmer decision-making. Some researchers tested the importance of variety attributes, such as pest resistance and suitability for food preparation, by including them in econometric models alongside farmer characteristics and other determinants (e.g., Adesina and Zinnah 1993; Smale, Bellon, and Aguirre 2001). More complete models were then derived in the framework of the household farm by Hintze (2003) and Edmeades and Smale (2006). Examples of recent applications include Katungi et al. (2011), Otieno et al. (2011) and Timu et al. (2012).

Our conceptual framework, summarized next, has been influenced by these paradigms. Specifically, we test the importance of variety traits in the decision to replace one higher-yielding wheat variety with another, and explore the relationship between this decision and sources of information at the time of adoption. We test for differences in adoption parameters by farm size.

b. Conceptual basis

We view the choice of wheat varieties in any wheat growing season from the general perspective of the well-known model of the agricultural household (Singh, Squire, and Strauss 1986). The agricultural household organizes family and hired labor in order to maximize utility over home-produced goods, purchased goods, and leisure time, given a farm production technology and an income constraint defined by net returns over tradable farm outputs, expenditures, and income from other sources or previous seasons. Profit maximization, and the separation of consumption and production decisions, constitutes a special case which may pertain for a very small minority of large-scale wheat farmers.

In the trait-based version of this model (Hintze 2003, Edmeades and Smale 2006), the agricultural household maximizes utility over the intrinsic attributes of the home-produced goods it consumes, a purchased good, and leisure time. In our case, the home-produced good is wheat. Utility is maximized conditional on household characteristics that shape preferences ($\mathbf{\Phi}_h$) and market characteristics ($\mathbf{\Phi}_m$) that affect purchases. Variety choices are also constrained by production technology, which is defined by the traits that are genetically embedded in a variety and expressed when the seed is planted ($\mathbf{z}$), and by availability of seed (for variety v_i). Expenditure constraints play an inconsequential role for wheat variety choice in Punjab of Pakistan, since seed costs are low, and the seed of higher-yielding varieties need not be replaced annually. Though expenditure constraints affect fertilizer and water use on wheat, fertilizer moisture response do not differ appreciably among current higher-yielding varieties, as would be the case between tall-statured and short-statured, or higher-yielding and landrace types. The production technology is conditioned on farm ($\mathbf{\Phi}_f$) and market characteristics. The variety supply $\boldsymbol{V}$ that is available in the farmer's location constrains choice, and reflects both the potential for farmer-to-farmer transfer and the delivery of wheat seed via formal channels (Edmeades and Smale 2006).

Variety attributes of new releases are not known to farmers before they variety is grown or observed in the field. Consistent with the social learning literature, and with both historical and current evidence for this region and crop, we hypothesize that farmers learn about variety traits from others, and particularly about new variety, by seeking variety information. The local supply of varieties (***V***), household, market and farm characteristics that influence the cost of obtaining information, and opportunities for social learning (**Ω**) affect the farmer's knowledge about wheat varieties.

A farmer i in the irrigated areas of Punjab, Pakistan, decides to replace an old with a newer, higher-yielding variety of wheat if the overall utility of adopting, U_{i1} , is larger than the utility of not adopting U_{i0}. In other words, $(U_{i1} - U_{i0}) > 0$. We can define an unobservable $v_i^* = (U_{i1} - U_{i0})$, and express it as a function of observable elements in a latent variable model

$$v_i^* = \boldsymbol{\omega}_i \gamma + u_i \, , \qquad (1)$$

In equation 1, $\boldsymbol{\omega}$ summarizes the vectors of explanatory factors described above (**z,** $\boldsymbol{V}$,**Φ**, **Ω**), conditional on variety information. The variable v_i refers to a binary choice that is observed at time *t*:

$$v_i \ (t) = \begin{cases} 1 & if \ v_i^*(t) > 0, \boldsymbol{\omega}_i \gamma \geq -u_i \\ 0 & if \ v_i^*(t) < 0, \boldsymbol{\omega}_i \gamma < -u_i \end{cases} \qquad (2)$$

γ is a vector of parameters to be estimated, and u_i is the error term, which is assumed to be normally distributed.

3. Empirical strategy

a. Duration model

Since the 1980s, duration models have been applied to the analysis the timing of economic events in the fields of labor economics and migration, human and business life cycles, stock market and firm investment behavior, and other topics; their widespread use reflects the growing importance placed on the dynamics of decision-making, and the role of information (Van den Berg 2001). In his review of duration analysis as applied to the study of unemployment, Kiefer (1988) noted that "short spells will be underrepresented" in a current sample of employed and unemployed, generating "length-biased sampling." Similarly, data recording variety use in a single period cannot adequately capture the timing of the decision to change from one state (variety) to another, or the duration of variety use once adopted.

Kiefer's (1988) perspective, which we assume here, is that econometric methods based on hazard functions provide a "natural" approach for analyzing data that can be modeled sequentially. He modeled the duration time (T) as a non-negative, continuous random variable with cumulative distribution function

$$F(t) = \int_0^t f(t)dt = \Pr(T < t). \tag{3}$$

The survivor function, which expresses the probability that duration time t is greater than some value of t, is defined as $S(t)=1-F(t)=\Pr(T>t)$. Duration analysis utilizes the related hazard function, $h(t)=f(t)/S(t)$. According to Kiefer (1988:11), $h(t)$ is "the rate at which spells will be completed at duration t, given that they last until t"—or more precisely,

$$h(t)=\lim h\rightarrow 0 \ \Pr(t\leq T<t+h|T\geq t)/h. \tag{4}$$

Conveniently, the hazard rate is equivalent to the inverse Mills' ratio of the sample selection literature (Kiefer 1988:11).

A common specification of hazard function is the proportional hazard model, in which the function h depends on a vector of explanatory variables **x** with estimable coefficients β. The baseline h_0 is factored out, and corresponds to the value of the function at 1 (Kiefer 1988):

$$h(t,\boldsymbol{x},\beta,h_0) = \varphi(\boldsymbol{x},\beta)\ h_0(t) \qquad (5).$$

The coefficients estimated with a proportional hazard model can be interpreted as partial derivatives, as in a linear regression model. Van den Berg (2001) refers to this approach as reduced-form, expressing an exit rate to a destination state as a function of observed and unobserved explanatory variables, and the elapsed time in the current state. The proportional hazard model has the advantage that it imposes no parametric form on the baseline hazard and allows the hazard to shift, in steps, over the duration (Burton et al. 2003).

The function $f(t)$ is often specified as exponential or Weibull in form. The Weibull has the form $f(t)=\gamma\alpha t^{\alpha-1}$, with parameter γ. The exponential distribution is a special case of the Weibull, when $\alpha=1$. The exponential distribution is characterized by a constant hazard function, which implies that the passage of time does not affect the hazard rate. The Weibull distribution is characterized by either an increasing or decreasing hazard, including the exponential as a special case when the rate is constant. The suitability of the Weibull as compared to the exponential form can be tested statistically. Parametric estimation is accomplished by maximizing the likelihood function.

Generally speaking, duration analysis enables us to identify the factors that have the potential to change the estimated probability that the state occupied by an individual will end in the next short time interval. More specifically, duration analysis can be applied to predict the time (t) to adoption of an agricultural innovation. For example, Abdulai and Huffman (2005) applied an investment timing model with perfect information as the conceptual basis for a duration model they applied to predict the time until adoption of cross-bred cows in Tanzania. In their model, farm-level heterogeneity in the time to adoption then depended on “rank, stock, and order” effects. Rank referred to differences in profitability among farms. Stock effects described the influence of the cumulative adoption rates in a location on farm profits. Order effects pertained to the farm’s position in the succession of adopters (early or late).

Other examples include Burton et al. (2003), who applied duration analysis to model the adoption of organic horticultural techniques in the UK, and Dadi et al. (2004), who modeled the time to adoption of fertilizer and herbicide on tef in the Ethiopian Highlands. Reflecting Kiefer’s (1988) point concerning “length bias,” Burton et al. (2003) present duration analysis as a means of including both adoption and diffusion components of agricultural innovation. Adoption studies, which are typically based on a single cross-section of data, fail to allow for the timing of the adoption event, but account for farmer heterogeneity in the decision. On the other hand, diffusion studies that model cumulative adoption in the aggregate ignore why some farmers adopt earlier than others.

Duration analysis can also be used to predict the time lag from the release of a newer, higher-yielding variety and its first year of use by a farm household. Recently, Matuschke and Qaim (2008) applied a duration model to test the effects of privatization of the seed industry on the adoption of pearl millet hybrids in India. Our application is closest to that of Matuschke and Qaim (2008), but differs in that we are examining the replacement of one higher-yielding variety by another rather the adoption of a hybrid for the first time. Our perspective differs substantially from those of Abdulai and Huffman (2005), Burton et al.(2003) and Dadi et al.(2004), in that the replacement of one higher-yielding wheat variety by another does not entail a major investment decision.

Where Matuschke and Qaim including social activity as one of their regressors, our focus is on the role of information sources. Burton et al. (2003) and Dadi et al. (2004) also view information as a major factor in the adoption process for organic practices, including both public sources of information and social network sources. Dadi et al. (2004) and Matuschke and Qaim (2008) differentiate between time-invariant and time-varying factors that influence the length of the adoption lag.

In our case, the hazard function represents the probability that the farmer in the irrigated areas of Punjab, Pakistan, replaces the currently grown, higher-yielding wheat variety with a new higher-yielding variety at time *t*, given that he continues to grow the current variety before time *t*. Variables are defined in greater detail below, after a summary of the data source.

b. Data

The data are drawn from a survey among wheat farmers conducted during October-November 2011 in Punjab, the largest province of Pakistan. Punjab includes 76 percent of the country's wheat area (GOPb, 2011). The sample covers 1116 wheat farmers in 93 villages, located in 23 districts of three agro-climatic zones (cotton-wheat, rice-wheat, and mixed zones).

A stratified two-stage (unequal size) cluster design was used to draw the sample. The three wheat production zones represented the strata, or first-stage sampling unit. The second-stage sample unit was the *mouza* (revenue village). The revenue villages were allocated proportionately across agro-climatic zones based on the share of total wheat land area. Proportional allocation ensures that the sampling fraction in each stratum is equivalent to the sampling fraction of the population. A systematic probability-proportionate-to-estimated-size approach was used for the selection of revenue villages (clusters) within each agro-climatic zone (stratum) using secondary data on the population size (total number of household) of each revenue village. In total 93 revenue villages from 23 districts were selected from the high wheat intensity Punjab.

Following the selection of revenue villages in the first stage, wheat farming households were selected at random within each village. From previous surveys and research conducted in Pakistan[1], the non-response rate is estimated at 33% for interviewing conducted at the second-stage selection. This rate was adapted in our study and prescribes 6 spare households to be selected within each revenue village. A total of 18 households were selected in each village of which 12 were interviewed. The final sample consisted of 1116 farmers, of which 41 percent

[1] Pakistan Integrated Household Survey , 1991 (PIHS 1991) of the World Bank

were selected from cotton-wheat zone, 32 percent from rice-wheat zone, and 27 percent from mixed zone.

c. Variables

Definitions of the dependent and explanatory variables, means and standard deviations, are shown in Table 1. Following Dadi et al. (2004), we group the operational variables we use to measure ($\mathbf{z}$, $\boldsymbol{V}$,$\boldsymbol{\Phi}$, $\boldsymbol{\Omega}$) as time –invariant and time-variant. As is common in this limited literature, many of our empirical variables are binary, potentially generating a step or shift in the hazard function.

Time to adoption

The dependent variable used in the analysis is the time to adoption of a variety grown by the farmer during the survey year, measured as the difference between the year of adoption and the year of release. The average time to adoption in irrigated areas of Punjab among farmers surveyed in 2011 was 6.5 years, ranging from 1 to 30 years.

A histogram of the dependent variable suggest a bi-modal distribution, reflecting the two most popular varieties grown by farmers surveyed, Inqilab, which was released in 1991, and Seher, which was released in 2006 (Figure 1). Inqilab was grown on over 70 percent of the wheat area for 13 years, and on nearly half of Punjab in 2007/08. However, Seher replaced Inqilab and became the most popular variety in 2010, occupying 42 percent wheat area in Punjab (Government of Punjab, 2011).

We treated the year of release of these two varieties as “regime changes” in terms of the rate of cumulative adoption, introducing dummy variables as time-varying covariates. Each dummy takes a value of one if release year of a variety is greater than 1991, zero otherwise.

Household characteristics

Respondents were the household members who were responsible for wheat production decision-making during the growing season. Household characteristics ($\mathbf{\Phi}_h$) include the age of the household member who is responsible for wheat production decisions at the time of adoption (a time-varying covariate), and endowments of human and financial capital. Human capital is represented by the quality and quantity of labor. Quality of labor is measured in terms of the respondent’s literacy. The active labor supply in the household, or quantity of labor, is measured as the number of persons between 15 and 65 years of age. Ownership of livestock with large relative economic value (cattle and buffalo) is used as the indicator of the asset base of the household, or financial capital. A priori, we expect a shorter time to replacement of the current variety with a newer, higher-yielding variety among farmers with greater capital endowments. While younger farmers are often thought to be less risk averse and therefore more willing to test a new technique or variety, some studies have shown that older farmers are likely to adopt a new technology because they are more experienced (Lapar and Pandey, 1999; Abdulai and Huffman, 2005).

Farm characteristics

We use whether the farmer is a tenant (renting land or sharecropping), and dummy variables for the size category of the farm, as farm characteristics ($\mathbf{\Phi}_f$). Following the standard classification used in Pakistan, we group farmers into three categories based on cultivated land: marginal (cultivate up to 5 acres) small-scale (cultivate up to 12.5 acres but more than 5 acres), and medium-large scale (cultivated land is greater than 12.5). Most wheat farmers (71%) belong to the marginal and small-scale categories. We hypothesize that large-scale farmers replace existing wheat varieties with new, higher-yielding varieties more quickly than small-scale and marginal farmers because they have better access to information and seed sources. A fundamental feature of Green Revolution technology was that it was largely considered to be scale-neutral (Hazell 2010), although Feder and Slade (1984) argued that scale-bias was introduced via access to water and fertilizer. During the post-Green Revolution period, differences in fertilizer or moisture-response among higher-yielding varieties are not likely to be as appreciable as between taller-statured and semi-dwarf wheat varieties, and farmers have already made related investments in irrigation. In 1990, Heisey et al. concluded that in the presence of other variables, farm size usually became a less significant determinant of variety change in areas where new varieties had already been widely adopted and smaller farmers become aware of them.

Market characteristics ($\mathbf{\Phi}_m$) are represented by the distance to input dealer (km) and the lagged wheat price. The larger the distance to the input dealer, the slower is the expected adoption of new wheat varieties. A negative sign is expected for the distance variable, as was found by Matuschke and Qaim (2008).

The survey data show that a majority of farmers (78 percent) acquired the seed of the varieties they planted from their own previous harvest or at some time in the preceding year from other farmers. Wheat seed prices were reported for less than one-third of farmers. Also, the relevant seed price for our model would be the price at the time of adoption, which was not recorded in the survey. As a proxy, we used time series data on the average wheat price in major cities of irrigated districts of Punjab in the year of variety adoption, lagged by one year. Wheat prices varied little across cities (GOP, 2011c. We hypothesize a negative sign on the coefficient of this variable.

We measure the supply of wheat varieties *V* as the total count of different wheat varieties grown in the *mauza*. Empirical research, and social learning theory, suggests that the higher the number of varieties grown, the more likely an individual farmer will be to test a new one. However, the new variety may not be the major variety, which we have measured here. A greater number of varieties grown in a mauza may also indicate a wider range of production constraints or consumption preferences in that location, and a slower time to adoption of a new, higher-yielding variety as a major variety. Thus we have no hypothesis concerning the direction of effect.

The social learning variables (**Ω**) are grouped into formal, informal and social categories. Each represents the source of information about the current major variety at the time of adoption Formal sources include extension services, print and electronic media, and internet. Village input dealers, large landlords, and shopkeepers are grouped as informal sources. Friends, neighbors and relatives are classified as "social." These categories follow previous empirical research conducted in Pakistan (Tetlay et al., 1987; Ahmad et al. 1991; Khan, Morgan and Sofranko, 1990; Muhammad and Garforth, 1999; Abbas et al. 2003; Taj et al. 2009). Though broad, this categorization underscores hypothesized differences in costs of information acquisition. A priori, we cannot predict the sign of the relationship between sources of information and speed of adoption.

In the adoption decision, we also consider variety traits. We began by developing a list of key traits with wheat scientists and experts in Pakistan, finalizing the list following the pre-test of the survey instrument. Farmers were asked to report the degree of importance of various traits in their choice of a wheat variety on a five point Likert scale (1=unimportant, 2=of little importance, 3=moderately important, 4=important and 5=very important). The most important production traits were grain yield and grain size; and the most important consumption trait was the taste of chapatti, which was cited as important or very important by over 90 percent farmers. Other important traits, identified by more than 80 percent of farmers, are panicle length, price, chapatti colour, and nutritional value. Labour requirement appeared to be the least important trait (Nazli et al. 2011).

Rather than including all traits individually in the regression, we used principal components with varimax rotation to reduce the number of variables based on correlation structure, selecting factors with eigenvalues greater than one in magnitude. The relative sizes of the coefficients that contribute to variation in the factors led us to name factor 1 as "input traits," factor 2 as "production traits," and factor 3 as "consumption traits." (see Table 1) First, farmers appear to differentiate agronomic and consumption traits. In factor 1, traits of interest are primarily those related to profitability, including the amounts of fertilizer and water needed, and labor requirements, followed by pest and rust resistance. Factor 2 is strongly affected by grain yield, grain and panicle length. The variables with the largest coefficients in factor 3 are chapatti quality (taste, colour, freshness) and nutritional value. Thus, the correlation structure in the data supports the underlying motivation of the trait-based model.

Finally, the dummy variables for the agro-climatic zones (rice-wheat, cotton-wheat, and mixed zone) are used to control for the regional effects.

4. Findings

In this section, we present a) the Kaplan-Meier curve, which provides guidance concerning the selection of the form of the hazard function (Weibull v. exponential); b) test results comparing models estimated with Weibull as compared to exponential forms; c) test results comparing the pooled model, which does not allow for us to distinguish duration parameters by farm size, to the separate models, and regression results for the separate models.

a. Kaplan-Meier curve

Before estimating the duration model, the Kaplan-Meier curve is often estimated in order to examine baseline survival times, independent of explanatory factors. The Kaplan-Meier curve represents the proportion of the study population still surviving at each successive point in time. The approach is non-parametric, and thus requires no assumptions regarding the underlying distribution of survival times (adoption lags). However, the shape of the curve provides some evidence concerning the appropriateness of the distribution we assume in our econometric analysis. The period of observation is divided into a series of intervals, each containing one or more adoption events at its beginning.

The Kaplan-Meier estimate of the time-to-adoption function for the full sample is shown in Figure 2. Here, the curve portrays the proportion of farmers who had not yet adopted the new, higher-yielding variety that was their major wheat variety in the survey year (2011), in each year from the earliest release represented in the data (1979). The function is valued “1” when time equals “0.” This means that initially, all farmers are considered to be non-adopters. The value of the function falls sharply in the first six years, indicating that most varieties are adopted within this time period. Between 6 to 20 years, the function declines at slower rate, and is almost flat between 20 to 30 years, for a very small proportion of varieties.

One point of reference for the length of adoption lag is the analysis by Heisey et al. (1990), which drew from a theoretical model developed by Heisey and Brennan (1989). The authors estimated that during the post-Green Revolution period, when yield gains attained in wheat through genetic improvement fluctuated around a trend line indicating 0.75% per year, it paid farmers to change improved varieties every four years. Differences in micro-environments, and biotic pressures such as rust diseases, influence the optimal rate of change. Figure 2 suggests that a substantial proportion of wheat farmers in the irrigated areas of Punjab may be meeting this mark, although wheat yield gains have also likely changed since that time period.

Apriori, as discussed above, we have strong reasons to expect that variety adoption parameters differ by farm size category. Figure 3 depicts the Kaplan-Meier curves differentiated by farm size group. Differences in time-to-adoption are most evident between the medium and large-scale group and the other two groups (both marginal and small-scale groups), and particularly in the range between 6 and 20 years. The step function is also slightly more steep for the medium-large scale farmers during the first 6 years.

b. Distributional form

The Kaplan-Meier curve shows that survival (hazard) is monotonically decreasing (increasing) over time. The data therefore support the application of a duration model that assumes a Weibull distributional form. Another way to compare and select the best fit model is to compare the Akaike Information Criterion (AIC) for different distributions. The AIC is defined as [-2lnL + 2(k+c)], where k is the number of independent variables in the model, and c is the number of model-specific distribution parameters (equal to one for the exponential distribution and two for the Weibull distribution).

In Table 3, we report the estimated coefficients and diagnostic test for duration models that assume the Weibull and the exponential distributions. Regression results are similar between the two models, although the significance of several individual coefficients and overall tests of significance favor the assumption of the Weibull distributional form. The AIC associated with the Weibull distribution is lower than that of the model estimated with the exponential distribution.

b. Farm size

Next, we applied the likelihood-ratio test, to compare the fit of regression that pools the sample across farm sizes to that of the regressions estimated separately for each farm size category. The null hypothesis, or the restricted regression, is that parameters are constant across farm sizes. Comparison of the values of the likelihood functions for the restricted regression to the sum of values for all three separate regressions generates a Chi-squared statistic of 63.28 (dof=51), which is greater than the critical value at the 10% level of significance. While this level of statistical significance is weak, we also have an analytical interest in distinguishing the effects of individual factors, such as information sources, by farm size. Thus, we reject the restricted model in favor of the unrestricted model.

The results of maximum-likelihood estimation of a duration models with Weibull distributions across three farm size groups are presented in Table 4. An important diagnostic test is the value of the Weibull parameter [ln (p)]. The value of ln(p) is greater than one in all three models indicates that the hazard (survival, or time to adoption) is increasing over time. At the 95% confidence interval, we reject the null hypothesis that [ln (p) =1], which, as noted above, would favor an exponential distribution.

Table 4 reports hazard ratios, with robust standard errors in parentheses. A hazard ratio greater (less) than one denotes that the variable shortens (lengthens) the time to adoption of new, high-yielding wheat varieties. Time-varying covariates representing major technological and diffusion shifts in wheat varieties (releases of Inqilab, Seher) are highly significant and large in magnitude for all groups of farmers. As hypothesized, higher wheat (seed) prices lengthen the time to adoption, for all farm sizes.

Findings confirm that hazard functions differ across farm size groups, providing additional insights on heterogeneity among farmers in the irrigated areas of Punjab. Statistically significant covariates, and the magnitudes of the hazard ratios are differentiated by farm size category.

With respect to household characteristics, literacy plays a significant role in the time to adoption for small, medium and large farmers, but not among marginal farmers. Family labor supply appears to matter for the rate of variety change among small-scale farmers only, reducing the adoption lag. This finding may reflect the fact that these farmers face labor constraints in wheat production. In addition, the age at the time of adoption reduces the adoption lag among marginal farmers, increases it among medium-large scale farmers, and has no discernible effect for the small-scale group. It may be that older farmers in the marginal group have gained experience and are better connected to seed and information sources, while younger farmers are more willing to try new varieties in the group of medium-large scale farmers.

Distance to input dealers is also significant only for smaller-scale farmers, indicating that it slows variety change. The number of varieties in the *mauza* is statistically insignificant when farmers are disaggregated by farm size, though the magnitude of the hazard ratio (less than one) is consistent with that of the pooled regression. Thus, variety richness (diversity across a spatial scale) at any point in time may have a dampening effect on variety change (diversity over time).

Unexpectedly, tenure has a strong effect only about medium-larger scale farmers. Capacity to rent-in land for wheat may enable this group of farmers to experiment with new wheat varieties sooner. Heisey et al. (1990) also found that larger farmers were more likely to grow more wheat varieties than smaller-scale farmers.

When we disaggregate by farm size group, relative to social sources of information, both formal and informal sources have strongly significant, positive effects on variety change among medium-large farmers.. Formal sources of variety information at the time of adoption reduce the adoption lag among small-scale wheat farmers in the irrigated areas of Punjab. The magnitudes of these effects are substantial. Among marginal farmers, neither formal nor informal categories have a significant effect on the adoption lag compared to social sources of variety information.

The effects of trait preferences are heterogeneous across farm size categories. An interest in input traits extends the adoption lag among marginal farmers, but reduces it among small scale farmers and does not have any significant impact on medium-large farmers. Another surprising result is the insignificant coefficient of production traits (which measures yield) in the case of smaller-scale and medium-larger scale farmers. Clearly, access to water and fertilizer, profitability and resistance to biotic presses, are greater constraints for smaller-scale than larger-scale farmers. This is not surprising given the environmental and economic challenges faced by farmers in these high-potential production zones.

Grain yield appears to be paramount importance to marginal farmers, speeding variety change. This finding indicates that the marginal farmers prefer higher-yielding varieties so that they can increase their total production of wheat on the limited land that they cultivate (less than 5 acres). Most of these farmers are subsistence farmers. An increase in production can enable them to produce surplus wheat.

Among small-scale farmers only, consumption traits also speed adoption. On the other hand, none of the trait factors matters in the hazard function estimated for medium-large wheat farmers. Overall, these results are consistent with the decision-making framework of the household farm, which includes profit maximization as a special case. Medium-larger farmers are more commercially-oriented, selling most of their harvest.

The only significant difference across agroclimatic zones is observed among medium-large scale farmers, where location in the mixed farming zone strongly slows variety change relative to other zones.

5. Conclusions

To design a strategy to promote zinc-fortified wheat varieties in Pakistan, policy makers need to understand why some varieties become more popular than others, and how the processes than influence popularity differ by target group. Referring to historical literature about the Green Revolution and findings from a recent baseline study in the irrigated areas of Punjab, we highlight recurring themes concerning the importance of farmer-to-farmer exchange of information alongside formal delivery mechanisms, the significance of traits other than yield in a heterogeneous farm population that both consumes and sells wheat, and farm size structure.

Based on these themes, we propose a trait-based conceptual approach for analyzing variety choice that incorporates the role of information source and social learning. In our empirical application, we merge elements of adoption and diffusion models in a duration analysis. In today's Pakistan, time to adoption refers to the number of years from the release of a high-yielding variety to its use by a farmer. Farmers in Pakistan have grown high-yielding varieties for decades, and adoption implies the replacement of one high-yielding variety by another.

As was the case in the earlier phases of the Green and post-Green Revolution, we find ample support of the argument that overall, wheat growers in the irrigated areas of Punjab are innovative, rapid adopters given that they have the seed and the information. The data also confirm that parameters that influence the time to adoption are heterogeneous among farm size groups. Some of this heterogeneity conforms to our expectations given the underlying conceptual framework of the household farm.

For example, distance to the nearest input dealer and availability of labor constrain adoption times among small-scale farmers (who tend to both sell and purchase), but not other groups. Marginal farmers are likely to be autarkic, and larger farmers are more likely to sell and not purchase. Concern for input traits (water and fertilizer, profitability, and resistance to biotic pressures) extends the adoption lag among marginal wheat growers, but reduces it among small-scale growers. A subsistence motivation may drive the focus of marginal farmers on grain yield above other variety traits, strongly reducing time to adoption. Smaller-scale farmers also value consumption traits, and these also drive their variety change decisions.

Relative to strictly "social" sources of information (friends, relatives), and informal (input dealers, large landowners), formal (agents, media) sources of information significantly affect rates of variety change for both small-scale and medium-larger scale farmers, but not marginal farmers. The role of literacy follows this pattern, while among marginal farmers, older age at adoption positive influenced variety change. By contrast, younger age has a positive influence among medium-large scale farmers.

The Kaplan-Meier curve, and the large magnitudes of the effects of shift variables indicating major breeding advances (Inqilab, Seher) attests to the relatively rapid rates of variety change among a substantial proportion of farmers in the irrigated areas of Punjab in 2011. For roughly half of farmers surveyed, time to adoption compares favorably with the optimal rates recommended in 1990 (4 years), although further research would be needed to produce fully comparable estimates to those calculated for that time period.

That said, policy attention is needed to meet the information needs of particular farmers, as evidenced by the persistent importance of variables such as literacy, labour supply, and distance to input dealers. Furthermore, it is likely that our results would look very different had they been estimated for rainfed wheat-growing environments of Pakistan.

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Table 1: Factor score coefficients, based on rotated factor matrix

	Factor 1	Factor 2	Factor 3
	Input and market traits	Production traits	Consumption traits
Maturity	0.01382	0.04583	0.11959
Grain yield	-0.01697	0.22625	-0.05956
Grain size	-0.08036	0.30757	0.00054
Panicle	-0.06177	0.28467	0.00587
Dry fodder yield	0.10674	0.12862	-0.07714
Insect resistance	0.21045	0.09623	-0.12395
Rust resistance	0.2043	0.10097	-0.11166
Lodging resistance	0.16892	0.12082	-0.09306
Water requirement	0.26809	-0.12373	0.02573
Fertilizer requirement	0.2467	-0.14843	0.05673
Labor requirement	0.24295	-0.09972	-0.0266
Good market price	-0.04547	0.16306	0.03956
Reliable demand	-0.06475	0.20498	0.03087
Chapati Taste	-0.04831	0.00852	0.29594
Chapati Color	-0.12113	0.03255	0.33488
Chapati Freshness*	-0.01822	-0.07172	0.30822
Nutritional value	0.03689	-0.12915	0.29194
Eigenvalue	4.88	2.08	1.88

Source: Authors. (*) Chapati can be kept overnight. N=1116

Table 2: Variable definitions and descriptive statistics

Variable	Definition	Mean	Std Dev.
Dependent variable			
Time to adopt	Number of years from the date of release to the date of adoption of variety grown in survey year	6.48	5.46
Independent variables			
Time-invariant covariates			
Age at adoption	Age of respondent in years at the time of adoption	46. 61	12.94
Literacy	1=if main respondent is literate	0.64	0.48
Labor	Number of working age members (age 15-65 years) per acre	1.13	2.20
Land rented-in	1= household rented-in or sharecropped-in some land for cultivation	0.29	0.45
Own livestock	Ownership of cattle, buffalo, cow=1, 0 otherwise	0.91	0.28
Distance	Distance to nearest input dealer (km)	8.76	8.20
Formal information	1=source of information at time of adoption of current major variety was extension agent or media; 0 else	0.17	0.37
Informal information	1= source of information at time of adoption of current major variety was input dealer, shopkeeper, landlord; 0 else	0.13	0.34
Social information	1= source of information at time of adoption of current major variety was friend, relative, or neighbour; 0 else	0.70	0.46
Variety supply	Number of wheat varieties grown in village	17.08	3.47
Marginal farm	1=if farmer's cultivated land is less than 5 acres, 0 else	0.28	0.45
Small-scale farm	1=if farmer's cultivated land is between 5 to 12.5 acres, 0 else	0.35	0.48
Medium-large farm	1= if farmer's cultivated land is greater than 12.5 acres, 0 else	0.37	0.48
Rice-wheat zone	1=farm in rice-wheat zone, 0 else	0.31	0.46
Cotton-wheat zone	1=farm in cotton-wheat zone, 0 else	0.43	0.50
Mixed zone	1=farm in mixed (farming system) zone, 0 else	0.26	0.44
Time-varying covariates			
Wheat price	One year lagged average price of wheat at the time of adoption in major cities, (Rs/40kg)	527.15	188.86
Release of Inqilab	1=year of variety release is greater than 1991, zero otherwise	0.85	0.36
Release of Seher	1= year of variety release is greater than 2006, zero otherwise	0.09	0.29

Source: Authors.

Table 3: Coefficient estimates of duration models assuming Weibull and exponential distributions

	Weibull	Exponential
Age at adoption	-0.0018	-0.0001
	(0.0027)	(0.0013)
Literacy	0.2021***	0.1232***
	(0.0776)	(0.0372)
Labor	0.0161**	0.0060
	(0.0082)	(0.0040)
Own livestock	0.0921	0.0284
	(0.1574)	(0.0658)
Distance	-0.0073	-0.0035
	(0.0054)	(0.0024)
Wheat price	-0.0009***	-0.0007***
	(0.0002)	(0.0001)
Land rented	0.2064**	0.0911**
	(0.0824)	(0.0365)
Variety supply	-0.0244*	-0.0097
	(0.0145)	(0.0064)
Release of Inqilab	2.0714***	1.2535***
	(0.0990)	(0.0398)
Release of Seher	1.9898***	0.9930***
	(0.0899)	(0.0454)
Input traits	0.0279	0.0177
	(0.0369)	(0.0186)
Production traits	0.0644*	0.0349**
	(0.0345)	(0.0173)
Consumption traits	0.1031**	0.0448
	(0.0511)	(0.0294)
Formal sources of information	0.1556*	0.0539
	(0.0916)	(0.0413)
Informal sources of information	0.0520	0.0411
	(0.1250)	(0.0569)
Small-scale	-0.0072	-0.0052
	(0.0947)	(0.0435)
Medium-large scale	-0.1280	-0.0708*
	(0.0852)	(0.0402)
Cotton-wheat zone	0.0417	0.0468
	(0.0999)	(0.0467)
Mixed zone	-0.2642**	-0.1216*
	(0.1297)	(0.0673)
Constant	-4.5054***	-2.3742***
	(0.3609)	(0.1537)
Model diagnostics		
AIC	2,474.96	3,239.42
BIC	2,585.28	3,344.48

Source: Authors. Sample size=1143.

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Table 4: Duration models by farm size group

	Hazard ratio (robust standard error)		
	Marginal farmers	Small farmers	Medium/large farmers
Age	1.0096*	0.9986	0.9902**
	(0.0054)	(0.0041)	(0.0040)
Literacy	1.2024	1.3040**	1.2172**
	(0.1615)	(0.1665)	(0.1202)
Labour	1.0078	1.0495***	1.0072
	(0.0258)	(0.0147)	(0.0189)
Own livestock	0.9087	1.4939	1.1717
	(0.1440)	(0.5367)	(0.2398)
Distance	0.9970	0.9916*	0.9894
	(0.0091)	(0.0048)	(0.0073)
Wheat price	0.9993*	0.9988***	0.9992***
	(0.0004)	(0.0003)	(0.0003)
Land rented	1.1476	1.2116	1.3735***
	(0.1507)	(0.1600)	(0.1458)
Variety supply	0.9859	0.9786	0.9762
	(0.0185)	(0.0169)	(0.0175)
Release of Inqilab	9.0760***	9.2782***	7.3536***
	(1.5253)	(1.4955)	(1.0153)
Release of Seher	5.6656***	8.3020***	7.5836***
	(0.9237)	(1.3115)	(0.9471)
Input traits	0.8991**	1.1955***	1.0490
	(0.0452)	(0.0772)	(0.0526)
Production traits	1.1720**	0.9931	1.0911
	(0.0723)	(0.0581)	(0.0608)
Consumption traits	1.0765	1.1943***	1.0068
	(0.0815)	(0.0748)	(0.0414)
Formal information	0.8725	1.3881**	1.2483*
	(0.1868)	(0.1940)	(0.1451)
Informal source	0.8034	1.0987	1.2418
	(0.1998)	(0.2003)	(0.1651)
Cotton-wheat zone	1.0416	1.1926	0.9522
	(0.1514)	(0.1720)	(0.1238)
Mixed zone	0.8069	0.7763	0.6982**
	(0.1547)	(0.1467)	(0.1144)
ln(p)	1.9028***	1.9575***	1.8848***
	(0.0716)	(0.0740)	(0.0665)
Log likelihood	-338.09	-402.51	-446.52
Observations	405	488	520

Weibull model. *** p<0.01, ** p<0.05, * p<0.1
Source: Authors.

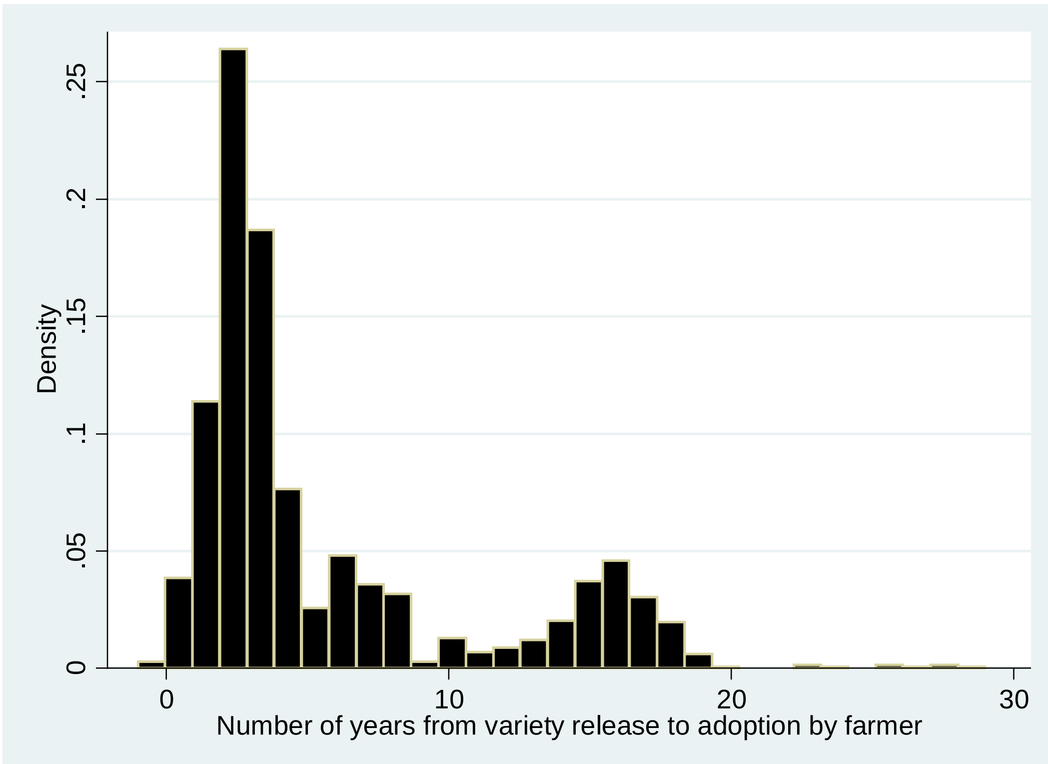

Figure 1. Time to adoption of major wheat variety grown in survey year

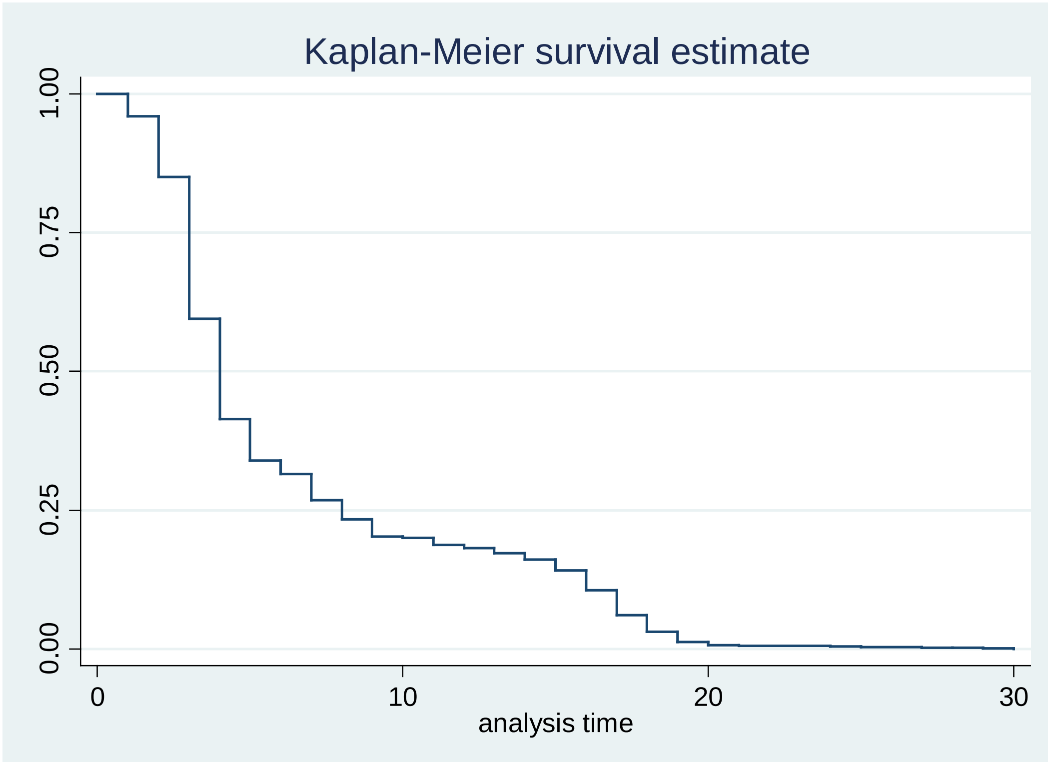

Figure 2. Baseline time-to-adoption function (Kaplan-Meier)

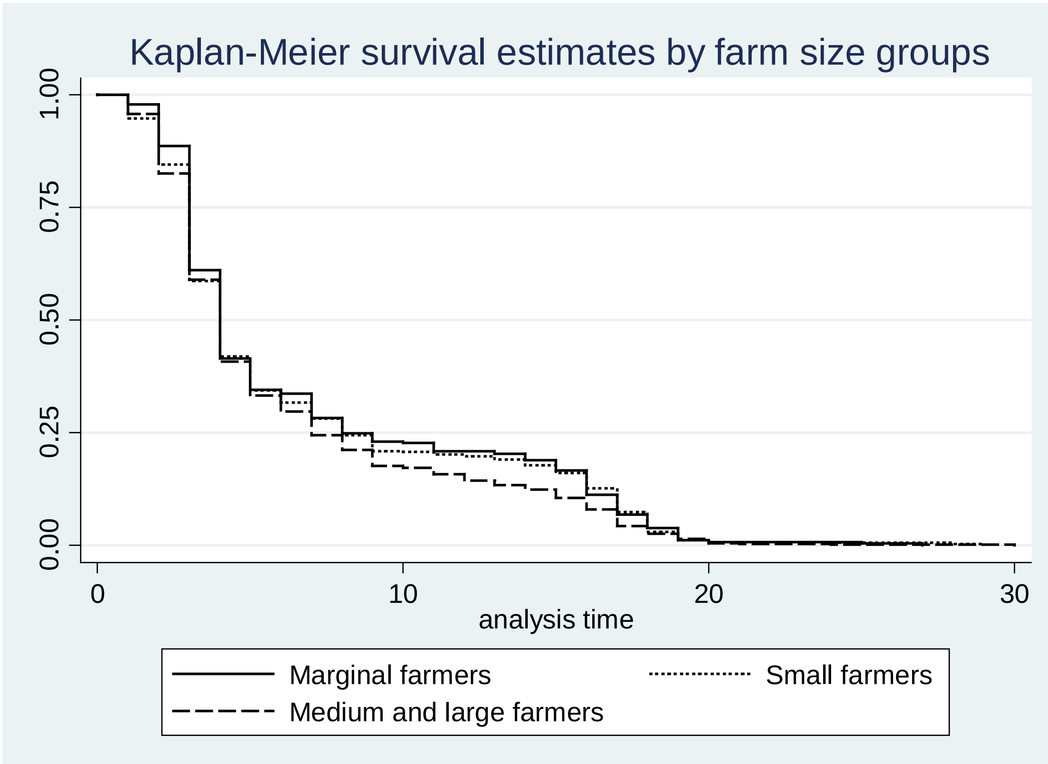

Figure 3. Baseline time-to-adoption function (Kaplan-Meier) by farm size groups