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Evidence from a Multiyear Field Experiment in India

Patrick S. Ward

Simrin Makhija

David J. Spielman

Environment and Production Technology Division

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AUTHORS

Patrick S. Ward (p.ward@cgiar.org) is a research fellow in the Environment and Production Technology Division of International Food Policy Research Institute (IFPRI), Washington, DC.

Simrin Makhija (s.makhija@cgiar.org) is a research analyst in the Environment and Production Technology Division of IFPRI, Washington, DC.

David J. Spielman (d.spielman@cgiar.org) is a senior research fellow in the Environment and Production Technology Division of IFPRI, Washington, DC.

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Drought-Tolerant Rice, Weather Index Insurance, and Comprehensive Risk Management for Smallholders: Evidence from a Multiyear Field Experiment in India

Patrick S. Ward[1], Simrin Makhija[1], and David J. Spielman[1]

[1] *Environment and Production Technology Division, International Food Policy Research Institute, Washington, DC, USA*

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Abstract

In rainfed production systems throughout India, agricultural activities are intimately tied to the summer monsoon, and any aberration in monsoon rainfall patterns—late onset or early cessation of rainfall, prolonged dry spells, or flooding—can have severe consequences for rice production. There is considerable public policy interest in designing programs to lower small-scale farmers' exposure to these types of risk given the regularity with which adverse monsoon events occur. This paper introduces a field experiment conducted with two risk–management options in the state of Odisha: a drought-tolerant (DT) rice cultivar and a weather index insurance (WII) product designed to complement the performance profile of the DT cultivar. Uptake rates for the DT cultivar itself and for the joint DT-WII product are compared across two years alongside an analysis of factors that predict uptake. Results indicate high demand for both the DT cultivar and the DT-WII product, albeit with a significant degree of price sensitivity. Sustained demand between the first and second years of the experiment is primarily explained by policyholders' receipt of a payout in year one and a large number of within-village peers also purchasing the product. Results also indicate that the withdrawal of discounts introduced in year one did not affect demand significantly in year two, providing some of the first evidence of moderate uptake of WII at rates at or above the actuarially fair cost.

JEL classification: O12, O13, Q12, G22

Keywords: Index insurance, drought tolerance, risk and uncertainty, agriculture, India

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1 Introduction

Reliance on the vagaries of the summer monsoon is an omnipresent risk for rainfed agricultural production in India. Delayed onset or early cessation of the monsoon, prolonged dry spells during the season, low overall volume of rainfall, or excessive rainfall resulting in floods can all affect crop cultivation by reducing both total cultivated area and yields. At the farm and household levels, the risks associated with reliance on the monsoons can also drive smallholder farmers toward more conservative farming practices, underinvestment in the use of modern inputs, sub-optimal livelihood strategies, and long-term poverty traps (Hansen et al. 2004; Elbers, Gunning, and Kinsey 2007; Hill 2009; Shiferaw et al. 2014; Emerick et al. 2016). At the national level, these risks can negatively affect rice production, prices, and food consumption across the country.

Among the myriad production risks faced by farmers in rainfed geographies in India, droughts pose perhaps the greatest threat. Estimates suggest that more than 70 percent of crop losses in India from 1985 to 2002 were attributable to droughts (Parchure 2002). Yet droughts are very complex phenomena, making them difficult to mitigate with improved cultivars, agronomic practices, or financial instruments. The challenge to managing drought risk begins with the difficulty in defining drought. Contrary to popular belief, droughts are more than just periods of inadequate rainfall, although this is a key contributing factor. Other factors include sustained high temperatures; high evapotranspiration rates via soils and plants; and other meteorological, hydrological, and biological variables. Similarly, the impacts of droughts on farm production and farmers' livelihoods require careful characterization. These impacts can be classified into two categories (Hansen et al. 2004): ex post and ex ante impacts. Ex post impacts are typically tangible and relatively straightforward: losses to crop and livestock production, degradation of natural resources such as soil and water, and depletion of household assets required to smooth consumption and manage the economic shocks associated with lost farm income. In many cases, particularly when food supplies are not managed properly, there is often a need for emergency food aid or other government handouts to ameliorate these food security impacts, which can exacerbate their effects by straining government coffers. Ex ante impacts are less visible—but arguably no less pernicious—impacts resulting from household decisions to avail lower-risk, lower-return production and livelihood strategies that can dramatically reduce the growth of their long-term income and welfare trajectories. Elbers, Gunning, and Kinsey (2007) estimated that the combined (ex ante and ex post) impact of drought is a reduction in long-term capital accumulation of roughly 50 percent, with nearly two-thirds of this reduction directly attributable to ex ante effects.

Given the magnitude of the impacts associated with drought risk, there is considerable interest among public policy makers in India and the broader development community in identifying strategies to help farmers effectively manage drought risk. India's public agricultural research and extension system and its international counterparts have invested considerable resources during the past decade in breeding and distributing improved cultivars—particularly rice cultivars—that can withstand prolonged periods of drought (for example, Pandey et al. 2012). They have also advanced crop and resource management practices such as zero-tillage wheat cultivation and directly seeded rice to reduce groundwater extraction, retain residual soil moisture, and mitigate the impact of droughts (Erenstein et al. 2007).

There has been considerable interest in expanding the coverage of agricultural insurance within India. India has a long history with agricultural insurance, dating back to at least 1920. The largest program, a yield index–based crop insurance program known as the National Agricultural Insurance Scheme, was introduced in 1999 and has grown to become the largest crop insurance program in the world, with more than 25 million participating farmers (World Bank 2012). Yet despite its size, the program covers fewer than approximately one-fifth of the farmers in the country (Nair 2010a).[1] Considerable issues remain, as well, with the design of these insurance policies, their integration with credit provision, land titles and other program requirements, and the extensive subsidy element required to make them marketable to smallholders. Furthermore, this program has been subject to considerable criticism for its reliance on crop cutting experiments as the basis for issuing payments, an exercise that significantly delays the claim settlement process.

Other programs, such as the Weather-Based Crop Insurance Scheme (WBCIS), have also been introduced. Because WBCIS is based on weather measurements instead of yield estimates from

[1] Farmers' insurance uptake varies considerably by state. According to 2013 data from the Agricultural Insurance Company of India, nearly 30 percent of farmers in Odisha held crop insurance covering kharif (monsoon)–season crops, compared with just 8 percent of farmers in Bihar and 4 percent in Uttar Pradesh.

crop cutting experiments, insured farmers have access to more timely indemnity payments. But despite the existence of these various programs, coverage has remained low, with only about 23 percent of cropped area covered by insurance. Increasing insurance coverage has thus become an important policy objective for Prime Minister Narendra Modi. In 2016, he introduced his own flagship program, Pradhan Mantri Fasal Bima Yojana (PMFBY), to supplant these other insurance programs. With this program, the government of India aims to increase insurance coverage to as much as half of the cropped area. Under PMFBY, farmers would pay incredibly low prices for insurance coverage: for monsoon crops such rice, farmers would pay only 2 percent of the sum insured. The remainder would be subsidized by the government (shared between the central and respective state governments), with no cap on the size of the subsidy. Although it is not uncommon for governments to intervene in insurance markets and provide subsidies to increase coverage, the structure of PMFBY—with a variable and unlimited subsidy amount—seems particularly unsustainable. Furthermore, as has been asserted throughout the history of public economics, subsidies such as these entail considerable opportunity costs. Arguably, other public investments could be made to support agriculture and rural development without distorting insurance markets.

This history suggests the need for innovation to increase the coverage of risk–management products and services for millions of smallholder farmers across India, without simply relying on large government subsidies to prop up insurance markets (Nair 2010a). Among such innovations is the possibility of exploiting potential complementarities between multiple risk–management products, especially where no single option in isolation fully mitigates risk. Consider, in particular, two products that have received considerable attention in both research and practice: drought-tolerant (DT) rice cultivars (for example, Verulkar et al. 2010; Ward et al. 2014) and weather-based index insurance (WII) (for example, Carter et al. 2014; Karlan et al. 2014; Hill et al. 2017). Although neither DT nor WII provides a perfect solution to agricultural risk management, Lybbert and Carter (2014) demonstrated that these two risk–management tools can be bundled to form a more comprehensive risk–management product. The key is calibrating the design of the WII product to the performance of the DT cultivar under different drought conditions to provide farmers with an accessible and monotonically nondecreasing benefit stream irrespective of the degree of drought stress.

This discussion is particularly relevant in the eastern state of Odisha (formerly Orissa), one of India's poorest and most vulnerable states. Odisha is often described as India's "disaster capital" owing to the frequency with which it has fallen victim to natural hazards including droughts, floods, and cyclones. The United Nations Development Programme has estimated that Odisha experiences rainfall deficiencies of 25 percent or more roughly once every five years (UNDP (United Nations Development Programme) 2003). Pandey, Bhandari, and Hardy (2007) estimated that the negative consequences of drought in Odisha include a 33 percent reduction in gross cropped area and cropping intensity, a 41 percent reduction in rice area, and a 60 percent reduction in rice production during drought years relative to normal years, and total income losses of 26 percent.

This paper provides some of the first empirical evidence on farmers' demand for two drought risk–management products: a recently released DT rice cultivar and a more comprehensive DT-WII risk–management bundle. The paper makes several noteworthy contributions. First, drawing on insights from extreme value theory, it demonstrates how a comprehensive risk–management product could be designed, highlighting the reduction in the cost of drought insurance achieved through the bundling approach. Second, it estimates the price sensitivity of demand and other predictors of uptake for the DT cultivar and the DT-WII product by drawing on survey data from a two-year field experiment in which sales of the DT cultivar and DT-WII product were randomly assigned to villages across three drought-prone districts in Odisha. Finally, it explores the novel finding that uptake of the WII product persisted into year two at prices higher than the actuarially fair cost.

The remainder of the paper is organized as follows. Section 2 describes the drought risk–management products examined in the present study and reviews the literature relevant to their development and evaluation. Section 3 details the study site, experimental design, and sampling frame. Section 4 introduces the household and rainfall data used in the study. Section 5 explains the empirical methods used to arrive at the estimates of determinants of product demand and details the results. Section 6 offers concluding remarks and recommendations for public policy.

2 Drought Risk-Management Products

Stress-Tolerant Cultivars

Until recently, drought tolerance has received relatively little attention from rice breeders, particularly with respect to rainfed lowland and upland production systems (Verulkar et al. 2010). Early breeding efforts designed to improve rice yields under drought conditions focused on the selection of secondary physiological or morphological traits, but were generally unsuccessful.[2] Similarly, early molecular analyses of quantitative trait loci (QTLs) emphasized secondary traits that were not directly linked to improving yields under drought conditions (Price and Cutrois 1999). The crux of the challenge has been that efforts to enhance a particular physiological process in the plant in order to address drought have not necessarily resulted in higher yields under drought conditions (Fukai et al. 1999; Kumar et al. 2008). In addition, identifying important drought-tolerance traits is complicated by the fact that genotype-environment interactions are dependent on the timing and duration of drought stress and upon other co-occurring abiotic stresses such as heat stress (Price and Cutrois 1999).[3]

Despite these challenges, research on drought-tolerance traits and cultivars continues at both the global and national levels. Of particular note is the Stress-Tolerant Rice for Africa and South Asia (STRASA) initiative, led by the International Rice Research Institute and AfricaRice, and supported by the Bill & Melinda Gates Foundation. Since its inception in 2007, STRASA has been actively developing and delivering stress-tolerant rice varieties across various risk–prone geographies. Operating through a participatory varietal selection model, STRASA has released several DT rice varieties in coordination with national agricultural research systems across South Asia. In India, the first of these DT varieties was Sahbhagi Dhan (designation IR74371-54-1-1), released in 2010 by the Central Rice Research Institute. Results from multilocational managed-drought

[2] Examples of secondary traits that were considered include duration (that is, short duration varieties that have been proven effective for escaping terminal drought stresses), root architecture (root depth and ability to penetrate hard soils), leaf water potential (for example, leaf rolling, which reduces water loss in addition to reducing leaf area exposed to heat and light radiation), panicle water potential, osmotic adjustment, and relative water content (Fukai et al. 1999; Price and Cutrois 1999; Liu et al. 2007; Kumar et al. 2008 and Serraj et al. 2009).

[3] Even dry spells of a relatively short duration can result in substantial yield losses if they occur around the crops' flowering stage (Serraj et al. 2009).

screening trials spanning different drought severity levels (Table 2.1) show that when compared with other commonly cultivated varieties, Sahbhagi Dhan suffered relatively small yield reductions under moderate and severe drought stresses while also providing high yields under optimal (irrigated) conditions (Verulkar et al. 2010).

Table 2.1: Performance of Sahbhagi Dhan relative to other rice varieties commonly grown in Odisha

Variety name	Days to 50 percent flowering	Grain yield (metric tons/ha) Control (irrigated)	Moderate drought stress	Severe drought stress
Sahbhagi Dhan	86	5.20	3.40	1.50
Swarna	107	5.30	2.20	0.60
Samba Mahsuri	107	4.80	3.20	0.10
MTU 1010	85	5.10	2.80	1.40
Vandana	66	2.60	1.70	0.60

Source: Verulkar et al. (2010).
Note: The observed stress intensity was classified as "moderate" if the yield reduction (compared with the irrigated control) was 30 to 65 percent. Similarly, the observed stress was classified as "severe" if they yield reduction was more than 65 percent.

However, these results should not imply that the adoption of a new DT rice cultivar will be either rapid or widespread across its target populations and geographies. Lybbert and Bell (2010) point out that the stochastic nature of droughts makes it difficult for farmers to learn about and assess the merits of a DT variety relative to a non-DT variety, or to assess the merit of a DT trait compared with traits that address more ubiquitous and frequent stresses such as pests.[4] This learning failure may be exacerbated by the fact that beyond some threshold drought stress level, farmers may not observe any benefits attributable to the DT trait—a condition that is far less common for other traits, such as biotic stress tolerance.

Sahbhagi Dhan's relatively recent entry into India's rice production systems has thus far precluded any rigorous analysis of its adoption patterns or dynamics. Yet studies from India and other developing countries provide some evidence on the demand for abiotic stress–tolerant traits

[4] As a point of comparison, Lybbert and Bell (2010) used the example of the insect-resistance trait conferred by the introgression of genes from *Bacillus thuringiensis* (Bt) into crops such as maize. In the absence of the Bt gene, infestations of the targeted pests are commonplace to the farmer, such that the introduction of a Bt cultivar provides observable and immediate learning about the trait's effectiveness. Droughts, on the other hand, are more unpredictable, occurring with some regularity but still somewhat sporadic, such that the relative benefits of the DT trait may not be realized in any given year.

in staple crops cultivated by smallholders. Fisher et al. (2015), for example, studied DT maize adoption rates across six countries in Africa South of the Sahara and found adoption rates ranging from 9 percent in Zimbabwe to 61 percent in Malawi. Among other important constraints, they found insufficient information, resource constraints, and high seed prices among the major barriers to adoption. In Malawi, Holden and Fisher (2015) found a substantial increase in DT maize cultivation from 2006 to 2012, attributing this growth primarily to the country's large input subsidy program but also noting that adoption is influenced by having recently experienced a drought and by an individual's level of risk aversion. In Uganda, Kijima, Otsuka, and Sserunkuuma (2011) found that low profitability relative to alternative crops and poor access to quality seed significantly explained high rates of disadoption of New Rice for Africa varieties between 2002 and 2006, despite the varieties' drought tolerance, high yields, and broad suitability for the country's upland rainfed geographies. In Odisha, Emerick et al. (2016) conducted a field experiment to study the impacts of a submergence–tolerant rice cultivar (Swarna-Sub1) disseminated to smallholders in the state's flood-prone areas, finding near-universal uptake among participants in the first year when the seed was offered free of charge and continued cultivation among 76 percent of participants in the second year. These uptake numbers point to an important gap in the seed market and a high level of latent demand from farmers for stress-tolerant varieties that protect them against the production risks to which they are most prone. Furthermore, adoption of the submergence-tolerant cultivar had the effect of crowding in modern agricultural inputs and cultivation practices, providing further evidence that managing weather-related production risks can enhance agricultural productivity.

Weather Index Insurance

Agricultural insurance has existed in various forms since at least the early to mid-19th century.[5] Historically, most agricultural insurance programs have taken the form of multiple peril, indemnity-based crop insurance, which protects against crop damage arising from a number of different hazards (for example, droughts, floods, or hail) by providing payments on the basis of assessed on-farm

[5] The concept of crop insurance goes back even further. After observing a severe storm in the French countryside in 1788, Benjamin Franklin commented, "I have sometimes thought that it might be well to establish an office of insurance for farmers against the damage that may occur to them by storms, blight, insects, etc. A small sum paid by a number of farms would repair such losses and prevent much distress" (Franklin 1788).

losses (for example, yields of less than a given percentage of historical average yield) (World Bank 2011). These traditional indemnity-based insurance programs are subject to a myriad of well-documented challenges, including information asymmetries in the form of moral hazard and adverse selection (Hazell 1992; Morduch 2006; Barnett, Barrett, and Skees 2008; Miranda and Farrin 2012).[6] Traditional indemnity-based crop insurance programs are also prone to other challenges, including high administrative costs (in particular, the cost of assessing losses) and the covariance of insured farmers' risks which increases the insurers' risk of insolvency or, at the least, increases their costs of reinsurance. All of these challenges are perhaps most pronounced in developing countries, where information asymmetries, knowledge gaps, and other structural and operational issues are even more widespread. Moreover, despite a great deal of research, there remains relatively scant evidence to suggest that traditional crop insurance positively affects farmer welfare in either developed or developing countries (Hazell 1992; Skees, Hazell, and Miranda 1999; Smith and Watts 2009). Most crop insurance programs in the developed world have been propped up by large government subsidies, and many developing countries exploring such programs are following suit.

In recent years, index insurance has emerged as an alternative to indemnity-based crop insurance because of its ability to reduce the information asymmetries and administrative costs associated with traditional crop insurance. Instead of basing indemnity payments on assessed losses, index insurance payouts are made based on the performance of an objective and easily verifiable index relative to some threshold. Typically, these indexes have been constructed to reflect weather conditions (in the case of WII) or the average yield in a particular geographic region. Because measurement and verification of losses at the farm or individual level are not required to determine payouts (and therefore payouts are independent of both farmer characteristics and farmer actions), index insurance significantly reduces the problems of moral hazard and adverse selection, as well as the delays and high costs of verification that are inherent in traditional crop insurance products (Carter et al. 2014; Barnett and Mahul 2007). Additional benefits of index insurance include its (relative)

[6] Moral hazard is sometimes referred to as the "hidden action" problem, because it entails farmers' altering their production practices (unbeknownst to the insurer) in such a way as to increase their likelihood of receiving a payout. Adverse selection is sometimes referred to as the "hidden information" problem, because the potential insured have more information about their production risks than does the insurer and are thus better able to assess the actuarial fairness of their insurance costs, resulting in the most risky producers' being the most likely to want insurance (Miranda and Farrin 2012).

simplicity, the lack of contextual knowledge that is required of insurers and reinsurers to understand their risk exposure, and low operational costs (Barnett and Mahul 2007).

The most prominent drawback of index insurance is the possibility that insured farmers may experience losses but not receive an insurance payout because of the imperfect correlation between weather conditions (such as rainfall) recorded at the weather station and production losses on the farm. The possibility that the insurance policy will fail to pay out when losses are experienced on the farm is referred to as "basis risk."[7] When farmers purchase index insurance, they incur the risk of paying a premium for an insurance policy that may not pay out even in the event of crop loss or yield reduction on their fields. By the same token, farmers also stand to benefit when adverse weather conditions are recorded at the weather station but not realized on their farms. Basis risk stems from two primary sources. First, it arises because of spatial heterogeneity in environmental conditions and the fact that weather variables may not be particularly strong proxies for the on-farm yields or profits that such insurance is meant to protect (Rosenzweig and Binswanger 1993; Binswanger-Mkhize 2012). Second, to the extent that erratic rainfall patterns, especially droughts, are an important cause of on-farm losses, they are far from being the sole cause. Pests, diseases, and animal attacks are among a host of other possible causes of crop loss.

Multiple studies have explored the uptake of weather index insurance. For the most part, uptake has been low in the context of developing-country agriculture (Giné, Townsend, and Vickery 2008; Cole, Giné, and Vickery 2013; Cai et al. 2009). Despite these findings, several recent studies have examined the determinants of insurance uptake and identified constraints on both the demand and supply sides of the market. Not surprising, price frequently emerges as a key constraint in empirical studies of index insurance programs, though, as in the developed world, price subsidies seems to successfully stimulate demand (Mobarak and Rosenzweig 2012; Cole, Giné, and Vickery 2013; McIntosh, Sarris, and Papadopoulos 2013; Karlan et al. 2014; Hill et al. 2017). Other constraints include wealth and credit constraints (Giné, Townsend, and Vickery 2008; Clarke and Kalani 2011; Hill, Hoddinott, and Kumar 2013), education and understanding or familiarity with the insurance

[7] The term "basis risk," adopted from the derivatives literature, refers to any form of contract nonperformance. In the insurance literature, it is similar to a form of contract nonperformance studied by Doherty and Schlesinger (1990), namely default risk. But with weather index insurance, there is the added possibility of upside contract nonperformance, in which the policy pays out when no losses are experienced on the farm (Clarke 2016).

product (Giné, Townsend, and Vickery 2008; Gaurav, Cole, and Tobacman 2011; Cole, Giné, and Vickery 2013; Hill, Hoddinott, and Kumar 2013), trust in the insurance provider (Giné, Townsend, and Vickery 2008; Cai et al. 2009; Dercon, Gunning, and Zeitlin 2011; Cole, Giné, and Vickery 2013), and one's own or one's peers' past experience with the insurance product (Cai, de Janvry, and Sadoulet 2015; Cole, Stein, and Tobacman 2014; Karlan et al. 2014).

Platteau, De Bock, and Gelade (2017) extended these insights with a review of the demand for microinsurance that, although specific to neither agriculture nor index-based insurance, identified several generalizable constraints that are worth noting. The authors pointed out that low uptake can typically be explained by characteristics of the potential insured (including such factors as risk and loss aversion, ambiguity aversion, present bias, low education levels, and poor understanding of the insurance product) as well as serious challenges associated with providing high–quality insurance in many developing countries, including supply-side factors such as high insurance prices (related to, among other things, the costs of administration, risk premiums, and the costs of reinsurance), high transaction costs (for example, the complexity of filing a claim), basis risk, and poor quality of service.

Across many of these studies is a common finding that runs counter to theoretical predictions about the relationship between risk aversion and insurance demand: the demand for index insurance is often low among the most risk averse (Giné, Townsend, and Vickery 2008; Cole, Giné, and Vickery 2013). Clarke (2016) suggested that this effect may exist because for risk–averse users, index insurance operates more like a derivative than an insurance product, demonstrating that the presence of basis risk in index insurance modifies standard theoretical predictions. In particular, for actuarially favorable insurance (which is common in many countries due to large government subsidies), Clarke (2016) demonstrated that indexed coverage increases expected wealth but decreases minimum wealth, such that extremely risk–averse individuals would optimally purchase little (or, in the extreme, no) indexed coverage. Moderately risk–averse individuals trade off the benefits of increased expected wealth against the costs of basis risk, particularly when the insured experiences a loss yet does not receive an insurance payout, resulting in a nonlinear relationship between risk aversion and index insurance demand. Mobarak and Rosenzweig (2012) combined the model of Clarke (2016) model with the Arnott-Stiglitz cooperative risk–sharing framework and demonstrated the existence of complementarities between informal risk–sharing mechanisms and index insurance, such that communities with superior informal mechanisms for insuring individual losses may have a higher demand for index insurance.

Bundled DT-WII Risk-Management Product

Taken separately, abiotic stress-tolerant cultivars and weather index insurance can help smallholders mitigate risk, smooth consumption, and invest in higher-risk, higher-return livelihood strategies. Empirical evidence from studies by Karlan et al. (2014), Emerick et al. (2016), and Hill et al. (2017) have demonstrated that such effects are both observable at the farm and household levels, and appreciable in magnitude. Yet neither an improved cultivar nor an index insurance product offers a complete risk–management solution, particularly when the hazard in question is drought in a smallholder-based, rainfed production system. For example, Sahbhagi Dhan may confer relative yield benefits vis-à-vis non-DT varieties under certain drought stresses, but there is some drought stress level beyond which the relative benefits are completely exhausted. A weather index insurance product, on the other hand, may provide monotonically nondecreasing benefit streams regardless of the degree of drought stress, but most products suffer from a nontrivial degree of basis risk, and most index insurance pilot projects to date have suffered from insufficient demand.

But by bundling these two products together—one technological, one financial—there is a possibility of overcoming their respective weaknesses through complementarity in design, along the lines of Lybbert and Carter (2014). Bundling an index insurance product with a DT cultivar ensures that the benefits stream is a monotonically nondecreasing function of drought stress, and bundling the DT cultivar with the index insurance product implies that a lower quantity of crop losses would need to be insured, thereby reducing the cost of the insurance. Given that plant breeding often requires 10–15 years of investment in research and development (McMullen 1987), it is a simpler proposal to design an insurance product that is optimized to complement the performance profile of the DT variety, rather than vice versa. Further, because most smallholders in developing-country contexts are likely to be more familiar with improved cultivars than complex financial instruments, it makes sense to initially develop the bundled product around the attributes of the DT cultivar.

We specify an insurance product that begins providing benefits at the approximate drought stress level at which the relative benefits of the DT cultivar start to decline. This approach has some inherent appeal because the relative benefits profile of the complementary product would be monotonically nondecreasing. Indeed, this is the approach that Ward et al. (2015) used in specifying the hypothetical DT-WII product for their ex ante valuation in Bangladesh. Of course, this approach ignores the reality that, even though the *relative* benefits may be increasing in the presence of moderate droughts, the variety still suffers *absolute* yield losses under these conditions. In the present context, we modify this approach slightly by specifying our insurance product such that it begins to provide benefits under moderate drought, with an increased payout under severe drought stress. This design may be suboptimal vis-à-vis the design strategy laid out by Lybbert and Carter (2014), but because Sahbhagi Dhan is a relatively new variety and there is insufficient data on its performance under a broad spectrum of environmental (including weather) and management conditions, insurance optimization is not as straightforward in practice as theory might suggest.

To determine the insurance payments that would be made under moderate and severe drought stress, respectively, we first estimated the value of lost output that farmers in three drought-prone districts in Odisha (Balasore, Bhadrak, and Mayurbhanj) might expect under moderate, severe, and extreme drought stress levels. Using historical data on district-level rice yields, we estimated a simple linear regression of yields against a time trend that smoothed out annual fluctuations due to weather variability. The results of this simple linear regression were then used to predict the expected yields under more or less optimal conditions for kharif 2015 and 2016. We further assumed that yield losses for Sahbhagi Dhan under moderate and severe drought stress conditions, respectively, would be 38 and 69 percent (Verulkar et al. 2010). Next, we used historical data on the minimum support price (MSP) for rice in India and extrapolated forward to generate an estimate of the price per kilogram of rice production. Because the farmgate price is often considerably less than the MSP (for example, due to transportation costs, transaction costs, or aggregators with market power offering sub-MSP prices), we estimated the value of a kilogram of rice at the farmgate to be 20 percent less than the MSP. With this price in mind, we arrived at an estimate for the value of lost output under both moderate and severe drought stress conditions.

Pricing index insurance requires consideration of the probability that index strike points will be realized and the corresponding payments that will be made if such strike points are reached, as well as any additional administrative loadings required by the insurer. The two strike points for our rainfall-based WII product were "moderate" and "severe" droughts, both of which warrant further explanation. Though a drought could simply be a deviation in cumulative rainfall over the course of the entire season relative to long-term averages, the most obvious form of drought in our monsoon-season context may be the occurrence of a prolonged dry spell during the course of the season, particularly during key periods of the season associated with crop emergence, establishment, and growth. Because prolonged dry spells can be classified as extreme weather events, it is appropriate to model these extrema using an extreme value distribution. The generalized extreme value (GEV) distribution function takes the form

$$F(x;\xi,\alpha,\kappa) = \exp\left\{-\left[1+\kappa\left(\frac{x-\xi}{\alpha}\right)\right]^{-1/\kappa}\right\}, \tag{1}$$

where x is a datum on an extreme event (that is, the length of a dry spell), $\xi \in \mathbb{R}$ is the distribution location parameter, $\alpha > 0$ is the distribution scale parameter, and $\kappa \in \mathbb{R}$ is the distribution shape parameter. These parameters can be estimated using maximum likelihood, and these estimates can in turn be used to determine return levels, return periods, and the probability of an extreme event's occurring. If the set $\{x_i\}$ is independent and identically distributed according to a GEV distribution, then the log-likelihood function for a sample of n observations $\{x_1, x_2, ..., x_n\}$ is

$$\ln\left[L\left(\xi,\alpha,\kappa|x\right)\right] = \sum_{i=1}^{n}\left\{-\ln\alpha - \left(1+\frac{1}{\kappa}\right)\ln\left[1+\kappa\left(\frac{x_i-\xi}{\alpha}\right)\right] - \left[1+\kappa\left(\frac{x_i-\xi}{\alpha}\right)\right]^{-1/\kappa}\right\}. \tag{2}$$

Using this log-likelihood function and daily rainfall data from each of the three focal districts from 1940 to 2011, we obtain estimates for the district-specific location, scale, and shape parameters characterizing the distribution of these maxima. With estimates of $\hat{\xi}$, $\hat{\alpha}$, and $\hat{\kappa}$, we can then estimate either the probability, p, of the occurrence of a specific event, x_p, or determine what event, x_p, will occur with specified probability, p. Based on figures reported in Kar et al. (2004), the probabilities of a moderate drought in Balasore and Mayurbhanj, respectively, are 26.67 percent and 20.94 percent, and the probabilities of a severe drought in Balasore and Mayurbhanj, respectively, are 2.23 percent and 2.33 percent.[8] We can then estimate the length of a dry spell corresponding to these different drought stress levels in each of the three districts:

$$x(p) = \hat{\xi} - \left(\frac{\hat{\alpha}}{\hat{\kappa}}\right)\left\{1 - \left[-\ln\left(1-p\right)^{-\hat{\kappa}}\right]\right\}. \tag{3}$$

Actuarially fair insurance is priced such that the cost of insurance equals the expected payout. Consider a simple index insurance product with discrete strike points, $i = 1, ..., n$, and let p_i define the probability that an event triggering strike point i occurs. Let I_i be the insurance payout under strike point i. Then an actuarially fair cost of insurance would be $A = \sum_{i=1}^{n} p_i I_i$.

Of course, because the actuarially fair cost of insurance reflects an insurer's expected payout, in the long run insurers should not expect to earn any economic profits, resulting in an unsustainable business model. Furthermore, because weather risk is primarily a covariate risk, insurers generally must be compensated for the risks they are exposed to in insuring many people who all share the same risk. To address both of these concerns, insurers almost always incorporate a sizable premium on top of the actuarially fair cost of the insurance to cover both risk and administrative burdens.

3 Experimental Design

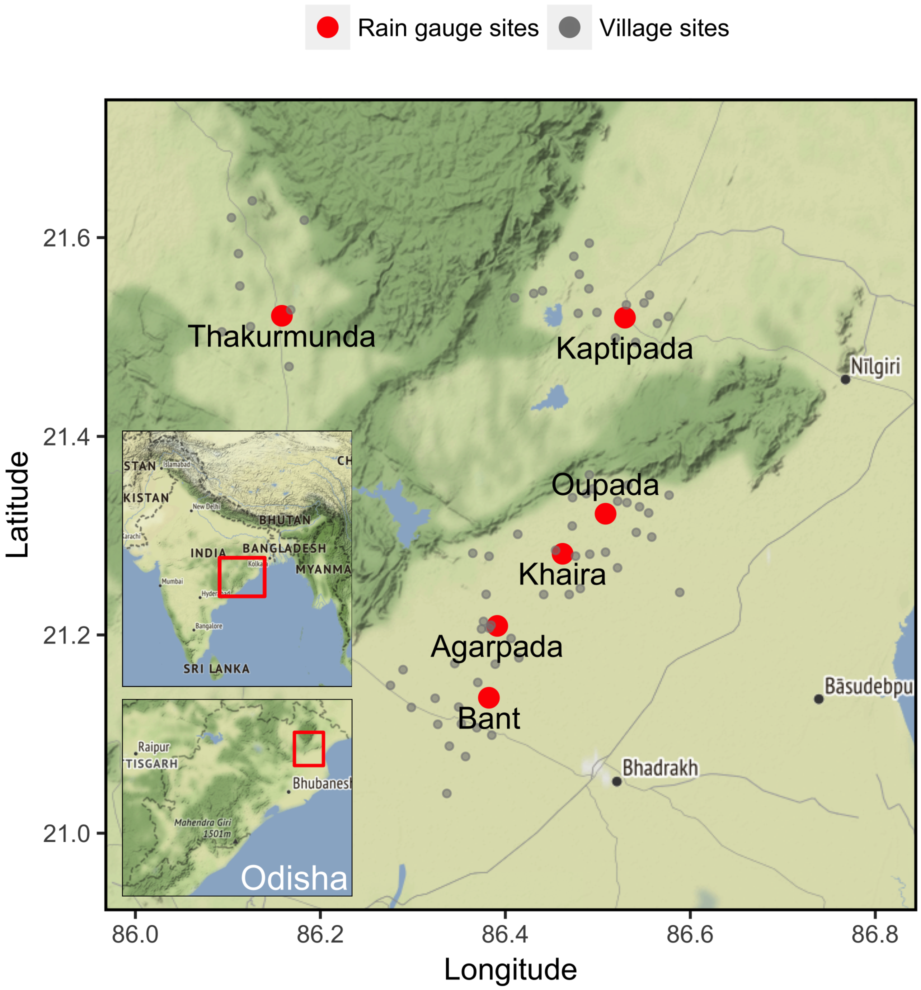
To better understand demand for our risk–management products, we designed a multiyear randomized controlled trial to be conducted during the kharif (monsoon) rice-growing seasons in 2015 and 2016. The study area spans six blocks (subdistrict administrative units) in three adjacent districts of Odisha: Khaira and Oupada in Balasore, Agarpada and Bant in Bhadrak, and Thakurmunda and Kaptipada in Mayurbhanj (Figure 3.1).[9] This region was identified for the study because its farmers predominantly grow rice and the region is extremely prone to drought. Sahbhagi Dhan was

[8] Bhadrak was carved out of Balasore in 1993. In light of this fact, and due to the similarities in agroecological conditions between Bhadrak and Balasore, the drought probabilities for Balasore double as the drought probabilities used in pricing the insurance component in Bhadrak.

[9] At the time this study began in 2015, Bant and Agarpada were two separate blocks. Soon after the project began, they were merged into one block. For the purposes of this study, however, we treat them as two separate blocks.

not available for purchase in local input markets in 2015 when this study was initiated.

Figure 3.1: Location of sample villages and rain gauge installation sites



Source: Authors, using source map data provided by the ggmap package (Kahle and Wickham 2013).

Sampling Frame

Using population data for the six blocks in the study area from the 2011 census, we selected 111 villages using probability proportional to size sampling.[10] Each of these 111 villages was then randomly assigned to one of three groups: a DT treatment arm (37 villages), a DT-WII treatment arm (37 villages), and a control group (37 villages). A total of 30 households were randomly sampled

[10] Villages with fewer than 100 households were deemed too small for this study and therefor excluded from consideration prior to village selection.

from each village, 20 of which were ultimately included in the sample, with 10 retained as potential replacement households should any of the other 20 households be unavailable to participate or otherwise not qualify for inclusion.[11] The resulting sample consisted of 2,220 households at baseline, with nearly all (2,160) of these households surveyed at midline in 2016 (a 97.3 percent retention rate).

As shown in Table 3.1, one-third of the 111 villages were offered DT rice seed, another third were offered the DT-WII bundle (the following section provides more details on the marketing of these products), and the remaining villages were assigned to the control group.[12] Households in the DT treatment were permitted to purchase 0 to 3 units, with each unit consisting of a 2-kg bag of Sahbhagi Dhan seed. Households in the DT-WII treatment group were similarly permitted to purchase 0 to 3 units of the bundle, with each unit comprising a 2-kg bag of DT seed and an insurance policy meant to cover 0.1 acres of area under rice cultivation.[13]

Table 3.1: Breakdown of sample villages into treatment and control arms

	Treatment group		
	DT seed	DT-WII bundle	Comparison
Number of villages	37	37	37
Unit of product offered	2-kg bag of seed	2-kg bag of seed & insurance policy for 0.1 acre of land	-
Maximum units offered	3	3	-

Source: Authors.
Note: DT = drought-tolerant seed; DT-WII = drought-tolerant seed combined with weather index insurance.

[11] We incorporated two inclusion criteria to determine eligibility for participation. First, households had to cultivate rice as their primary crop. Second, they had to own at least some of the land they were cultivating. Due to the prevalence of rice cultivation in Odisha and widespread landownership (although holdings are small in size), few households were ultimately excluded from participation. There were no requirements in terms of landholding size, so the resulting sample resulted in a fairly wide socioeconomic distribution.

[12] One village that was originally allocated to the DT group was accidentally left out of the marketing sessions and is thus treated as part of the control group for the analysis.

[13] Although it may seem intuitive that an additional treatment group offered only a WII product would be useful, we note that a stand-alone WII product meant to provide similar levels of risk management would be considerably different (and more expensive) than the specially calibrated WII product bundled with the DT cultivar and therefore would have generated little in terms of valid comparative analysis against the other treatments.

Marketing of the Risk–Management Products

In May 2015, following baseline data collection and prior to sowing for the 2015 kharif season (Table 3.2), marketing agents employed by Balasore Social Service Society, a local nongovernmental organization (NGO), were trained on the features of the two risk–management products. In pairs, agents conducted marketing visits in each treatment village, where they explained the product, drew a random discount in a public lottery, and facilitated the sale of DT seed or the DT-WII bundle. The agents conducted three marketing sessions in each sample village. The price of a 2-kg bag of seed was fixed at 80 Indian rupees (Rs), or Rs 40 per kg), whereas the price of a unit of the insurance policy varied by district due to different drought probabilities and different expected yield losses under drought conditions. After adding a 30 percent premium to the actuarially fair cost of insurance, the cost of the complementary insurance component was Rs 130 in Balasore, Rs 150 in Bhadrak, and Rs 100 in Mayurbhanj.[14] To maximize the likelihood that price would not be an inhibiting factor in the take up of treatment and to enable estimation of demand elasticities, a random discount of 10, 15, 20, 25 or 30 percent on both the DT rice seed and the DT-WII product was offered to participants based on village-level randomization. In each treatment village, the discount was chosen by means of a public lottery conducted by the marketing agents at the culmination of the first marketing session. The randomly selected amount was then fixed for all purchases during that year in the given village. Although the discount rate was randomly selected, the distribution of the discount rate was skewed in favor of higher discount rates.

In May 2016, following the second round of data collection and prior to nursery preparation for the kharif 2016 season, agents once again received training and conducted three marketing sessions in each treatment village. In this second year, the actuarially fair price for the complementary insurance component was recalculated to factor in changes in the MSP and secular yield growth, both of which would contribute to interannual differences in the value of lost output under different drought scenarios. Each treatment group was randomly divided into subgroups, with households in one subgroup offered a discount (a fixed 20 percent discount in the case of DT and a fixed

[14] In reality, the 30 percent premium is considerably lower than what insurance companies would likely add, but because this product was designed for a pilot program with a population that has had very little experience with insurance, we were reluctant to charge more than this modest premium.

Table 3.2: Timeline of research and agricultural activities during study period

	2015												**2016**												2017			
Activity	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**J**	**F**	**M**	**A**	**M**	**J**	**J**	**A**	**S**	**O**	**N**	**D**	**J**	**F**	**M**	**A**
Baseline survey			■	■																								
Product marketing sessions					■																							
Insurance coverage period						■	■	■	■	■																		
Insurance payouts delivered											■																	
Midline survey														■	■													
Product marketing sessions																	■											
Insurance coverage period																		■	■	■	■	■						
Insurance payouts delivered																							■					
Endline survey																											■	■

Source: Authors.

25 percent discount in the case of DT-WII) and households in the other sub-group not offered a discount. For the former, the initial (prediscount) prices were specially calibrated so that the effective price (after applying the discount) would be exactly the same as the price offered to the latter group. This arrangement necessarily implies that the initial prices for the first group were artificially inflated (above and beyond the 30 percent premium discussed above). The rationale for this "illusory" discount is rather straightforward. Considerable evidence suggests that demand for insurance (including index insurance) is quite sensitive to price. As a result, governments in many developed countries rely on large subsidies to increase participation in crop insurance programs, and developing–country governments are following suit, perhaps for good reason. Recent research on the behavioral dimensions of farmer decision making has demonstrated that subsidies can provide an important inducement, particularly into making investments in agricultural technologies (Bell et al. 2017). Yet at the same time, large subsidies distort prices and are almost always unsustainable. There is, therefore, a lingering question about the appropriate role for government interventions in encouraging uptake of risk–management products like the ones explored here. Particularly relevant for the two products we consider in the present manuscript, other government interventions can potentially increase uptake in a more sustainable and less distortionary way. For example, governments could invest in seed research and development to generate DT cultivars with even greater tolerance or resistance traits. This strategy would have the dual benefit of protecting yields from droughts while also lowering the cost of the complementary insurance product in a DT-

WII bundle like the one evaluated here.[15] Alternatively, governments could invest in constructing weather stations or in developing remote sensing technologies that could result in lower basis risk, potentially making WII products more attractive without necessarily increasing moral hazard. The introduction of this illusory discount—in conjunction with findings on price sensitivity from the first year of the pilot—will enable us to determine the extent to which uptake is driven by the bottom line alone versus the psychological inducement of a subsidy.

It has also often been observed that the demand for a particular risk–management instrument can be influenced by sociological factors. For example, particularly in the case of insurance, which entails an up-front payment with the potential of a future return, participants may engage in the market only if they trust the insurer (Cole, Giné, and Vickery 2013; Karlan et al. 2014; Hill et al. 2017). This trust factor may be particularly important in the context of rural India. In focus group discussions prior to the implementation of the present study, several farmers reported a series of NGOs that would visit their village, promise various services (including insurance), and then disappear with villagers' money, never to be heard from again. Another sociological factor that may arise as a result of the manner in which the products were marketed (that is, in group settings rather than on an individual basis) is social desirability bias. In other words, it is possible that observed participation in the risk–management markets could reflect individuals' desire to be seen participating in the NGO's activities, rather than truly reflecting utility-maximizing behavior.

The index insurance component was designed to provide coverage for 0.1 acres of area under rice cultivation, while the 2-kg bag of Sahbhagi Dhan seed was recommended for cultivation on precisely the same area of land.[16] The cost and structure of these insurance products across the

[15] Recall the earlier assumption (drawn from published estimates in Verulkar et al. 2010) that Sahbhagi Dhan yields decline by 38 and 69 percent under moderate and severe drought stress, respectively. These yield reductions are considerably less than the yield reductions for Swarna, the most commonly grown variety in our sample area (58 and 89 percent under moderate and severe drought stress, respectively). Assuming that the two varieties produce a homogeneous output that can be sold at the same market price, these differences in potential loss imply that cultivating Sahbhagi Dhan results in smaller overall crop production losses that would need to be insured. Because the potential insured losses are less, the cost of insuring production losses is also less. In this way, the DT component reduces the cost of drought insurance, a reduction that amounts to roughly Rs 50 in Balasore, Rs 56 in Bhadrak, and Rs 35 in Mayurbhanj (32–33 percent of the actuarially fair cost of insuring farm income losses from drought). This calculation does not even consider the fact that bundling DT seed with WII also reduces the insurer's value at risk, which has significant implications for the cost of reinsurance.

[16] The recommended seeding rate for Sahbhagi Dhan assumes transplanted rice cultivation, as is commonly practiced in the study area; cultivation by broadcasting or direct seeding methods would require larger quantities of seed, and study participants were provided information on the appropriate seeding rates for these alternative methods.

three districts are shown in Table 3.3. The effective price of the 2-kg bag of seed was fixed at Rs 80 in both years, reflecting the generally invariant price of rice seed—irrespective of variety—produced and disseminated by the public research system and state seed production facilities in Odisha. The actual price of the bundled product includes both the insurance component described above and the price of the seed, less any discounts described above. Households were permitted to purchase up to 3 units (2-kg bags or bundles)—limited to the quantity needed to cover their landholding—so if a household maxed out its purchase quota, it would be covering, on average, approximately 20 percent of its area under rice cultivation.

Table 3.3: Product price structure and discounts offered

	DT Group		DT-WII Group	
Block	(Rs per 2-kg bag)	Discount (percent)	(Rs per bundle)	Discount (percent)
Year 1				
Balasore	80	Random	210	Random
Bhadrak	80	Random	230	Random
Mayurbhanj	80	Random	180	Random
Year 2	DT Group 1		DT-WII Group 1	
Balasore	100	20	270	25
Bhadrak	100	20	290	25
Mayurbhanj	100	20	230	25
	DT Group 2		DT-WII Group 2	
Balasore	80	None	200	None
Bhadrak	80	None	220	None
Mayurbhanj	80	None	170	None

Source: Authors.
Note: DT = drought-tolerant seed; DT-WII = drought-tolerant seed and weather index insurance; Rs = Indian rupees

4 Data

Household Data

Baseline and midline data were collected through household surveys conducted in March–April 2015 and February–March 2016, respectively. Table 4.1 presents a summary of household characteristics at baseline, including a comparison of means between the DT and DT-WII groups. In the villages allocated to the DT-WII group, the household questionnaire included an experiential learning component on the concepts of basis risk and drought risk. The concepts of insurance and basis risk were explained to farmers through an experiential learning exercise (Appendix A) that was a variation of the one conducted by Marenya, Smith, and Nkonya (2014) in Malawi. The concept of drought risk was also explained using an experiential learning exercise (Appendix B). Each of these experiential learning exercises was carried out at both baseline and midline. In both years, therefore, these important concepts were explained to farmers prior to their purchase decisions so that participants would be well informed. Marketing agents went over these concepts again at the three marketing sessions conducted in each DT-WII village prior to the sale of the bundled product.

Additionally, a simple laboratory-in-the-field experiment was used to elicit farmers' subjective beliefs about the length of the longest dry spell. These experiments were similar in scope to those introduced by Luseno et al. (2003) and Lybbert et al. (2007). Farmers were given 20 beans and a sheet of paper with six bins, each representing a range of days (specifically, 0–7 days, 8–14 days, 15–21 days, 22–28 days, 29–35 days, and 36 or more days). Farmers were then asked to allocate the 20 beans across these bins based on how likely they expected the longest dry spell to be in the coming kharif season. Prior to this exercise, farmers undertook a series of similar—but simple—bean allocation exercises to ensure that they understood the concept of representing probability using the beans. Following data collection, the research team was able to take the recorded allocation of the beans across the six bins and calculate the moments of each individual's drought risk belief distribution by treating each bin as a uniform distribution defined over its range, with each such uniform distribution in turn being a component of a stepwise distribution. The probability that the farmer places in a given bin functions as a weight on the corresponding distribution, and because

Table 4.1: Characteristics of households in randomly allocated DT and DT-WII treatment villages

	(1) Full sample	(2) DT treatment arm	(3) DT-WII treatment arm	(4) DT-WII - DT difference
HH head age (years)	52.273	52.267	52.658	0.361
	(13.295)	(13.258)	(14.011)	(0.672)
HH head male	0.945	0.957	0.942	0.020*
	(0.228)	(0.203)	(0.234)	(0.012)
HH size	5.656	5.622	5.52	−0.199
	(2.475)	(2.45)	(2.376)	(0.131)
Land owned (acres)	1.541	1.504	1.293	−0.313
	(3.81)	(1.404)	(1.228)	(0.238)
Rice area cultivated (acres)	1.665	1.58	1.453	−0.371
	(3.818)	(1.435)	(1.282)	(0.238)
Rice output (tonnes)	2.044	2.091	1.736	−0.209
	(5.214)	(5.253)	(1.802)	(0.325)
Rice yield (tonnes/acre)	1.678	1.686	1.378	−0.275
	(7.473)	(7.648)	(3.695)	(0.456)
Used irrigation (=1)	0.405	0.453	0.423	0.109***
	(0.491)	(0.498)	(0.494)	(0.025)
Used pesticides (=1)	0.917	0.881	0.943	−0.046***
	(0.276)	(0.325)	(0.232)	(0.015)
Used fertilizer (=1)	0.977	0.967	0.982	−0.016**
	(0.148)	(0.180)	(0.131)	(0.008)
Trust index	−0.016	0.033	−0.084	−0.017
	(1.021)	(0.944)	(1.109)	(0.049)
Technology adoption peer effects	0.968	0.967	0.957	−0.012
	(0.177)	(0.180)	(0.204)	(0.008)
Savings (INR)	4,749.77	4,058.92	4,382.79	−1,702.66
	(24,009.869)	(20,091.861)	(20,524.567)	(1,330.02)
Experienced crop loss	0.954	0.958	0.969	0.023*
	(0.209)	(0.200)	(0.174)	(0.012)
Asset index	−0.054	−0.138	0.028	−0.242***
	(1.026)	(1.048)	(0.992)	(0.052)
Annual food consumption expenditure (INR)	39,738.68	39,733.56	39,477.24	−264.529
	(29,941.679)	(29,109.167)	(30,897.416)	(1,532.72)
Discount rate for INR 100 (30 days)	5.245	5.782	4.829	0.639***
	(4.401)	(4.729)	(3.89)	(0.240)
Discount rate for INR 100 (60 days)	1.776	1.982	1.594	0.223**
	(1.617)	(1.675)	(1.322)	(0.090)
N	2,220	720	740	1,460

Source: Authors.
Note: * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Annual food consumption expenditures computed using village means for food product prices. Figures in column 4 are coefficient estimates (and their associated standard errors) from linear regressions of the form $x_{ij} = \alpha + \beta T_i + \varepsilon_{ij}$, where x_{ij} is the characteristic over which balance is being tested (i.e., the variable described in the row header) and T_i is an indicator variable capturing the difference in random assignment between DT and DT-WII groups. Statistical significance of these differences was based on a t-test of the estimated coefficient β for each household characteristic. DT = drought-tolerant seed; DT-WII = drought-tolerant seed and weather index insurance; HH = household; Rs = Indian rupees.

each component is a uniform distribution, we rely on the assumption that farmers place equal probability on each value of the corresponding bin.[17] We calculate both the mean and the standard deviation of individuals' belief distributions, with the mean serving as a clear proxy for individuals' subjective beliefs about the severity of the longest dry spell in the forthcoming season, and the standard deviation providing a proxy for the uncertainty around this subjective belief. Although it is possible that individuals' subjective expectations could evolve over time (for example, as they gather more observations with which to update their beliefs), we treat these belief parameters as fixed because they were collected only once, during endline data collection.

Rainfall Data

Because one measure of the quality of a weather index insurance product is the degree to which it minimizes basis risk—an important source of which is the mismatch in weather conditions on a farmer's field and those at the location where index measurements are collected—we measured rainfall using rain gauges installed in the vicinity of the block headquarters in each of the six blocks (refer again to Figure 3.1).[18]

Actual rainfall data were collected during the summer monsoon seasons in 2015 and 2016, specifically from June 15 to October 15, at all six rainfall measurement stations. In kharif 2015 a moderate drought was recorded in two blocks, namely Bant and Khaira, and a severe drought was recorded in Thakurmunda (a dry spell of 25 days). In kharif 2016 only a single drought was observed: a moderate drought in Thakurmunda.

Though there is some variation in households' distances from the rain gauges, and these differences are relevant to the insurance product, the vast majority of households were within 10 km of the rain gauge site, with no household more than approximately 15 km from the gauge. Although

[17] See Attanasio and Kaufmann (2008) for a further discussion of the stepwise uniform assumption in the calculation of subjective belief distributions.

[18] Although participants were informed that the index would be based on such localized rainfall measurements, they were not explicitly informed of where the rain gauges were to be installed, thus eliminating an important source of moral hazard that could imperil the insurance product. We note that although the use of rain gauges at a lower level of geographic aggregation (that is, at the block level rather than the district level) may reduce basis risk by reducing the probability that weather conditions on farmers' fields would differ significantly from conditions at the gauge where index measurements were recorded, basis risk is not completely eliminated due to spatial heterogeneity in rainfall patterns, even at this lower level.

farmers might not have known exactly where the gauges were installed, they were informed that the gauges would be installed in their block headquarters, so their distance from the block headquarters (proxied in this case by the more objective measurement of the distance from their homestead to the actual gauge site) may prove an important determinant of their risk–management product purchase decisions.

5 Demand for Drought Risk–Management Products

Empirical Approach

In the process of modeling the demand for these two risk–management products, an important factor that merits careful consideration is the high percentage of nonpurchases, revealed as 0s in the data. Although 0s potentially appear for several different reasons, their interpretation has a crucial bearing on how the demand relationship is subsequently estimated. Given the extent of control we had over data collection efforts, we posit that these 0s result from corner solutions in our participants' utility-maximization problem. On this basis, we consider demand for our risk–management products to be a sequential decision–making process in which the participating individual ultimately makes two decisions when being offered these products. First, the individual considers whether to participate in the market for these risk–management products, which is a binary decision. Second, those individuals that enter the market decide how many units to purchase, which is a count or semi-continuous decision. It is assumed that the decision on how much to purchase is made *after* the decision to participate in the market, rather than simultaneously. To better understand this sequential decision–making process, we estimate a two-part model that comprises a linear probability model followed by least squares.[19] We estimate each of these regression models for each risk–management product (DT and DT-WII) in each year (2015 and 2016), for a total of eight

[19] The grouped nature of our sampling frame suggests that error terms should be correlated within village clusters, thus introducing a very specific form of heteroskedasticity that would bias parameter estimates in the maximum likelihood estimation of an econometric model (such as a logit or a probit model) that is nonlinear in the parameters (Greene 2003, 673–674). Furthermore, although our data are experimental in nature, potential endogeneity (arising from, among other potential sources, omitted variables) precludes clean identification in our first–stage regression. For this reason, we report the first–part estimates from a linear probability model with robust standard errors, rather than a logit or probit model. We note that estimating probits for the first step yields similar results (not reported here).

regressions.

In the first year (2015), because farmers had no prior experience with the products (either their own experience or the experience of their peers) that could potentially condition their purchase decisions, the determinants of product uptake include product price, relevant household- and farm-level characteristics, and individual preferences that may influence risk–management decisions. The binary market participation regression equation can be written as

$$y_{i1} = \alpha_{11} + \theta_1 p_{i1} + \lambda_{11} y_{-i,1} + \sum_{j=1}^{J} \gamma_{j1} z_{ij1} + \nu_{i1}, \tag{4}$$

where y_{i1} is a binary indicator variable equal to 1 if individual i was observed to have participated in the risk–management market (that is, purchased either DT or DT-WII) in 2015, p_{i1} is the effective price of the risk–management product (gross or market price less any subsidy) in 2015, $y_{-i,1}$ is a measure of the share of farmer i's social network (that is, other members of his or her village, excluding farmer i) who participated in the market in 2015, and $\mathbf{z}_{i1} = \langle z_{i1,1}, z_{i2,1}, ..., z_{iJ,1} \rangle$ is a vector of individual-, household-, and farm-level characteristics specific to individual i in 2015. The randomization of the discount rate in the first year implies that individuals faced a range of effective prices, which permits us to assess the price sensitivity of market participation. Then, the quantity purchased among those participating in the market is estimated as

$$q_{i1} = \alpha_{21} + \theta_2 p_{i1} + \lambda_{21} y_{-i,1} \sum_{j=1}^{J} \beta_{j1} x_{ij1} + \varepsilon_{i1} \tag{5}$$

where q_{i1} is the number of units (2-kg bags of DT seed or bundles of DT-WII consisting of a 2-kg bag of DT seed and a single WII policy), and p_i, $y_{-i,1}$, and $\mathbf{x}_{i1} = \langle x_{i1,1}, x_{i2,1}, ..., x_{iJ,1} \rangle$ are defined as before.[20] In equations (4) and (5) the ν_1 and ε_1 terms are idiosyncratic error terms that are independent from each other for each individual i, but given the clustered nature of the interventions, we adjust them for within-village correlations.

In the second year (2016), we allow for farmer decisions to be conditioned by past experiences.

[20] In the present context we permit all characteristics that condition the participation decision also to condition the consumption decision.

Additionally, although the effective price for all participants was the same in 2016 (within products), the introduction of the randomly allocated "illusory" discount affords us the opportunity to understand the extent to which farmers' purchase decisions are driven by preferences for risk management versus preferences for subsidies. To study the market participation decision in 2016, we consider the following equation:

$$
\begin{aligned}
y_{i2} = \alpha_{12} + \phi_1 s_i + \psi_1 y_{i1} + \eta_1 d_{i1} + \mu_1 \left(y_{i1} \times d_{i1}\right) + \tau_1 y_{-i,1} + \\
\lambda_{12} y_{-1,2} + \zeta_1 \left(y_{-i,1} \times d_{i1}\right) + \sum_{j=1}^{J} \gamma_{j2} z_{ij2} + \nu_{i2},
\end{aligned} \tag{6}
$$

where now y_{i2} is an indicator variable taking the value 1 if farmer i participated in the market in 2016 and 0 otherwise, $y_{-i,1}$ is a measure of the share of farmer i's social network who participated in the market in 2015, s_i is a dummy variable that equals 1 if the village was randomly allocated to receive a subsidy, d_{i1} is a dummy variable that equals 1 if the rainfall conditions in the block were consistent with drought conditions (as defined in the insurance contracts) in 2015, $y_{-i,t}$ is a measure of the share of household i's village members who purchased one of the products in year t, and $\mathbf{z}_{i2} = \langle z_{i1,2}, z_{i2,2}, ..., z_{iJ,2} \rangle$ is a vector of household- and farm-level characteristics specific to household i during 2016. The interaction terms $(y_{i1} \times d_{i1})$ and $(y_{-i,1} \times d_{i1})$ allow us to capture, respectively, the effects of one's own and one's village network's experiences with the drought risk–management products during drought scenarios (that is, scenarios in which some benefits from the drought risk management products were presumably reaped). A priori, we would expect that having purchased a drought risk–management product in 2015 ($y_{i1} = 1$) and having experienced a drought during that year ($d_{i1} = 1$) would have a positive effect on a farmer's risk–management purchasing decisions in 2016. For farmers that purchased a DT-WII product in 2015 but resided in blocks in which the rainfall conditions were not consistent with drought conditions (and hence did not receive an insurance payout), we would expect these experiences to have a neutral to slightly negative effect on their drought risk–management purchasing decisions in 2016.

Thus, the consumption equation in 2016 is modeled as

$$q_{i2} = \alpha_{22} + \phi_2 s_i + \psi_2 y_{i1} + \eta_2 d_{i1} + \mu_2 \left(y_{i1} \times d_{i1}\right) + \tau_2 y_{-i,1} + \\ \lambda_{22} y_{-1,2} + \zeta_2 \left(y_{-i,1} \times d_{i1}\right) + \sum_{j=1}^{J} \beta_{j2} x_{ij2} + \varepsilon_{i2}, \quad (7)$$

where q_{i2} measures the number of units purchased by household i in 2016, and all other terms are defined as before.

Before proceeding with describing our econometric results, it is important to recognize that, due to correlations between unobserved individual characteristics that would similarly affect purchase decisions in both 2015 and 2016, the one-year lagged purchase variables are likely not exogenous and thus should be instrumented. Using a model similar to that of Karlan et al. (2014) to study learning and social influences on insurance demand, we instrumented for the lagged binary purchase decision and the interaction between the lagged binary purchase decision and the occurrence of a drought with the randomly assigned price from 2015 and the interaction between the random price from 2015, and the occurrence of a drought. Due to the poor correlation between price and demand in 2015 we find this instrument to be extremely weak. As is well established in the statistics and econometrics literature (for example, Bound, Jaeger, and Baker 1994), when there is a weak correlation between the instrument and the endogenous variable, even a weak correlation between the instrumental variable and the error term can seriously bias estimates and do more harm than good. Thus, we have chosen not to present the results of the model using instrumental variables, but instead to rely on least squares estimates, noting that (assuming a positive effect of lagged purchase decisions on contemporaneous decisions) the estimates of experiential effects will be biased upward.

Results

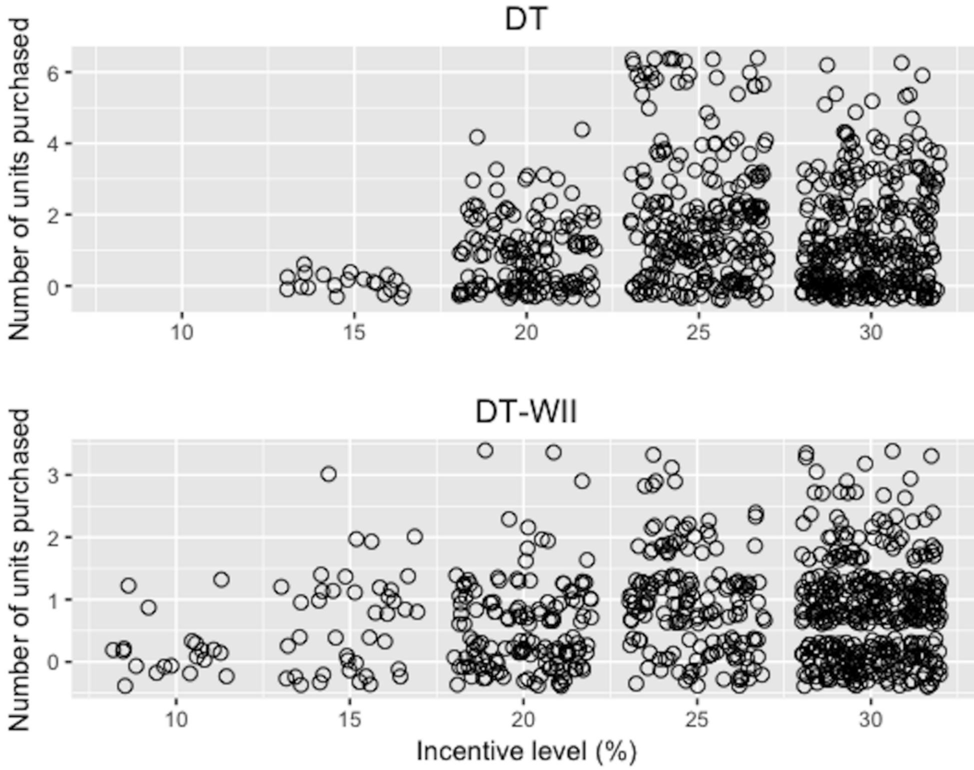
In the first year, we find relatively high uptake for both products: 63.1 percent of treated farmers offered the DT cultivar purchased seed, and 58.7 percent of treated farmers offered the DT-WII product purchased the product. In the second year, the uptake rates of both products fell, to 45.3 percent uptake of the DT cultivar and 35.7 percent uptake of DT-WII product.

Figure 5.1 plots the number of units purchased (for both DT and DT-WII) against the five discount levels randomly offered in 2015, with DT uptake in the upper panel and DT-WII uptake in the lower panel. For both the DT cultivar and the DT-WII product, there is greater heterogeneity in purchasing behavior at higher discounts (lower prices), though across both products the absolute degree of heterogeneity in purchasing behavior is thin. Figure 5.2 presents the difference in average demand among those allocated to the artificial discount group and those offered the fixed price, for both the DT-WII and the DT treatment arms. Uptake patterns in the second year indicate no significant differences between these two groups for either product. These results suggest that although demand for both risk–management products appears to be somewhat price sensitive, the manner in which the lower price is framed (for example, whether or not the effective price is the result of a subsidy) does not affect demand. Though these visualizations are only bivariate representations and do not control for the influences of other factors, they provide a first indication that demand might be commensurate with pricing that approaches actuarially fair levels.

Tables 5.1 and 5.2 present estimation results from the two-part model for DT and DT-WII uptake in the first year of the experiment. In each table, column 1 presents linear probability model estimates of the determinants of market participation (a binary choice), and column 2 reports least squares estimates of the intensity of market participation (that is, the number of units purchased). Few of our expected determinants of DT demand are particularly useful in explaining either participation in the DT market or the intensity of participation, including price, though notably the price of the DT seed is not appreciably different from the prices of other improved varieties available in the market. For DT-WII, we find a significant negative relationship between price and both the decision to purchase the product and the number of units purchased, but this latter effect loses its statistical significance when the proportion of neighbors purchasing the product is also included as a covariate, suggesting that the effect of price on purchasing decisions is correlated across participants within a given village. Other factors explain relatively little of the variation in purchases, though this result is likely attributable to insufficient variation in the dependent variable, which inhibits the identification of a causal effect on product demand.

Based on our econometric specification, the effective price per bundle can be thought of as

Figure 5.1: Scatter plot of purchased DT-WII and DT by incentive type in 2015

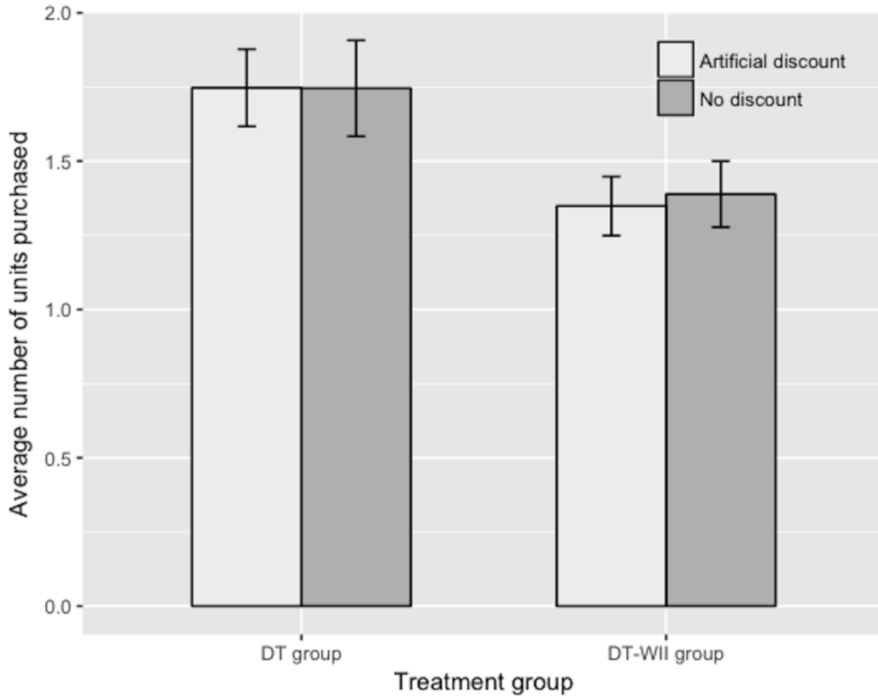


Source: Authors.
Note: Farmers did not purchase negative amounts of the product; the scatter plot is "jittered" to avoid overplotting. DT = drought-tolerant seed; DT-WII = drought-tolerant seed and weather index insurance.

having two effects: first on the decision to participate and second on the intensity of participation. From these year one regressions, we know that both of these effects are negative when it comes to the bundled DT-WII product. Interestingly, though, it seems that market participation is more sensitive to price than is the intensity of participation. We estimate that a Rs 10 increase in the effective price of the DT-WII bundle would reduce the probability of market participation by about 4 percent. Conditional on participating in the market, however, price changes have relatively little effect on the number of units purchased. It is not until the price increase approaches Rs 100 (which is close to a 66 percent increase) that we see uptake fall by anything close to a full unit.[21] In addition to relatively inelastic demand among those interested in participating in the DT-WII market, there

[21] These figures are based on regression estimates omitting the proportion of other villagers who also purchased, which, as noted above, is also influenced by the effective bundle price.

Figure 5.2: Bar plot of purchased DT-WII and DT by incentive type in 2016



Source: Authors.
Note: Vertical bars represent a 95 percent confidence interval. DT = drought-tolerant seed; DT-WII = drought-tolerant seed and weather index insurance.

are likely two other factors that contribute to this effect, both of which reflect a form of rationing. First, for various reasons—including budget limitations and a need for the program implementers to maintain solvency in the midst of considerable covariate risk—farmers were exogenously restricted in the number of units they were allowed to purchase, resulting in limited variation in observed purchasing behavior. Second, and perhaps more noteworthy, the DT-WII product represents a very new and arguably complex product—and, importantly, one that entails at least some basis risk—with which farmers had no prior experience, and therefore farmers may have purposefully limited their exposure to the DT-WII product. Both of these factors might be expected to wane at scale and over time. At a larger scale and with adequate reinsurance, the provider rationing described above may not be a limiting factor. Similarly, as farmers gain more experience with and better understand the nuances of this type of risk–management product, they may be less likely to ration their own exposure to the product and its complexities.

Table 5.1: Two-part model regression results: Market participation and uptake of DT in 2015

Variable	LPM: Participation	Least squares: Total units
Effective unit price of seed	−0.002	−0.044
	(0.003)	(0.035)
Share in village who purchased DT (2015)	0.818***	1.132
	(0.055)	(0.756)
Time discount rate	−0.001	0.006
	(0.006)	(0.022)
Is ambiguity averse	0.009	−0.104
	(0.033)	(0.147)
Risk aversion coefficient	−0.018	0.109
	(0.012)	(0.074)
Trust index	0.014	0.021
	(0.025)	(0.069)
Subj. beliefs about longest dry spell (mean)	0.003	−0.001
	(0.003)	(0.021)
Subj. beliefs about longest dry spell (std. dev.)	−0.001	0.004
	(0.001)	(0.005)
R^2	0.17	0.18
N	658	419

Source: Authors.
Note: * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Standard errors clustered at the village level. Regressions also control for household head age and sex, household size, land owned (acres), total input expenditure in 2014, total paddy output (metric tons), savings (Rs 000s), assets (asset index), annual consumption expenditure, and distance to rain gauge (as a proxy for susceptibility to basis risk). DT = drought-tolerant seed; LPM = linear probability model.

For both the DT cultivar and DT-WII product, the share of other farmers in the village who purchased these products has a large, positive, and significant relationship with the decision to purchase but, once again, not with the number of units purchased. We are cautious to ascribe causality here because we cannot disentangle whether household i's behavior directly influences (or is directly influenced by) the behavior of the members of i's village, or whether these behaviors are simply correlated because of other factors, either observable or unobservable (Manski 1993). Suffice it to say, however, that the persistent positive effect suggests some level of peer influence even if this influence is limited in the first year to encouraging market participation but not affecting the intensity of market participation.

We find evidence that a higher degree of impatience (indicated by a higher discount rate) is positively associated with the decision to purchase but not the decision of how many units

Table 5.2: Two-part model regression results: Market participation and uptake of DT-WII in 2015

Variable	LPM: Participation	Least squares: Total units
Effective unit price of bundle	−0.002***	−0.002
	(0.001)	(0.002)
Share in village who purchased DT-WII (2015)	0.471***	0.199
	(0.106)	(0.221)
Time discount rate	0.015*	−0.002
	(0.009)	(0.013)
Is ambiguity averse	0.006	0.006
	(0.034)	(0.069)
Risk aversion coefficient	0.001	−0.051**
	(0.018)	(0.019)
Trust index	−0.004	0.042*
	(0.019)	(0.022)
Subj. beliefs about longest dry spell (mean)	0.001	−0.001
	(0.018)	(0.007)
Subj. beliefs about longest dry spell (std. dev.)	−0.001	0.001
	(0.001)	(0.002)
R^2	0.08	0.07
N	689	408

Source: Authors.
Note: * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Standard errors clustered at the village level. Regressions also control for household head age and sex, household size, land owned (acres), total input expenditure in 2014, total paddy output (metric tons), savings (Rs 000s), assets (asset index), annual consumption expenditure, and distance to rain gauge (as a proxy for susceptibility to basis risk). DT-WII = drought-tolerant seed combined with weather index insurance; LPM = linear probability model.

to purchase, implying that farmers who value present more than future consumption are more likely to purchase DT-WII. At first glance, this finding may seem somewhat surprising, given that such purchases entail a current expenditure with an uncertain future return. Nevertheless, this phenomenon has been observed elsewhere in regard to insurance purchases (for example, Ito and Kono 2010; Hill et al. 2017; Platteau, De Bock, and Gelade 2017).[22] These findings may suggest that farmers were aware of their own lack of self-control and thus purchased the DT-WII risk–management product to manage the self-control problem, although other, equally valid, explanations are worth exploring.

For farmers' decisions to purchase DT, there are some interesting effects of drought expectations,

[22] For example, in the context of a health insurance program in India, Ito and Kono (2010) argued that this phenomenon reflects individuals' use of insurance as a commitment device that facilitates "prepayment" of healthcare expenses, relying upon the assumption that individuals are aware of their own self-control failures and inability to save to buffer against future expenses.

though the effects are not statistically significant at conventional levels. From Table 5.1, column 1, we see that the mean of individuals' subjective drought severity distribution is positive, but the standard deviation of the drought severity distribution is negative. All else equal, the implication is that if individuals expect a longer dry spell, they are more likely to purchase some DT, though this may be partially offset if they are very uncertain in their beliefs.

Although neither risk aversion nor trust seems to have an effect on the binary purchase decision for either DT or DT-WII, both have an effect on the decision of how many DT-WII units to purchase. In particular, our results imply that farmers with a higher overall degree of trust are likely to purchase more units of DT-WII, whereas those who are more risk averse are likely to purchase fewer units of DT-WII, conditional on choosing to purchase. This situation does not arise among farmers who decide to purchase DT, so it could be explained simply by farmers' wariness of a new concept such as index insurance, or simply by farmers' sensitivity to basis risk, which is inherent in virtually all index insurance products.

For the second year of the experiment, Tables 5.3 and 5.4 present the results from the demand estimations for DT and DT-WII, respectively. As before, column 1 presents estimates from a linear probability model corresponding to the binary market participation decision, and column 2 reports estimates from a least squares regression on the intensity of market participation. One of the principal interesting findings for both DT and DT-WII purchases in 2016 is the small and insignificant coefficients on the artificial discount. This noneffect is fairly ubiquitous in the 2016 estimates, regardless of whether we are talking about market participation or the subsequent determination of intensity of market participation, and regardless of whether we are referring to DT or DT-WII. The evidence fairly strongly implies that farmers are not drawn to purchase these risk–management products simply due to the presence of a subsidy or discount. Rather, although the data from 2015 suggest they are somewhat sensitive to price, there is also considerable evidence that farmers in our sample area are willing to pay more than the actuarially fair price for the bundle and would therefore not need to rely on a subsidy to encourage their participation in risk–management markets. This is a very important result, with significant implications for agricultural insurance policies in India. Recall the nature of the existing agricultural insurance program, PMFBY. Under this program, farmers pay only a small amount of the sum insured, with the remainder covered by government subsidies. Although this program design has the effect of significantly lowering the cost that farmers have to pay for insurance, which is likely to result in increased insurance uptake, it does so at considerable expense to the government. Our results suggest that these public funds might be more effectively allocated toward investments that can lower the cost of risk management in a more sustainable fashion and without distorting insurance markets. Examples of more sustainable investments might include investing in crop research and development (for example, to generate varieties that exhibit even greater drought tolerance), expanding the coverage of weather stations, or increasing the utilization of remote sensing or satellite images for weather indexes. Developing better DT varieties could result in lower-cost complementary insurance products because crops would need to be insured only against droughts whose severity exceeds a particular threshold, which would be higher (and therefore less likely to be exceeded) for improved DT varieties exhibiting greater drought-tolerance. By improving the coverage of weather stations or using lower-cost technologies, policy makers can improve the design of the complementary index insurance products, reduce the administrative costs, and reduce basis risk, all of which would either reduce the actuarially fair cost of insurance, reduce the administrative loads that would need to be charged, or change the perceived benefit-cost ratio in favor of increased uptake.

Farmers' DT purchases in 2016 seem to be heavily influenced by experiences with DT in 2015. Regardless of whether farmers resided in blocks that were affected by droughts during 2015, the results suggest that those who purchased DT during 2015 were more likely to purchase DT again in 2016, though farmers residing in blocks that were not affected by droughts were actually about 9 percent more likely to purchase DT again than those who resided in drought-affected blocks (the p-value associated with the linear combination of these coefficients was about 0.05). There is also some evidence of learning from the experiences of others in the farmers' communities. For example, although there is no evidence of peer experiences' influencing DT market participation in blocks unaffected by droughts, there is evidence of a positive influence of peer experiences in drought-affected blocks. For a given share of village peers who purchased DT in 2015, observing peers' fields during drought conditions in 2015 increased DT market participation by about 30 percent.

Table 5.3: Two-part model regression results: Market participation and uptake of DT in 2016

Variable	LPM: Participation	Least squares: Total units
Purchased DT (2015)	0.205***	0.214
	(0.069)	(0.202)
Drought occurred (2015)	−0.177*	−1.111
	(0.097)	(0.686)
Purchased DT (2015) × drought occurred (2015)	−0.094	−0.320
	(0.087)	(0.316)
Share in village who purchased DT (2015)	−0.184	−1.917**
	(0.148)	(0.866)
Share in village who purchased (2015) × drought occurred (2015)	0.314*	2.328**
	(0.162)	(1.002)
Share in village who purchased DT (2016)	0.634***	0.209
	(0.093)	(0.590)
Allocated to artificial discount group	−0.003	0.102
	(0.027)	(0.162)
Time discount rate	0.003	0.027
	(0.009)	(0.023)
Is ambiguity averse	0.016	0.146
	(0.043)	(0.130)
Risk aversion coefficient	−0.037**	0.000
	(0.014)	(0.056)
Trust	0.031*	0.093
	(0.017)	(0.072)
Subj. beliefs about longest dry spell (mean)	−0.037**	−0.005
	(0.014)	(0.013)
Subj. beliefs about longest dry spell (std. dev.)	0.002*	0.004
	(0.001)	(0.004)
R^2	0.17	0.14
N	632	287

Source: Authors.
Note: * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Standard errors clustered at the village level. Regressions also control for household head age and sex, household size, land owned (acres), total input expenditure in 2014, total paddy output (metric tons), savings (Rs 000s), assets (asset index), annual consumption expenditure, and distance to rain gauge (as a proxy for susceptibility to basis risk). DT = drought-tolerant seed; LPM = linear probability model.

Similarly, experiences with DT-WII in 2015 generally have a significant effect on DT-WII uptake in the second year, though it depends critically on whether the household experienced a drought during 2015 (and thus received a payout from the insurance policy). Among households who purchased DT-WII and did not experience a drought during 2015 (that is, no drought was recorded at the block weather station site), although there is no effect on participation in the DT-WII

Table 5.4: Two-part model regression results: Market participation and uptake of DT-WII in 2016

Variable	LPM: Participation	Least squares: Total units
Purchased DT-WII (2015)	0.073	-0.144^{**}
	(0.046)	(0.065)
Drought occurred (2015)	−0.079	−0.081
	(0.084)	(0.515)
Purchased DT-WII (2015) × drought occurred (2015)	0.222^{***}	0.363^{**}
	(0.079)	(0.141)
Share in village who purchased DT-WII (2015)	−0.061	−0.306
	(0.090)	(0.321)
Share in village who purchased (2015) × Drought occurred (2015)	−0.001	0.215
	(0.166)	(0.839)
Share in village who purchased DT-WII (2016)	0.799^{***}	0.519^{**}
	(0.061)	(0.236)
Allocated to artificial discount group	0.014	−0.065
	(0.023)	(0.106)
Time discount rate	−0.000	−0.020
	(0.005)	(0.020)
Is ambiguity averse	−0.014	−0.074
	(0.037)	(0.050)
Risk aversion coefficient	0.009	−0.035
	(0.011)	(0.026)
Trust	−0.015	−0.018
	(0.012)	(0.029)
Subj. beliefs about longest dry spell (mean)	0.005	0.001
	(0.004)	(0.009)
Subj. beliefs about longest dry spell (std. dev.)	−0.001	−0.0001
	(0.001)	(0.003)
R^2	0.26	0.27
N	666	236

Source: Authors.
Note: * Significant at 10 percent level; ** significant at 5 percent level; *** significant at 1 percent level. Standard errors clustered at the village level. Regressions also control for household head age and sex, household size, land owned (acres), total input expenditure in 2014, total paddy output (metric tons), savings (Rs 000s), assets (asset index), annual consumption expenditure, and distance to rain gauge (as a proxy for susceptibility to basis risk). DT-WII = drought-tolerant seed combined with weather index insurance; LPM = linear probability model.

market, these households purchased 0.14 fewer units than farmers who had not purchased DT-WII during 2015. Farmers who purchased DT-WII during 2015 and lived in blocks that were affected by droughts in 2015 were 22 percent more likely to purchase DT-WII again in 2016, and they purchased more than 0.20 more units of DT-WII in 2016 than those not living in drought-affected blocks, though the linear combination that makes up this partial effect is not statistically significant at conventional levels ($p = 0.12$). In some regards, this effect is discouraging because it may point to receipt of an insurance payment as the primary motivator behind subsequent risk–management decisions, particularly in light of the scant evidence of positive effects on subsequent DT purchases from having cultivated DT in the midst of a drought during 2015.

Consistent with findings from 2015, we find evidence of a generally strong peer influence on participation in the DT and DT-WII products in 2016, with additional evidence of peer influences on the intensity of uptake of the DT-WII product in 2016. Rather than this arising as a result of learning from one's neighbors, the evidence seems to suggest that the primary driver behind this peer effect is a form of peer pressure or herd behavior during the product marketing sessions. A plausible explanation is the existence of some social desirability about participating in an NGO's activities: in other words, farmers in the sample villages want to be seen purchasing the DT and DT-WII products being marketed by the NGO, even though there is evidently not significant pressure on them to participate to the maximum extent possible (illustrated by the limited evidence of social influences on the intensity of participation).

For farmers offered DT in 2016, the effects of individuals' subjective drought severity beliefs are reversed relative to 2015. For this second year, we see that the longer the expected drought, the less likely a farmer is to purchase DT, though the more uncertain farmers are in these expectations, the more likely they are to purchase. In tandem with the aforementioned evidence of cultivating DT during drought in 2015, this finding may point to disappointing performance of the DT variety during drought conditions.

In this second year, we find that neither trust nor risk aversion influences uptake of the DT-WII product, in terms of either market participation or the number of units purchased. Thus, whereas the more trusting farmers in our sample purchased more units of DT-WII during 2015, conditional on entering the market, experiences in this first year must have been sufficient for farmers in the sample to feel comfortable enough with the complex product and the NGO marketing the product that trust and risk became less of a concern, to the extent that these factors were rendered essentially irrelevant.

6 Concluding Remarks

Indian agriculture remains highly susceptible to weather-related production risks, most notably droughts and floods. This statement is especially true in rainfed production systems, which account for roughly 60 percent of the gross cropped area in India (Nair 2010b). When these risks are realized, there can be large impacts on crop production, but even when droughts and floods do not materialize the risk of their occurring entices farmers to opt for conservative farming practices and livelihood strategies. Despite the existence of various government programs over the years, coverage has remained dismally low. In 2016, the government of India launched a new flagship program, PMFBY, aiming to increase insurance coverage to as much as half of the cropped area by providing large subsidies on the cost of insurance (farmers pay only 2 percent of the sum insured for kharif crops such as rice, with the rest of the cost provided as government subsidies). The structure of insurance pricing under PMFBY—with a variable and unlimited subsidy amount—seems particularly unsustainable, and other public investments could arguably be made to support agriculture and rural development without distorting insurance markets.

This paper provides some of the first evidence on the demand for a bundled risk management product consisting of a DT rice cultivar and a specially calibrated index insurance product. By doing so, it offers important evidence about a potential alternative risk–management product that may be viable without massive government subsidies such as those offered under PMFBY.

In the first year of our study, when offered modest discounts, more than half of the participants in each of two treatment arms purchased some form of risk management, with 63 percent of treated farmers purchasing the DT seed and nearly 59 percent of treated farmers purchasing the bundled DT-WII product. Adoption rates for both products fell during the second year, with 45.3 percent uptake of the DT cultivar and 35.7 percent uptake of the DT-WII product. Given the low levels of WII uptake recorded in the literature, even in the presence of discounts and subsidies, this study's uptake of DT-WII without financial incentives is relatively high. Furthermore, the decline in uptake from the first year to the second year cannot be explained by the removal of product discounts. Thus, although, farmers may be sensitive to the price of risk–management coverage, framing a price reduction as a subsidy or discount does not influence farmer demand. In light of the distortionary nature of subsidies—not to mention the political challenges associated with removing subsidies once they are in place—our findings suggest an alternative role for government in promoting risk management. Rather than allocating scarce resources to subsidizing crop insurance programs, government resources might be more appropriately allocated to investments that can reduce the cost of risk management without distorting markets, such as research and development for seed technologies, expanding the coverage of weather stations, or increasing the utilization of remote sensing or satellite images for weather indexes.

Our results also suggest an important role for learning from experience, with experiences from the first year of the experiment seeming to have a significant impact on purchase decisions during the second year. Importantly, however, the effect of learning seems to differ somewhat across the two products. In the case of DT, there is evidence of learning from both one's own experiences and the experiences of others, especially if one or one's peers experienced a drought (or, at least, if a drought was recorded at the block weather station) during the first year. In the case of DT-WII, having purchased the product in 2015 and experiencing a drought in that year has a positive effect on purchasing decisions in 2016, presumably because farmers begin to appreciate the benefits of the bundled product. They do not learn much from the experiences of their peers, however, because peers' experiences with the DT-WII product in 2015 have no effect on farmers' purchasing decisions in 2016. We attribute this result to product complexity more than anything else: although it is easy to look out into someone's field and observe the performance of a particular variety vis-à-vis another variety, it is not easy to observe one's experiences with insurance, particularly a small-scale insurance program like the one introduced here.

Another significant takeaway from this paper is that social networks matter during product marketing. The one factor that is almost ubiquitous in explaining demand, for both products across both years, is within-village peer effects—farmers' purchase decisions are highly correlated with the purchase decisions of other farmers in their village. Although we cannot truly identify the nature of this effect, it may prove beneficial for public- and private-sector efforts to increase insurance coverage across India.

Finally, this study points to the need for ongoing assessments of development initiatives. Although the nature of the intervention did not change from one year to the next, we did find evidence that the factors affecting demand changed somewhat from one year to the next, suggesting that there is much to be gained by studying demand over multiple time periods, particularly if the product in question is relatively novel or complex. One would hope that over time the demand determinants would converge to some steady state, but in early years it may be difficult to draw generalizable inferences.

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Appendix A Insurance and Basis Risk Experiential Learning Module

Instructions: In this section you will be guiding the respondents through an experiential learning exercise in which the respondents will be learning about concepts of weather index insurance and basis risk through a series of questions and experiences in drawing different-colored balls out of a bag. Because understanding risks requires some basic understanding of randomness and probability, it is important that these experiences help the respondents garner a rudimentary understanding of these sometimes complex and abstract concepts. Through these learning experiences, respondents will ideally be well informed to make choices about whether to purchase risk management. This script has been specifically created to maximize the learning potential, so it is very important that you read through the script word for word. When there are directions for you (not to be read aloud to the respondent), these will be indicated by square brackets: [...]. Read through these instructions and questions slowly so that the respondent understands. Do not try to guide or influence the respondents in any way.

Q. What would you do if you experienced a moderate or severe drought and were to face serious income/crop losses, and needed to find some money to feed your family or meet other family obligations?

[**Enumerator:** There are many possible answers to this question. Some of the coping mechanisms used by respondents include the following alternatives:

- Using personal savings
- Selling assets
- Cutting down on food consumption
- Selling crop inventory to meet household obligations
- Relying on others: relatives, neighbors, social organizations such as religious groups
- Using financial instruments such as credit.]

Q. Have you ever heard of insurance as a way of managing drought risk?

Enumerator: Drought index insurance is one way that farmers can deal with drought risk. With this insurance, farmers pay a small amount now and receive a cash payment at the end of the season if a drought occurs during the kharif season.

We determine whether a drought has occurred based upon rainfall measurements collected at weather stations throughout the Khaira and Oupada blocks in Balasore, Agarpada and Bant blocks in Bhadrak, and Kaptipada and Thakurmunda blocks in Mayurbhanj. At these weather stations, we will collect information on the amount of rain that falls during the kharif season. If a drought is recorded at these stations, the insurance will provide a payment at the end of the season. In your case, the weather measurements will be based on the weather station in your block.

The amount of the cash payment depends upon the severity of the drought, but these payments are meant to reflect the average losses in farm income from these types of droughts on a 10-decimal (0.1-acre) plot of land. For example, during a moderate drought, farm income losses for a farmer growing Swarna on a 10-decimal plot of land might be approximately Rs _____. Therefore, if the farmer purchased insurance to protect against these losses in farm income, then the payment would be Rs _____ if there was a moderate drought. Similarly, during a severe drought, farm income losses for the same farmer growing Swarna on a 10-decimal plot of land might be approximately Rs _____. If the farmer purchased insurance to protect against these losses in farm income, then the payment would be Rs _____ if there was a severe drought.

If the farmer does receive a payment from the insurance, there are no rules about how this payment is to be spent. Payments can be used in these or other ways

- To offset costs of additional irrigation to supplement deficient rainfall
- For purchasing seed or fertilizer, or renting land for future cultivation
- For financing food purchases for the household
- To pay for school fees, medical costs, clothing, and so on
- For investments such as purchasing oxen, cows, donkeys, and so on

Q. Are there any restrictions about what insurance payments can be used for?

[**Enumerator:** Ensure that the respondent understands that there are no restrictions on how the insurance payments can be spent.]

Q. Are the weather conditions at your farm always the same as the weather conditions at the block headquarters?

[**Enumerator:** Ensure that the respondent understands that weather conditions vary from one location to the next.]

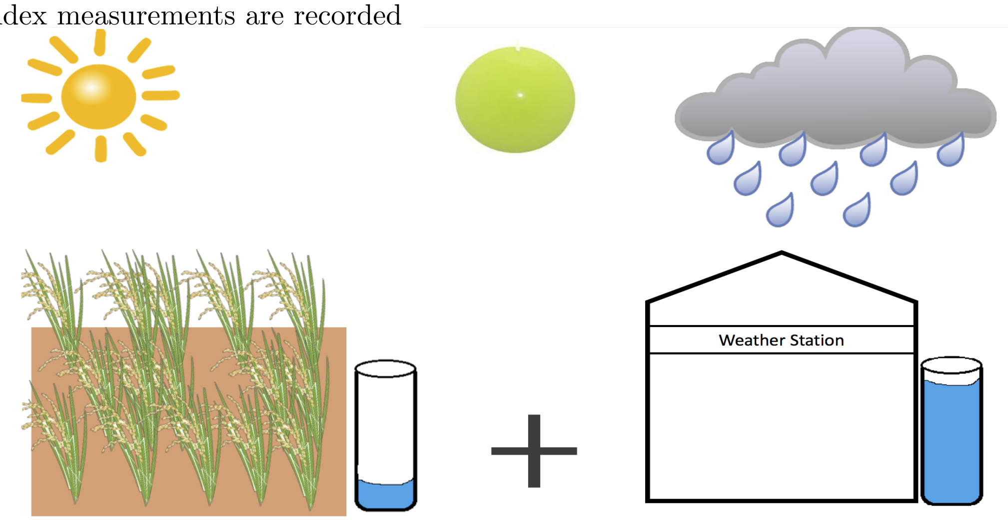
As we have mentioned, the insurance will pay out if a is drought measured at the weather station that is located in your block. Because your farm may be located far away from the weather station, there is a chance that the weather conditions on your farm may not be the same as the weather conditions at the weather station. Recall that the insurance depends upon the observed rainfall at the weather station, not rainfall on your field.

To illustrate this scenario, consider this bag, which has one pink ball and one green ball. In just a moment, I will ask you to draw a ball out of this bag. If you draw a pink ball, then the weather conditions on your farm will be the same as the weather conditions at the local weather station. If you draw a green ball, then the weather conditions on your farm will be different from the weather conditions at the local weather station. This is meant to reflect the fact that your conditions may not be the same as the weather conditions at the weather station.

It is possible that you may experience poor weather conditions on your field, but the weather conditions may be fine at the weather station. This situation is illustrated by the green ball, which indicates that the weather conditions do not match. Because the insurance contract is based on the rainfall measurements at the local weather station, and not your actual farm income losses or the actual rainfall you experience on your farm, there is a chance that the insurance contract would not compensate you for farm income losses even if you experience a loss in farm income resulting from a drought.

[**Enumerator:** Show the respondent Figure A.1. Ensure that the respondent understands that he/she may experience drought conditions on his/her farm but that there might not be drought conditions at the closest weather station.]

Figure A.1: Example of mismatch between weather conditions on farmer's field and weather station where index measurements are recorded



Source: Authors.

Alternatively, it may be the case that weather conditions on your farm are very similar to the weather conditions at the weather station. If there is a drought on your farm, there is also a drought at the weather station. Under this situation, you would receive a payout from the insurance policy. Because the weather conditions on your farm are similar to the weather conditions at the local weather station, this would be like the situation of drawing a pink ball from the bag.

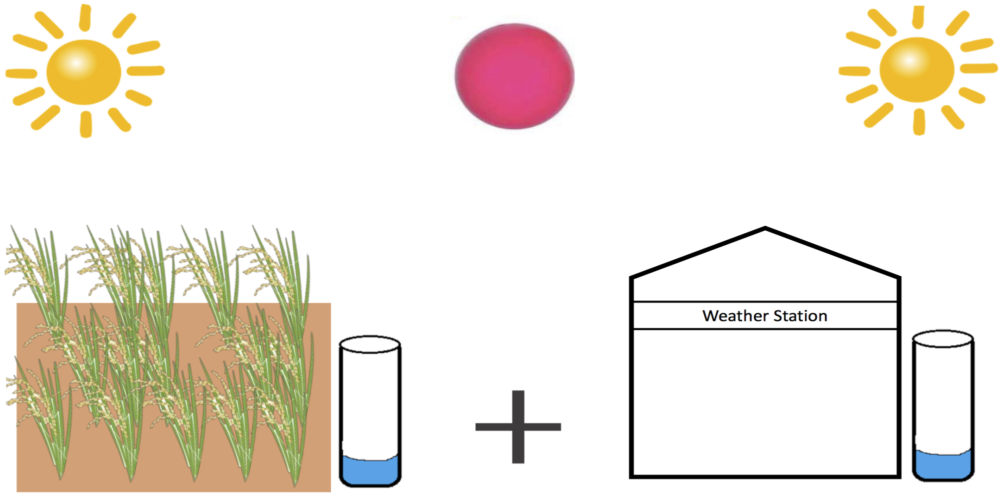
[**Enumerator:** Show the respondent Figure A.2.]

Q. Do you understand how the insurance payouts operate? Are the payouts based on income losses on your farm? Or are the payouts based upon observed rainfall at a weather station?

[**Enumerator:** Ensure that the respondent understands that the payouts are not based on income losses on his/her farm but are based upon measured weather at a local weather station in his/her block.]

Now, imagine that you have experienced a drought on your farm. There was little rainfall during the year, and your paddy crop suffered. If you had purchased insurance, you may be entitled to a payment from the insurance contract if a drought was detected at the local weather station. But the weather conditions at the local weather station might not be the same as the weather conditions on your field. If the weather conditions are different, you will not receive a payment from the

Figure A.2: Example of match between weather conditions on farmer's field and weather station where index measurements are recorded



Source: Authors.

insurance, because these payments are based on the weather conditions at the local weather station and do not depend upon the actual weather conditions on your farm.

Please draw a ball from this bag to see whether or not the weather conditions on your farm were the same as the weather conditions at the local weather station.

[**Enumerator:** Please have the respondent draw a ball from the bag.]

Q. What color is the ball?

Q. If you had insurance and experienced farm income losses from a drought that occurred on your farm, what would drawing this color ball imply for receiving a payout?

[**Enumerator:** Ensure that the respondent understands that if he/she drew a pink ball, the weather conditions on his/her farm would be the same as the weather conditions at the local weather station, so he/she would receive an insurance payment. If, however, he/she drew a green ball, the weather conditions on his/her farm are different from the weather conditions at the local weather station, and he/she would not receive an insurance payout.]

Appendix B Drought Risk Experiential Learning Module

Instructions: In this section you will be guiding the respondents through an experiential learning exercise where the respondents will be learning about the concept of drought risk through a series of questions and experiences in drawing different-colored balls out of a bag. Because understanding risks requires some basic understanding of randomness and probability, it is important that these experiences help the respondents garner a rudimentary understanding of these sometimes complex and abstract concepts. Through these learning experiences, respondents will ideally be well informed to make choices about whether to purchase risk management. This script has been specifically created to maximize the learning potential, so it is very important that you read through the script word for word. When there are directions for you (not to be read aloud to the respondent), these will be indicated by square brackets: [...]. Read through these instructions and questions slowly so that the respondent understands. Do not try to guide or influence the respondent in any way.

Enumerator: As a farmer, you face many different types of risks related to your paddy production.

Q. In your opinion, what are some of the most serious risks to paddy production during the kharif season?

[**Enumerator:** Some of the possible responses include the following:

- Pests, weeds, diseases
- Crops' being eaten or trampled by animals
- Lack of seed/fertilizer
- Soil type
- Frost/wind
- Lack of rainfall (drought)
- Excess rainfall (flooding)

- Sickness in the household, death, and so on (influencing labor supply)

You may need to guide or nudge the respondent in the identification of these risks. Ensure that the respondent acknowledges weather to be a significant constraint, particularly drought.]

Enumerator: In this exercise, we are interested in understanding your preferences toward various methods for managing risks related to paddy production—particularly those related to droughts during the kharif season. There are many instances in which droughts can occur during the kharif season, including late monsoon arrival or early monsoon cessation, or prolonged periods without rainfall, or simply just below–average rainfall. The India Meteorological Department defines a moderate drought as any occurrence in which rainfall is between 26 and 50 percent below normal and a severe drought as any occurrence in which rainfall is more than 50 percent below normal. The impact of the drought on paddy production depends on several key factors, including the paddy variety that you cultivate, the timing of the drought, the severity of the drought, whether or not you have access to irrigation, your soil type, and many other potential factors. Some of these factors are directly under your control, but others are not. You do not have control over the weather, so you cannot influence the timing or severity of droughts if they occur.

Q. Do you understand how droughts can affect paddy production?

[**Enumerator:** Ensure that the respondent understands that droughts can affect his/her paddy production. It should be pretty obvious to respondents that droughts affect their paddy yields. They may also indicate that they delay transplanting or cultivate less land if the monsoon is delayed.]

Enumerator: Droughts are the result of weather. Weather is risky because it is difficult to predict with a great deal of certainty. To illustrate drought risk, consider this bag, which contains five balls: some of these balls are green, and some balls are red. In a moment, we will ask you to draw a ball from this bag. Imagine that drawing a ball from a bag is like observing weather during a given kharif season. If the ball is green, this is like observing good weather during the kharif season. If the ball is red, this is like observing a moderate drought during the kharif season.

[**Enumerator:** Please ask the respondent to draw a ball from the bag.]

Q. What color is the ball?

Q. Does this indicate observing good weather or observing a moderate drought during kharif?

[**Enumerator:** Depending upon the color of the ball that is chosen, make sure that the respondent understands what weather outcome is implied by the drawn ball.]

[**Enumerator:** Place the ball back in the bag]

Enumerator: Now, I am going to have you draw five balls from the bag, one at a time.

[**Enumerator:** Please have the respondent go through a sequence of drawing five balls from the bag, replacing the drawn ball each time (there should always be five balls in the bag each time the respondent makes his/her draw).]

Q. How many green balls did you draw? How many red balls did you draw?

Q. There are five balls in this bag. How many do you think are green? How many do you think are red?

[**Enumerator:** After the respondent has guessed how many green and red balls he/she thinks are in the bag, take all of the balls out of the bag to show him/her the actual number of green and red balls there are.]

Because there are four green balls and one red ball, we should expect that, if we draw five balls in a row, we would draw one red ball. This is similar to observing weather over five years: we would expect that one of those years would be a moderate drought year.

I am now going to have you draw five more balls from the bag.

Q. How many red balls do you expect to draw?

[**Enumerator:** Make sure the respondent understands that he/she should expect to draw one red ball from the bag].

[**Enumerator:** Please have the respondent go through a sequence of drawing five balls from the bag, one at a time, replacing the drawn ball each time (there should always be five balls in the bag when the respondent makes his/her draw).]

Q. How many green balls did you draw? How many red balls did you draw?

Q. Is this more or less than you expected (or exactly as many as expected)?

Enumerator: You can never know for sure what color ball you will draw until you actually draw it. You may expect that you will draw one red ball in five draws, but there is nothing guaranteeing that pattern. You may draw two red balls in a row, or you may go several draws without drawing a red ball.

The same is true for weather.

Weather is difficult to predict. We may expect one moderate drought every five years, but we can never be sure that we will observe only one moderate drought in any five-year period or that we will observe a single drought during that period. In other words, we may observe several moderate drought years in a row, or we may observe a period of several years without a moderate drought.

So far, we have talked only about moderate drought. We expect that we should observe a moderate drought one time during any five-year period. But, as we have seen, we may experience more or fewer moderate droughts than what we expect.

Severe droughts have a greater impact than moderate droughts. They either last longer or result in a greater shortage in rainfall compared with moderate drought. But severe droughts occur less often than moderate droughts. We would not expect a severe drought to occur one time every five years. As such, if we had balls in a bag of balls representing observed weather, we would not have one red ball representing a severe drought and four green balls representing normal rainfall. If we wanted to use balls like these to represent the likelihood of a severe drought, we would need one red ball and 49 green balls.

Q. Based on what we have discussed, if you were to observe weather over a five-year period, during how many of those years would you expect to observe a moderate drought?

[**Enumerator:** Ensure that the respondent understands that he/she would expect to observe one moderate drought over a given five-year period].

Q. Is it possible that you could experience more than one moderate drought during a five-year period?

[**Enumerator:** Ensure that the respondent understands that it would indeed be possible that he/she could observe more than one moderate drought over a five-year period].

Q. Is it possible that you would not experience a single moderate drought during a five-year period?

[**Enumerator:** Ensure that the respondent understands that it would indeed be possible that he/she could fail to observe a single moderate drought over a five-year period].

Q. Which is more likely to occur, a moderate drought or a severe drought?

[**Enumerator:** Ensure that the respondent understands that a moderate drought is more likely to occur than a severe drought. On average, we expect a moderate drought to occur one time every 5 years. We would only expect a severe drought to occur only one time every 50 years. The actual occurrence of moderate and severe drought may be more or less frequent than what we expect].

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www.ifpri.org

IFPRI HEADQUARTERS

1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org