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Climate Risk and Planting Patterns: An Examination of the Direct and Indirect Effects of Changing Precipitation on the Behavior of Bangladeshi Farmers

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Abstract

Weather variability, risks, and mitigation strategies figure prominently in agriculture; however, climate change creates additional challenges that require adaptation. Bangladeshi farmers face regionally variable risks associated with salinity, submergence, and drought. Farmers can adopt newer stress tolerant varieties or adjust their cropping patterns. This paper examines the factors that contribute to the adoption and adoption shares of stress-tolerant rice varieties, with a particular emphasis on the role of weather and preferences. This paper uses Rice Monitoring Survey data collected by the International Rice Research Institute with funds from the Bill and Melinda Gates Foundation (RMS, 2019) as well as data collected from 2007 through 2017 from the Climate Hazards Group Precipitation with Stations at the 0.05 arc degree level (Funk et al., 2014). The paper takes a three-step approach to estimate the determinants of planting behavior, with a particular emphasis on the direct and indirect effects of changing precipitation patterns. First, with the approach suggested by Nguyen (2011) and Liebenehm and Waibel (2015), household risk and time preferences are estimated using data from the 2013 survey along with measures of precipitation patterns in the five years preceding the 2013 survey. The research uses that model to construct estimates of risk and time preferences at the beginning of the 2016 crop year using the precipitation data in the five years preceding 2015 along with the other household demographic and economic data from the 2016 survey period. We then estimate planting shares through the use of a hurdle as follows. Using Roodman's (2011) conditional mixed processes procedure, the hurdle model jointly estimates a Probit of whether a farmer plants anything in a given season and a set of two-limit Tobit models on planting shares. We find that direct effects of changing precipitation on planting shares for the Aus and Boro seasons. Negative deviations in mean daily precipitation from recent trends in the Boro season yield modest increases in planting shares of stress-tolerant modern varieties and hybrid varieties with corresponding declines in planting of traditional varieties. Results also suggest that large and positive deviations in precipitation in the Aus season would imply substantial declines in planting shares of stress-tolerant modern varieties, hybrids, and other crops with corresponding growth in traditional varieties. In considering the indirect impacts of changing weather conditions on planting shares, a positive precipitation deviations would yield changes in risk and time preferences that would cause, on average, a 4.34% decline in planting of stress-tolerant modern varieties and a 27.08% decline in hybrid variety planting shares across all seasons. This indirect effect is the only effect for the Aman season precipitation deviation, but it would be a compounding effect for the Aus season and an offsetting effect in the Boro season. Given these findings and ongoing efforts at encouraging climate adaptation, it would be clear that incentives would need to reflect both the recent conditions as well as the potential longer-term effects of recent conditions on farmer risk and time preferences.

JEL: O33, Q12, Q15, Q54

keywords: climate change, risk preference, time preference, planting behavior

Introduction

Weather variability, risks, and mitigation strategies have long figured prominently in agriculture; however, climate change creates additional challenges, including extreme heat events, prolonged droughts, and higher than normal precipitation can be attributed to climate change (National Academy of Sciences, 2016). In addition, rising oceans will certainly cause increasing salinity in coastal areas and estuaries. Howden et al. (2007) suggest that climate change presents a wide range of adaptive challenges for the agricultural sector and suggest a variety of practices that farmers may adopt, including altering inputs such as plant varieties, changing irrigation patterns, changing other water management practices, altering timing and location of cropping, improving effectiveness of practices related to pest and weed management, as well as considering alternative income sources in order to mitigate climate risk. In Bangladesh, Shaw, Mallick, and Islam (2013) provide evidence that the risks faced by Bangladesh are not uniform but vary regionally, with salinity and flooding relevant in some areas, drought more significant in others, and temperature variability affecting all. For example, Dasgupta et al. (2015) note that the coastal divisions of Chittagong, Dhaka, and Khulna could lose up to 30% of cultivable land, and Mottaleb et al. (2015) find that drought and submergence substantially reduce yields in Bangladesh during the Aman and Aus seasons. In that context, this paper examines two dimensions of farmers responses to changing weather patterns: adoption of stress tolerant varieties and changing shares of rice and non-rice crops in general.

An important starting premise in this paper is a recognition, as suggested by Arslan (2017) and noted above, that adaptation to climate change is not simply a question of adopting a specific technology but involves a menu of activities, and as explained by Holden and Quiggen (2017), adoption of new stress tolerant varieties represents but one possible varietal choice, suggesting that some local varieties represents an alternative risk mitigation strategy. Consequently, we will consider adoption of technology as not necessarily adoption of a specific technology but to consider stress tolerant varieties and crop diversity as alternative, and perhaps competing technologies to mitigate the risks of climate change for farmers in Bangladesh. This paper considers the following key questions: (1) What factors contribute to the adoption and adoption shares of stress-tolerant rice varieties? and (2) In the broader context, what explains the overall planting shares of different crops in general? While we will include multiple correlates with farmer behavior, our central question is to measure the extent to which changing precipitation patterns affect behavior (1) as a direct measure in our estimation and (2) indirectly through the impact of changing precipitation on farmer risk and time preferences.

In order to inform the adoption process, this paper is outlined as follows. We review the technology adoption literature as a mechanism to inform both our understanding of the various factors contributing to different behaviors among farmers. We next consider the specific technological environment within which Bangladeshi farmers operate. That is, we consider the menu of stress tolerant varieties made available to Bangladeshi farmers, the other modern varieties, the various local varieties, and the other crops which are commonly planted (with specific reference to the ways in which such crops help to mitigate such risks). In addition, we summarize the key varietal usage across regions within our sample, thus laying the groundwork for our subsequent analysis. In the subsequent section, we provide a conceptual framework that will motivate our empirical specification that allows us to make reasonable predictions about the impacts of socioeconomic, market/infrastructural, and weather-related patterns in the adaptation of farmers.

We then explain in greater detail our empirical approach. In short, we employ methods of estimating risk and time preferences from Liebenehm and Waibel (2014) and Nguyen (2011) to estimate the effects of changing precipitation patterns in the five years preceding the 2016/17 planting year on individual risk and time preferences. The next step of our approach draws on triple hurdle models suggested in other areas of the literature (i.e., Burke et al. (2015) and Fan and Garcia (2018)) but with appropriate modifications given our data and question. Using Roodman's (2011) conditional mixed progress package for Stata, we estimate hurdle model: (1) First, we estimate a probit of whether a farmer plants anything in a given season to control for selection, and (2) We then estimate a two-limit Tobit model on planting shares.

Subsequently, we provide a summary of the data, with some preliminary bivariate relationships highlighted, and we then present our baseline econometric analysis along with a further examination of the implications of these findings on understanding these patterns of adoption. The contributions of this research would be its control for the multi-seasonal nature of agriculture in many environments and permits exploration of how changing weather patterns will directly affect planting choices perhaps through a change in expectations and affect behavior and choice through the impact of such changes on preferences themselves. Specifically, by determining first how risk and time preferences are affected by changing weather patterns, we can measure how changing weather patterns affect behavior both through changing preferences and directly through the weather changes themselves.

Understanding the Nature and Process of Technology Adoption in Agriculture

The technology adoption literature in agriculture has identified several factors that affect farmer adoption of new technologies, including (1) experience and extent of exposure to risk, including especially weather-related risk; (2) risk preferences and perceptions; (3) human capital, social networks, and learning; (4) accessibility and availability of new technologies and complementary inputs; (5) cognitive abilities and psychological attributes of farmers, (6) crop attributes such as marketability or household consumption property, and (7) farm scale, wealth, and credit; and more recently. While not considered in detail, time preferences also figure into technology adoption because it involves a process of intertemporal optimization. To a lesser extent, scholars have also considered the role of gender in adoption processes, and in the specific context of choice of seed varieties, a number of papers also consider the role of the varied attributes of different seed varieties (e.g., market value, production attributes, and/or consumption attributes).

Weather, Climate, and Climate-Related Stress

Weather variability and other abiotic stresses have long been considered an important determinant in the technology adoption process (Hiebert (1974), Roumasset (1976), Feder, Just, and Zilberman (1985)). There are three ways in which researchers have considered the role of climate related events in adoption decisions: (1) general variability and changing trends in weather patterns, (2) perceptions of climate change and risk, and (3) experience of climate-related shocks.

In the first area of research, Pitt and Sumodinigrat (1991) found that Indonesian rice farmers were more likely to adopt modern varieties in drought prone areas where irrigation was possible. Many more recent papers have attempted to directly measure weather patterns, weather variability, and agroecological conditions in an effort to understand their roles in adoption processes, including DiFalco, Chavas, and Smale (2006); Mottaleb, Mohanty, and Nelson (2015); Arslan, Belotti, and Lipper (2017); and Asfaw, DiBatista, and Lipper (2018). Mottaleb, Mohanty, and Nelson (2015) remark on the importance of considering local weather and agro-ecological conditions, and they note that higher rainfall and higher temperatures on average led to lower likelihoods of adopting either modern or hybrid varieties in favor of traditional varieties, and farmers facing such stresses increased the share of land allocated to traditional varieties. DiFalco, Chavas, and Smale (2006) also find evidence that individuals in marginal farming and drought prone areas would tend to have a higher species diversity, thus suggesting the signal importance of controlling for such factors. In addition, Arslan, Belotti, and Lipper (2017) and Asfaw, DiBattista (2018) find that higher rainfall variability and lower maximum temperature can increase use of modern varieties while at the same time finding that greater variability may reduce use of organic fertilizers and some modern input use could fall. This literature thus suggests that farmers will tend to move, where possible, toward risk reducing technologies.

In considering farmer perception of climate risk or experience of climate shocks, Mishra, Pede, and Barboza (2018), in the context of land allocation in the Vietnamese Delta Region, found that greater recognition of climate change affected planting of paddy on own versus rented land, and in the context of aquaculturists, Ahsan and Brandt (2015) find that farmer perception of climate risk is affected by recent experiences of climate related events, thus suggesting that the extent to which a farmer will perceive a risk or possible future risk is shaped by recent experiences of risk.

In considering shock exposures more specifically, research has focused on drought alone, flooding alone, or climate change impacts in general. Cavatassi, Lipper, and Narloch (2011) note that experiences of crop losses due to drought appear to cause farmers to be more likely to maintain usage of sorghum landraces over modern varieties, but with the advent of stress tolerant varieties, Holden and Quiggen (2017) find that previous year shock exposure increased adoption of drought tolerant maize, reduced use of other modern varieties, and increased use of local varieties. In considering more specific events, Katengeza, Holden, and Lunduka (2019) find that adoption and adoption intensity of drought tolerant maize varieties increase when individuals experienced early season dry spells and that the share of area planted increases for individuals exposed to late season droughts. In the context of floods, Yamano et al. (2018) find that farmers in northern Bangladesh who experienced significant submergence problems in an earlier season were more likely to adopt recently released submergent tolerant varieties (BR11-Sub1 and Swarna-Sub1 rice), with Tran et al. (2019) finding in Vietnam a greater willingness to adopt a whole package of technologies denoted as climate-smart agriculture. In a more limited finding due to the binary structure of the dependent variable, Ullah et al. (2015) suggest that farmers will reduce their level of diversification when confronting abiotic stresses such as floods and droughts.

Role of Risk and Risk Preferences

Farmers experience changing weather conditions, precipitation, and possibly, changing soil conditions, and they face not only the decision to adopt a new technology but an array of possible technological choices, and they do this within an environment already fraught with market and biotic risks. Modern techniques, inputs, and new varieties will tend to have a wide range of impacts on possible outcomes, bringing further to the fore both uncertainty and risk faced by farmers. As farmers consider the adoption process and their adaptive reactions to climate change, they will have a sequence of possible choices: (1) whether to adopt or change behavior at all, (2) if adoption or new planting patterns on part of a property is possible, on what share of land will the farmer change their behavior, and (3) if intensity of adoption can be measured (perhaps extent of fertilizer use), how much to use the actual technology or by how much to change their planting varieties or shares. In the context of Bangladesh, pre-planting and pre-harvest technologies would include seed varieties, fertilizers, herbicides, pesticides, irrigation and water systems, planting methods (direct seeding versus transplanting), and various types of machinery or planting/cultivating equipment. The early literature provides a theoretical foundation for understanding such risk, and more recent literature has expanded upon this early work and connected risk aversion to new seed and technology adoption as well as crop diversification strategies.

The early technology adoption literature suggested that more risk averse farmers would use less fertilizer and plant fewer crops in modern varieties (Just and Pope, 1979, Hiebert, 1974, and Moscardi and De Janvry, 1977). Feder (1980) asserts that higher risk aversion and greater output variability will slow adoption of modern varieties which require complementary inputs and thus can increase risk; however, Lindner and Fischer (1981) more risk averse could be more rapid adopters of risk-reducing technologies. While in the U.S. context, Chavas and Holt (1996) find that risk preferences and greater yield variances of one crop can cause re-allocations across crops.

Concerns about significant downside risks also likely affect farmer practices and technology adoption. This safety first has been explained by Roumasset (1976) and empirically validated (Moscardi and DeJanvry (1977), Smale, Just, and Leathers (1995), and Smale, Heisey, and Leathers (1995). As suggested in the latter two papers, this aversion to downside risk or 'safety first' approach can explain reduced shares of modern varieties and certainly suggests something about how farmers may consider new stress-tolerant varieties or other risk mitigation strategies, and Dercon and Christiaensen (2009) explain how differences in ability to self-insure against downside risk (i.e., differences in wealth, assets, and the like) can explain differential practices in the case of fertilizer.

More recent literature which specifically focuses on seed technology adoption considers risk aversion, ambiguity aversion, as well as subjective probability assessments as motivating factors in adoption. For example, Liu (2013) finds that the lower the degree of risk aversion will speed adoption of a new technology, with Brick and Visser (2015) similarly finding in a hypothetical context that the more risk averse a farmer is the more likely they will choose traditional seed varieties. In the developed country context, Barham et al. (2014) consider how risk and ambiguity aversion affect GM corn and soy adoption in the United States, and they find that risk aversion had a modest effect on GM soy adoption while ambiguity aversion strongly affected GM corn adoption.

Literature which considers broader production choices beyond just seed technology includes Warnick, Escobal, and Laszlo (2011), Mukasa (2018), and Asravor (2019). Specifically, Warnick, Escobal, and Laszlo (2011) find evidence to suggest that ambiguity aversion and not risk aversion causes farmers to be less likely to plant more than one variety of their main crop, and Asravor (2019) notes that risk aversion will increase crop diversification and market risk will increase the use of improved seed varieties. In addition, Ullah et al. (2015) find that growing risk aversion will increase the likelihood of adopting diversification strategies to cope with increased risk. Mukasa (2018) also finds that both risk aversion and aversion to the kurtosis of the production distribution would reduce the likelihood of using chemical fertilizers, improved seeds, and pesticides. While focused on learning effects, Islam et al. (2018) also find that risk aversion appears to lower the likelihood of adopting a rice intensification technology.

In considering a non-seed risk mitigation strategy, Schimamoto, Yamada, and Wakono (2018) find that risk averse farmers are more likely to adopt a moisture meters to shield against post-harvest storage loss while their degree of loss aversion and probability weighting had little effect on such choices. While many papers have considered the role of risk aversion in affecting the adoption of a particular technology, Kaleab , Nillesen, and Tirivayi (2020) examine how the adoption of a risk-mitigating strategy (weather index-based crop insurance) can both reflect lower levels of risk aversion and can actually lower an agents risk aversion in other domains of work. This last component points to the interconnected nature of the adoption of risk-mitigating strategies and the evolution of preferences themselves.

Many papers consider how climate related issues interact with farmer risk preferences. Holden and Quiggen (2017) find that relative risk aversion increases the intensity of use of drought tolerant and local maize varieties as they tend to perform better under drought conditions while they tend to lower the usage of other modern varieties. They also find that greater loss aversion increases the probability of adopting drought varieties. In general, they only appear to show that risk aversion plays a statistically important role in behavior. Lybbert and Bell (2010) found that risk aversion increased the likelihood of choosing a drought tolerant variety over status quo and that more loss averse individuals are more likely to choose drought tolerant varieties as well. Ward and Singh (2015) find that increasing risk aversion and increasing loss aversion increase the likelihood of adopting drought tolerant seeds, with ambiguity aversion having limited effect.

Learning and Social Networks

As explained in their extensive early review Feder, Just, and Zilberman (1985), learning processes, farmer ability, and extension efforts in understanding adoption process will figure prominently in adoption. As early as Rogers (1962), it was noted that the process of adoption must first begin with an awareness of a technology, and of course then farmers must learn about the technology, experiment with it, assess it, and determine its appropriateness. In outlining this process, Lindner, Pardey, and Jarrett (1982) make clear that the three important questions in the technology adoption process include: (1) How and when to individuals gain an awareness of a technology? (2) What is the individual's capacity to understand and attitude toward adoption, and (3) How does an individual learn about the use of the technology as well as the potential value of use of such a technology?

As to the first question, individuals may learn of the technology from extension agents or be directly exposed to the technology by neighbors and friends. Doss (2006) cites several studies that measure extension visits as (1) whether or not a farmer received extension visits in a particular period and (2) whether the farmer attended a demonstration and acknowledges their role in affecting farmer decisions. Information coming from off the farm will come through various routes: (1) Extension agents and private sector actors (dealers), (2) Media and publications, and (3) Social networks and observation. As noted by both Feder and Slade (1984) and Lindner, Pardey, and Jarrett (1982) convenient access to information will figure prominently in adoption and changing management processes, and the role of extension is well noted in the literature, with Nkonya, Schroeder, and Norman (1997) noting its importance in fertilizer use, with a wide range of scholars finding evidence of the importance of extension agents in adoption, including Diagne and Demont (2007), Simtowe, Asfaw, and Abate (2016), Dibba et al. (2015), and Fisher et al. (2015), with the last paper specifically focused on their role in the adoption of stress tolerant varieties.

Upon exposure, however, education will influence information processing on the one hand in considering a technology or practice and reduce the potential for allocative error once adoption occurs. Both Feder and Slade (1984) and Linder, Pardey, and Jarret's (1982) examine the importance of human capital or education as acting as a possible substitute for easier access to information and positively influencing adoption where appropriate. Pitt and Sumodiningrant (1991) suggest that education may augment the skills needed in the allocation of resources, especially if a technology is complex. (Pitt and Sumodiningrat, 1991) Further supporting this observation, Feder, Just, and Zilberman (1985) cite that the literature had discovered that more educated farmers were earlier adopters perhaps because they could use the technique more efficiently, and this was further validated in the context of seed adoption (Lin, 1991).

Conditional on education, once farmers have become aware of a technology, they engage in a learning-by-doing or in learning-from-others about a process, variety, or technology. Foster and Rosenzweig (2010) remark on the broad findings of the importance of learning in the adoption of new technologies. In early work, Hiebert (1974) explains that as farmers gain more information about a technology, they gain the necessary information in order to choose adoption in a manner that minimizes possible allocative errors, but the flow of information becomes an important mechanism for this reduction in allocative error. Linder, Pardey, and Jarrett (1982) note that in the various stages of the adoption process, farmers will depend on both off-farm information and on-farm experimentation, and as Feder and Slade (1984) explain, this information gathering can occur either via a (1) costly and active process or (2) a low cost and passive process. Bandiera and Rasul (2006) then argue that farmers will then maximize expected profits from adoption or non-adoption as a result of individual and social learning, and the farmer adopts the new crop (or practice as the case may be) if the expected intertemporal profits of adoption exceed those from non-adoption.

Farmers must learn from others and by experience, and the speed of adoption depends on the capacity for on-farm learning as well as the ability to learn from others. In the context of either seed varieties or technology packages, Smale, Just, and Leathers (1994) and Smale, Heisey, and Leathers (1995) validate the role of learning processes in general. In terms of modeling the process, Foster and Rosenzweig (1995) develop models of learning-by-doing in the adoption of high yield varieties, and they show that quality of information, learning-by-doing, and learning from others all affect the rate of adoption of this technology. On farm-learning can expedite adoption especially for larger farmers who have more room for experimentation (Lindner, 1981), and forward learning behavior by some farmers can lead to learning externalities that either increase or reduce the rate of adoption by neighbors (Besley and Case, 1994). Similarly, Conley and Udry (2010) note that observation of neighbor behaviors affected use depending on farmer previous experience as well as the extent to which the observed individual share similar circumstances as the observer. In addition, Bandiera and Rasul (2006) note that information acquired by learning by doing and learning from others can serve as substitutes for one another such that farmers with better information are less sensitive to the choices of others. The role of neighborhood effects is well-documented whereby having neighbors who adopt a technology (Holloway et al. (2002)), being proximate to better trained and better informed neighbors (Islam et al. (2018), or being neighbors of individuals who received stress-tolerant seed kits (a new technology) (Yamano et al. (2018)) all appeared to be positively related to the adoption of a technology. Of some note, however, is that while many papers construct Bayesian learning models are posited as theoretical motivations for adoption processes, Barham et al. (2015) find significant heterogeneity in learning behaviors and that no one learning process better predicts the rate of adoption of GM seeds.

Cognitive Traits, Non-Cognitive Traits, and Abilities

A smaller literature explores the roles of specifically measured cognitive traits and abilities. Barham et al. (2018) explored how differing cognitive abilities and willingness to accept advice related to adoption of GM corn seeds, and they found that cognitively able individuals that were not receptive to advice were, in fact, more likely to adopt. Yamano, Rajendran, and Malabayabas (2015) note that a higher rating of self-perception increased usage of stress tolerant varieties; however, it would be difficult to disentangle the self-perception from the fact that such ratings were correlated with education, scheduled cast status, and landholding/wealth of farmers. Finally, Ayalew, Bowen, and Deininger (2019) explore how a variety of non-cognitive skills relate to the production decisions of Ghanaian rice farmers and found that work centrality appears to lower adoption likelihood, polychronicity increases adoption, and education increases likelihood (the last point echoing earlier findings in the literature). Abay, Blalock, and Behane (2017) examine the role of a person's locus of control in their technology adoption decisions, and they find that strong locus of control is predictive of farmer fertilizer, seed use, and irrigation choices. While this literature does not figure prominently, it points into another direction for future research; however, of some relevance would be considering the extent to which such factors as learning style, willingness to take advice, and other cognitive traits are correlated with other metrics such as farm size, education, age, et cetera.

Accessibility

Echoing Feder, Just, and Zilbermann (1985) on the cost of technology, Katengeza, Holden, and Lunduka (2019) and Holden and Quiggin (2017) find that access to subsidies can affect input adoption. Duflo, Kremer, and Robinson (2011) find that specialized time-limited subsidies can increase use of fertilizer in a manner consistent with the idea that farmers are present biased in their decision-making. Alene and Manyong (2006) and Shiferaw et al. (2008) find that capacity to adopt new Pigeon pea varieties is constrained by poor seed delivery systems and other access constraints. In further considering the accessibility of technologies, market channels also appear to play important roles as Bold et al. (2017) note that "lemons" problems in input markets limit the ability of farmers to learn about the true value of a technology.

Further reflecting both the capacity to obtain inputs and reach output markets, Mottaleb, Mohanty, and Nelson (2015) test the importance of sub-district level agricultural infrastructure as important factors affecting adoption of modern rice varieties in Bangladesh as do Smale et al. (2001) in considering maize varietal selection in Mexico. Finally, Suri (2011) eschews some of the earlier concerns with learning in the context of adoption and focuses on other reasons for heterogeneity, including infrastructure and finds that a substantial portion of differences in adoption can arise from differential distances from input markets.

Attributes

More specific to the adoption of a portfolio of seed varieties, an increasing literature addresses the wide variety of attributes that farmers might consider in using particular seed varieties. Lunduka, Fisher, and Snapp (2012) find that, in addition to concerns about yield and drought tolerance, Malawian farmers often consider factors such as storability, poundability, flour-to-grain ratio, and taste. Similarly, Smale et al. (2001) and Nazli and Smale (2016) find that traits associated with other factors such as consumability affect the choices of smaller farmers. Moreover, Mehar, Yamano, and Panda (2017) find that gender differences arise in varietal selection where female farmers choose rice varieties based on factors such as good taste, high cooking quality, and good straw quality in addition to traits such as stress tolerance and are much less likely to adopt based on market-oriented concerns. Finally, Xu, Yanrui, and Jingdong (2016) find that, aside from other values, farmers ex ante willingness to adopt insect-resistant rice may be affected by the health benefits associated with planting a crop that requires less pesticide use.

Assets, Land Size, Wealth, Credit, and Institutions

Farm size, wealth, and credit appears play multiple roles in the adoption process, with some aspects intrinsically linked with earlier discussions of risk. Ruttan's (1977) early survey of the adoption of Green Revolution technologies suggests that long-term differences in adoption will be muted but that adoption rates could vary by farm size of the medium term, depending on the technology. In the theoretical literature, Feder (1980) links credit-worthiness, land holdings, and risk preferences and suggests that if credit availability increases more than proportionately with land size that adoption could be more rapid among larger farmers, and both Feder and O'Mara (1981) and Just, Zilberman, and Rauser (1980) suggest that fixed costs of adoption place a greater barrier to adoption for smaller farmers. Similarly, Feder (1982) finds that the lumpiness of some technologies can hinder their adoption by smaller farmers. Just and Zilberman (1983) show that if the correlation of outputs under old and new technologies is low or negative and if the modern technology is sufficiently more risky than the traditional technology, then larger farms will devote more land in absolute terms but less in proportionate terms to new technology than will smaller firms if relative risk aversion is increasing and absolute risk aversion is decreasing in farmer's wealth.

In the empirical literature, Smale, Just, and Leathers (1994) as well as Smale, Heisey, and Leathers (1995) find evidence that input fixity is one of four key factors affecting adoption, including portfolio selection, safety-first behavior, and learning as noted above. In the U.S., Barham and Foltz (2004) find that technological complementarity plays a relevant role in this process in the dairy sector such that scale matters. In the adoption of stress-tolerant varieties context, Fisher et al. (2015) find that adoption shares are higher for farmers with larger land holdings, perhaps reflecting Lindner's (1981) reflection on greater learning and credit opportunities.

Emphasizing the concern about credit availability, Doss (2006) argues that access to credit plays an important role in technology adoption and suggests metrics for such access, including whether a farmer had received credit in the past, the size of owned land, and the value of previous year crop stocks on hand. Earlier work by Pitt and Sumodiningrant (1991) finds that credit availability increases adoption of modern varieties. Gine and Yang (2009) investigate the uptake of loans to purchase seeds and found that willingness to take such loans was reduced as a person became more risk averse, thus providing some evidence that overcoming credit availability alone would not alone overcome barriers to adoption and hearkening back to the previous points on the important role of risk preferences in the adoption process.

Adaptive Environment of Bangladesh

Bangladeshi agriculture has evolved relatively rapidly over the last several decades with the spread of modern varieties through the early and later phases of the Green Revolution. As one considers scientific and agricultural literature, some important factors are worth mentioning. First, with three traditional farming seasons (Aman, Boro, and Aus), agriculture in Bangladesh is characterized by heterogeneity across regions and agroecological zones, thus suggesting different stressors and potential solutions. Second, irrigation has grown dramatically throughout Bangladesh and largely gave rise to dramatic increases in Boro rice. Moreover, there is evidence of increased irrigation in order to shore up possible water resources during what is normally the rainy season, particularly in high salinity areas. Third, while a variety of new stress tolerant varieties have been developed, there are several other alternative crops appropriate for more stressed environments, and several traditional varieties have been known to withstand some degree of stress. To that end, we briefly review the heterogeneity of planting practices, explain the role of irrigation as a potential risk reducer (and enhancer as water resources decline in some areas), summarize and discuss the wide variety of seeds available and used both local varieties and modern varieties. Finally, we discuss the alternative choices that farmers have after experiencing stresses.

Heterogeneity of Regions

The risks faced by Bangladeshi farmers are as diverse as the geography of the country. As explained by Nasim et al. (2017), in the high and medium uplands, water scarcity is common, and the vast lowland areas are more prone to flood. In addition, the nutrient rich *haor* in northwestern Bangladesh are especially subject to flooding in the monsoon season but are important productive areas in dry seasons. Nasim et al. (2017) describe three major types of agricultural ecosystems: irrigated ecosystems (subject to flooding and drought), deep water ecosystems (only cultivable during the dry season and even then subject to flooding), and freshwater and saltwater tidal regions (subject to flooding, drought, and in the latter case, salinity, either through salinity build up in soils in off-season floods or through saltwater infiltration into wells). Within each system, agricultural experience will be highly dependent on precipitation patterns, and each farmer's experience depending on the exact nature of their landholding.

Given these varied conditions, farmers have adapted their planting patterns. In the dry Boro season, rice is regularly planted in irrigated areas, while transplanted Aman rice is grown in the rainfed lowlands and tidal wetlands during the monsoon period. Traditionally, Aus rice had been planted in the period between the wet and dry seasons in the rainfed uplands, but such planting has fallen as dry season Boro rice has increased in use and fallow or other alternative crops are planted in the traditional Aus season. Finally, a small share of rice is grown in the deep-water rice ecosystem via broadcast methods known as B. Aman rice. (Nassim et al., 2017).

Irrigation Growth

While discussed in more detail in the context of the data, the Bangladesh Rice Research Institute and the Bangladesh Institute of Nuclear Agriculture have introduced stress-tolerant varieties including various submergent tolerant varieties (BRRI dhan 51, BRRI dhan 52, Bina dhan 11, Bina dhan 12), drought tolerant varieties (BRRI dhan 56), and salt tolerant varieties

(Bina dhan 8 and Bina dhan 10). BRRI (2012, 2018) reports the extent to which these varieties can withstand such stressors and thus could reduce the extent of the risk faced by farmers. However, in terms of adoption behavior, some evidence suggests that some local landraces in Bangladesh (BRRI, 2012, Rahman et al. (2016), Ali et al. (2016), Rahman et al. (2019), Yesmin et al. (2014)) already have some tolerances to abiotic stress such as flooding/submergence, drought, and soil salinity, thus perhaps attenuating the demand for newly released stress tolerant varieties in the short run.

In terms of changing behaviors, technology, and adoption due to climate-related changes more generally, Kabir, Alauddin, and Crimp (2017) examined the changing dynamics of farm management and cropping practices as a result of changing climate conditions in western Bangladesh. Notwithstanding Gupta et al's (2015) evidence on the increasing salinity of coastal regions of Bangladesh, few, if any papers, have considered in depth the adoption of saline tolerant seed varieties. As salinity is likely to be an increasing and significant stressor to crops over the coming decades, such factors will matter in farm behavior, and researchers have considered adaptive strategies. Specifically, Kabir et. al. (2018), while not exploring the adoption process, do address the general technological and farm management practices that will need to occur with increasing soil salinity. Relative to other crop stressors, understanding adoption of salinity-tolerant crops and rice seeds represents an important area of further inquiry.

Conceptual Framework

In the context of this literature and specific environment of Bangladesh, small rice farmers in Bangladesh face a unique set of challenges. As noted above, the degree to which farmers will adopt new methods, change planting patterns, or adopt new technologies will depend on (1) real and perceived changes in weather, (2) experiences of changes in weather, (3) nature and degree of risk and time preferences, (4) education and availability of information and ability to learn from others, (5) access to technologies and markets, and (6) farm size and credit availability. Important factors meriting consideration include the following: (1) historical patterns of weather and proneness toward crop stressors, (2) recent experience to crop stressors, (3) farmer perception of the extent of the possible weather or climate-related risk, and (4) how different technologies, or in this case varieties, react to stress. As a result, appropriate measures for weather patterns, recency of stress, and farmer perception could be considered as correlates with farmer adoption and adoption shares of particular technologies. Each of these would, according to the literature, then be expected to exert some influence on the adoption behaviors. Consequently, as suggested by the findings of Holden and Quiggen (2017), Katengeza, Holden, and Lunduka (2019), and Yamano et al. (2018), the adoption of stress-tolerant varieties should be positively affected by recent experiences of such stresses. At the same time, depending on the traits of modern varieties that were not bred for stress tolerance, one might expect based on Cavatassi, Lipper, and Narloch (2011) findings a declining relative share of such varieties over either landraces/local varieties or stress-tolerant varieties as stressors increase, with the caveat that in some drought prone areas, irrigation systems would largely mitigate possible risks associated with limited rainfall as suggested by the findings of Pitt and Sumodiningrat (1991).

As one considers the adoption and seed variety usage, while risk averse farmers may be less likely to adopt or use less modern varieties (Just and Pope, 1979, Hiebert, 1974, Feder, 1980), if particular seed varieties are risk-reducing, more risk averse farmers may be more likely to adopt the technology (Lindner and Fischer (1981)). Moreover, depending on whether the seed variety has greater downside risk (non stress-tolerant modern varieties) or less downside risk than the status quo would be important determinants of their adoption and adoption shares (Roumasset, 1976, Moscardi and De Janvry, 1977, Smale, Just, and Leathers, 1994). In the more recent empirical literature, the question of risk aversion and ambiguity aversion have figured prominently in understanding both crop diversification or seed adoption (Liu (2013), Asravor (2019), Ward and Singh (2015), and Warnick, Escobal, and Laszlo (2011)). In considering the models of adoption of stress tolerant varieties as well as overall crop diversity, therefore, the previous empirical findings and research suggest that increased risk aversion should increase the degree of diversification of seed varieties (and potentially whole crops) by farmers, and the adoption/use of seed varieties will depend on the degree of risk aversion and whether the crop is risk-enhancing or risk-reducing. At the same time, some literature suggests that integrating other crops or practices may also represent either complementary of substitutable risk mitigation strategies relative to adoption of new seed varieties. Of course, the degree of risk aversion and the nature of weather-related risks are not the sole limiting or accelerating factors in the adoption process, but the literature suggests it should play an important role in influencing farmers.

Given this literature, as one considers other key determinants of adoption, **basic awareness** becomes a sine qua non of adoption, but then the roles of **education, extension, learning-from-others, and learning-by-doing** become the key factors in adoption. By and large, education in general and access to extension would play positive roles in the adoption of all modern varieties (either stress tolerant or other), and then there would be questions of the sources of information and **proximity to other adopters**. Note, in the current version of this paper, we do not incorporate this but expect to in subsequent versions. Finally, in considering adoption shares, the level of previous experience, perhaps based on years of previous use would then figure in the decision of farmers. As with awareness, access to seed varieties will play a role; therefore, **distances from input supply market**, **pricing of inputs (seed varieties)**, and the local infrastructure all could play relevant roles in the adoption of new seed varieties. While we do have some data on pricing in given locations, this element is not considered in the current model. Given the above discussion, seed adoption and other adaptive strategies, like all technologies, may depend on **farm size, farmer wealth, and access to credit**. For data reasons, this paper will not consider non-cognitive traits as well as other non-market reasons such as desire for particular attributes directly in the paper, but these, to be sure would also play a role, depending on where practices reside.

In order to synthesize these findings conceptually, let us consider the planting choice of a single farmer in a given season. In the developing country context, one might consider the profit maximizing aspect of farming firm as inseparable from the consumption utility maximization of the household in large part because many farmers consume a substantial proportion of their farm output. As the farmer considers their planting choices each season, they consider their total plots available, current seed stocks (if any), their knowledge and/or experience of other seed stocks and crops, the accessibility of alternative crop or rice crop seeds, their previous experiences with weather and or other conditions (salinity) as well as their expectations of the future. Within this context, they must assess their uncertainty about new alternative relative to old alternatives against the known and or anticipate risks. Moreover, they will consider the potential future value of experimentation with newer varieties. That is, not only might they be concerned about a given season's outcome, but they could consider the potential value of gaining experience with a newer variety that might yield less risk not just in a given season but over multiple seasons/years, thus suggesting some role for time preferences in explaining farmer behavior.

Empirical Approach

In order to explore how changing weather patterns and consequently changing preferences affect planting behavior, we take a three-step approach to estimating the determinants of planting behavior, with an emphasis on the indirect effects of changing precipitation patterns. First, following Nguyen (2011) and Liebenehm and Waibel (2015), we estimate a model of household risk and time preferences using data from the 2013 survey along with measures of precipitation patterns in the five years preceding the 2013 survey.[2] We then use that model to construct estimates of risk and time preferences at the beginning of the 2016 crop year using the precipitation data in the five years preceding 2016 along with the other demographic and economic data. These predicted risk and time preferences become a measure of household risk and time preferences in the next step of our procedure.

Conceptually, the decision to plant a particular share of fields using a particular type of seed or crop in a given season proceeds in three stages. While all farmers in this sample are rice farmers, they do not all farm rice in each season, or they might not farm at all in a given season. Some of these differences arise from the fact that some areas cannot be planted or can only be planted with greater effort during certain seasons. For example, in the saline estuaries, farmers might be less able to farm during the Boro (dry) season because of the increased salinity of the estuaries, high soil salinity, and ground water salinity. Alternatively, some farmers may simply rely on rainfed-only agricultural practices. So, the first stage of each season involves a decision of whether to plant anything. At the next stage, farmers have a choice

[2] Specific details on the estimation procedures used here are relegated to Appendix 1 as this estimation is not a central focus of the research and is dealt with in greater detail in a companion paper.

between the different rice varieties to use or whether to plant some non-rice crop as well. In the final stage, for all crops for which a positive share of land will be planted, the farmer must decide what share of their acreage they will allocate to that crop.

In the first stage, the choice is strictly binary. Specifically, farmer's must assess their conditions in a given year (or perhaps over time in a region) and discern whether planting anything at all is appropriate in a given season. As discussed earlier, the wide variety of geographies and water sources can help to explain some of this in any given season. Given that a farmer is a producer in a given season, they then must decide whether to plant traditional varieties (either non-stress tolerant or stress tolerant), hybrids, modern varieties (either non-stress tolerant or stress tolerant), or plant some other crop altogether. In other recent studies, the double hurdle for understanding adoption dates attributable to Cragg (1971) has been used to explore seed technology adoption literature (Amare, Asfaw, and Shiferaw, 2012; Ricker-Gilbert, Jayne, and Chirwa, 2011; and Holden and Quiggen, 2017). However, our approach draws on triple hurdle models used by Burke et al. (2015) and Fan and Garcia (2018); however, instead of using either the log normal hurdle model of Burke et al. or the truncated normal model, the most appropriate model here as explained by Wooldridge (2010, 703-705) would be a two-limit Tobit model to account for the fact that acreage shares have high concentrations at 0 percent and 100 percent for some seed variety or crop types. Consequently, each choice of k variety represents a two-limit Tobit Model and thus represents a double hurdle model where farmers will plant 0 percent, 100 percent, or some share between 0 and 100 of their acreage in crop k. The following explains conceptually the construction of the log likelihood functions to support the estimation process.

Stage 1. $I_{1ij} = I_{1ij}(X_{1ij})$ where I_1 is an indicator that takes a value of 1 if farmer i plants anything in a given season j, and where X_{1ij} are appropriate observed characteristics of farmer i in season j.

Stage 2. The second relates to whether farmer i plants crop k in season j. Because many farmers will plant 0 percent of their acreage in crop k, and a reasonable proportion will plant 100 percent of their acreage in crop k, we confront a two-corner solution problem. If we speak of crop shares as s_{kij}, then, consistent with Wooldridge (2010, 704), our second stage model is specified as follows:

$$s_{kij}^{*} = \boldsymbol{X'_{2ij}\alpha'} + u_{kij}, u_{kij}|\boldsymbol{X'_{2ij}} \sim N(0,\sigma^2)$$

$$s_{kij} = 0 \; if \; s_{kij}^{*} \le 0$$

$$s_{kij} = s_{kij}^{*} \; if \; 0 < s_{kij}^{*} < 1$$

$$s_{kij} = 1 \; if \; s_{kij}^{*} \ge 1$$

As discussed in Fan and Garcia (2017), we describe the formulation of the probabilities and likelihood function. For the second stage, we explain in terms of the two-limit model discussed in Wooldridge (2010, 704). In Stage 1, the respective seasonal participation probabilities can be stated as follows:

(1) $\Pr(I_{1ij} = 1|\boldsymbol{X_{1ij}}) = \Phi(\boldsymbol{X'_{1ij}\beta}) \; and \; Pr(I_{1ij} = 0|\boldsymbol{X_{1ij}}) = 1 - \Phi(\boldsymbol{X'_{1ij}\beta})$

In Stage 2, the probabilities on the limits can be stated as follows:

(2.lower) $\Pr(s_{ijk} = 0, I_{1ij} = 1|\boldsymbol{X_{2ij}}, \boldsymbol{X_{1ij}}) = \Phi(\boldsymbol{X'_{1ij}\beta})\Phi(-\boldsymbol{X'_{2ij}\alpha}/\sigma)$

(2.upper) $Pr(s_{ijk} = 1, I_{1ij} = 1|\boldsymbol{X_{1ij}}, \boldsymbol{X_{2ij}}) = \Phi(\boldsymbol{X'_{1ij}\beta})(\Phi(-(1 - \boldsymbol{X'_{2ij}\alpha})/\sigma)$

In Stage 2, the interior conditional density can be written as follows:

(2.interior) $f(s_{ijk} = s_{ijk}^{*}, I_{1ij} = 1|\boldsymbol{X_{2ij}}, \boldsymbol{X_{1ij}}, 0 < s_{kij}^{*} < 1) = \Phi(\boldsymbol{X'_{1ij}\beta})\left(\frac{\varphi\left(\frac{s_{kij} - \boldsymbol{X'_{2i}}\alpha}{\sigma}\right)}{\sigma}\right)$

Based on this understanding, then the unconditional density associated with planting of crop k in season j by farmer i should be written as follows:

$$f(s_{kij}|\boldsymbol{X_{2ij}}, \boldsymbol{X_{1ij}}) = \left(1 - \Phi(\boldsymbol{X'_{1ij}\beta})\right) *$$

$$\Phi(\boldsymbol{X'_{1ij}\beta})\left\{\Phi(-\boldsymbol{X'_{2ij}\alpha}/\sigma)(\Phi(-(1 - \boldsymbol{X'_{2ij}\alpha})/\sigma)\left(\frac{\varphi\left(\frac{s_{kij} - \boldsymbol{X'_{2ij}\alpha}}{\sigma}\right)}{\sigma}\right)\right\}$$

We can specify for any observation that the triple-hurdle model for crop shares would have the following likelihood function over all observations ij:

$$L_{ij} = f\left(\boldsymbol{I}_{\boldsymbol{1ij}}, \boldsymbol{s}_{ij} \middle| \boldsymbol{\alpha}, \boldsymbol{\beta}\right) = \prod_{I_{ij}=0} \left[1 - \Phi\left(\boldsymbol{X}'_{\boldsymbol{1ij}}\boldsymbol{\beta}\right)\right] *$$

$$\prod_{I_{ij}=1} \Phi\left(\boldsymbol{X}'_{\boldsymbol{1ij}}\boldsymbol{\beta}\right) \left[\prod_{s_{ijk}=0} \Phi\left(-\boldsymbol{X}'_{\boldsymbol{2ij}}\boldsymbol{\alpha}/\sigma\right) \prod_{s_{ijk}=1} \left(\Phi\left(-(1 - \boldsymbol{X}'_{\boldsymbol{2ij}}\boldsymbol{\alpha})/\sigma\right) \prod_{s_{ijk}=s^*_{ijk}} \left(\frac{\varphi\left(\frac{s_{kij} - \boldsymbol{X}'_{\boldsymbol{2i}}\boldsymbol{\alpha}}{\sigma}\right)}{\sigma}\right)\right]$$

In order to estimate the parameters of this likelihood function, Fan and Garcia (2018) use the Roodman (2011) conditional mixed process procedure in order to achieve the triple hurdle approach. The approach allows for the model used to be conditioned on the data and allows for the suppression of equations that do not apply for specific data.

Data Sources and Construction

This paper uses the Rice Monitoring Survey (RMS) data collected by the International Rice Research Institute with funds from the Bill and Melinda Gates Foundation (RMS, 2019). The panel data includes an initial 1,485 households collected in the 2013 and 2016 planting years from 16 districts in six divisions of Bangladesh. The data set includes demographic and economic measures for each household. To control for wealth and changes in economic condition, we imputed total and non-land wealth using values for land, physical assets, and animal assets from our survey, with prices or expected values coming from the International Food Policy Research Institute's (IFPRI) Bangladesh Integrated Household Survey (Ahmed, 2013 and IFPRI, 2016).

This survey incorporated a risk and time preference elicitation element. Specifically, in order to elicit risk preferences a gamble choice game based on Binswanger (1980) and related to those used in other studies (Barr & Genicot, 2008; Cardenas & Carpenter 2013; Cameron & Shah, 2015; Eckel & Grossman, 2008) was developed. A multiple price list survey consistent with Coller and Williams (1999) was used to elicit time preferences.

In addition to this information, data associated with climate/weather risk was also match to this household data. Data from Dasgupta et al. (2015) were used to match individuals to expected proneness to salinity stress, and survey information on the proportion of land which households farm that is characterized as high land and low land measures the proneness of fields to dryness or submergence, respectively. In addition, daily precipitation data was gathered from the Climate Hazards Group Precipitation with Stations at the 0.05 arc degree level (Funk et al., 2014). This data was matched to each household based on GPS data collected at the time of the household surveys. Seasonal mean and standard deviations of this data were calculated for each year from 2007 through the first two months of 2017 to capture the end of the final planting season for the survey period. Note, the start and end of the planting season varies somewhat widely by area in Bangladesh; therefore, we adopted the widest bounds on our seasonal calculations, with Aman being measured as between July and December, Boro being measured from November through May, and Aus consisting of the months of March to August. Other approaches to measuring precipitation variability are considered in Bangladesh (Rahman et al. (2017)) and in general (Arslan et al. (2017) and Asfaw et al. (2016)). Specific metrics of changing climate calculated to permit estimation of risk and time preferences are following: (1) the deviation seasonal daily mean precipitation in the immediately preceding season from the average of the previous five years and (2) the variability of the seasonal daily coefficient of variation across the previous five years. The former permits a measure of the extent to which deviations from expected values affect preferences, and the latter captures the extent to which higher or lower variability in risk affects preferences.

Summary of Key Elements of Data

Table 1 provides the general traits of the samples. The data summarized here is only that data which is ultimately included in the final empirical specifications. The original panel of data contained 1485 households, but because the first stage required a risk and time preference elicitation, we only include households where the respondent was constant over time which leads us to have 865 households as a complete panel. Because of some omitted responses to questions on wealth or landholdings across the two sample periods, the sample was further reduced to 833 to ensure observations were matched across periods. With that preliminary information, we note that the average age rose three years, and the level of education was, for somewhat obvious reasons was unchanged at approximately six years over the period. Similarly, family size remained nearly constant at approximately 6 individuals. In addition, two areas which might signal a household's capacity to mitigate risk included irrigation and distance from output markets. Families in this survey did not re-locate between the two surveys, so the distance from output markets remained fairly constant, and irrigation use fell modestly from 77 percent to 70 percent. Given that constant prices were used, the data suggest significant increases in wealth within this sample set from approximately 630,000 Taka to 730,000 Taka. In addition, we note a wide variability in household wealth in terms of Taka[3].

We find that the mean salinity in the data is slight but that the communities within the data set range from very high salinity to no salinity. In terms of land shares in high land versus low land, it appears that despite the fact that farmers did not re-locate between the two periods, a few things might have occurred to explain the changes here. That is, both the shares in high land and the shares in low land changed, with shares in high land growing from 7% to 15% on average and shares in low land growing from approximately 30% to 50% in the same period. As these level of land assessments are self-reports, they could reflect the farmer perception during a given season. That is, given that precipitation was higher than average during the Aman and Aus season in the year previous to this survey, farmer's might have experienced more submergence and then would be more likely to assess their land as low land. At the same time, during the Boro season, conditions were modestly dryer, suggesting that farmers might perceive more of their land as high land as well.

As noted, we calculated the standard deviation of the coefficient of variation across the five years preceding the previous year. Since risk and time preferences are calculated based on experiences preceding the current planting season, no current precipitation measures are used in this estimation. In any case, this calculation should pick up how the variability of precipitation changed across the five years, controlling for mean levels of precipitation. Higher variability of this metric in some areas versus others would imply greater perceived risk of

[3] Taka denoted ৳ is the national currency of Bangladesh.

precipitation experience. Notably, the level of variability of this metric did not change substantially between the two survey periods, but it does appear to be higher in the Boro season (likely reflecting the lower mean precipitation). On the other hand, as we observe the preceding season's deviation of mean daily precipitation from the five-year average, this measure changed substantially over the two periods under consideration. In the first period, the mean daily precipitation fell across all seasons relative to five-year averages. At the same time, in the latter period, mean daily precipitation rose for the Aman and Aus seasons relative to previous years, but it fell modestly for the Boro season. While age, education, irrigation, and salinity condition will also be used in the crop shares regressions, other variables will also be used in those regressions. Specifically, measures of awareness of stress tolerant crop varieties, distance from input markets, frequency of meeting extension agents, and owned acreage are also considered as appropriate predictors.

Table 1. Summary Statistics of Variables Used in Estimation of Risk and Time Preferences

Household and Farm Characteristics	#obs	Mean	Std. Dev.	#obs	Mean	Std. Dev.
		2013/14			2016/17	
Age	833	46.62	12.03	833	49.03	12.04
Education	833	6.17	3.96	833	5.99	4.31
Family Size	833	5.61	2.10	833	5.63	2.47
Distance from Output Market	833	2.08	1.89	833	2.08	1.89
Irrigation	833	0.77	0.42	833	0.70	0.46
Ln(Total Wealth (Taka))	833	13.35	1.12	833	13.50	1.30
Salinity Index (0 None to 7 Very High)	833	0.98	1.68	833	0.98	1.68
% of Land on High Ground	833	0.07	0.19	833	0.15	0.26
% of Land on Low Ground	833	0.30	0.39	833	0.46	0.42
Stress Measures						
5-Year Seasonal Standard Deviation of Seasonal Coefficient of Variation						
		2007-2011			2010-2014	
Aman Season	833	0.19	0.09	833	0.17	0.09
Boro Season	833	0.41	0.22	833	0.46	0.24
Aus Season	833	0.11	0.06	833	0.11	0.05
Deviation of Mean Daily Precipitation in Season from 5-Year Mean Daily Precipitation						
		2012 from 2007-2011			2015 from 2010-2014	
Aman Season	833	-2.98	11.17	833	30.25	16.24
Boro Season	833	-13.45	11.00	833	-2.63	33.65
Aus Season	833	-13.45	11.00	833	25.99	6.81
Additional Variables Used in the Crop Shares Estimations (2016/2017 seasons)						
				#obs	Mean	Std. Dev.
Aware of Stress Tolerant Varieties				833	0.43	0.50
Distance from Input Markets				833	1.80	1.68
LN(Frequency of Meeting Extension Agents + 1)				833	1.69	1.42
LN(Acreage Owned + 1)				833	0.84	0.58

In Table 2, the average planting shares of the five different rice variety types[4] as well other crops and fallow land are shown for each of the three planting seasons. Of note in terms of changing average shares, we observe that the share of land planted in modern stress

[4] Note, farmers planted a wide variety (approximately 200) of modern varieties, traditional varieties, and other varieties. In consultation with experts, we categorized rice varieties among four basic categories: Stress-Tolerant Modern Varieties, regular Modern Varieties, Traditional Varieties, and Hybrids. We also had broader categories that separated stress tolerance types (flood, salinity, and submergence), but as these are relatively small proportions, we did not perform estimations with those category levels at this point.

tolerant varieties grew from 5.28% to 7.37% across the two periods, and the share in modern non-stress tolerant varieties also grew from 24.12% to 29.78%. At the same time the share planted in traditional varieties fell from 61.66% to 51.22%. In the Aus season, for those who planted anything during that season, rice planting fell with a large decline in planting in traditional varieties from 36.11% to 21.59%; while planting of Other Crops grew by 14.52 percentage points from 52.61% to 69.79%. In the Boro season, rice planting overall saw large declines in planting shares by 6.26, 5.60, and 7.31 percentage points for modern stress tolerant varieties, modern non-stress tolerant varieties, and traditional varieties, respectively. At the same time, the average planting share of other crops grew 20.46 percentage points.

Table 2. Cropping Patterns Between Survey Periods

		2013/2014			2016/2017			
	Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Change in Mean
Aman	Modern Variety - Stress Tolerant	784	5.28%	0.17	829	7.37%	0.22	2.08%
	Modern Variety - Non- Stress Tol.	784	24.12%	0.36	829	29.78%	0.40	5.67%
	Traditional Variety	784	61.66%	0.40	829	51.22%	0.43	-10.44%
	Hybrid	784	0.26%	0.04	829	1.66%	0.11	1.40%
	Other Crop	784	8.68%	0.21	829	8.85%	0.21	0.17%
	Fallow	784	0.00%	0.00	829	1.12%	0.08	1.12%
Aus	Modern Variety - Stress Tolerant	214	2.87%	0.14	329	1.58%	0.12	-1.29%
	Modern Variety - Non- Stress Tolerant	214	4.00%	0.16	329	5.18%	0.21	1.18%
	Traditional Variety	214	36.11%	0.44	329	21.59%	0.39	-14.52%
	Hybrid	214	1.36%	0.09	329	0.30%	0.06	-1.06%
	Other Crop	214	52.61%	0.47	329	68.79%	0.45	16.18%
	Fallow	214	3.05%	0.15	329	2.56%	0.11	-0.49%
Boro	Modern Variety - Stress Tolerant	604	32.10%	0.38	765	25.84%	0.38	-6.26%
	Modern Variety - Non- Stress Tolerant	604	16.59%	0.30	765	10.99%	0.26	-5.60%
	Traditional Variety	604	17.76%	0.33	765	10.45%	0.28	-7.31%
	Hybrid	604	6.47%	0.21	765	4.67%	0.18	-1.80%
	Other Crop	604	24.58%	0.35	765	45.04%	0.44	20.46%
	Fallow	604	2.50%	0.13	765	3.01%	0.14	0.51%

As explained in the method section and in Appendix 1, we estimated both risk and time preferences a function of the regressors explained. We then used those to calculate the estimated risk and time preferences using the within-sample data (i.e., the data from the 2013 survey as well as the weather data from the time periods before that), and we then used the estimated parameters from that regression to create an out-of-sample estimate of the risk and time preferences using the information from the 2016 survey as well as the weather data immediately preceding that period as discussed. As shown in Table 3, estimated risk preferences were 0.13 (highly risk averse) in 2013 on average, with the risk aversion parameter rising to 0.21 in the 2016/2017 period, suggesting a declining level of risk averse, albeit still highly risk average on average. At the same time, the average discount rate in 2013/14 was 0.75 (or 75%) with a wide range from 0.42 to 1.21, a relatively high discount rate but within reason for such methods. The average discount rate rose in 2016 to 1.16 (or 116%) again with a similarly wide range from 0.64 to 1.77. These findings would suggest that both risk aversion and time preference changed for this sample of the population.

Table 3. Estimates of Risk and Time Preferences

	Observations	Mean	Std. Dev.	Min	Max
σ (2013/14)	833	0.1289	0.0290	0.0632	0.2107
δ (2013/14)	833	0.7488	0.1428	0.4154	1.1638
σ (2016/17)	833	0.2140	0.0324	0.1152	0.3382
δ (2016/17)	833	1.1567	0.1605	0.6438	1.7655

Statement of Key Hypotheses

While we include a large number of co-variates in this particular study, and general predictions on direction have been discussed earlier. As our focus will be heavily on the effects of weather and preferences on the planting patterns of farmers, we re-iterate predictions here. This estimation process will consider the allocation of land to modern stress tolerant varieties, modern non-stress tolerant varieties, traditional varieties, hybrids (as distinct from other varieties), other crops, and share of land placed in fallow. Aside from having some land in fallow, the five cropping options represent both competing and complementary options in any given season. Modern varieties and hybrids are more resource intensive than traditional varieties as they will often require more modern inputs or irrigation relative to traditional varieties, and some seasons are better suited or more traditionally used for planting other crops. This shows up on the planting data discussed above. Given the above, modern varieties and hybrids, on average, tend to be more productive, but they also tend to be more costly in terms of inputs or in accessing seed (if the current season is the first season to use in the case of modern varieties). So, these products could be risk enhancing in some cases in an environment where climate/weather risks exist. Comparatively, however, stress-tolerant modern varieties would tend to add less risk than other modern varieties. Other crops enter as another alternative, and while farmers often planted other crops, crops like mustard as an oil seed crop has been found useful in areas subject to flash flooding (Sumon and Islam, 2013, 202), and a number of alternative crops are discussed as viable alternatives and lower risk crops in Shaw, Mallick, and Islam (2013).

In that context, and given our earlier discussion of the literature, there are two key hypotheses we will examine.

(1) Deviations in precipitation in the previous planting season would signal two possible factors of importance in decision-making: (i) a change in the expected planting environment and (ii) increased risk overall. We will not be able to identify differences between these two effects, but if increased risk corresponds with higher concern about wasted input costs, then farmers may become more likely to plant traditional varieties because while they represent higher output risk, the input risk is substantially lower. Conversely, farmers would be less prone to plant modern varieties of all kinds as well as hybrids. We remain somewhat neutral on the planting of other crops because the granularity of the exact other crops planted is not available in the data.

(2) Second, greater levels of risk aversion should correspond with a declining willingness to plant input risky crops such as all modern varieties (both stress-tolerant and not) as well as hybrids.

(3) Higher levels of patience should correspond with greater willingness to adopt modern varieties and hybrids.

Econometric Results

The methods and variables discussed above were used to estimate both the probability of planting in a given season and the planting shares. Note, because of the simultaneous estimation process using Roodman's (2011) conditional mixed process, we first present the overall regression statistics. Note, the method of estimation considered the planting of each farmer for each season in the 2016 planting year; therefore, each farmer's characteristics are matched with their planting shares in each season, yielding 2,547 observations. The Wald Chi^2 with 95 degrees of freedom was 4416.56, the Log likelihood was 1,598.06, thus providing evidence for the overall statistical significance of the regression.

Note, in the first stage Probit regression, the specification was kept quite simple to reflect the fact that the decision to plant at all in a given season in Bangladesh is largely driven by the region, the season, and the basic land type of the farmer. Otherwise, farmer's have strong incentives to plant in as many seasons as appropriate. Dummy variables for Chittagong, Dhaka, Khulna, Rajshahi, and Rangpur with Barisal being the baseline region, and dummy variables for the Boro and Aus season are included. Unsurprisingly, the probability of planting in Aus and Boro is lower than that for Aman as that season is the primary planting season throughout much of Bangladesh. In addition, as low ground is less likely to be planted during the wettest seasons and periods, we note that the share of land on low ground figures prominently in determining the probability of planting. More detailed use of the marginal effects will appear in the analysis of the complete results.

Table 4. First Stage Probit Regression – Probability of Planting in Season

	Coefficient	z	P>z	Lower Bound	Upper Bound
Aus	-2.35	-11.49	0.00	-2.76	-1.95
Boro	-0.61	-2.70	0.01	-1.04	-0.17
Chittagong	0.05	0.29	0.77	-0.28	0.38
Dhaka	-0.25	-1.60	0.11	-0.57	0.06
Khulna	0.26	1.37	0.17	-0.11	0.62
Rajshahi	-0.10	-0.60	0.55	-0.44	0.23
Ranjpur	-0.18	-1.06	0.29	-0.51	0.15
% of Land on Low Ground	-0.45	-3.22	0.00	-0.72	-0.17
Constant	2.15	8.96	0.00	1.68	2.62

Table 5 provides the key results from the estimations associated with the determinants of planting shares. One relevant methodological point is that the sum of the coefficients associated with any variable, with the exception of previous planting share, would be zero to ensure that the joint effect of the change in any one variable would ensure that total allocations summed to one. As a reminder, the key demographic data that were considered as key factors in determining planting choices were age and education. Factors picking up the capacity to adopt certain crop varieties or capturing the potential flexibility of planting include Irrigation and the natural log of land owned. Access to and knowledge of different planting possibilities are captured by the distance from input markets, the awareness of stress tolerant varieties, and the natural log for the frequency with which a household met extension workers. Factors capturing typical rates of exposure to crop stresses include the percent of land classified as lowland and the index of salinity. Recent exposure to excess precipitation in the Aman, Boro, and Aus season is captured by the deviation of mean daily precipitation in 2015 from the previous 5-year mean daily precipitation. Perhaps most importantly, we incorporate the measures of risk preferences (σ) and time preferences (δ). Given that some seasons are more amenable to planting certain types of crops, dummy variables associated with the Aus and Boro season are included in this context as well.

Table 5. Determinants of Land Use by Bangladeshi Farmers in 2016/2017

	MVST		MVNST		TV		Hybrid		Other Crop		Fallow	
	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z	Coef.	P>z
Age	-0.0001	0.92	0.0003	0.71	0.0044	0.00	-0.0014	0.00	-0.0026	0.01	-0.0006	0.08
Education	0.0050	0.01	-0.0026	0.29	-0.0140	0.00	0.0068	0.00	-0.0074	0.01	0.0099	0.00
ln(Own Acreage)	-0.0179	0.01	-0.0035	0.70	0.0130	0.16	-0.0099	0.02	0.0174	0.10	0.0009	0.79
Irrigation	0.2277	0.00	-0.0975	0.00	0.3052	0.00	-0.0408	0.00	-0.3854	0.00	0.0262	0.01
Distance Input Mkt.	0.0010	0.81	-0.0006	0.91	0.0139	0.01	0.0006	0.80	-0.0161	0.01	0.0012	0.55
Aware ST Varieties	0.0119	0.35	0.0462	0.01	-0.0190	0.25	-0.0145	0.05	-0.0283	0.14	0.0038	0.55
ln(Extension)	0.0043	0.35	0.0013	0.83	0.0250	0.00	0.0016	0.54	-0.0340	0.00	0.0019	0.39
Salinity Index	-0.0092	0.05	0.0052	0.38	0.0284	0.00	-0.0187	0.00	-0.0057	0.41	0.0000	0.98
% of Land Classified as Low	-0.0070	0.71	-0.1234	0.00	0.1588	0.00	-0.0453	0.00	-0.0093	0.74	-0.0092	0.41
Deviation of Mean Daily Precipitation in Season from 5-Year Mean Daily Precipitation												
Aman	-0.0002	0.90	0.0012	0.49	0.0028	0.11	-0.0004	0.65	-0.0034	0.09	-0.0001	0.86
Boro	-0.0025	0.00	0.0004	0.69	0.0069	0.00	-0.0027	0.00	-0.0022	0.07	0.0000	0.93
Aus	-0.0060	0.00	0.0008	0.73	0.0188	0.00	-0.0069	0.00	-0.0053	0.03	-0.0013	0.11
σ	20.9661	0.00	-10.7359	0.19	-12.4662	0.13	10.9685	0.00	-10.7331	0.26	2.0006	0.53
δ	-4.1072	0.00	2.2682	0.18	0.6792	0.69	-1.4636	0.05	3.1161	0.11	-0.4928	0.45
Past Planting Share	0.3690	0.00	0.1880	0.00	0.2113	0.00	0.4392	0.00	0.3877	0.00		
Aus Season	-0.0553	0.00	-0.5330	0.00	-0.0712	0.00	0.0376	0.00	0.6091	0.00	0.0129	0.13
Boro Season	0.1092	0.00	-0.1910	0.00	-0.3341	0.00	0.0133	0.08	0.3803	0.00	-0.0010	0.88
Constant	2.4217	0.00	-1.2521	0.23	1.2434	0.24	0.2673	0.57	-2.3350	0.05	0.4346	0.28

For completeness, Appendix 2 discusses the other relevant coefficients, but as the direct and indirect effects of precipitation the following will highlight only the findings related to changing weather patterns and in the risk and time preferences of farmers. One important caveat in interpreting the findings on risk and time preferences is that these two variables are quite highly correlated; therefore, the net effect of the two would ultimately be of greatest interest. In any case, we observe that greater than normal precipitation had no statistically significant bearing on the planting shares during the Aman season. The Aman season is the wettest season; therefore, high levels are generally predicted; therefore, greater than normal levels (as occurred on average in that period) would not necessarily have a major impact. On the other hand, it is of some interest that deviations from normal precipitation in the previous Boro season had a negative and statistically significant effect on planting shares of stress-tolerant and hybrid varieties in that season, while the relationship with traditional varieties was positive. These effects are relatively modest; however. Given the mean deviation for the Boro season of -2.63, this would imply an average planting share increase of 0.66 percent and 0.72 percent for stress-tolerant modern varieties and hybrid varieties, respectively, and the reduction in traditional varieties of 1.83 percent. In the Aus season and given the smaller number of individuals farming during that season, we observe similar relationships for stress-tolerant modern varieties, hybrids, and traditional varieties in terms of signs and significance. Notably, in this particular case, the impact on other crops is negative and statistically significant. Given the large deviation in mean precipitation in 2015 from the mean of the previous years and leaving all other factors changed, these results imply that planting shares would have fallen by 15.6%, 17.9%, and 13.8% respectively for stress-tolerant modern varieties, hybrids, and other crops while planting shares for traditional varieties would have grown by 49%. These capture the direct effects of weather on planting shares.

The effects of risk preferences and time preferences are large and statistically significant for stress-tolerant modern varieties and hybrids but appear to have no statistical effect in other cases. These results are similar for time preferences. As noted above, the predicted values for risk and time preferences are strongly positively correlated with a Pearson correlation coefficient of 0.9986, thus while we show both results in this version of the paper, it seems likely that the estimated values are picking up the same aspects of an individuals preferences. Nonetheless, if we note that δ is a linear function of σ, we can more accurately capture the economic impact of differences in preferences on planting shares. Performing a simple OLS, we find that the estimated value of δ is 0.615 + 4.96*σ. Using this formulation, we can infer how changing risk preferences and time preferences would affect the planting shares where they are significant in a statistical sense (i.e., for stress-tolerant modern varieties and hybrids). Specifically, as risk preferences increase in 0.05 increments from 0.10 to 0.15 to 0.2, the corresponding time preferences are 1.11, 1.36, 1.61. For each incremental change, the increase in share planted in stress tolerant modern varieties would be 2.97% and the increase in share planted in hybrid varieties would be 18.55%. That is, as individuals become more risk preferring and more patient, their willingness to increase planting shares in stress-tolerant varieties and hybrids is positive and relevant.

At the same time, these risk and time preferences are determined, in part, by the changing weather patterns; therefore, in order to demonstrate the indirect effects of changing weather on planting shares, we note that the statistically significant coefficients in the estimation of risk preferences show that for the Aman and Aus seasons, a one mm increase in seasonal mean precipitation above the mean precipitation in the previous five seasons would cause the risk coefficient to decline by 0.005 or rise by 0.003, respectively. Considering the 2014/2015 season where the daily precipitation was 30.25 mm higher for the Aman season and approximately 26 mm higher in the Aus season, we observe that the net effect on risk preferences would be to cause σ to fall by 0.073 units. That is, individuals would become more risk averse. This would imply that δ would fall by 0.363 units and thus individuals would become more patient.   Holding all other factors constant, the indirect effects of weather on preferences and then on planting shares would be for shares of stress tolerant modern varieties to fall by 4.34% and for hybrid planting to fall by 27.08% on average and not conditional on season. Of some note here is that the deviation in precipitation alone has no direct effect on planting in the Aman season, but we do observe that such changes affect planting shares in that season through the mechanism of changing risk and time preferences. At the same time, we observe that the effect of increased precipitation in the preceding Aus season had a direct and depressing effect on stress-tolerant modern varieties and hybrids which would have been compounded by the indirect effect of such precipitation on risk and time preferences. The indirect effects are smaller but nonetheless of reasonable magnitudes.

Conclusions

This paper has attempted to address direct and indirect effects if precipitation patterns on farmer planting shares in Bangladesh. Specifically, the paper employs a two-stage estimation process to arrive at these results. In the first stage, the paper estimates farmer risk and time preferences as a function of relevant covariates, with specific emphasis on weather covariates across the three key planting seasons in Bangladesh. Using these results, farmer risk and time preferences were estimated to be used in the second stage where farmer planting patterns were estimated. In this second stage process, Roodman's (2011) conditional mixed process is used to estimate a double hurdle model where the first hurdle is a Probit model of whether a farmer plants anything in a season and the second stage is a two-limit Tobit model where the planting shares of modern varieties (both stress tolerant and non-stress tolerant), traditional varieties, hybrids, other crops, and fallow choices are estimated with appropriate coefficient constraints.

The key findings are that deviations from seasonal averages increase risk aversion among farmers and that increased risk aversion among farmers reduces planting shares of stress-tolerant modern varieties as well as hybrids. This indirect effect holds across all seasons. The direct effects of precipitation deviations compound the indirect effects for the Aus season but offset the effects of the Boro season. Precipitation deviations have no direct impact on planting shares of stress-tolerant modern varieties during the Aman season. The contribution of this paper to the conversation on the role of changing weather and climate on farmer behavior and adaptation is its focus on identifying the direct and indirect mechanisms that may affect farmer adaptations. The significance of the contribution is that it shows that not only do risk and time preferences shape planting and adaptation patterns but that the interplay between changing environmental experiences and preferences implies that as weather patterns continue to evolve and change, the reactions to such changes in farmer's behavior will not be static. That is, because the preferences themselves change in response to changing weather patterns, then the reaction to changing weather in terms of planting behavior itself will be different between two periods even if the marginal change in weather is the same at each point in time. These may complicate the dynamics of adaptations and require adjusting incentives and inducements to adapt.

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Appendix 1. Empirical Methods for Risk Estimation

In order to estimate the relationship between observable traits, wealth, and reported or measured stressors and the households risk and time preferences, this paper will employ the approach articulated by Liebenehm and Waibel (2014) and Nguyen (2011) to estimate the effects of changes on climactic stress on risk and time preferences. This method recognizes Andersen et al's (2008) argument that estimating time preferences separately from risk preferences may affect the estimates of individuals measured time preference. Let x be some immediate payment and y be some payment to be received in the future and where D represents some function of the vector of discount parameters Γ and the delay in time is t. When one finds the discount function by solving the following equation: $x = D(\Gamma, t)*y$, one assumes that individuals are not considering potential risk of receiving some reward by some future date. Both Nguyen (2011) and Liebenehm and Waibel (2014) propose that it may be appropriate to derive the estimates such that $U(x) = D(\Gamma, t)*U(y)$ so that, if a person's risk preferences are embedded in their utility function, then one can gain a more appropriate measure of individual discounts on money.

The following discussion adheres to the explanations provided by Liebenehm and Waibel (2014) and Nguyen (2011). Before explaining this model in greater detail, we make a brief aside on the empirical approach taken here. In our experimental elicitation procedure, there were two activities where individuals were asked their preferences of risk opportunities and about their level of willingness to delay risks. In the risk preference elicitation, individuals were asked which prospect they preferred among five possible prospects. These options were ordered in terms of riskiness, ranging from a certain reward to increasingly risky opportunities. While Liebenehm and Waibel (2014) and Nguyen (2011) presented a larger number of purely binary options to respondents, they enforced monotonic switching in the decision process. For example, in their first risk elicitation activity these authors presented individuals with 14 pairs of options A and B where option A remained constant over the range of pairs and option B became increasingly risky. Individuals were permitted to choose all A, all B, or switch from A to B at a single time. This sequence of choices became a binary variable in their econometric method. As we apply this econometric method, we treat the five risk options as if they were a series of four comparisons between A and B so that if a person preferred the certain option to the next less certain option, then transitivity would imply that they preferred that option to all others as well. For the time preference elicitation in this survey, individuals were given the opportunity of choosing between a delayed reward with a delay of one year or an immediate reward. While much less variability in delay and reward values occurred as a result of the original survey design, this elicitation process more closely aligns with those used in Liebenehm and Waibel (2014), thus no modifications are required in this element of the study.

We now explain the empirical approach taken. If the individual chooses A, they receive an instantaneous utility of U(A), and if the person chooses to receive B, they receive an instantaneous utility of U(B) and the discounted utility of D(Γ, t)*U(B). For estimation purposes, as explained by Nguyen (2011), we must assume a utility function as part of the random utility function approach to estimation. Let V be the assumed utility function, and let D be the assumed discount function. In the final estimation, the extent of errors will be greater or lesser depending on the proximity of the assumed function to the individual's true function. In this project, V is assumed to follow a simple utility function that aligns well with multiple models of utility (i.e., $V(x) = x^{\alpha}$). Let Z_i be the economic and demographic characteristics of individual i. As will be explained further later, the exponential model with a fixed cost present bias is used for the D function. In addition, denote U_i^{Aj} and U_i^{Bj} as the utilities that individual i receives when faced with choice j. In theory, for any given sequence of selections, it is assumed that error terms ε_i^{Aj} and ε_i^{Bj} are identically and independently distributed across individuals such that $\{\varepsilon_1^{Aj}, \varepsilon_2^{Aj}, \varepsilon_3^{Aj}, \dots, \varepsilon_N^{Aj}\}$ are independently and identically distributed (i.i.d.) and follow a normal distribution, and $\{\varepsilon_1^{Bj}, \varepsilon_2^{Bj}, \varepsilon_3^{Bj}, \dots, \varepsilon_N^{Bj}\}$ are independently and identically (i.i.d.) and follow a normal distribution.

For the risk experiments, we can summarize the relevant utilities as follows:

$$U_i^{Aj} = V_i^j\big((A_j, p); Z_i\big) + \varepsilon_i^{Aj} \qquad (1)$$

$$U_i^{Bj} = V_i^j\big(B_j, (1-p); Z_i\big) + \varepsilon_i^{Bj} \qquad (2)$$

For the time experiments, we can summarize the relevant utilities as follows:

$$U_i^{Aj} = V_i^j\big(A_j; Z_i\big) + \varepsilon_i^{Aj} \qquad (3)$$

$$U_i^{Bj} = D_i(\Gamma; t; Z_i) V_i^j(B; t; Z_i) + \varepsilon_i^{Bj} \qquad (4)$$

Given the distribution of error terms, let the joint density of the distribution of errors across individuals be written as follows f(ε). As explained in Nguyen (2011), we derive the likelihood function as follows for the case of intertemporal choice, but this approach applies with very slight notational modifications to the choices under uncertainty as well. Let the probability that the agent chooses option A be the following.

$$\Pr(A) = \Pr\,(U_i^{Aj} - U_i^{Bj} \geq 0)$$

$$= Pr\{V_i^j(A_j; Z_i) + \varepsilon_i^{Aj} - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) - \varepsilon_i^{Bj} \geq 0\} \quad (5)$$

This expression can be modified to be restated as follows:

$$\Pr(A) = Pr\{V_i^j(A_j; Z_i) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) \geq \varepsilon_i^{Bj} - \varepsilon_i^{Aj}\} \quad (6)$$

As a result, the probability that the person chooses A can be determined by the cumulative distribution of the error term $\Phi(x) = \int_x f(\varepsilon)d\,\varepsilon$ and can be stated as follows

$$\Pr(A) = Pr\big(V_i^j(A_j; Z_i) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i)\,\big) \quad (7)$$

Following on that, we can define the latent option for A and B in each scenario j as follows.

$$I_i^{Aj} = V_i^j(A_j; Z_i) - D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) \quad (8)$$

$$I_i^{Bj} = D_i\ (\Gamma; t; Z_i)V_i^j(B; t; Z_i) - V_i^j(A_j; Z_i) \quad (9)$$

From this, we can speak of $\Pr(A) = \Phi(I_i^{Aj})$ and $\Pr(B) = \Phi(I_i^{Bj})$. To apply the maximum log-likelihood estimation technique, we note that the log-likelihood for each individual depends on the utility function parameters (α) under expected utility theory and (δ, κ) under the exponential time discounting function with a fixed cost present bias component. As explained by Liebenehm and Waibel (2014), the utility of each lottery pair in scenario j can be expressed as a latent index $I_i^j(\Delta U) = U_i^{Bj} - U_i^{Aj}$, and this latent index for individual i and choice j is linked to the observed binary choices (or in our case, the constructed binary choice for risk and observed for time) made by survey respondents in the experiments through the standard cumulative distribution function $\Phi(I_i^j)$. In order to permit the statement of the likelihood, assume that Z_j corresponds with the relevant choice-based information (i.e., time and payoffs for the time-based choices and probabilities and payoffs for the risk-based choices). If $y_i^j = 1$ then individual i has chosen option A in scenario j and when $y_i^j = 0$ then individual i has chosen option B in scenario j. Given that statement, we express the log likelihood function as follows.

$$lnL^i \ (\alpha, \delta, \kappa; y^j, X_i, Z^j) = \sum_{j=1}^{14} \{[ln\varphi(I_i^{Aj})|y_i^j = 1] + [ln\varphi(I_i^{Bj})|y_i^j = 0]\} \qquad (10)$$

For a given agent i, likelihood is maximized over the 14 choices that individuals made during the experimental rounds (four in Activity 1 and ten in Activity 2). The procedure used was a modified version of code developed by Liebenehm and Waibel (2014).

While estimation of the constant relative risk aversion parameter estimation is common in such settings, we assume, as with Nguyen (2011) and Liebenehm and Waibel (2014), that the value or utility function takes a much simpler form such that the utility of some value x can be written as $V(x) = x^\sigma$, where σ represents the degree of risk aversion of the individual. Unlike other studies, our survey approach does not permit a nesting of this within the context of cumulative prospect theory. The estimation method also permits the consideration of multiple discounting models (exponential, quasi-hyperbolic, and a fixed-cost present bias model), but given the relative simplicity of our elicitation procedures relative to the above authors, we only consider the exponential discounting model. We first estimate without controls for observable characteristics of individuals is as follows where σ represents the risk preference parameter and δ represents the discount rate. The parameter estimates should all take a positive value in theory.

$$U = e^{-\delta t} * x^\sigma \qquad (11)$$

After performing the baseline regression, we use the estimated parameters as the initial values when performing the maximum likelihood estimation of the parameters as a function of the individuals observed characteristics, reported experiences, and measured precipitation experiences.

We implemented this estimation method with multiple alternative specifications, and we present four key models from this exercise. Note, wherever the model converged (even for those models not shown here), the key findings are largely robust. Table 3 summarizes the common variables used and the model specific variables. Model 1.1 includes respondent opinion of submergence, drought, and salinity as a problem. Self-reported stress measures may lead to a reverse causality problem (Liebenehm, 2018) in the estimation of risk and time preferences because individuals who claim greater problems with such stressors might, in fact, be more risk averse and thus more attuned to risk, but as a comparison tool, we include it.

Three measures in the regression control for, to some extent, farmer's ability to mitigate risk or a measure of their most recent experience of a change in such ability to cope. Specifically, farmer's total current wealth affects and provides some insurance against risk. Similarly, whether a farmer has an irrigation system can act as insurance against risk and allows longer cropping time horizon, but it is obviously the case that farmers with greater degrees of risk aversion and more patience might well be more likely to purchase the equipment necessary for irrigation if they are able. We include distance from the nearest output markets to reflect a farmer's ability to mitigate the risk of lost crops due to stressors. That is, if a farmer is closer to an output market, they may have less risk because they have easier access to supplementary supplies, credit, and other resources should they have shortfalls in crops due to a crop stressor. It also likely reflects some possibility for access to alternative income sources. Other regressors such as age, education, and family size are common in such methods and act as proper controls on observable differences in individuals. Measures of stress proneness include the local measure of salinity, the share of land on low ground, and the share of land on high ground. The first captures proneness to damage from salinity, the second captures proneness toward submergence, and the third captures proneness toward excessive dryness. Including such metrics allow for the fact that individuals experience of risk and need to exercise tolerance for risk and patience may well be conditioned by such factors. Finally, the measures discussed earlier that capture farmer recent experience of changing conditions as measured by the standard deviation in the seasonal coefficient of variation as well as the preceding season deviation from the longer-term mean level of precipitation captures how larger deviations may affect preferences.

Appendix Table 1. Stage 1 Parameter Estimates of Risk Preferences Using Attributes and Weather Experiences Preceding 2013/14 Survey

	Coefficient	p	95% Confidence Interval Lower Bound	Upper Bound
σ (Risk Preference)				
Constant	0.328	0.000	0.215	0.440
Age	0.001	0.139	0.000	0.001
Education	0.001	0.398	-0.001	0.003
Family Size	0.001	0.615	-0.003	0.005
Distance from Output Markets	0.001	0.768	-0.004	0.005
Irrigation	-0.004	0.752	-0.026	0.019
Salinity Index	-0.008	0.016	-0.014	-0.001
% of Land Classified as High	0.049	0.006	0.014	0.083
% of Land Classified as Low	0.019	0.101	-0.004	0.042
Ln(Total Wealth + 1)	-0.004	0.260	-0.010	0.003
5-Year Seasonal Standard Deviation of Seasonal Coefficient of Variation				
Aman	-0.025	0.729	-0.164	0.115
Aus	-0.121	0.154	-0.287	0.045
Boro	-0.158	0.000	-0.224	-0.092
Deviation of Mean Daily Precipitation in Season from 5-Year Mean Daily Precipitation				
Aman	-0.005	0.000	-0.006	-0.003
Aus	0.003	0.011	0.001	0.005
Boro	0.001	0.270	-0.001	0.002
Wald chi2(15)	81.21			
Log pseudolikelihood	-5895.26			
Prob > chi2	0			
Standard Adjusted for Clusters at the Household ID Level				

Appendix Table 2. Stage 1 Parameter Estimates of Time Preferences Using Attributes and Weather Experiences Preceding 2013/14 Survey

			95% Confidence Interval	
	Coefficient	p	Lower Bound	Upper Bound
δ (Time Preference)				
Constant	0.867	0.003	0.304	1.429
Age	0.005	0.008	0.001	0.009
Education	-0.008	0.191	-0.019	0.004
Family Size	0.001	0.931	-0.021	0.023
Distance from Output Markets	0.006	0.643	-0.019	0.030
Irrigation	-0.056	0.416	-0.190	0.079
Salinity Index	-0.049	0.002	-0.080	-0.017
% of Land Classifed as High	0.146	0.113	-0.035	0.328
% of Land Classified as Low	0.061	0.331	-0.062	0.185
Ln(Total Wealth + 1)	0.010	0.579	-0.026	0.046
5-Year Seasonal Standard Deviation of Seasonal Coefficient of Variation				
Aman	0.606	0.058	-0.020	1.232
Aus	-2.042	0.000	-2.912	-1.171
Boro	-0.815	0.000	-1.118	-0.512
Deviation of Mean Daily Precipitation in Season from 5-Year Mean Daily Precipitation				
Aman	-0.019	0.000	-0.029	-0.010
Aus	0.005	0.327	-0.005	0.015
Boro	0.001	0.683	-0.005	0.008

Appendix 2. Examining Additional Covariates in Planting Share Estimation

The literature suggests that education, experience, and information should play relevant roles in the adoption of new technologies or changes in practice. The role of age is likely somewhat ambiguous because it could cause increased innovation at certain stages of experience but may correspond with less willingness to change practices at other stages of life. If the use of stress tolerant modern varieties, modern varieties of any kind, and hybrids are considered more innovative, then age could lead to declining usage the latter effect dominates. Similarly, given that Other Crops could be considered as additional coping technologies arising from greater risk in the environment, this could also be considered similarly innovative. The shares of modern varieties are not statistically affected by age. At the same time, however, age corresponds with increased usage of traditional varieties and decreased planting of hybrids and other crops. Alternatively, education should be related to increased willingness to innovate and use modern varieties and hybrids, and at least in terms of sign, this holds true with the exception of non-stress tolerant modern varieties. Nonetheless, greater education corresponds with lower use of traditional varieties.

Large land acreage should correspond with a greater willingness to experiment with newer crop varieties, but the results do not support that and suggest that planting of modern stress-tolerant varieties and hybrids would in fact be lower on such farms.

An awareness of stress tolerant varieties has a modestly positive but not statistically significant effect on the planting share of stress tolerant varieties. At the same time, and to some extent, contrary to expectation, a higher salinity index corresponds with a lower planting share of stress tolerant varieties. That being said, the effect is also negative for hybrids, but the effect is relatively large, positive, and statistically significant for traditional varieties. Notably, because some landraces have some stress tolerance, this increase may reflect (1) that existing stress tolerance and (2) the fact that the inputs are cheaper and thus less input cost is at risk if the salinity is not sufficiently diluted by rains. Shares of land considered to be lowland corresponds with a negative planting share for all crops except for traditional varieties, and this effect is statistically significant for non-stress tolerant and hybrid varieties. The end result is that for individuals with large shares of land that are more submergent prone, they would plant an economically significantly large share of land in traditional varieties. The mean share of land measured as lowland was 0.46 (or 46%). Given the coefficient size of 0.1588, that would imply a 7.3% larger share of land planted in traditional varieties than someone who had no lowland.

Because habit-formation and past planting behaviors, the share of land planted in a specific crop should be positively related to the share planted in the earlier survey period, and the results seem to support this.