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Risk management in agricultural production

Jesse Tack* **and Jisang Yu**†

Department of Agricultural Economics, Kansas State University, Manhattan, KS, United States

**Corresponding author: e-mail address: jtack@ksu.edu*

Chapter outline

np8650 †Senior authorship is shared equally.

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s0010 ## 1 Introduction

p0010 For decades there existed a view within the agricultural production literature that we could have our cake and eat it too. We recognized the important distinction between risk attitudes that resided inside of utility functions versus technological relationships that resided inside production functions; but we also believed that we could estimate these sets of parameters jointly. The 1980s and 90s were the height of structural econometric applications at the nexus of agricultural production and risk management.[1] One would build a theoretical model that accounted for many specific, nuanced aspects of the decision-making process, derive some relationships among observable variables, and take them to the data. This period was followed by a movement away from structural econometric approaches, following a pattern seen in many other economic disciplines as well. Within the agricultural production literature specifically, there were a few key papers that were likely born in spirit around the turn of the century that accelerated this change (e.g., Just & Just, 2011; Lence, 2009). Insightful research that pointed out the empirical difficulty of disentangling estimates of risk aversion from production parameters and/or price elasticities was published and had a strong affect on the literature.

p0015 Which brings us to the present day. When you look deeply at the literature on risk management in agricultural production, as we have been forced to confront in writing this article, you see a fragmented set of very specific research questions and a lack of appreciation for how all these pieces are interwoven with each other. More researchers have been focusing on singular parameters from various parts of the combined environment in which producers make decisions. While the estimation and the identification of singular parameters have benefited from the recent innovations in empirical tools born in the era of credibility revolution,[2] the challenge is that we need to start thinking about how all these pieces can fit back together.

p0020 Price risk, production risk, and government programs are all important drivers of producer welfare and are not likely to be separable in the decision-making process.

np0010 [1]Moschini and Hennessy (2001) is the previous handbook chapter on risk and agricultural production in this series, and provides an excellent canvassing of the literature.

np0015 [2]See Angrist and Pischke (2010) for the summary.

For example, around planting time of the 2021 spring/summer crop season we had high (output) crop prices coupled with high (input) fertilizer prices, many major production regions in the United States were experiencing moderate to severe drought, and some producers had access to highly subsidized crop insurance. There are many other examples of joint decision-making across multiple dimensions. Access to credit can depend on institutional limitations (e.g., thin to nonexisting loan markets) as well as characteristics of the producer (e.g., diversified revenues and/or agricultural insurance availability). Management of price risk through forward contracting can be very much tied to production risk as highly volatile production increases the probability that a producer will not be able to deliver output at harvest. Similarly, the management of price risk through storage also creates a linkage to production risk as large unexpected (and typically highly spatially correlated) *positive* production shocks often provide strong incentives to store output after harvest to wait out nearby price declines. New technologies are often a "bundle" of individual components (e.g., new seed varieties that often package both biotic and abiotic stress resilience) and their adoption is often driven by whole-farm risk considerations (e.g., smoothing of household income).

p0025 With this in mind, the goal of this handbook chapter is twofold. First, the scope includes important research findings within the literature in the last 10 years. We do not solely focus on "seminal" contributions. Focusing on seminal contributions alone can be dangerous as they can often be a tombstone for a vein in the literature. Instead we focus on a range of empirical findings in an effort to demonstrate the breadth of interesting, researchable topics contained in the literature. Second, we propose a simplistic theoretical model to serve as a road map to the literature. Once a topic is mastered, one can write down a very complex model that accommodates many dimensions of on-farm decision-making and show how various nuances/applications are restricted versions thereof; but this is a challenging position to start from, especially for young researchers gaining an initial familiarity with the literature. It is much easier to start with a simple restricted model, master it, and then learn how it can be tweaked in subtle ways to accommodate more nuanced environments. One can then layer those tweaks on top of each other to build multidimensional nuance and complexity as needed.

p0030 It is virtually impossible to build a conceptual model that can accommodate all of these managerial decisions simultaneously, but a good starting point is to view the farm as a portfolio that aggregates many dimensions of decisions as is common in financial economics. Here we seek to first strip down the problem into many constituent parts and model them individually using a common stylized (and hopefully accessible) model that mimics the framework of asset pricing models. With each of these pieces in hand, one can then build up the model to include any combination of the fundamental pieces as needed and the components will be (mechanically) synergistic since each is derived within a common framework. A key strength of asset pricing models is that the marginal decisions on each asset (i.e., the first order conditions of the optimization model) are (literally) summable in an intuitively appealing manner that aggregates up to the portfolio level. Taken from the perspective of a producer, one can think of inputs such as land and labor as assets to be managed within the context of the whole-farm portfolio.[3]

p0035 Breaking down the decision-making process with an eye toward building it back up using various combinations of risk management strategies as the context necessitates is constructive for a variety of reasons. First, it provides a simplified theoretical structure for young researchers to utilize as they navigate the literature on various topics. By showing that individual topics can be thought of as slight tweaks from a common model, the model itself serves as a road map (or tour guide) for interacting with the empirical literature. These tweaks can also help build some comparative statics (marginal effects) *ceteris paribus*, which is helpful in building intuition regarding a relationship between two variables. For people further along in their professional development, building models up by combining various pieces provided here could be useful, especially in the context of causal inference. One can start with the *ceteris paribus* insight, then build in other decision variables to add additional layers of complexity to the decision-making process and thus provide insights for endogeneity concerns, especially as they relate to confounders and/or heterogeneous marginal effects (perhaps resulting from important interactions and/or feedbacks). Finally, for the well-established practitioner that is already out on the frontier of risk management and agricultural production, perhaps the model might provide a slight reframing of focus that can sometimes shake loose a deeper insight. In either case, this chapter adds value by providing a topical overview of various interesting research questions and/or empirical results within the recent literature.

p0040 The model we employ is a very stripped down version of Pope, LaFrance, and Just (2011) in that the dimensions of the input-output space are greatly reduced. It employs some simple dynamics of wealth allocation, incorporates risk, and borrows insights from asset-pricing models. This version is just realistic enough to be useful, and we show in the various sections of the chapter how simple modifications to the model can accommodate more nuanced aspects of on-farm decision-making. We aim to give early career researchers a simple yet foundational model that they can carry around in their hip pocket to help them conceptualize risk management in agriculture. This model also serves as a road map for all the fragmented segments of the empirical literature as little modifications to this model can be made to study various hyper-focused aspects of risk in production.[4]

p0045 A note on the structure of this chapter is worth making. Section 2 introduces the behavioral model and then the subsequent sections demonstrate the usefulness of, and ease in which, this model can be modified to accommodate a wide range of

np0020 [3]It is important to note here that we are not proposing a new model, but rather stripping an existing model down to its simplest form and then tweaking it to show how broadly applicable it could be.

np0025 [4]Another appreciable aspect of this model is that it contains the spirit of the structural econometric models that were guiding the literature in past decades. In this way, and very much in line with the goals of a middle sibling, we hope to provide a bridge between dichotomous empirical approaches within the profession. If one is not going to embrace the use of structural approaches for their empirical applications, that is fine, but one can still very much appreciate them for the economic intuition that they provide. And who knows, maybe someday soon the literature will include carefully identified treatment effects within the context of structural econometric estimation….

nuances for conceptualizing farm decision-making. Section 3 focuses on on-farm production with modeling nuances related to technology adoption and management of both biotic and abiotic stressors. Section 4 focuses instead on marketing decisions that can affect output price through forward contracting, hedging, and storage mechanisms. Section 5 shows how the model can be extended to include off-farm decision-making and provides conceptual frameworks for land rental as well as off-farm labor and investment decisions. Section 6 considers the role of both credit-availability and insurance contracts, while the final Section 7 discusses some potential avenues for generalizing the model to allow for more nuanced risk attitudes both within and beyond the expected utility framework. Within each of these sections, the subsections have a parallel structure and are meant to stand alone. They begin with a motivating example showing how the stylized model can be extended to accommodate various nuances in the decision-making process, followed by a summary of current topics in the literature and a discussion of contributions from specific papers.

s0015

2 Modeling agricultural decisions under risk

p0050 Risk aversion is often conceptualized behaviorally as a preference for a gamble that has the same mean but with less risk, which in turn begs the question of how to define "risk" in a way that is practical and relevant. One broad class of approaches is the risk-return model whereby the utility function itself includes a very directly specified distaste for risk given a fixed return (e.g., the mean-variance model and generalizations thereof[5]). Another class does not include a measure of risk directly in the utility function but instead conceptualizes risk as a curvature property of that function; for example the expected utility approach whereby the (random) utility function is specified as $u(c)$ with risk aversion then defined as declining marginal utility $u'' < 0$.

p0055 The model proposed in this section is an example of the latter and incorporates life-cycle household consumption, agricultural production, and financial decisions in one coherent framework as highlighted and discussed in Pope et al. (2011). The producer's decision process is representative of a farm business, in which the agent controls the means of production and makes investment decisions to generate wealth that can be used for consumption good purchases. If one is uncomfortable with using consumption to index the value of on-farm activities, it could in turn represent an annual payment received by the producer which may include farm profit, a rental payment, and/or a dividend to be split among shareholders of a company (limited liability or otherwise). At the end of this section we address the applicability of this model in the context of subsistence farms.

p0060 The farm's production technology is represented by $y = F(x, a)\epsilon$ where x is a variable input, a is land, y is output, and ϵ is a stochastic production shock with $E(\epsilon) = 1$ and $Var(\epsilon) = \sigma^2$. Pope et al. (2011) show how this model can scale up to any number of

np0030 [5]See Chambers, Genius, and Tzouvelekas (2021) for a great overview of this approach, including a discussion on the shortcomings of using variance to measure risk and a recent model contribution.

inputs (both variable and fixed) and outputs, and also its ability to accommodate more general representations of technology in which σ^2 is a function of inputs.[6] While one can consider more flexible models with an implicit production function represented by $F(x, a; \epsilon)$, the current functional form provides convenient tractability and interpretability.[7] Much of the intuition that the model provides remains valid under a more general representation of technology. Initial wealth in period t, W_t, is allocated at the beginning of the period to land, input, and consumption m according to

$$W_t = a_t + x_t + m_t.$$

Here we are measuring inputs and consumption in expenditure terms to reduce notational burden. One can think of prices as being normalized to unity. If this is grating, one can easily add in prices and the insights provided in this chapter will remain. The on-farm investments generate end-of-period wealth W_{t+1}

$$W_{t+1} = \delta_{t+1} a_t + p_{t+1} F(x_t, a_t)\epsilon_{t+1}$$

where δ captures the relative change in the value of farmland and $F(x_t, a_t)\epsilon_{t+1}$ is ex post realized output that sells at output price p_{t+1}.

p0065 The farm's objective is the maximization of the expected stream of utility flows from consumption at time t,

$$V_t = E_t\left[\sum_{j=0}^{\infty} \rho^j U(m_{t+j})\right]$$

where V_t is the expected present value in period t, $E_t(\cdot)$ is the conditional expectation at the beginning of period t given available information, and $\rho \in (0, 1)$ is the single period discount factor.[8] The problem can be summarized by considering it as a dynamic programming problem with corresponding Bellman equation[9]

$$V(W_t) = \max_{a_t, x_t, m_t} \quad U(m_t) + \rho E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = a_t + x_t + m_t, \text{ and, } W_{t+1} = \delta_{t+1} a_t + p_{t+1} F(x_t, a_t)\epsilon_{t+1}.$$

np0035 [6]The classic example being Just–Pope technology whereby ϵ in the model is replaced with $e^{h(x)v}$ such that $\ln y = f(x) + h(x)v$ with $E(v) = 0$ and $Var(v) = 1$ (Just & Pope, 1978).

np0040 [7]An important restriction of this homogeneous, multiplicative specification is that it assumes that inputs are risk increasing (Just & Pope, 1978); thus while Sections 3–5 provide applications using this simpler version of technology, we also demonstrate how the model can accommodate a more general form $y = F(x, \epsilon)$ in Section 6.

np0045 [8]This objective represents an expected utility model with time additive preferences that is subject to the "Allais paradox" and to the "equity premium puzzle". We discuss the former in Section 7. The latter is discussed by Epstein and Zin (1991) in the context of restrictive assumptions imposed by expected utility regarding the intertemporal substitution of consumption.

np0050 [9]Note that while the periodic discount factor ρ is included here as it should be to reflect discounted future utility, it is omitted for simplicity in the subsequent sections of this chapter.

The associated Lagrangian is

$$\mathcal{L} = U(m_t) + \rho E_t[V_{t+1}(\delta_{t+1}a_t + p_{t+1}F(x_t, a_t)\epsilon_{t+1})] + \lambda_t(W_t - a_t - x_t - m_t).$$

Assuming an interior solution for consumption and noting from the envelope theorem that λ is equivalent to the marginal value of wealth, we have the fundamental consumption smoothing equation

$$\frac{\partial \mathcal{L}}{\partial m} = U_t' - \lambda_t = 0 \Rightarrow U_t' = V_t'$$

in which the marginal value of wealth is equivalent to the marginal utility of consumption. Also assuming an interior solution for land and input, a restriction that we relax below, the first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial x} = \rho E_t\left[V_{t+1}' p_{t+1} F_x \epsilon_{t+1}\right] - V_t' = 0$$

$$\frac{\partial \mathcal{L}}{\partial a} = \rho E_t\left[V_{t+1}'(\delta_{t+1} + p_{t+1} F_a \epsilon_{t+1})\right] - V_t' = 0$$

where in both equations the first term is the (discounted expected) marginal benefit (MB) and the second is the marginal cost (MC).[10] Note that MCs are incurred in period t while MBs are stochastic and realized in $t + 1$. Also note that the marginal values of wealth play a crucial role here in that they convert dollars into utility; in essence they are exchange rates with period t's exchange, V_t', being known while period $t + 1$'s is unknown (stochastic). This is important because it disentangles two sources of randomness in the producers MB: those arising from the holding of risky assets and engaging in production (i.e., δ, p, and ϵ) and the other from their combined effect on future utility-dollars exchange V' which depends on the aggregate effect of all risk sources through stochastic wealth W_{t+1}.

p0070 One could stop here with the model and it would be entirely in line with conventional "at-the-margin" decision models commonly used in the economics literature. However, it is worth pushing it a little further with the aid of some insights from asset pricing models, especially at it relates to portfolio theory. The following approach hinges on the idea that all decisions on a farm can in some sense be accumulated up to the "whole farm" level. This is the outermost layer of what we commonly refer to as the extensive margin of the decision-making process in which all activities are aggregated into a single "farm" portfolio. This can be accomplished in a straightforward manner by literally adding up the first order conditions and rearranging to get

$$E_t[s_{t+1}R_{t+1}] = 1$$

which is the product of two random variables, the ratio of marginal wealth

np0055 [10]Here and throughout the chapter V_t' is shorthand for the marginal value of wealth in period t, i.e., $\partial V\ (W_t)/\partial W$, and F_x is shorthand for the partial derivative of F with respect to x, i.e., $\partial F/\partial x$.

$$s_{t+1} = \rho \frac{V'_{t+1}}{V'_t}$$

and the ratio of aggregated MBs over aggregated MCs[11]

$$R_{t+1} = \frac{\delta_{t+1} + p_{t+1}(F_a + F_x)\epsilon_{t+1}}{1+1}.$$

This happens to be the canonical relationship between a decision makers stochastic return-on-investment from their portfolio R and their stochastic discount factor s from the asset pricing literature; but hopefully it is clear that it has a foundation in marginal decision-making of economics.

p0075 A confusing aspect of the current form of the model is the sense in which the decision-maker is "at the margin" because there are two margins that are simultaneously in play, one for land and the other for the input.[12] This confusion only grows if we were to scale the model to M outputs and N inputs; thus we would ideally prefer a measure of R that is a bit more intuitive. The approach we recommend, and follow here and in the various subsections below, is to work with the more general Kuhn–Tucker optimization conditions of the decision variables:[13]

$$\frac{\partial \mathcal{L}}{\partial x} x_t = \rho E_t\left[V'_{t+1} p_{t+1} F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial a} a_t = \rho E_t\left[V'_{t+1}(\delta_{t+1} + p_{t+1} F_a a_t \epsilon_{t+1})\right] - V'_t a_t = 0.$$

Now summing the conditions and rearranging generates the same general form of solution

$$E_t[s_{t+1} R_{t+1}] = 1$$

and the same stochastic discount factor

$$s_{t+1} = \rho \frac{V'_{t+1}}{V'_t}$$

np0060 [11] With a more general production function notation, $y = F(x, a; \epsilon)$, one can simply replace $(F_a + F_x)\epsilon_{t+1}$ with $F_a(x, a; \epsilon) + F_x(x, a; \epsilon)$.

np0065 [12] Recall prices for both are being normalized to 1, which is why we have 1 + 1 in the denominator; if we instead had modeled land and input prices as say, w_t^a and w_t^x, then these prices would be the marginal costs and the sum of them would appear in the denominator of R above.

np0070 [13] Note that this effectively relaxes the interior solution assumption, which is not a major concern here but could be in more general settings where farms' do not necessarily use the same inputs nor produce the same outputs across space and time; or in cases where off-farm activities (e.g., labor) are only used by a subset of farms. More succinctly, it alleviates concerns about so-called "zeroes" problems associated with corner solutions.

but now the return is given by

$$R_{t+1} = \frac{\delta_{t+1}a_t + p_{t+1}(F_a a_t + F_x x_t)\epsilon_{t+1}}{a_t + x_t}$$

where the denominator captures the total cost of the farmland (and operations) investment as a whole and not just at the margin. It is constructive to think of it as the total outlay expenditure. The numerator is the associated payoff from this outlay and includes total capital holdings of land, plus the weighted sum of the marginal products valued by the output price. Note that in the particular case where the production function exhibits constant returns to scale, *ex post* output y_{t+1} replaces $(F_a a_t + F_x x_t)\epsilon_{t+1}$ and the return becomes

$$R_{t+1} = \frac{\delta_{t+1}a_t + p_{t+1}y_{t+1}}{a_t + x_t}$$

which has a very clean economic meaning as the payoff is now the sum of the capital gain and production revenues. Through this perspective the farm can be viewed very much like a financial stock that provides both a capital gain ($\delta_{t+1}a_t$) and a dividend payment ($p_{t+1}y_{t+1}$), but the key difference is that the dividend is comprised of production revenues and thus very much endogenous to the farm operator.

p0080 Homogeneity of the production function may or may not be a credible assumption in various contexts, but either version of the return is equally useful for interpretation since they both obey the general form of $E_t[s_{t+1}R_{t+1}] = 1$. To convince the reader that this is indeed a model of risk, note from above that both the stochastic discount factor and the farmland return are functions of the stochastic variables p_{t+1} and ϵ_{t+1}, so they themselves are stochastic and thus it must be the case that

$$E_t[s_{t+1}R_{t+1}] = E_t[s_{t+1}]E_t[R_{t+1}] + Cov[s_{t+1}, R_{t+1}].$$

Furthermore, the covariance linkage arrives through the marginal value of wealth so that

$$\text{sign}\{Cov[s_{t+1}, R_{t+1}]\} = \text{sign}\{Cov[V'(p_{t+1}\epsilon_{t+1}), p_{t+1}\epsilon_{t+1}]\} < 0.$$

This implies that as either p_{t+1} or ϵ_{t+1} increases, the return on farmland will increase but the stochastic discount factor will decrease (i.e., decreasing marginal value of wealth). Put another way, there is a negative covariance between the random variables s_{t+1} and R_{t+1} and this covariance will influence the optimal levels of land and other inputs.[14] Sections 3.1 and 4.1 explicitly show how both production and price risk influences on-farm decision-making through their influence on the value of the marginal product for inputs.

p0085 There is a broader point here that is worth emphasizing as it is perhaps THE core insight for conceptualizing risk management in agricultural production: nearly every decision the producer makes—whether it be at the intensive or extensive margin or

np0075 [14]It is worth noting that this covariance term can often be difficult to sign in practice, especially under more general forms of technology. Also, the assumption of a declining marginal value of wealth can be thought of as an assumption of risk aversion.

with a factor that does or does not directly affect the price/production shocks—will affect both the stochastic discount factor and the aggregate return. In the following subsections we consider perhaps the broadest scope that any one model has been applied to, and in every case the relevant decision variables influence both stochastic channels. Furthermore, risk preferences play a crucial in moderating the relationship between these two stochastic variables through their affect on the stochastic discount factor. This can be seen by starting with the "consumption smoothing" condition (i.e., $U_t' = V_t'$ from above) and noting that parameters that influence the rate of marginal utility will thereby influence the rate of marginal wealth. This too is relevant for all model variations that we present in this chapter since nothing we do changes the first order condition for consumption.[15]

p0090 The reader may have major concerns at this point: (i) the model is too complicated in that it requires working knowledge of stochastic dynamic modeling, and/or (ii) the model is not applicable to subsistence nor semisubsistence farming in a developing country context.[16] The first concern is assuaged by considering a two-period version of the model, which is the smallest possible dimension one can use and still include risk[17] :

$$\max_{a,x,m_0} U(m_0) + \rho E[U(m_1)]$$

subject to

$$W = a + x + m_0, \text{ and, } m_1 = \delta a + pF(x,a)\epsilon.$$

Here we still have an initial wealth endowment, but assume that returns from farming are fully consumed in the second period and thus the objective is to maximize the sum of utilities in the two periods.[18] The model solution proceeds the same as above with the marginal utilities of consumption $U'(m_0)$ and $U'(m_1)$ replacing the marginal values of wealth $V'(W_t)$ and $V'(W_{t+1})$ in the Kuhn–Tucker conditions and the

np0080 [15]In the various subsections, we do not include the consumption smoothing condition since it is the exact same in every case; but it remains relevant to the decision-making process as discussed here. It is also worth noting that there are other forms of dynamics that could be included, such as dynamic risk exposure (e.g., climate change; correlated production/price shocks; and/or producer "learning" over time).

np0085 [16]The more seasoned reader may have additional concerns regarding the (potentially) restrictive assumptions of expected utility and "output-cubical" technology. Models that are similar in spirit to the one used here but employ generalizations of expected utility theory and state-contingent technology are discussed in Section 7.2.

np0090 [17]Much of the literature on risk management in agricultural production has ignored timing completely and focused on instantaneous decisions, which we believe is too drastic of a simplification given the timing lags inherent in production; put another way, risk always involves time.

np0095 [18]Note that if we omit x from the model then the payoff at the end of the period is simply the capital gain associated with holding the land asset δ, and the model is identical to the Consumption Based Capital Asset Pricing Model (CCAPM) (Breeden, 1979; Lucas, 1978; Rubinstein, 1976) as defined in Cochrane (2009). If this material is not familiar, the authors highly recommend reading chapter 1 of Cochrane's textbook which is available free online as a sample chapter at https://www.johnhcochrane.com/s/samplechapters-dy5d.pdf. In its more general dynamic form with the value function, the model is in the same spirit as Merton's (1973) Intertomporal Capital Asset Pricing Model (ICAPM) which is discussed in chapter 9 of Cochrane (2009).

stochastic discount factor. The return to farming is the exact same expression except time subscripts are dropped. In general, all models in this chapter can be equivalently expressed as a two-period problem by (i) replacing the objective with $U(m_0)+\rho E[U(m_1)]$ and (ii) replacing end-of-period wealth with m_1.

p0095 The next concern centers on the applicability of the model in a developing country context. It is worth noting that the model already shares some striking similarities with commonly used models in that literature, both the traditional agricultural households models (e.g., Bardhan & Udry, 1999; Haddad, Hoddinott, & Alderman, 1997; Singh, Squire, & Strauss, 1986) as well as more recent intertemporal optimization models of consumption and investment (e.g., Janzen, Carter, & Ikegami, 2020). These models essentially start with the model used here and then embed resource/input constraints to reflect a core tenet of development microeconomics: thin, fragmented, or altogether missing markets. This can be accommodated mechanically by adding additional constraints in the same way that development models can, and we offer illustrations of this in both the off-farm labor and credit-constraint settings in Sections 5.2 and 6.4, respectively.

p0100 Another observation worth mentioning is that, while we do frame the model in terms of an asset pricing model and emphasize the interaction of the discount factor and returns, it has some important differences. First, we make no assumption about the driving forces behind the price variables in the model. They need not be market-based prices but could rather be subjective (personal) valuations of inputs/outputs. In the case of land, the expenditure could reflect the rental of land in which case the payoff would exclude the capital gain completely (i.e., $\delta=0$ above). In that setting there is not an asset that requires managing at all, and indeed we focus on this simpler case within many of the subsections below, which leads to the second important difference. The purpose of the model is not to provide a market clearing price of an asset at the margin in equilibrium as is typically the goal of asset-pricing models, but rather to leverage some risk-related mechanics from those models to provide behavioral insights for agricultural producers.

s0020 3 On-farm production risk

p0105 This section is organized into five subsections covering the management of production inputs (conventional, biotic, and abiotic), effects that risk has on production, and technology adoption.

s0025 3.1 Standard factors of production

p0110 The next three subsections all focus on particular aspects of the relationship between risk and various factors of production. The focus of this subsection is so-called standard factors of production and include inputs that are typically under direct control of the producer (e.g., land, capital, labor, fertilizer), while the next two subsections focus on other types of factors that are environmental and include both biotic (e.g., pests) and abiotic (e.g., weather) inputs. Here, we first demonstrate how the stylized model can provide insights on the effects that risk has on production through its influence on optimal input levels for standard factors of production x. Define the model as

$$V(W_t) = \max_{m_t, x_t} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t, \text{ and } W_{t+1} = p_{t+1}F(x_t)\epsilon_{t+1}.$$

p0115 Using the envelope theorem the first order condition for the optimal input can be expressed as

$$E_t[s_{t+1}p_{t+1}F_x\epsilon_{t+1}] = 1$$

where s_{t+1} is the stochastic discount factor, $p_{t+1}F_x$ is the deterministic component of the value of the marginal product (VMP), and 1 is the marginal factor cost (MFC) since the input is measured in expenditure terms. The key insight here is that the above expectation is taken over two random variables and can be equivalently expressed as

$$E_t[s_{t+1}\epsilon_{t+1}]\text{VMP} = \text{MFC}$$

which demonstrates how the presence of risk can shift the VMP. Using the relationship between the expectation of two random variables and covariance, coupled with the insight that the production shock is part of the stochastic discount factor; under certain conditions it can be shown that an increase in the variance of the production shock σ^2 will reduce $E_t[s_{t+1}\epsilon_{t+1}]$ and thus shift the VMP leftward, thereby reducing the optimal input level.[19]

p0120 The relationship between input levels and output variability has been a perennial topic of research, but one should be careful of the causal direction here. *Ex ante* (unabated) output variability will drive input decision-making, which can in turn influence the *ex post* risk that the producer faces. This is why we simultaneously see papers in the literature that focus on the effect that risk has on inputs, while also seeing other papers that focus on the effect that inputs have on risk. There is room for both types in the literature, but readers should pay careful attention to how risk is being measured in each context. Instead of focusing on output risk, some papers will focus on the risk of the input itself, which can arise from availability concerns (e.g., labor) or uncertain effects of the input (e.g., fertilizer leakage). Sharing factors of production among producers in order to reduce risk exposure has also been a vein in this research.

np0100 [19]It is important to note that this is an illustrative example where the variance is not a function of the input itself, i.e., homeskedastic. This need not be the case in practice and much research has considered heteroskedastic input effects, which can be accounted for in the production function specification as in Just and Pope (1978), Antle (1983b), and Antle (2010). In general, inputs can be risk decreasing, neutral, or even decreasing; and these effects can also change across ranges of a specific inputs usage.

p0125 The linkage between input use and output variability (in both directions) continues to play an important role in the literature. Antle (2010) proposes partial-moment functions as a flexible way to characterize and estimate asymmetric effects of inputs on output distributions. Du, Hennessy, and Yu (2012) analyze four corn yield experimental plot datasets using a flexible Bayesian model to incorporate skewness and find that it provides strong evidence favoring negative skewness at common nitrogen levels. Kumbhakar and Tsionas (2010) propose a multistage nonparametric estimation procedure to estimate production and risk parameters, and an empirical application leveraging farming data in the Philippines suggests that labor is risk decreasing while fertilizer, land, and materials are risk increasing. Li, Rejesus, and Zheng (2021) extend this approach to include categorical variables alongside continuous ones, and an empirical application using corn production data from university field trials in Wisconsin quantifies the effect of GE adoption on production risk. Boyer, Brorsen, and Tumusiime (2015) apply a linear response stochastic plateau production function to four long-term nitrogen experiments and results suggest that negative skewness reduces optimal nitrogen rates while positive skewness increased them. Dercon and Christiaensen (2011) utilize historical rainfall distributions to identify consumption risk in Ethiopia and results suggest that the possibility of low consumption outcomes when harvests fail discourage the application of fertilizer. Alem and Broussard (2018) use panel data from rural Ethiopia to investigate whether participation in a safety net program enhances fertilizer adoption and find that it increased fertilizer adoption in the short run but not in the long run. Mukasa (2018) studies smallholder farmers in Tanzania and Uganda using household panel datasets and a moment-based approach reveals that the first four moments of production output help explain input decisions.

p0130 Sometimes the risk of the input itself is a focus of study as farm labor is often associated with availability concerns while the effects of a particular fertilizer application might be uncertain. Paulson and Babcock (2010) use a model of optimal input use under uncertainty to show that input uncertainty may cause farmers to over-apply nitrogen.[20] In response to input uncertainty, and/or because of prohibitive cost, producers might consider sharing factors of production. Wolfley, Mjelde, Klinefelter, and Salin (2011) develop a multifarm economic simulation model of locations in Texas, Colorado, and Montana to provide insight associated with sharing combines, and find that it is risk reducing. Brooks and Donovan (2020) collect detailed annual household surveys to study contemporaneous effects of flooding with results suggesting that households manage labor market risk and agricultural risk simultaneously, and better market access improves welfare by eliminating risks.

p0135 Chavas (2011) provides a nice overview of the current food situation and provides some historical perspectives on its evolution over time, and an analysis stresses the joint role of uncertainty and externalities in the analysis of efficiency issues in the

np0105 [20]This particular application is a good example of more general research that models available (i.e., useful) input levels as a stochastic function of applied input levels.

agricultural sector. Vigani and Kathage (2019) use survey data from French and Hungarian farms to estimate the impacts of different risk management strategies and portfolios under varying levels of risk on total factor productivity, and find that more complex risk management portfolios are associated with larger negative productivity impacts. Aderajew, Trujillo-Barrera, and Pennings (2019) quantify the determinants and speed of adjustment to the target capital structure for a panel of Dutch farms spanning just over a decade and find that farm profitability, earnings volatility, asset tangibility and growth opportunity are important determinants of leverage.

s0030 3.2 Biotic factors of production

p0140 Biotic stress factors are typically associated with pests in crop production environments and/or disease in livestock management. The damage function approach of Lichtenberg and Zilberman (1986) provides a convenient distinction between standard factors of production (e.g., land, labor, fertilizer, and capital) versus damage control agents (e.g., pesticides). The distinction is worth making as damage control agents z do not necessarily increase potential output, but rather increase the realized share of potential output by reducing damage from the stressors through the damage abatement function $G(z)$.

p0145 The generalization of the model occurs by expanding the production function to include $G(z)$ as an additional argument and including expenditures on z as a decision variable (here again we are normalizing input prices to unity):

$$V(W_t) = \max_{m_t, x_t, z_t} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + z_t + m_t, \text{ and } W_{t+1} = p_{t+1} F(x_t, G(z_t)) \epsilon_{t+1}.$$

Working with the Kuhn–Tucker first order conditions

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1} p_{t+1} F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial z} z_t = E_t\left[V'_{t+1} p_{t+1} F_G G_z z_t \epsilon_{t+1}\right] - V'_t z_t = 0$$

one can show by summing these together that the optimal solution will satisfy

$$E_t[s_{t+1} R_{t+1}] = 1$$

when R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{p_{t+1}(F_x x_t + F_G G_z z_t)\epsilon_{t+1}}{x_t + z_t}.$$

Note that this model could apply equally well to livestock production where standard inputs would include animals and feed while damage abatement agents could include antibiotics and/or biosafety measures. Also note that we have not accounted for externalities of pest management in which one producer's effectiveness can reduce damage on other farms by decreasing pest populations, nor temporal dynamics in which pesticide resistance can evolve over time.[21]

p0150 A long-standing topic in the literature has been the quantifying of demand for damage control agents and their drivers, with recent research documenting the role that risk plays alongside other factors as well. The possible coordination of pest management activities is an important topic given the potential for very large externalities across decision makers. Government policies will typically be employed to reduce the risk of pest and/or disease outbreaks both within and across populations, and these policies can have both intended and unintended outcomes. Often a single occurrence of a disease can quickly scale to a widespread outbreak, with a typical focus being disease management in animal production systems and examples including avian influenza as well as foot and mouth disease. Antimicrobial use in the hog and cattle sectors also remains a relevant topic as consumers have recently begun to express some preference for reduced usage.

p0155 Risk exposures and attitudes toward such exposures are important drivers of on-farm decision-making, but there are other factors as well. Gong, Baylis, Kozak, and Bull (2016) consider the case of smaller, semisubsistence, and subsistence farmers in China using a field experiment to measure risk aversion and find that risk aversion significantly increases pesticide use particularly among subsistence farmers. Sheahan, Barrett, and Goldvale (2017) explore the relationship between pesticide use and the value of crop output at the plot-level combined with human health outcomes at the household level using large-scale panel survey data from Africa and find that pesticide use is strongly correlated with increased value of harvest, but is also correlated with higher costs of human illness. Möhring, Bozzola, Hirsch, and Finger (2020) consider different pesticide indicators and an empirical application leveraging panel data of Swiss wheat producers with highly detailed information on pesticide use reveals that indicator choice affects the magnitude and sign of estimated risk effects. Rosburg and Menapace (2018) develop a multidisciplinary conceptual model of the fungicide treatment decision and find that it is positively related to perceived economic gains but heuristic factors also have a strong influence. Walker (2012) highlights the importance of considering labor costs in addition to monetary costs when assessing the adoptability of protection strategies, and finds a low rate of adoption for known protection methods in Gabon.

p0160 We discuss the role that genetically modified/engineered (GE) varieties have had in agricultural production more generally in Section 3.5, but we note a few studies

np0110 [21]To accommodate these, one could introduce additional dimensions/complexity to the damage abatement function; or alternatively one could use a traditional production function $F(x_t, z_t)\epsilon_{t+1}$ and model the variance of the production shock as $\sigma_t = \alpha\sigma_{t-1} + \beta\sum_{i=1}^{N} z_{it-1}$ where $i = 1, ..., N$ indexes spatially relevant producers. This suggestion was provided by Terry Hurley and could be an attractive approach as one can allow the effectiveness of pesticides to evolve dynamically across space and time according to current population levels and resistance.

here that relate directly to biotic stress. Sanglestsawai, Rodriguez, Rejesus, and Yorobe (2017) showed how the damage abating effects of certain GE traits (e.g., Bt) can be included in a damage abatement specification, and an empirical application using data from corn farmers in the Philippines finds that the trait reduces downside risk (skewness) of yields. Perry and Moschini (2020) exploit a novel dataset containing more than 89,000 farm-level surveys over a 17-year period to investigate how neonicotinoid seed treatments in maize have affected the use of other insecticides, and an empirical application finds that adoption of genetically engineered insect-resistant maize varieties significantly reduced the use of other insecticides, thereby reducing toxicity exposure. Perry, Ciliberto, Hennessy, and Moschini (2016) analyze the effect of GE adoption on pesticide use and find that glyphosate-tolerant soybeans was associated with increased herbicide usage while insect-resistant maize was associated with less insecticide usage. Other work has shown that these traits can help control general pest populations and thus has spillover effects that are important to consider (e.g., Brown, Connor, Rejesus, & Yorobe, 2021; Hutchison et al., 2010).

p0165 There are also extensive efforts to coordinate pest management activities given the potential for very large externalities across decision makers. Singerman and Useche (2019) elicit a measure of strategic uncertainty from growers by using an experimental game that accounts for coordinated pest management, and findings help explain a lack of participation in area-wide pest management programs. Reeling and Horan (2015) demonstrate that strategic relations can be endogenously determined and depend on the relative endogeneity of risk, and show that the potential for coordination failure may arise when it is sufficiently small. Bekkerman and Weaver (2018) use farm-level data to estimate the expected losses associated with wheat stem sawfly and find that strategies minimizing long-run infestation levels are preferred to those that seek to maximize yield potential. Yang, Elbakidze, Marsh, and McIntosh (2016) use an intraseasonal bioeconomic model to explicitly take into account biological interactions among pests and their natural enemies and find that inclusion of enemies into pest mitigation strategies can increase returns.

p0170 A common goal of government policy is to influence the risk of pest and/or disease outbreaks both within and across populations, and these policies typically lead to both intended and unintended outcomes. Böcker, Britz, Möhring, and Finger (2020) develop a normative modeling approach based on damage abatement functions and show that for silage maize cultivation in Germany, a glyphosate ban slightly reduces net profits and yields while also leading to a significant reduction in the overall toxicity of pesticide use. Yano and Blandford (2011) focus on a required reduction in the use of a potentially damaging input under an agri-environmental scheme and show that risk aversion can mitigate the moral hazard problem. Hong, Gallardo, Fan, Atallah, and Gómez (2019) estimate producer profits by an orchard's quarantine status subject to a phytosanitary regulation requiring an additional cold storage period and find an unintended consequence of increased chemical applications.

p0175 Disease management in livestock production is an important feature of decision-making as a single case can quickly transmit to a widespread outbreak.

Gilbert and Rushton (2018) review the characteristics of infectious disease and disease control interventions, and the potential for bias in implementation decision-making at the primary producer level with specific focus given to the generation of externalities. Hennessy and Wolf (2018) lay out several perspectives on how information problems and other externalities affect biosecurity incentives and uses the principal–agent framework to examine livestock disease management in the presence of potential moral hazard and adverse selection. Schulz and Tonsor (2020) conduct national surveys of livestock producers in the United States to gain insight into decisions regarding on-going and prospective biosecurity investment, and findings suggest that producer and operation characteristics and diverse views on expected frequency of disease outbreaks, anticipated disease duration, and possible financial impact on operations underlie current and likely future biosecurity adoption. Hagerman, McCarl, Carpenter, Ward, and O'Brien (2012) examine emergency vaccination as a risk management strategy and results indicate that response enhanced with emergency vaccination is inferior to standard culling under short diagnostic delays because it causes, on average, greater animal and national economic welfare losses.

p0180 Recent outbreaks of avian influenza as well as foot and mouth disease are important case studies within the broader spectrum of livestock disease. Ifft, Roland-Holst, and Zilberman (2011) develop a model that jointly estimates both scale response and behavioral changes to Highly Pathogenic Avian Influenza (HPAI) outbreaks, and an empirical application finds that disease prevention efforts are not separable from production choices and thus they have to be investigated simultaneously. Egbendewe-Mondzozo, Elbakidze, McCarl, Ward, and Carey (2013) use an integrated economic-epidemic partial equilibrium model to empirically simulate HPAI outbreaks in three different poultry regions within the State of Texas and find that risk aversion influences vaccination decisions for HPAI. Niemi and Lehtonen (2011) use a stochastic dynamic programming model to simulate the market implications of alternative foot and mouth disease scenarios in the Finnish pig sector, and results suggest that the risk of a prolonged ban increases disease losses considerably. Pendell, Lusk, Marsh, Coble, and Szmania (2016) develop an economic framework to evaluate the economic consequences of a Rift Valley Fever outbreak and find the agricultural firms bear most of the negative economic impacts, followed by regional nonagricultural firms, human health and government. As a result of these outbreaks animal identification and tracing have remained important issues and results from an analysis in Pendell, Brester, Schroeder, Dhuyvetter, and Tonsor (2010) suggest that a modest increase in domestic demand for beef would offset the costs of an animal identification system. Pouliot and Sumner (2008) show a more general result detailing how exogenous increases in food traceability create incentives for farms and marketing firms to supply safer food by increasing liability costs.

p0185 The use of antimicrobials in the hog and cattle sectors also remains a relevant topic as consumers have recently begun to express some preference for reduced usage. Dennis, Schroeder, Renter, and Pendell (2018) develop a new framework to map animal disease to producer profitability and determine societal economic impacts surrounding metaphylactic use of antimicrobials in beef cattle production, and results indicate a large positive direct net return value of metaphylaxis. Key and McBride (2014) use a stochastic frontier model and data from the USDA Agricultural Resource Management Survey of feeder-to-finish hog producers to estimate the potential effects on hog output and output variability resulting from a ban on antibiotics, and results suggest that antibiotic use is associated with increased productivity and reduced production risk.

s0035 3.3 Abiotic factors of production

p0190 There are many ways to manage abiotic stress on-farm, some more effective than others. Drought stress can be mitigated through the use of irrigation while heat stress can be mitigated by heat-tolerant varieties (and irrigation of course). Other weather events such as hurricanes and hail are almost impossible to prevent from reducing production. Much like with biotic stress factors, the goal is to utilize available agents to mitigate damage, and thus the same modeling approach as in the previous section can be utilized if the variable is defined in such a way that its occurrence always reduces yield, for example a measure of heat or drought *stress*. For more general measures that have a range of both beneficial and detrimental effects on production such as precipitation or temperature, the damage abatement function approach may not be appropriate. Thus, here we provide another way to incorporate stress mitigation efforts into the model.

p0195 The goal of this extension is to endogenize the effects (i.e., parameters) associated with some of the weather variables, not the occurrence of the weather variables themselves as they remain stochastic, while leaving other stochastic inputs that cannot be managed in the production shock.[22] For example, if one has access to irrigation, its not as if precipitation ceases to occur. It will still occur and it will continue to affect crop growth, but the response function will change as the large negative effects of low precipitation can be abated by supplying water to relieve soil moisture deficits. With this in mind the generalization of the model occurs as follows. First, we expand the production function to include a weather variable (e.g., precipitation) z_{t+1}, essentially pulling it out of the shock ϵ_{t+1} and including a residual (smaller variance) shock ν_{t+1} in its place. Second, we allow the effect (i.e., parameter) of the weather variable α to depend on a costly endogenous variable (e.g., water) w_{t+1}. We have

$$V(W_t) = \max_{m_t, x_t, w_t} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + w_t + m_t, \text{ and } W_{t+1} = p_{t+1}[F(x_t) + \alpha(w_t) z_{t+1}]\nu_{t+1}.$$

Working with the Kuhn–Tucker first order conditions

np0115 [22]One limitation of our model is that it cannot represent a sequential decision-making process under uncertainty. As shown by Fafchamps (1993), labor allocation within a season can be affected by the timing of rainfall and intertemporal labor-leisure trade-off. If the objective is to model such dynamics one can utilize stochastic dynamic control approaches such as Fafchamps (1993) and Antle (1983a).

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1} p_{t+1} F_x x_t \nu_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial w} w_t = E_t\left[V'_{t+1} p_{t+1} \alpha_w w_t z_{t+1} \nu_{t+1}\right] - V'_t w_t = 0$$

one can show by summing these together that the optimal solution will satisfy

$$E_t[s_{t+1} R_{t+1}] = 1$$

where R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{p_{t+1}(F_x x_t + \alpha_w w_t z_{t+1})\nu_{t+1}}{x_t + w_t}.$$

p0200 Recent research has highlighted the important role that temperature and precipitation play as drivers of production variation. Irrigation has been shown to have large effects on mitigating weather risk and much research has focused on quantifying this.[23] However, existence of irrigation infrastructure does not in and of itself guarantee access to water, thus much research has been devoted to examining water rights and the activities farmers engage in to secure them. Technological improvements to water use efficiency has also been a response to such concerns. In the absence of irrigation, another option for producers is to select seed varieties that provide some resilience to various weather stressors as evidenced by drought-tolerant seed varieties. More generally, other on-farm management decisions can be affected by efforts to mitigate risk exposure to abiotic stress.

p0205 Weather is a well recognized abiotic driver of production variation, with both precipitation and temperature playing a prominent role.[24] Finger, Dalhaus, Allendorf, and Hirsch (2018) investigate determinants of dairy producers' risk exposure and their analysis of German dairy farms reveals that animal health and heat stress indicators influence mean and semivariance of revenues. Perry, Yu, and Tack (2020) leverage a publicly available dataset consisting of roughly 30,000 county-by-year observations on insurance-based measures of yield risk for US corn

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np0120 [23]Note that we are including research related to irrigation in this section rather than the technology section below. This is a subjective decision based on its direct connection to water-stress management, as one should view irrigation as a component of a farm's technology. Same for drought-tolerant seed varieties

np0125 [24]In the following we focus more on the management of weather/climate effects rather than the effects these drivers have on-farm outcomes. That research is more closely tied to the climate change literature, and some recent touchstones include: Schlenker and Roberts (2009), Lobell et al. (2013), Roberts, Braun, Sinclair, Lobell, and Schlenker (2017), Ortiz-Bobea, Wang, Carrillo, and Ault (2019), Hendricks (2018), Gammans, Mérel, and Ortiz-Bobea (2017), Tack, Barkley, and Nalley (2015), Tack, Lingenfelser, and Jagadish (2017), Ortiz-Bobea (2020), Urban, Roberts, Schlenker, and Lobell (2012), Urban, Sheffield, and Lobell (2015), Attavanich and McCarl (2014), Burke and Emerick (2016), Butler and Huybers (2013), and Ortiz-Bobea, Ault, Carrillo, Chambers, and Lobell (2021). ORTIZHANDBOOKCHAPTER provides a more general and exhaustive discussion of this literature.

and soybeans and results suggest that yield risk increases in response to warmer temperatures. Yu and Babcock (2010) examine temporal aspects of drought tolerance by regressing county level corn and soybean yields on a drought index and time, and results indicate that corn yield losses from drought of a given severity have decreased over time. Huang, Wang, and Wang (2015) use survey data on rice farmers in China and an econometric analysis shows that the severity of drought and flood significantly increases the downside risk of rice yield. Du, Yu, Hennessy, and Miao (2015) provide a theoretical and empirical understanding of the effects of exogenous geographic and climatic factors on the first three moments of crop yields, and an analysis of a large crop insurance data set for corn, soybean, and wheat suggests skewness is dependent on natural resources.

p0210 Much work has focused on management strategies and/or technology innovations for mitigating weather risk, with irrigation being a common strategy. Foudi and Erdlenbruch (2012) analyze the way French farmers manage the risk of drought using the European Farm Accountancy Data Network, and joint estimation of farmers' attitudes to risk and their production decisions reveals that irrigating farmers have higher means and lower variance of profits than nonirrigating farmers. Wibowo, Hendricks, Kisekka, and Araya (2017) utilize a modeling framework capable of assessing optimal irrigation along both the intensive and extensive margins, and an empirical application focused on Kansas corn shows that risk aversion significantly increases total water use, especially for low and medium well capacities. Tack, Harri, and Coble (2012) propose the use of moment functions and maximum-entropy techniques as a flexible approach for estimating conditional crop yield distributions, and an empirical application using US cotton data demonstrates how climate and irrigation affect production risk. Olen, Wu, and Langpap (2016) use Farm and Ranch Irrigation Survey data to assess the impact of water scarcity and climate on irrigation decisions for producers of specialty crops, and find that producers use sprinkler technologies or additional water applications to mitigate risk of crop damage from extreme weather. Tack, Barkley, and Hendricks (2017) utilize over 7000 observations of wheat yields across Kansas field-trial locations to show that irrigation significantly reduces the negative impact of hot temperatures. Li, Xu, and Zhu (2019) develop an economic model to analyze how the risk of water shortages affects farmers' land irrigation decision and results indicate that a more left-skewed distribution of stream-flow significantly discourages land irrigation among farmers. Schuenemann, Thurlow, Meyer, Robertson, and Rodrigues (2018) use an integrated modeling framework to simultaneously evaluate the returns to irrigation arising from both economic and biophysical impact channels and the results confirm that the returns to irrigation cannot cover the costs in Malawi. Takeshima and Yamauchi (2012) analyze panel data on investment behavior of Nigerian farmers who received financial assistance on productive assets and find that farmers facing higher rainfall risks are more likely to invest in irrigation pumps. Hendricks and Peterson (2012) demonstrate how irrigation water demand can be estimated using field-level panel data by exploiting the cost of pumping which varies over time due to changes in energy prices and across space due to differences in the depth to water.

p0215 Having irrigation infrastructure on-farm does not ensure water availability and there are typically crucial periods within the growing season when it provides the highest value, thus much research has been devoted to securing access to water. Rigby, Alcon, and Burton (2010) examine the economic value of irrigation water to horticultural producers in southern Spain using a choice experiment and results suggest that marginal water values are typically above those currently paid. Rey, Garrido, and Calatrava (2016) present a theoretical assessment of farmers' expected utility for two different water option contracts and a drought insurance policy, and a numerical application to a water-stressed Spanish region suggests that water option contracts and insurance may help farmers manage water supply availability risks. Fonseca, Pfaff, and Osgood (2012) utilize experiments in Brazil and England to consider the coordination of farmers' decisions when they must divide an uncertain water supply and find that water resource queues have greater coordination success than does the spot market. Zuo, Nauges, and Wheeler (2015) analyze farm-level survey data from Australia and find that purchasing water allocations on the market is a risk-reducing strategy. Feinerman and Tsur (2014) study orchard management under stochastic drought events and an empirical application in northern Israel reveals that the stabilization value of recycled water due to its role in eliminating the drought hazard far exceeds its supply cost. Loch, Boxall, and Wheeler (2016) apply a zero-one inflated beta regression to model irrigators' preferences for market-based water policy programs and finds that market-based arrangements are more likely to provide efficient solutions to water reallocation problems. Juárez-Torres, Sánchez-Aragón, and Vedenov (2017) use an analytical model of water allocation and historical data from an irrigation district in Central Mexico to show that weather derivatives could encourage interseasonal reallocation of water from wet to dry season, generating new Pareto-optimal water allocations that improve overall welfare among producers. Katic and Ellis (2018) use an experimental approach applied to households in Northern Ghana and find that losses from the riskiest investments on agricultural water management technologies may fall more heavily on the poor. Sampson and Perry (2019b) isolate the role of peer effects in the acquisition of groundwater rights for agricultural irrigation in Kansas, and an empirical application using groundwater rights from 1943–2014 and a nearest neighbor peer-group definition finds that one additional neighbor adopting groundwater for irrigation increases groundwater adoption by an average of 0.25 percentage points. Edwards (2016) examines the distribution of economic benefits from groundwater management as a consequence of underlying aquifer characteristics, and finds that the portions of an aquifer where water moves rapidly, those with high hydraulic conductivity, as well as those that receive less yearly recharge, face a more costly common-pool problem and therefore receive higher benefits from management.

p0220 In some cases producers will have access to only a limited supply of water, potentially because natural resource levels are low, in which case water use efficiency is an important consideration that has received attention in the literature. Tang, Folmer, and Xue (2016) analyze adoption of farm-based irrigation water-saving techniques using cross-sectional data of farmers in China and finds that both community-based irrigation infrastructure and farm-based irrigation water-saving techniques have mitigating effects on production risk. Schoengold and Sunding (2014) provide an empirical implementation of a model that relies on data on water price and irrigation technology adoption observed in a California irrigation district and results show that a stable input price increases the adoption of precision technology. Sampson and Perry (2019a) investigate the role of peer effects in the diffusion of water-saving irrigation technology, and an analysis of detailed irrigation behavior data for growers in Kansas provides evidence of peer influence in adoption, net of environmental factors. Drysdale and Hendricks (2018) estimate how farmers adapted to a water restriction imposed through local governance and find that farmers reduced water use due to the policy with most of the response due to reductions in water use intensity on the same crops rather than through reductions in irrigated acreage or changes in crops.

p0225 In the absence of irrigation, another option for producers is to select seed varieties that provide some resilience to various weather stressors. This is perhaps best evidenced by drought-tolerant (DT) seed varieties which have received some attention in the literature. Holden and Quiggin (2017) assess the adoption responses of food insecure farmers in Malawi where DT maize was recently introduced and a field experiment reveals that more risk-averse households were more likely to have adopted it. Kostandini, Mills, and Mykerezi (2011) present a model to estimate potential benefits of drought-tolerant varieties of maize, sorghum and millet in Kenya, Uganda and Ethiopia with results suggesting that drought resistance generates substantial benefits from both mean yield improvements and yield variance reductions.

p0230 As we would expect, efforts to mitigate risk exposure to abiotic stress are often associated with other on-farm management decisions. Magnan, Lybbert, Mrabet, and Fadlaoui (2011) develop a simulation model calibrated with data from Morocco to demonstrate how no-till agriculture, a technology that the authors argue delays input use, creates a quasi-option value for farmers faced with the possibility of catastrophic drought. Alem, Bezabih, Kassie, and Zikhali (2010) analyze panel data from the Central Highlands of Ethiopia matched with corresponding village-level rainfall data and find that rainfall variability negatively impacts fertilizer use. Kato, Ringler, Yesuf, and Bryan (2011) investigate the impact of different soil and water conservation technologies on the variance of crop production in Ethiopia and finds their effectiveness is often linked to other technologies such as irrigation, fertilizer, and improved seeds. Di Falco (2014) reviews the evolution of the literature on climate change economics in agriculture and presents some evidence that rainfall variability is positively correlated with risk aversion.

s0040 3.4 Production diversification

p0235 A common risk management tool is to diversify production outputs.[25] Here we show how the model can accommodate this by allowing for multiple outputs y_1 and y_2. Technology is captured through the embedding of a cost function $C(\overline{y}_1,\overline{y}_2)$ where

np0130 [25]Note that agronomic and environmental factors play an important role in the diversification decisions as the productivity of different crops differs across fields and locations. While we focus on the production diversification decisions as a risk management tool, one should note that, especially in the context of empirical analyses, there are multiple factors affecting production diversification other than "risk". This also applies to many other production decisions as well (e.g., crop rotation).

we have omitted input price arguments for convenience and we assume *ex post* realized output follows $y_i = \overline{y}_i \epsilon_i$.[26] Here the decision variables $\overline{y}$ can be thought of as production targets around which actual output varies. The model becomes

$$V(W_t) = \max_{m_t, \overline{y}_{1t}, \overline{y}_{2t}} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = C(\overline{y}_{1,t}, \overline{y}_{2,t}) + m_t, \text{ and } W_{t+1} = p_{1,t+1}\overline{y}_{1,t}\epsilon_{1,t+1} + p_{2,t+1}\overline{y}_{2,t}\epsilon_{2,t+1}.$$

Working with the Kuhn–Tucker first order conditions

$$\frac{\partial \mathcal{L}}{\partial \overline{y}_1}\overline{y}_{1,t} = E_t\left[V' p_{1,t+1}\overline{y}_{1,t}\epsilon_{1,t+1}\right] - V'_t C_{\overline{y}_1}\overline{y}_{1,t} = 0$$

$$\frac{\partial \mathcal{L}}{\partial \overline{y}_2}\overline{y}_{2,t} = E_t\left[V' p_{1,t+1}\overline{y}_{2,t}\epsilon_{1,t+1}\right] - V'_t C_{\overline{y}_2}\overline{y}_{2,t} = 0$$

one can show by summing these together that the optimal solution will satisfy

$$E_t[s_{t+1}R_{t+1}] = 1$$

when R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{p_{1,t+1}\overline{y}_{1,t}\epsilon_{1,t+1} + p_{2,t+1}\overline{y}_{2,t}\epsilon_{2,t+1}}{C_{\overline{y}_1}\overline{y}_{1,t} + C_{\overline{y}_2}\overline{y}_{2,t}}.$$

p0240 Here the optimal diversification among crops will depend on risk preferences in conjunction with the stochastic nature of the joint distribution(s) of output prices as well as production shocks. Also note that if the cost function is homogeneous of degree one in output targets then the denominator becomes total cost.

p0245 The literature focusing on the effects that risk has on the production of various outputs in combination with one another has focused on a few major themes over the last ten years. Research has shown that *ex ante* risk and risk attitudes are drivers of crop diversification, and that if used effectively this diversification can reduce ex post risk exposure. The research recognizes the distinct roles that production versus price risk can have on the farm enterprise, and also that impacts can be seen at both the extensive and intensive margins. Other work has highlighted the production of new crops to tap into emerging markets.

p0250 One of the major themes within this literature has been the relationship between risk exposure and output diversification. Di Falco and Chavas (2009) investigate the effects of crop genetic diversity on-farm productivity and production risk in the highlands of Ethiopia, and an empirical application leveraging a moment-based approach finds that the effect of diversity on skewness dominates its effect on variance in the

np0135 [26]The embedding of an *ex ante* cost function is the approach taken in Pope et al. (2011), and can be considered nonsensical in some settings without strict regularity conditions linking the moments of the output distributions.

sense that its overall effect reduces the cost of risk. Baumgärtner and Quaas (2010) analyze the choice of agrobiodiversity by risk-averse farmers who have access to financial insurance and find that increasing environmental risk leads farmers to increase their level of on-farm agrobiodiversity. Bezabih and Sarr (2012) analyze panel data from Ethiopia consisting of experimentally generated risk aversion measures combined with rainfall data and results suggest that covariate shocks from rainfall variability are found to positively contribute to diversity with individual risk aversion having a positive but less significant role. Chavas and Falco (2012) assess economies of diversification using a certainty equivalent measure and an econometric analysis of Ethiopian farms documents how risk affects diversification, including both variance and skewness effects. Kandulu, Bryan, King, and Connor (2012) focus on a case study in Australia and a combination of APSIM modeling with Monte Carlo simulation reveals that enterprise mix diversification can be an effective strategy for hedging against climate-induced risk. Nalley and Barkley (2010) apply portfolio theory to wheat varietal selection decisions and an analysis based on data from Mexico's Yaqui Valley suggests that sowing a portfolio of wheat varieties could lower yield variance. Rao (2019) apply a stochastic production frontier model to the Tanzania Living Standards Measurement Study data, and find that land fragmentation diversifies production risk among separate land plots with heterogeneous agronomic conditions.

p0255 The evaluation of alternative drivers of land use allocations has also played a prominent role and several notable findings have emerged. Livingston, Roberts, and Zhang (2015) analyze crop choices at the plot level in Iowa spanning several decades and focus on agronomic benefits and price risk, with results suggesting that always rotating, regardless of prices, is close to optimal. Hendricks, Smith, and Sumner (2014) use US field-level data to estimate the response of corn and soybean acreage to price shocks while accounting for crop rotation, and show that farmers who change crops due to a price shock have an incentive to switch back to the previous crop to capture the benefits of crop rotation. Pates and Hendricks (2021) analyze a field-level dataset that accounts for most of the US corn-producing area and results show a high degree of rotational response heterogeneity such that imposing a uniform response could seriously bias aggregate elasticity estimates. Ouattara, Kouassi, Egbendéwé, and Akinkugbe (2019) analyze the effect of production uncertainty on farmland allocation decisions between perennial and annual crops using a dynamic stochastic optimization model, and find that a risk-averse farmer tends to reduce land allocation to perennial crops under uncertainty. Arnade and Cooper (2012) provide a theoretical formulation for measuring the impact that price variability has on risk preferences, and estimate acreage response elasticities as a function of prices and price variances using US county-level data for multiple crops. Haile, Kalkuhl, and Braun (2014) provide estimations of monthly (i.e., seasonal) versus annual global acreage response models for the world's principal staple food crops, and the econometric results indicate that global crop acreage responds to crop price levels as well as price risks. There can also be some strategic considerations for entering new markets as Harou, Walker, and Barrett (2017) examine the intertemporal welfare impact of the timing of a farmer's entry into the export pineapple market in southern Ghana and find that earlier adoption of the new crop brings greater welfare gains than does later uptake.

s0045 ## 3.5 Technology adoption

p0260 An important insight within production economics is that technology adoption essentially endogenizes the *parameters* of the production function. For example, adopting a genetically engineered variety with the Bt trait reduces the effect of applied pesticides, and thus when a producer is contemplating that decision they will take into account that their choice will effectively change the marginal effects of various inputs. Here we expand the definition of the production function by including the parameters β and assume that there is an underlying (latent) continuous range of technologies available. The model becomes

$$V(W_t) = \max_{m_t, x_t, \beta} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t, \text{ and } W_{t+1} = p_{t+1} F(x_t, \beta)\epsilon_{t+1}.$$

Working with the Kuhn–Tucker first order conditions

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1} p_{t+1} F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial \beta} \beta = E_t\left[V'_{t+1} p_{t+1} F_\beta \beta \epsilon_{t+1}\right] = 0$$

one can show by summing these together that the optimal solution will satisfy

$$E_t[s_{t+1} R_{t+1}] = 1$$

where R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{p_{t+1}\left(F_x x_t + F_\beta \beta\right)\epsilon_{t+1}}{x_t}.$$

p0265 Here there are two marginal products, F_β and F_x, which can be thought of as the production effects at both the extensive (adjust technology) and intensive (adjust inputs given technology) margins; and, its clear from the model that they should be considered jointly. One could also specify that the variance of the production shock is a function of β as well, in which case the production-risk-altering effects of the technology could be modeled. We have ignored potential one-time and/or on-going costs for the technology, but they could easily be built into the wealth allocation constraint if warranted.

p0270 The literature on technology adoption is long standing and continues to evolve. Recently, seed variety selection decisions have gained much attention due to their implications for other on-farm management decisions. No variety type has been more controversial in society than those that have been genetically engineered (GE), and the associated academic literature is still rapidly expanding as the global diffusion of GE varieties continues across crops and locations. Perhaps in response to the widespread diffusion of GE into the food supply chain, consumers have placed value on sustainable and/or organic production systems/technologies and an important vein in the literature focused on farm-level implications has materialized.

p0275 Technology adoption continues to play a prominent role in the literature as studies such as Shen and Odening (2013) shows that yield risks are changing over time. Particular recent emphasis has been on the network and learning aspects of technology adoption. Crane-Droesch (2018) explores the mechanisms through which social learning mediates technology diffusion by exploiting an experiment on the dissemination of soil enhancements and find that as farmers observe factors associated with outcomes in their networks, they constrain the distribution of their own potential outcomes. Sauer and Zilberman (2012) study factors for technology adoption at the firm level and results underscore the importance of risks faced by the agents, network externalities and peer-group learning, and previous innovation experiences. Läpple and Kelley (2015) apply Bayesian models to survey data of Irish drystock farmers and findings reveal the importance of farmer interactions in adoption decisions. Wossen, Berger, and Falco (2015) provide evidence of the effects of social capital across households with heterogeneous risk attitudes using cross section and panel data from Ethiopia. Larsen (2019) finds that networks effect the adoption of improved banana cultivation in Tanzania.

p0280 Variety selection is a key component of a farm's technology, and recent advancements have shed light on its role in producer welfare as well as its potential to affect input decisions. Emerick, de Janvry, Sadoulet, and Dar (2016) use a randomized experiment in India to show that improved technology enhances agricultural productivity by crowding in modern inputs and cultivation practices. Cavatassi, Lipper, and Narloch (2011) analyze data from Ethiopia in a year of extreme weather conditions and results show that risk-factors coupled with access to markets and social capital drive farmers' decisions to adopt modern varieties. Hurley, Koo, and Tesfaye (2018) explore how weather risk affects the value of nitrogen fertilizer use and improved seed variety adoption for sub-Saharan African maize farmers and finds that they are not always advantageous, especially when considering the potentially high cost to farmers of obtaining them.

p0285 Among seed varieties, no type has been more controversial than GE varieties. Although deep, this literature is still rapidly expanding as the global diffusion of GE varieties continues across crops and locations. Studies have explored the adoption decision itself as Barham, Chavas, Fitz, Ríos-Salas, and Schechter (2015) analyze experimental and survey data among US grain farmers and find evidence of substantial unobserved heterogeneity in learning among farmers, while Ma and Shi (2015) use a dynamic adoption model with Bayesian learning and find evidence of forward-looking behavior. Fuller, Brester, and Boland (2018) provide a case study on adoption of a new genetically engineered potato variety and explore how price and production risk interact to influence decision-making at each link in the supply chain. Ramsey, Bergtold, Canales, and Williams (2019) present a conceptual model of perceived yield risk and an empirical application using survey data shows that on-farm trialing may encourage adoption. Gbègbèlègbè, Lowenberg-DeBoer, Adeoti, Lusk, and Coulibaly (2015) use a choice experiment to estimate the *ex ante* economic impact of GE Bt cowpea and find that growers in Nigeria prefer it to conventional cowpea for health safety reasons.

p0290 An interesting aspect of GE varieties is that they are not typically a single trait but rather a bundled (or stacked) group of traits, and much research has focused on the influence that this has for both adoption and production effects. Foltz, Useche, and Barham (2013) demonstrate the value of a trait-based approach to studying technology adoption by empirically analyzing how the valuation of technological traits may depend on factors beyond standard price considerations, with results suggesting that some farmers do indeed have tastes/preferences for GE versus non-GE varieties. Aldana, Foltz, Barham, and Useche (2011) theoretically demonstrate how uncertainty with a package technology can lead to an adoption pattern in which farmers move from single trait to stacked varieties. Shi, Chavas, and Lauer (2013) analyzed grain yield data from annual field experiments during 1990–2010 in Wisconsin and find that reducing yield risk is an important source of benefits of transgenic technology, especially for stacked traits. Chavas and Shi (2015) use conditional quantile regression to analyze the effects of GE seed technology on production risk and results suggest that the effects are heterogenous across traits and locations. Perry, Moschini, and Hennessy (2016) develop a test for complementarity between glyphosate-tolerant soybeans and conservation tillage within a structural discrete choice framework, and an empirical application using a large panel of farm-level data finds that glyphosate-tolerant soybeans and conservation tillage are complementary practices. Huffman, Jin, and Xu (2018) examine the economics of technical change and the interaction between weather and technology using panel data on US Midwest rainfed corn yields and finds that GE corn plants abate yield damage caused by soil moisture stress but not excess heat. Goodwin and Piggott (2020) consider side-by-side data collected under the Biotech Endorsement to the US Federal Crop Insurance Program between 2008 and 2011 and find that risk was significantly lower for GE crops, and that the difference in risk tends to be greater when growing conditions are less favorable.

p0295 In response to changes in consumer demand, many farms have adopted alternative production systems, such as organic production and/or "sustainability". A literature has developed to understand the risk implications of these alternative production systems. Tiedemann and Latacz-Lohmann (2013) quantify the importance of production risk and technical efficiency in German organic and conventional farming and results indicate that output variability in both systems is mainly caused by production risk. Gardebroek, Chavez, and Lansink (2010) compare the production risk of organic and conventional farms in the Netherlands and analysis of panel data provides evidence that organic farms face more output variation than conventional farms. Mohan (2020) elicits risk preferences of Nepali small-scale tea farmers and results indicate that farmers who are more risk averse have a higher propensity to get certified organic. Kallas, Serra, and Gil (2010) propose a new multi-criteria decision-making methodology to measure farmers' objectives and an empirical analysis of farm-level data from a sample of Spanish vineyard farms suggests that farmers who are not risk averse are more likely to adopt organic farming. Kuminoff and Wossink (2010) develop a theoretical model to assess the dollar compensation required to induce conventional growers to convert to organic and results suggest that sunk costs coupled with uncertainty about future returns can help explain why there is so little organic farmland in the United States. McBride and Greene (2013) use ARMS data to examine the characteristics of organic soybeans adopters and found that they were younger, had less acreage, were less likely to work off-farm compared to their conventional counterparts. In a companion study McBride and Greene (2009) find that significant returns to organic systems result from similar yields and lower costs than conventional systems, but the high returns to commercial organic production can only be attributed to the significant price premiums paid for organic soybeans. Trujillo-Barrera, Pennings, and Hofenk (2016) examine the underlying motives of producers to adopt sustainable practices while focusing on expected economic, social and personal rewards, and results from personal interviews with hog producers show that the adoption of sustainable practices is affected by expected economic rewards but not by social and personal rewards.

s0050 4 On-farm price risk

p0300 This section is organized into four subsections covering an overview of price volatility and its relationship with production, followed by common approaches that farms use to manage price risk including contracting, hedging, and storage.

s0055 4.1 Price volatility

p0305 Producers typically have some expectation for the harvest price of their output when inputs are committed to production. This could be a current spot price, a weighted average of previous years harvest prices, or a futures price from publicly traded markets. Whatever the source, there is always a nonzero probability that the realized harvest price will deviate from that initial expectation. Here we define the *ex post* realized harvest price as the sum of the price expectation and a mean-zero random variable, $p_{t+1} = \overline{p} + \epsilon_{t+1}$, and abstract away from production risk in the decision problem:

$$V(W_t) = \max_{m_t, x_t} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t, \text{ and } W_{t+1} = (\overline{p} + \epsilon_{t+1})F(x_t).$$

p0310 As with production risk, price risk in the output market can reduce on-farm production through a retraction in inputs under certain conditions.[27] Using the envelope theorem the first order condition for the optimal input can be expressed as

$$E_t[s_{t+1}(\overline{p}+\epsilon_{t+1})F_x]=1$$

where s_{t+1} is the stochastic discount factor, F_x is the deterministic component of the value of the marginal product (VMP), and 1 is the MFC since the input is measured in expenditure terms. The key insight here is that the above expectation is taken over two random variables and can be equivalently expressed as

$$E_t[s_{t+1}(\overline{p}+\epsilon_{t+1})]\mathrm{VMP}=\mathrm{MFC}$$

which demonstrates how the presence of risk will shift the VMP. Using the relationship between the expectation of two random variables and covariance coupled with the insight that the price shock is part of the stochastic discount factor, it can be shown that an increase in the variance of the price shock σ^2 will shift the VMP leftward, thereby reducing the optimal input level.

p0315 The recent literature on price volatility and forecasting has focused on many important dimensions. Decision-making on farm typically starts with some expectation of the output price, but producers also recognize that there is likely to be some deviation around this expectation. Research often focuses on both aspects of stochastic prices, and some studies will focus on the differential effects that this exposure can have across farms. Forecasting methods are commonly used in an attempt to quantify how much risk is present at any point in time, which then facilitates consideration of available methods to mitigate the effect of this exposure. These methods recognize that there are often both regional/national/global drivers of price variation in addition to local drivers, and this is an important distinction because it is rare that a single risk-mitigating strategy can protect producers from both types of variation. Stochastic quality attributes of farm outputs can also be an important dimension of price risk.

p0320 Producers typically have some reference price in mind, which can change and evolve over time, and the variation around it has welfare implications for producers. Mattos and Zinn (2016) explore how producers' reference prices are formed, adapt over time, and how they affect marketing decisions with results indicating that producers focus on three major variables to form their reference prices: current market price, highest price to date, and their expectation about price behavior. Haile, Kalkuhl, and Braun (2016) estimate worldwide aggregate supply response for key agricultural commodities by employing a multicountry, crop-calendar-specific, seasonally disaggregated model, and show that output price volatility reduces supply. In a paper that calls into question some classical theoretical results, Bellemare, Lee, and Just (2020) utilize experimental techniques in labs with US college students as well as in the field with Peruvian farmers, and results suggest that price risk does not affect

np0140 [27] This is a long-standing topic in the literature dating back to Sandmo (1971) and beyond.

production output at the extensive margin and has a nonmonotonic relationship with output at the intensive margin. Lambarraa, Stefanou, and Gil (2016) analyze the Spanish olive sector using farm-level data by estimating a dynamic stochastic frontier model and combine this with a real options approach to show that mitigating price uncertainty can improve production returns. In an older but still relevant paper, Kim, Hayes, and Hallam (1992) examine the impact of changes in the variance of output prices on the bias and intrafirm diffusion rate of technological change, and results indicate that a variance reduction increases adoption rates and the intrafirm diffusion speed of yield-increasing technologies.

p0325 Exposure to price risk has heterogeneous implications across farms. Bellemare, Barrett, and Just (2013) develop an analytical framework and an empirical strategy to evaluate the effects of commodity price volatility on producers and, coupled with results from a comment by McBride (2016), an application to Ethiopian households suggests that welfare gains from eliminating price volatility depend on household income. Magrini, Balié, and Morales-Opazo (2017) propose an empirical strategy to investigate and compare the different effects of higher versus more volatile cereal prices and an empirical application using nationally representative household survey data from four sub-Saharan countries suggests that while the negative impacts of a cereal price increase substantially outweigh the effects of price volatility on household welfare across the entire income distribution, price volatility mainly harms the poorest quantile of the population.

p0330 Forecasting prices can provide some protection against price variability if done well, and futures markets can provide valuable information on expected price changes. Trujillo-Barrera, Garcia, and Mallory (2016) develop and evaluate quarterly out-of-sample individual and composite density forecasts for US hog prices using time series models and demonstrate the economic value that more accurate expected price probability distributions can provide to producers, paying particular attention to the added value of composite forecasts. Hart, Lence, Hayes, and Jin (2016) propose a model that incorporates mean reversion in spot-price levels and includes a correction for seasonality, and the results of an empirical analysis suggest that longer term forecasts might be unnecessary in markets that exhibit mean reversion.

p0335 An important component of the price producers actually receive is the basis, which measures a local deviation from the futures price and can vary across space and time; thus basis risk prediction is an important topic as well. Coffey, Tonsor, and Schroeder (2018) analyze basis prediction errors for live cattle in the five major Mandatory Livestock Price Reporting areas in the United States and results suggest that volatility in cost-of-gain and delivery costs have greater effects on basis prediction error than do general market trends. Thompson, Edwards, Mintert, and Hurt (2019) evaluate practical methods of forecasting corn and soybean basis in the eastern Corn Belt and results suggest that basis forecasts based on 2–5 year moving average perform well.

p0340 For many commodities, another important dimension of price risk regards the quality of the output which will depend on both management considerations and idiosyncratic shocks from biotic and abiotic factors. Fausti, Wang, Qasmi, and Diersen (2014) conduct a 7-year comparative study of grid pricing versus average pricing of slaughter cattle to evaluate carcass quality market signals using time series models and find that quality variation can induce price variation under grid pricing. Belasco, Schroeder, and Goodwin (2010) evaluate quality, production, and price risk within the context of overall profit variability in fed cattle production and the results help explain why price signals through grid quality grade premiums may not generate intended producer responses. Thompson, DeVuyst, Brorsen, and Lusk (2016) estimate the value of using genetic information to make fed cattle marketing decisions and finds a wide range of effects depending on how a producer currently markets cattle and the grid structure.

s0060

4.2 Contracting

p0345 Contracting is a way for producers to mitigate their exposure to price risk by locking in a fixed price at the beginning of the season, but they are then contractually obligated to deliver a certain quantity at harvest.[28] We can modify the model to recast price risk as a form of downside production risk where the penalty is dictated by the stochastic spot market price. Suppose the target quantity is α and the producer is paid $\overline{p}$ for delivering this amount. If *ex post* production is above that target, then the producer receives $\alpha\overline{p}$ from the contract and generates additional revenue from selling excess production on the spot market for p_{t+1}. If on the other hand production is below, the seller must fulfill the contract by purchasing the deficient output on the spot market.

p0350 More specifically, noting that revenue will be $\overline{p}\alpha + p_{t+1}[F(x_t)\epsilon_{t+1} - \alpha]$ if *ex post* production is above target and $\overline{p}\alpha - p_{t+1}[\alpha - F(x_t)\epsilon_{t+1}]$ if below, then the combined revenue function can be written as

$$\overline{p}\alpha + p_{t+1}\left(\underbrace{\max[F(x_t)\epsilon_{t+1} - \alpha, 0]}_{\text{excess quantity}} - \underbrace{\max[\alpha - F(x_t)\epsilon_{t+1}, 0]}_{\text{deficient quantity}}\right)$$

which reduces to

$$\overline{p}\alpha + p_{t+1}[F(x_t)\epsilon_{t+1} - \alpha].$$

Using this as the payoff function and allowing the contract target α to be a decision variable, the model is given by

$$V(W_t) = \max_{m_t, x_t, \alpha} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

np0145 [28]In this setting producers do seek to reduce their exposure to risk, but more generally they are transferring it to buyers who (through aggregation) are often better able to use hedging instruments.

subject to

$$W_t = x_t + m_t, \text{ and } W_{t+1} = \overline{p}\alpha + p_{t+1}[F(x_t)\epsilon_{t+1} - \alpha]$$

The Kuhn–Tucker first order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1} p_{t+1} F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial \alpha} \alpha = E_t\left[V'_{t+1}(\overline{p} - p_{t+1})\alpha\right] = 0$$

and summing these together implies that the optimal solution will satisfy

$$E_t[s_{t+1} R_{t+1}] = 1$$

where R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{\overline{p}\alpha + p_{t+1}(F_x x_t \epsilon_{t+1} - \alpha)}{x_t}.$$

p0355 The recent literature on contracting has focused on many important dimensions including the various drivers of, and on-farm effects thereof, its use.[29] There is an ever-present and on-going feedback between theoretical modeling of contract negotiations and empirical results that provide confirmation of modeling assumptions or further needs for generalizations. Contract farming is not any one thing but rather can take a variety of forms and thus the on-farm implications are often nuanced. Contracting can be used to support emerging markets and/or production targets for environmental programs, and there is a long-standing tradition of contracting through local organizations such as cooperatives.

p0360 Drivers of the use of contracting and its on-farm effects have a long-standing tradition in the literature and continue to be relevant. Bellemare (2012) studies the relationship between tenurial insecurity and land tenancy contracts, and an empirical application using data on landlords' subjective perceptions in rural Madagascar supports the hypothesis that insecure property rights drive contract choice but offer little support in favor of risk sharing. Wendimu, Henningsen, and Czekaj (2017) investigate the unique contractual arrangement between a large sugar factory and its adjacent associations of outgrowers in Ethiopia using cross-sectional plot-level data and finds that outgrower-operated plots are more productive than factory-operated plots. Mohapatra, Goodhue, Carter, and Chalfant (2010) utilize publicly available data for the fresh strawberry market and time series models, and finds that informal contracts increased spot prices and have regional effects

np0150 [29]In this section we are largely focusing on contracting in output markets, but it is important to note that there is a longstanding literature on agrarian contracts and organization dating back to seminal work by Stiglitz (1974), Braverman and Stiglitz (1986), and Eswaran and Kotwal (1985). Some recent papers related to land rental and sharecropping are discussed in Section 5.1.

on spot-price volatility. Saenger, Qaim, Torero, and Viceisza (2013) analyze the effectiveness of existing contracts between a processor and smallholder farmers in the Vietnamese dairy sector, and a framed field experiment shows that contract parameters are a more important driver of input use than risk aversion. Fischer and Wollni (2018) analyze data from a discrete choice experiment among the Ghanaian pineapple farmers and find that experimental measures of trust, risk and time preferences can predict preferences for contract attributes with trust having economically important negative effects on the willingness to pay for high transparency in quality controls. Vassalos, Hu, Woods, Schieffer, and Dillon (2016) analyze data from a mail survey administrated to wholesale tomato growers and findings validate the transaction cost hypothesis and indicate heterogeneity in preferences, while risk preferences had limited impact on contract choice. Taylor, Tonsor, and Dhuyvetter (2014) study Kansas wheat basis price patterns and found a substantial increase in the cost of forward contracting paid by farmers as a results of several factors including basis volatility. Du, Ifft, Lu, and Zilberman (2015) investigate the effect of crop insurance enrollment on contract terms and farmers' participation in marketing contracts, and a mechanism design framework shows that improved terms of crop insurance (lower premiums, higher subsidies) make contracts less appealing to farmers as mechanisms for mitigating risk. Elliott, Elliott, Te Slaa, and Wang (2020) provide an overview of a new generation of grain contracts in corn and soybean markets.

p0365 There have been many theoretical and empirical findings that focus on our ability to realistically capture the nuances of contract bargaining, as well as encapsulate new forms of contracting that are direct to consumer. Wu (2014) develops a model to illustrate how classic methodological approaches can be combined with recent developments in contract and game theory to construct applied theory models that are useful for capturing some important features of agricultural contracts. Royer (2011) measures the magnitude of transaction costs incurred by milk producers in their contractual relations with dairy processors using interviews and surveys and find evidence of heterogeneous costs across farmers. Steiner (2012) uses stylized wine industry facts to assess predictions on the optimal sharing rule from a principal–agent model in the presence of double-sided moral hazard. Sabasi, Bastian, Menkhaus, and Phillips (2013) use lab experiments to analyze the impacts of committed procurement on privately negotiated transactions, and results illustrate that those who do not engage in prior trading are at a bargaining disadvantage due to matching and inventory loss risks. Sproul and Kropp (2015) derive a theory of community-supported agriculture contract pricing using a two-period expected utility model and illustrate several testable hypotheses.

p0370 Contract farming is not any one thing but rather can take a variety of forms and thus have nuanced implications. Bellemare and Lim (2018) note that contract farming is far from monolithic and describes how it varies in cross-sectional data covering households across six regions of Madagascar. Mishra, Kumar, Joshi, and D'Souza (2018) use farm-level data and endogenous switching regression methods to show that contract farming adoption increases food security and varies with the revealed risk preference of smallholders. Mishra, Rezitis, and Tsionas (2020) investigate production risk, technical efficiency, output price uncertainty and risk attitudes of contract and independent farmers, and a Bayesian estimation method using farm-level data from Nepal shows that contract farmers are more risk-averse. Bellemare, Lee, and Novak (2021) consider whether participation in contract farming is associated with lower levels of income variability in a sample of farm households in Madagascar, and results from a framed field experiment suggest that contract farming is associated with a decrease in income variability and can serve as partial insurance mechanisms. Dubbert (2019) uses survey data of cashew farmers in Ghana combined and an application leveraging an endogenous switching regression model shows that contract farming significantly increases labor productivity, price margins, yields, and net revenues. In a somewhat related topic of land rights, Bellemare (2013) studies the relationship between land rights and agricultural productivity, and results from an empirical application that leverages data containing precise soil quality measurements suggest that formal land rights have no impact on productivity as compared to informal land rights which are found to have heterogeneous impacts on productivity.

p0375 Contracting can also be used to support emerging markets and/or production targets for environmental programs. Ricome, Chaïb, Ridier, Képhaliacos, and Carpy-Goulard (2016) utilize a numerical application based on a stochastic model for a representative farm in southwestern France and find that marketing contracts can encourage farmers to adopt green practices. Yang, Paulson, and Khanna (2016) show that long-term contracts are likely to be critical to induce production of perennial energy crops as a feedstock for the emerging cellulosic biofuel industry. Krah et al. (2018) employ a choice experiment to examine producer preferences for contracts to produce a risky bioenergy crop and find that price, biorefinery harvest, and establishment cost-share have significant positive effects, whereas contract length has a negative effect.

p0380 Contracting through local organizations such as cooperatives has a long-standing tradition among producers. Hernández-Espallardo, Arcas-Lario, and Marcos-Matás (2013) analyze data from a survey of members of marketing cooperatives specializing in fresh fruits and vegetables and find that transaction costs are an important driver for member satisfaction. Mérel, Saitone, and Sexton (2015) extend previous analyses on the use of revenue pooling across alternative quality levels by cooperatives and show that the revenue-pooling benefits of cooperation may be sufficient to cause high-quality producers to join a cooperative and pool revenues with lower-quality producers. Saitone, Sexton, and Malan (2018) develop an analytical model to study a farmer's choice of selling to a private trader versus cooperative and find that modest improvements in either timeliness of payment or probability of default can induce a substantial increase in a cooperative's market share and economic viability. Ito, Bao, and Su (2012) examine the treatment effects of the agricultural cooperative on individual household economy using data collected from watermelon-producing farm households in rural China, and results suggest that the cooperative system is an important avenue for farmers to improve their economic status.

s0065
4.3 Hedging with futures

p0385 Another way to reduce price risk is to hedge using the futures market. Producers do not typically deliver on the contract, but rather use futures to mitigate a large portion of price risk while still selling their output locally at harvest.[30] Note that local prices can be represented as the (common) futures price plus a local adjustment called the basis, $p_{t+1} = \hat{p}_{t+1} + b_{t+1}$, which shows how eliminating the variation attributed to the futures price will reduce (but not completely exhaust) the variation in received price. In practice, the producer short sells a futures contract for α units at the futures price $\hat{p}_t$ and then at harvest buys a contract at $\hat{p}_{t+1}$ to close out their position while simultaneously selling their production at p_{t+1}.[31]

p0390 More specifically, noting that revenue will be $p_{t+1}\alpha + (\hat{p}_t - \hat{p}_{t+1})\alpha + p_{t+1}[F(x_t)\epsilon_{t+1} - \alpha]$ if *ex post* production is above target and $p_{t+1}\alpha + (\hat{p}_t - \hat{p}_{t+1})\alpha + p_{t+1}[\alpha - F(x_t)\epsilon_{t+1}]$ if below, then the combined revenue function can be written as

$$p_{t+1}\alpha + (\hat{p}_t - \hat{p}_{t+1})\alpha + p_{t+1}\left(\underbrace{\max\left[F(x_t)\epsilon_{t+1} - \alpha, 0\right]}_{\text{excess quantity}} - \underbrace{\max\left[\alpha - F(x_t)\epsilon_{t+1}, 0\right]}_{\text{deficient quantity}}\right)$$

which reduces to

$$[F(x_t)\epsilon_{t+1} - \alpha]\hat{p}_{t+1} + F(x_t)\epsilon_{t+1}b_{t+1} + \hat{p}_t\alpha.$$

This highlights that production is fully exposed to basis variation but only partially exposed to futures price variation.[32] This can be equivalently expressed as

$$\hat{p}_t\alpha + b_{t+1}\alpha + p_{t+1}[y_{t+1} - \alpha]$$

which shows that revenue can also be thought of as the revenue sold at the futures price plus basis on those volumes plus the excess (deficit), which is sold (bought) at the market price. Note in both cases if the producer could hit the target deterministically then the exposure to futures price variation would be eliminated completely.

np0155 [30]Note here that we are assuming the harvest quantity coincides with the marketed quantity, which essentially abstracts away from the possibility of storage. In the presence of storage, producers will often hedge with contracts that have delivery dates well after the harvest date.

np0160 [31]Although we are largely focused on crop production in this leading example, it is worth noting that hedging is also utilized by livestock producers. This example is useful in that context as well, where "slaughter" or "maturity" serves as the "harvest" and short positions are sometimes closed out via actual delivery thereby exchanging basis for a transportation cost.

np0165 [32]In practice producers can also engage in activities to manage basis risk as well, e.g., basis contracts, transaction size, and spatial arbitrage, and thus are not pure basis takers.

Using revenue as the payoff function and allowing the contract target α to be a decision variable (i.e., could purchase multiple contracts),[33] the model is given by

$$V(W_t) = \max_{m_t, x_t, \alpha} \; U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t, \text{ and } W_{t+1} = \hat{p}_{t+1}[F(x_t)\epsilon_{t+1} - \alpha] + F(x_t)\epsilon_{t+1}b_{t+1} + \alpha\hat{p}_t.$$

The Kuhn–Tucker first order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial x}x_t = E_t\left[V'_{t+1}(\hat{p}_{t+1} + b_{t+1})F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial \alpha}\alpha = E_t\left[V'_{t+1}(\hat{p}_t - \hat{p}_{t+1})\alpha\right] = 0$$

and summing these together implies that the optimal solution will satisfy

$$E_t[s_{t+1}R_{t+1}] = 1$$

where R_{t+1} is the return from farming defined by

$$R_{t+1} = \frac{\hat{p}_{t+1}[F_x x_t \epsilon_{t+1} - \alpha] + F_x x_t \epsilon_{t+1} b_{t+1} + \alpha\hat{p}_t}{x_t}.$$

p0395 The recent literature on hedging has focused on many important dimensions including long-standing questions on optimal decision-making for the amount of production to hedge and the timing of the position. Not all farm outputs have an associated futures market contract, so the potential to cross-hedge using contracts for commodities whose prices co-vary has been a focus as well. Other considerations in the literature include profit margin hedging, electronic trading, and the maturity length of available contracts.

p0400 Hedging with futures contracts has been a topic of research for a long time and often centers around the optimal hedge ratio, the length of time positions are held, and the roles of hedging versus speculative trading. Jacobs, Li, and Hayes (2018) develop a theoretical model that describes optimal hedging and nests expected utility theories and an empirical analysis finds that hedging activity is reference dependent. Stefani and Tiberti (2016) derive an analytical formula for the multiperiod hedging ratio and investigates the performance of various estimators. Fishe, Janzen, and Smith (2014) show theoretically that when traders exhibit differences of opinion about the expected value of a commodity, futures prices may diverge from equilibrium, and an empirical analysis suggests that prices change by more on average than

np0170 [33] Including α as an endogenous variable allows one to consider "optimal hedge ratios", a long-standing topic in the literature with classic papers including Feder, Just, and Schmitz (1980), Lapan and Moschini (1994), and Hirshleifer (1988).

producers think they should and by less than managed money thinks they should. Sproul, Kropp, and Barr (2015) note that a potential downside of hedging price risk is the removal of the natural hedge of prices against yields due to their negative correlation.

p0405 If a futures contract for a specific farm output is not offered, producers can still cross-hedge using a contract on another commodity. Drugova, Pozo, Curtis, and Fortenbery (2019) provide evidence that conventional futures can be used to cross hedge organic wheat price risk, but effectiveness depends on the method used to impute missing values. Newton and Thraen (2013) examine the risk management opportunities for fluid milk market participants in the United States and find that using class III manufacturing milk futures contracts to cross-hedge fluid milk has the ability to reduce risk and provide revenue stability to market participants.

p0410 Other considerations in the literature include profit margin hedging, electronic trading, and the maturity length of available contracts. Kim, Brorsen, and Anderson (2010) derive optimal conditions on the producer's utility function and price processes for profit margin hedging to be optimal, and find that it is only under a highly restricted target utility function even in an efficient market. Frank and Garcia (2011) use a modified Bayesian method to estimate liquidity costs and their determinants for the live cattle and hog futures markets and find that volume and volatility are simultaneously determined and significantly related to the bid-ask spread, and that electronic trading has a significant competitive effect on liquidity costs. Jin, Lence, Hart, and Hayes (2012) develop and implement a procedure to generate long-term futures curves from existing futures prices using data on lean hogs and soybeans to show that longer term maturities (8–10 years) would have value as price forecasts and as a way to structure long-term swaps and insurance contracts.

s0070 4.4 Storage

p0415 Storage of an output can be an on-going decision made throughout the calendar year in which stocks are added to at harvest and then slowly drawn down by sequential marketing decisions based on economic relationships in real time.[34] As a general rule, every day that a commodity is stored is a day in which an economic decision has been considered and made. Here we focus on the interaction between storage and production decisions by assuming that the storage decision occurs at the beginning of the period when wealth allocations to inputs are made. Conceptually, the producer has access to wealth W_t as before, but it is important to note that this may indeed include value from previous stocks. The producer decides to continue to store some quantity z_t of that stock, alongside allocations to production inputs and consumption. There are two costs of storage: the opportunity cost of the wealth allocation which is valued at the known price p_t, as well as the direct cost of storage s that we assume is paid at the end of the period. In this way, storage can be thought of as an asset

np0175 [34] Storage can occur on- and/or off-farm and both types are common in practice.

in the general sense with outlay $p_t z_t$ and payoff $(p_{t+1} - s)z_t$. Under this set up the model is given by

$$V(W_t) = \max_{m_t, x_t, z_t} \; U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t + p_t z_t, \text{ and } W_{t+1} = p_{t+1} F(x_t)\epsilon_{t+1} + (p_{t+1} - s)z_t$$

The Kuhn–Tucker first order conditions are given by

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1} p_{t+1} F_x x_t \epsilon_{t+1}\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial z} z_t = E_t\left[V'_{t+1}(p_{t+1} - s)z_t\right] - V'_t p_t z_t = 0$$

and summing these together implies that the optimal solution will satisfy

$$E_t[s_{t+1} R_{t+1}] = 1$$

where R_{t+1} is the return from farming activities defined by

$$R_{t+1} = \frac{p_{t+1} F_x x_t \epsilon_{t+1} + (p_{t+1} - s)z_t}{x_t + p_t z_t}.$$

p0420 One of the main components of the storage literature that has evolved recently is identifying some behavioral drivers of the decision-making process.[35] Cotty, d'Hôtel, Soubeyran, and Subervie (2019) provide farmers in Burkina Faso the opportunity to participate in an inventory credit system (warrantage) in which they receive a loan in exchange for storing a portion of their harvest as a physical guarantee and find evidence that farmers use warrantage as a means to commit to saving a portion of their crop until the lean season. Kadjo, Ricker-Gilbert, Abdoulaye, Shively, and Baco (2018) analyze panel data from smallholders in Benin covering multiple seasons and results suggest that policies to provide liquidity will be more helpful in motivating storage. Miranda, Mulangu, and Kemeze (2019) develop and analyze a formal stochastic dynamic model of seasonal commodity marketing that exposes the transaction cost and risk reallocation problems that undermine the benefits of warehouse receipt financing to smallholders. Vollmer, Hermann, and Musshoff (2019) conduct an incentivized online experiment with German farms and results indicate that there is a robust disposition effect in farmers' selling behavior and that more loss-averse farmers exhibited a higher realization of gains. Burke, Bergquist, and Miguel (2019) study the commonly observed "sell low and buy high" phenomena among small-scale farmers in developing countries and data from a field

np0180 [35] Here we are focused on the micro farm-level storage decision and its producer-level effects, see Wright (2011) for a nice overview of the more aggregate price volatility/storage literature that dates back to Working (1948), Working (1949), and Brennan (1958).

experiment in Kenya show that credit market imperfections limit farmers' abilities to leverage storage in order to move grain intertemporally. Cardell and Michelsone (2021) propose an additional explanation to the phenomena whereby they use market data from 25 African countries over 20 years to show that prices fail to rise after harvest approximately 30% of the time. They show that risk aversion combined with the probability of negative returns can induce farmers to sell at harvest.

s0075 5 Off-farm income generating opportunities

p0425 This section is organized into three subsections covering various opportunities for farms to generate income from sources other than their own agricultural production: land rental/sharecropping, off-farm labor, and off-farm financial investment.[36]

s0080 5.1 Land rental

p0430 A key insight is to note that when a farm rents out some (or all) of its farmland, its decoupling the decision-making process of production on that land from their own operation and in return receive a fixed (nonstochastic) rental payment. In this sense it becomes a form of off-farm revenue, or at the very least a deterministic component of total farm revenue. Define by a_t and b_t acres of land devoted to on-farm production and rental, respectively, and the decision problem by

$$V(W_t) = \max_{m_t, x_t, a_t, b_t} U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = a_t + b_t + x_t + m_t, \text{ and } W_{t+1} = \delta_{t+1}(a_t + b_t) + p_{t+1}F(a_t, x_t)\epsilon_{t+1} + rb_t.$$

Here δ_{t+1} captures the stochastic gain/loss in land values across periods and r is the fixed nonstochastic rent paid by the tenant. Working with the Kuhn–Tucker first order conditions for the on-farm activities

$$\frac{\partial \mathcal{L}}{\partial a} a_t = E_t\left[V'_{t+1}(\delta_{t+1}a_t + p_{t+1}F_a a_t \epsilon_{t+1})\right] - V'_t a_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1}(p_{t+1}F_x x_t \epsilon_{t+1})\right] - V'_t x_t = 0$$

one can show that the on-farm decisions are guided by

$$E_t\left[s_{t+1}R^f_{t+1}\right] = 1$$

np0185 [36]Barrett, Reardon, and Webb (2001) provide a nice overview and synthesis of earlier work on these topics in the development context.

when R^f_{t+1} is the return from farming defined by

$$R^f_{t+1} = \frac{\delta_{t+1}a_t + p_{t+1}(F_a a_t + F_x x_t)\epsilon_{t+1}}{a_t + x_t}.$$

p0435 Assuming that the production function exhibits constant returns to scale (HOD 1) in (a_t, x_t), the payoff can be seen to be comprised of a capital gain/loss on the farmland asset $\delta_{t+1}a_t$ coupled with a dividend based on revenues from agricultural production of ex post realized output $y_{t+1} = F(a_t, x_t)\epsilon_{t+1}$:

$$R^f_{t+1} = \frac{\delta_{t+1}a_t + p_{t+1}y_{t+1}}{a_t + x_t}.$$

A similar solution can be found for the off-farm acres based on the Kuhn–Tucker condition

$$\frac{\partial \mathcal{L}}{\partial b} b_t = E_t\left[V'_{t+1}(\delta_{t+1}b_t + rb_t)\right] - V'_t b_t = 0$$

which also implies

$$E_t\left[s_{t+1}R^o_{t+1}\right] = 1$$

as above, but here the off-farm return takes the form

$$R^o_{t+1} = \frac{\delta_{t+1}b_t + rb_t}{b_t}.$$

Note that both the on- and off-farm usage of land generates a capital gain/loss and a dividend, but the dividend from farming is stochastic while the dividend from renting is not. Thus, in a practical sense these are very different types of assets comparable in some way to risky financial assets such as stocks versus relatively risk-free assets such as bonds. Subtracting the two conditions provides the arbitrage equation between on- and off-farm land usage in terms of the excess return

$$E_t\left[s_{t+1}R^e_{t+1}\right] = 0.$$

where

$$R^e_{t+1} = R^f_{t+1} - R^o_{t+1}.$$

p0440 The recent literature on land renting has focused on many important dimensions including characteristics of the owners and renters, and the decision whether to use a fixed versus variable (sharecropping) payment. Rental and/or sharing is not exclusively limited to farmland as other assets can be shared as well.

p0445 Landowners have forgone selling land preferring instead to rent it out for a long time, and the reasons for this fixity are probably a combination of both economic considerations and social norms. In the case of a livestock rental market in western Nepal, Aryal and Holden (2012) find that wealthier households were more likely to rent out land and/or livestock, whereas less wealthy were more likely to rent. On the tenant side, Das, Janvry, and Sadoulet (2019) use a randomized experiment and shows that increased access to credit helps tenants take more efficient land rental contracts.

p0450 The form of the rental agreement can vary as well between a fixed rent payment versus a sharecropping arrangement in which some portion of costs and/or revenues allocated to the owner. Fukunaga and Huffman (2009) investigate the role of risk aversion on land contract types among US tenants and landlords and finds that the contract choices are consistent with risk aversion. Gebregziabher and Holden (2011) develop a household model for poor landlords that explains their contract choices in response to downside production shocks and an econometric analysis suggests that fixed-rent contracts are preferred when *ex ante* production risk is low while sharecropping is more likely where production risk is high. Kalkuhl, Schwerhoff, and Waha (2020) study how sharecropping works as an insurance to mitigate climate risk, and farm-level data from African countries show that farms in low-precipitation areas are more likely to be in sharecropping contracts.

p0455 Rental and/or sharing is not exclusively limited to farmland as other assets can be shared as well. Lagerkvist and Hansson (2012) examine interpersonal choices related to machinery-sharing collaborations between farmers in the presence of strategic uncertainty and results suggest that risk aversion was uncorrelated with machine sharing. Tadesse, Holden, Øygard, and McPeak (2016) investigate different types of cattle sharing and rental contracts in Ethiopia and an econometric analysis of household panel data finds that contracts help cash poor and credit constrained households to improve their herd dynamics, to get access to nonlivestock resources (land, labor, and cash), and share risks that could have been difficult without the contract.

s0085 5.2 Off-farm labor

p0460 Off-farm labor is another way for farm's to diversify their income stream to reduce risk exposure. It is similar in spirit to farmland rental, but the production input that is moved off-farm is labor while all land remains in production. Providing a more stable income source is one reason for considering this, but many farms are also interested in the fringe benefits that typically accompany the job. Here we define a fixed wage w as the payoff for off-farm labor which may or may not include the value of these fringe benefits. We also implicitly assume that the labor market is not affected by friction.

p0465 Defining on-farm labor l^f, off-farm labor l^o, and the time endowment T_t, the decision model takes the form

$$V(W_t) = \max_{m_t, x_t, l_t^f, l_t^o} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = x_t + m_t + w_t(l_t^f + l_t^o - T_t), \text{ and } W_{t+1} = p_{t+1} F(l_t^f, x_t)\epsilon_{t+1} + w_{t+1} l_t^o.$$

The term, $w_t(l_t^f + l_t^o - T_t)$, in the wealth constraint of time t illustrates the followings: (i) if one chooses the two labor inputs greater than their time endowment, T_t, then there is an excess labor demand, $(l_t^f + l_t^o - T_t)$ with an expenditure of $w_t(l_t^f + l_t^o - T_t)$, and (ii) if the chosen labor inputs are less than their time endowment, T_t, then one increases the "wealth" with the rate of w_t. Here, we implicitly assume that remaining portions of the time endowment can be used as "leisure" and this "leisure" can be converted to the monetary value with the rate w_t.

p0470 Following a similar approach as with the land rental model the on- and off-farm decisions are guided by

$$E_t\left[s_{t+1}R_{t+1}^f\right] = 1 \text{ and } E_t\left[s_{t+1}R_{t+1}^o\right] = 1$$

where R_{t+1}^f and R_{t+1}^o are the on- and off-farm returns defined by

$$R_{t+1}^f = \frac{p_{t+1}(F_x x_t + F_l l_t^f)\epsilon_{t+1}}{x_t + w_{t+1}},\ R_{t+1}^o = \frac{w_t}{w_{t+1}}.$$

Subtracting these provides the arbitrage condition between on- and off-farm labor in terms of the excess return

$$E_t\left[s_{t+1}R_{t+1}^e\right] = 0, \text{ where } R_{t+1}^e = R_{t+1}^f - R_{t+1}^o.$$

p0475 The recent literature on off-farm labor has focused on many important dimensions including its ability to reduce overall risk exposure. Some interesting insights include the role that environmental/weather risk may play in driving this decision, and the potential feedback effect it can have on-farm productivity. There are also some hidden costs and benefits associated with the decision, with the biggest component of these being health care/insurance. Research has also focused on migration as an extreme version of off-farm labor as well as gender roles within the agricultural household.[37]

p0480 Using off-farm labor to reduce risk exposure is common among farm households. de Mey et al. (2016) provide empirical evidence on household risk-balancing behavior by estimating a fixed effects seemingly unrelated regression model using Swiss farm data, and findings suggest that farmers make strategic off-farm decisions by altering their share of off-farm income and relative consumption. Khandker and Koolwal (2016) use household panel data spanning over 20 years in Bangladesh to examine the effects of rural credit expansion and find that microcredit has raised

np0190 [37]This chapter only skims the very surface of the important topic of gender roles in agriculture. The 2010–11 FAO report Women in Agriculture is a great resource as it makes the "business case" for addressing gender issues in agriculture and rural employment, documents the different roles played by women in rural areas of developing countries, and provides solid empirical evidence on the gender gaps they face in agriculture and rural employment. It further details how gender gaps can impose real costs on society in terms of lost agricultural output, food security and economic growth. The report can be found online at http://www.fao.org/publications/sofa/2010-11/en/; and a more thorough treatment of the conceptual and empirical basis of this report can be found in Quisumbing et al. (2014).

nonfarm income diversification for all households. Nordin and Höjgård (2019) provide a comprehensive analysis of income of Swedish farmers and the results indicate that farm households do well from a standard-of-living perspective and off-farm earnings from their spouse have increased over time. Chavas, Cooper, and Wallander (2019) present a conceptual analysis of risk under general risk preferences and the application of the approach to a sample of US farms suggests that nonfarm work reduces risk. El-Osta, Mishra, and Ahearn (2004) study the impacts of decoupled payments and other government payments on both farm and off-farm labor allocations using data from the Agricultural Resource Management Survey (ARMS), and results indicate that government payments tend to increase the hours operators work on their farm and decrease the hours they work off the farm regardless of whether the payments come from programs tied to current year production or not.

p0485 A vein of this literature has focused on weather/climate as a particular risk factor that drives off-farm income. Dillon, Mueller, and Salau (2011) investigate the extent that Nigerian households engage in internal migration to ensure against *ex ante* and *ex post* agricultural risk due to weather-related variability and shocks, and find evidence of household response to *ex ante* risk by sending males to migrate. Mathenge and Tschirley (2015) analyze household data from rural Kenya and find that rural households engage in off-farm work as a long-term strategy to deal with the effects of anticipated weather conditions on their farming operations. Skoufias, Bandyopadhyay, and Olivieri (2017) combine nationally representative household-level survey data with a measure of rainfall variability at the district level, and an empirical analysis finds that high rainfall variability has significant negative effects on the agricultural specialization of within-household occupational choices. Awondo, Ramirez, Colson, Fonsah, and Kostandini (2017) investigate how self-protection from weather risk via the adoption of improved maize varieties or off-farm income affects risk premiums for smallholder maize producers in Uganda using unique plot-level panel data, and results show that both reduce risk premiums.

p0490 This off-farm decision is clearly linked to on-farm decision-making as well, and an important consideration is whether moving labor off-farm reduces productive efficiency on-farm. Chang and Wen (2011) use a nationwide survey of rice farmers in Taiwan to estimate stochastic production frontier models, and find that off-farm work is not necessarily associated with lower technical efficiency and that farmers with off-farm work face higher production risk. Sabasi, Shumway, and Astill (2019) present a theoretical framework linking off-farm work and technical efficiency, and stochastic frontier analysis of two nationally representative samples of US dairies suggests that an increase in off-farm work is associated with a significant decrease in technical efficiency. Dedehouanou, Araar, Ousseini, Harouna, and Jabir (2018) study farm households in Niger and find that participation in off-farm self-employment is linked to increased agricultural spending on crop and livestock inputs, but a lower propensity to hire labor. Babatunde and Qaim (2010) analyze farm survey data from Nigeria and find that off-farm income has a positive net effect on food security and nutrition, and contributes to higher food production and farm income by easing capital constraints. Chikwama (2010) examines the widely held view that earnings from rural wage employment can help farm households overcome constraints on-farm investments, however results from an analysis of a panel of farm households in Zimbabwe does not find evidence to support this hypothesis in general.

p0495 There are also often hidden costs and benefits associated with the decision, as well as traditional gender norms. Chang and Yen (2010) find that off-farm employment by a farm operator increases food expenditure away from home, but decreases secondary food expenditure at home. D'Antoni and Mishra (2013) examine the links between government farm program payments and fringe benefits from off-farm employment and results from farm-level data show that the marginal effect of government payments on hours worked off-farm will decrease in magnitude when accounting for fringe benefits. Jodlowski (2019) addresses how off-farm income earned by the farm spouse and the farm operator differentially affect farm financial viability, and an empirical analysis using farm-level Agricultural and Resource Management Survey (ARMS) data provides evidence that operators and spouses use the income they earn off-farm differently, and more generally, that farm households accept a financial penalty in order for the primary operator to remain male. Dzanku (2019) uses panel data for six African countries to examine the association between off-farm income and household food security and results suggest that off-farm income has stronger association with food security among female-headed and poor region households than it has among male-headed and rich region households in most countries.

p0500 The biggest component of the (potentially) unseen benefits of working off-farm is health care/insurance. Ahearn, El-Osta, and Mishra (2013) note that the majority of farm households allocate time to off-farm work that often provides employer-sponsored insurance. Liao and Taylor (2010) estimate the impact of the introduction of a universal health insurance plan in Taiwan and results based on a difference in-differences approach indicate that it reduced off-farm labor force participation. Mishra, El-Osta, and Ahearn (2012) use a large cross-sectional farm household-level dataset to estimate the impact of the source of health insurance on health care expenditures for farm households and results suggest that farm households purchasing individual health insurance directly from vendors are likely to spend more on health care than those with other sources of health insurance. Ahearn, Williamson, and Black (2015) discuss the implications of healthcare reform for the source of health insurance for farm households and potentially how much of their time they allocate to off-farm jobs.

p0505 Research has also focused on migration as an extreme version of off-farm labor. Kinnan, Wang, and Wang (2018) study the effects of access to internal migration in China and results show that improved access to migration leads to lower consumption volatility and lower asset holding. Using a panel data set from rural Mexico, Böhme (2015) investigates the impact of remittances on agriculture and livestock investments and shows that international migration has a significantly positive effect on the accumulated agricultural assets.[38]

np0195 [38]There is an extensive literature on the economics of migration, see for example Clemens (2011).

s0090 5.3 Off-farm financial investment

p0510 Yet another way that farms can diversify their income is through financial markets. In this case no inputs are moving off-farm, but a portion of wealth is. Modeling off-farm investment can also help clarify the opportunity cost of farming in a broad sense in that the farm could be sold at anytime with proceeds being invested elsewhere. In practice these investments can be spread across risky assets such as stocks or relatively risk-less ones such as bonds. Define by b the dollars invested in bonds and assume they generate a risk-free payoff r, and by f the dollars invested in stocks that generate a stochastic payoff δ that could be due to a capital gain and/or dividend. The decision model takes the form

$$V(W_t) = \max_{m_t, x_t, s_t, b_t,} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})]$$

subject to

$$W_t = f_t + b_t + x_t + m_t, \text{ and } W_{t+1} = \delta_{t+1} f_t + r b_t + p_{t+1} F(x_t) \epsilon_{t+1}$$

The three Kuhn–Tucker conditions are

$$\frac{\partial \mathcal{L}}{\partial x} x_t = E_t\left[V'_{t+1}(p_{t+1} F_x x_t \epsilon_{t+1})\right] - V'_t x_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial f} f_t = E_t\left[V'_{t+1} \delta_{t+1} f_t\right] - V'_t f_t = 0$$

$$\frac{\partial \mathcal{L}}{\partial b} b_t = E_t\left[V'_{t+1} r b_t\right] - V'_t b_t = 0$$

which all take the form

$$E_t\left[s_{t+1} R^i_{t+1}\right] = 1$$

where

$$R^x_{t+1} = \frac{p_{t+1}(F_x x_t)\epsilon_{t+1}}{x_t}, \; R^f_{t+1} = \delta_{t+1}, \; R^b_{t+1} = r.$$

This in turn generates a system of two arbitrage conditions for on-farm decision-making, each of which represents a different margin for off-farm investments

$$E_t\left[s_{t+1}(R^x_{t+1} - \delta_{t+1})\right] = 0 \text{ and } E_t\left[s_{t+1}(R^x_{t+1} - r)\right] = 0.$$

p0515 Here we focus on some of the interesting angles of off-farm investment that have been recently studied. Chambers and Voica (2017) develop a model to show a very interesting policy implication that if farmers have off-farm investment and employment opportunities, production decisions are decoupled from lump-sum subsidies in the presence of risk and uncertainty. Imai and Malaeb (2015) reconstruct cash and asset balances using detailed household transaction data on-farm households in rural

India and an empirical analysis finds that households cope with temporary shocks quite well by using crop inventory, currency, and capital assets as buffer assets. Picazo-Tadeo and Wall (2011) use cross-sectional survey data of Spanish rice farms to estimate risk aversion coefficients of farmers and find that off-farm income is associated with reduced risk aversion. Mishra and Chang (2011) explore factors affecting tax-deferred retirement savings of farm households using farm-level panel data and results indicate that savings increase with farm size but decrease with operator's age, and that cash grain and dairy farmers have lower retirement savings.

s0095

6 Agricultural insurance and credit

p0520 This section is organized into four subsections covering various aspects of agricultural credit and insurance markets. The extension of the model is presented here, and then each of the various subsections discusses different aspects of the model along with recent developments in the literature. The extension of the model to include access to agricultural insurance and/or credit is given by:

$$V(W_t) = \max_{x_t \geq 0,\ \chi_t} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})] \tag{1}$$

subject to

$$W_t = x_t + \chi_t + m_t, \text{ and } W_{t+1} = p_{t+1}F(x_t, \epsilon_{t+1}) + h(\chi_t, x_t; p_{t+1}, \epsilon_{t+1})$$

where χ_t represents the amount of intertemporal and interstate resource reallocation from the current wealth and $h(\cdot)$ is the transformation of the reallocated wealth. This general form is appealing because it includes credit and insurance as special cases: $\chi_t < 0$ represents "borrowing" from the future period (e.g., a loan) while $\chi_t > 0$ indicates "lending" to the future period (e.g., an insurance contract).[39] The function $h(\cdot)$ can be interpreted as a payback function and it too can be positive or negative depending on the context: for a loan $h(\cdot) < 0$ is the repayment and will typically take on a value of the loan amount (plus interest) or collateral in the case of default, while for insurance $h(\cdot) \geq 0$ serves as the indemnity function. Thus, $h(\cdot)$ depends on the realizations of stochastic variables.

p0525 In the remaining parts of this section, we explore the following aspects of the model. We first move to the topics related to agricultural insurance where an insurance contract can be represented by the pairs of premium, $\chi_t < 0$, and indemnity, $h(\chi_t)$. The topics include (i) designing and pricing insurance contracts, (ii) understanding the choice of crop insurance, which in this context represents insurance demand, and discuss innovations in both conceptual modeling and empirical estimation, and (iii) investigating interactions between insurance choices and on-farm production management x. We then focus on the conceptual and empirical issues related to the role of

np0200 [39]The signs can be a little confusing, note that in the case of a loan of amount A the input and consumption expenditures will be constrained by $W + A = x + m$, which implies $W = x - A + m$ and thus $\chi < 0$.

agricultural credit markets in the context of risk management. That is, we focus on $\chi_t > 0$ and examine how the choice of and the constraint on agricultural credit contribute to the risk management and production decisions.

s0100 ## 6.1 Designing and rating insurance contracts

p0530 Now, we further specify χ_t and $h(\chi_t)$ in Model (1) to focus on the issues related to insurance contract. Let us define $\chi_t = \pi_t(\theta_t, x_t) > 0$ as the price of the insurance contract (i.e., premium) and $h(\chi_t) = \xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}) \geq 0$ as the insurance payment (i.e., indemnity). As there are typically a range of coverage levels (e.g., high deductible versus low deductible) available, we specify the choice of insurance as the choice of the quantity of insurance, θ_t. These specifications lead to the following modified model:

$$V(W_t) = \max_{x_t,\ \theta_t \geq 0} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})] \tag{2}$$

subject to

$$W_t = x_t + \pi_t(\theta_t, x_t) + m_t, \text{ and } W_{t+1} = p_{t+1}F(x_t, \epsilon_{t+1}) + \xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}).$$

where the premium $\pi_t(\theta_t, x_t)$ and indemnity $\xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1})$ can take on many different forms depending on the type of insurance being considered. Note here that input x is showing up in both the premium and indemnity, but in practice insurers only observe a subset of general on-farm practices (e.g., irrigation) when offering a premium. In more general settings with multiple inputs, one can think of a (possibly) empty subset of inputs being in the premium while all inputs are likely to play a role in the indemnity. This is because of the limited ability of insurers in monitoring the insured. Inputs such as fertilizer, pesticides, or management are difficult to be incorporated in the ratings formula as they are normally determined *ex post* and not observable to insurers. We keep the general notation of x_t for brevity in this section. The overall discussion should not be affected by expanding the variable x_t to multiple variables.

p0535 Revenue-based, yield-based, and index-based products are examples of different types insurance contracts that can all be accommodated by the model. For example, the indemnity of yield-based products can be specified as $E_t(p_{t+1})\xi_t(\theta_t, x_t; \epsilon_{t+1})$ where $E_t(p_{t+1})$ is the projected price observed at time t.[40] Note that ξ_t is now contingent only on production shocks. Alternatively the indemnity payment of an index-based insurance contract can be expressed as $\xi_t(\theta_t, x_t; I(p'_{t+1}, \epsilon'_{t+1}))$ where p' and ϵ' are measures of price and production risks and I is an index over them.

p0540 In this subsection, we first describe innovations in designing insurance contracts, especially developing indemnity structures that can effectively mitigate risks. Many of these recent innovations are on designing index-based insurance products, which provide indemnity payment ξ based on indices of price p or production risk ϵ.

np0205 [40]One could build in a harvest price option in a straightforward manner, e.g., using $\max\{p_{t+1}, E(p_{t+1})\}$.

Designing these index-based products has gained great interest as "conventional" insurance contracts that indemnify based on individual losses face asymmetric information problems such as moral hazard and adverse selection (Miranda & Farrin, 2012) as well as high program costs. We then turn to another important issue in insurance contracts—pricing. Researchers have developed many empirical approaches in estimating yields or losses to obtain "actuarially fair" premiums, which is the premium that is equal to the expected indemnity, i.e., $\pi_t(\theta_t, x_t) = E(\xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}))$.[41] The literature on the pricing of the US federal crop insurance is particularly rich given the importance of the program within the broader US farm policy.

p0545 In the case of US crop insurance, area-based yield and revenue insurance products have been the first index-based insurance products (Glauber, 2013). Recently, index-based products such as weather-index disaster payments (Belasco, Cooper, & Smith, 2020), climate-index cattle insurance (Belasco, Cheng, & Schroeder, 2015), drought-index insurance for water users (Maestro, Barnett, Coble, Garrido, & Bielza, 2016), and area-index whole farm insurance (Chalise, Coble, Barnett, & Miller, 2017) have been proposed and/or extensively analyzed. Other noticeable examples in the context of developing index insurance for rice farms in China are area-yield insurance (Shen & Odening, 2013) and weather-index insurance that accounts for growing phases (Shi & Jiang, 2016). Furthermore, various innovative applications of estimation techniques have been growing in the literature. Some examples include Quantile Regression (QR) for incorporating the yield-index dependency (Conradt, Finger, & Bokusheva, 2015) and estimating copulas to design a hypothetical temperature-based insurance with spatial dependency accounted for (Okhrin, Odening, & Xu, 2013) or to design a rainfall index insurance product (Awondo, 2019).

p0550 Basis risk is perhaps the key element of index insurance performance as it has been extensively linked to demand (or lack thereof) and much research has focused on identifying, measuring, and ultimately reducing it. While we discuss the interaction between basis risk and the demand for index insurance in the next subsection, it is important to highlight that how well the index $I(p'_{t+1}, \epsilon'_{t+1})$ is correlated with the outcome of the agent as such correlation dictates the benefit from index insurance. This is closely related to the issues with "basis risk", which is the risk of not being covered by insurance when the insured face losses.

p0555 Focusing on an index-based livestock insurance product in northern Kenya, Jensen, Barrett, and Mude (2016) estimate that the insured are left with about 69% of their original risk. Yu, Vandeveer, Volesky, and Harmoney (2019) examine basis risk for US rainfall index insurance for pasture, rangeland, and forage growers and finds that the degree of basis risk is substantial for Kansas and Nebraska producers. Elabed, Bellemare, Carter, and Guirkinger (2013) propose a multiscale contract that has two levels of indices to lower basis risk. Dalhaus, Musshoff, and Finger (2018)

np0210 [41]Note that many crop insurance programs, especially the US Federal Crop Insurance Program, provide premium subsidies which makes $\pi_t(\theta_t, x_t) < E(\xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}))$. This makes estimating the "actuarially fair" insurance crucial in the context of understanding the cost of the insurance programs.

show that utilizing phenology reports and considering crop growth phases can reduce basis risk in weather-index insurance. The potential for utilizing remote-sensing data can be explored to improve product design and performance, and thus the quality of index insurance (Benami et al., 2021).

p0560 Pricing insurance accurately has been a perennial topic in the literature, and largely depends on the estimation of yield/revenue distributions or (more rarely) direct examination of observed premiums, liabilities, and indemnities. Government-sponsored agricultural insurance programs often aim to set actuarially fair premiums, i.e., $\pi_t(\theta_t) = E(\xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}))$, to induce stable market participation and there is often a segment of the literature evaluating potential mis-pricing at the product or program level. Researchers have also focused on asymmetric information such as adverse selection (e.g., Makki & Somwaru, 2001), advantageous selection (e.g., He, Rejesus, Zheng, & Yorobe, 2018) or moral hazard (e.g., Babcock & Hennessy, 1996; Horowitz & Lichtenberg, 1993; Smith & Goodwin, 1996), which can affect the risk distribution of the insureds and eventually influence the actuarially fair rates.

p0565 Empirical studies such as Woodard, Sherrick, and Schnitkey (2011) and Woodard, Schnitkey, Sherrick, Lozano-Gracia, and Anselin (2012) examine the premiums of the US FCIP and find substantial levels of biases in premium rates. As shown by the simulations of Ramirez, Carpio, and Collart (2015), biases in premium rates can result in an inequitable distribution of premium subsidies. On the other hand, Walters, Shumway, Chouinard, and Wandschneider (2015) argue that there is little evidence that rating or design issues, if there are any, lead to opportunistic behavior of participating farms.

p0570 There is a deep literature on employing new statistical methods for modeling outcome distributions, with particular emphasis on leveraging both temporal and cross-sectional information to improve rating accuracy. New methodological innovations continue to arrive and suggest some promising avenues for more accurately estimating yield distributions and actuarially fair premium rates, including mixture models (e.g., Woodard & Sherrick, 2011), flexible parametric models (e.g., Zhu, Goodwin, & Ghosh, 2011), maximum-entropy techniques (e.g., Tack, 2013), and Bayesian approaches to incorporate spatial information (e.g., Ker, Tolhurst, & Liu, 2016; Park, Brorsen, & Harri, 2019; Ramsey, 2020). Others also highlight the importance of heteroscedasticity assumptions in estimating premium rates (e.g., Harri, Coble, Ker, & Goodwin, 2011; Ker & Tolhurst, 2019).

p0575 One of the most challenging aspects of rate estimation is the ability to accurately estimate risk exposure in the presence of small samples, and the extent to which spatially pooling or "borrowing" information across space can improve accuracy. Using farm-level crop insurance data, Claassen and Just (2011) show that systematic intra-county variation is substantial and Adhikari, Knight, and Belasco (2013) find that sampling error in yields can reduce producer welfare. To resolve the issues associated with small samples, data can be pooled and the literature has developed statistical tests (e.g., Annan, Tack, Harri, & Coble, 2014) and a novel estimator (e.g., Zhang, 2017) along with the description or estimation of the relationship between county- and farm-level yields (e.g., Gerlt, Thompson, & Miller, 2014).

Pooling data in estimating yield distributions are also relevant in the context of unit-structure discounting (Knight, Coble, Goodwin, Rejesus, & Seo, 2010).

p0580 Innovative methods also have been developed for rating products that insure revenue or profit margins. Generalizing Copula assumptions is probably the largest area of innovation for revenue products where the price-yield correlations can be highly state dependent. Leading examples include Goodwin and Hungerford (2015), Ahmed and Serra (2015), and Ramsey, Goodwin, and Ghosh (2019). Bozic, Newton, Thraen, and Gould (2014) use copula models for Livestock Gross Margin Insurance for Dairy Cattle, and other papers consider using them in the development of index-based products (e.g., Awondo, 2019; Okhrin et al., 2013). Additionally, Goodwin, Harri, Rejesus, and Coble (2018) explore the possible application of the Black–Scholes model in rating revenue products.

p0585 A common goal of insurance programs is to minimize the transaction costs for producers, and it is rare that any information beyond a recent yield history and some general practice information (i.e., irrigated vs dryland) is requested, however recent research has considered what types of additional information may improve rating accuracy. Examples of the additional variables are weather (e.g., Du, Hennessy, Feng, & Arora, 2018; Rejesus et al., 2015), ENSO forecasts (e.g., Tack & Ubilava, 2015; Yi, Zhou, & Zhang, 2020), soil or land quality (e.g., Du et al., 2018; Woodard & Verteramo-Chiu, 2017), or expert knowledge or opinion (e.g., Shen, Odening, & Okhrin, 2016). Methods like classification (e.g., Rejesus et al., 2015), Bayesian estimations (e.g., Shen et al., 2016; Yi et al., 2020), or copulas (e.g., Du et al., 2018) have been explored to incorporate this additional information in estimating premium rates. Additional considerations include the potential effects of warming temperatures driven by climate change (e.g., Perry et al., 2020; Tack, Coble, & Barnett, 2018).

p0590 The literature has evolved rapidly by developing newer insurance products or providing improved statistical or empirical methods on estimating and calculating actuarially fair premiums. With growing data availability and the development of empirical methods, particularly in the space of statistical learning and "big-data" techniques, developing new index-based products with potentially lower degrees of basis risk is and will continue to be an active research area. Along with the development of new products, measuring and assessing the quality of those products also can benefit from future research. Especially, in the context of index insurance in developing countries, it is important to carefully measure the degree of basis risk and the "quality" of the product as they ultimately drive produce welfare implications (Benami & Carter, 2021; Benami et al., 2021). Related to premium rate-making methods, a quickly evolving research area with clear policy implications is premium adjustment for certain conservation practices or lack thereof. In the earlier part of this subsection, we express the premium as a function of the input and this approach can be expanded to include various conservation practices such as cover crops or reduced tillage. Finally, noting that most crop insurance programs are subsidized, an important policy-relevant thought experiment is how global warming and climate change might affect program costs and social welfare (e.g., Perry et al., 2020; Tack et al., 2018). Discussions on alternative policy tools will be important.

s0105 6.2 Insurance demand

p0595 From Model (2), we can derive the Kuhn–Tucker conditions that characterize optimal choices:

$$\left(E_t\left[s_{t+1}\xi_{t,\ \theta_t}(\theta_t, x_t; p_{t+1}, \epsilon_{t+1})\right] - \pi_{t,\ \theta_t}\right)\theta_t = 0, \tag{3}$$

$$\left(E_t\left[s_{t+1}(p_{t+1}F_x(\epsilon_{t+1}) + \xi_{t,\ x_t}(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}))\right] - 1 - \pi_{t,\ x_t}\right)x_t = 0. \tag{4}$$

Eq. (3) states that the condition for no insurance demanded is if the marginal cost of insurance is greater than the expected marginal benefit evaluated at $\theta = 0$. For the positive insurance demand case, they indicate that farms would choose θ to equalize the marginal cost of insurance and the expected marginal benefit. Expanding the expected "marginal benefit" term of Eq. (3) leads to

$$E_t\left[s_{t+1}\xi_{t,\ \theta_t}\right] = E_t[s_{t+1}]E_t[\xi_{t,\ \theta_t}] + Cov(s_{t+1},\ \xi_{t,\ \theta_t})$$

which implies that for a given premium schedule, $\pi_{t,\ \theta_t}$, the demand for insurance depends on the distribution of s_{t+1} and $\xi_{t,\ \theta_t}$. That is, in sum, the structure of an insurance contract and the shape of the value function V are crucial as they determine these distributions. Also note that the choice of x_t (which we will discuss further in the later subsection) simultaneously affects demand by affecting s_{t+1} through Eq. (4). In this subsection, we focus on the studies that offer some decision-theoretical foundations for modeling the insurance decision as well as more empirically based studies aiming to quantify insurance demand itself or determinants thereof.

p0600 The core foundational issue in the literature over the last ten years is the role that expected utility versus prospect theory should play in modeling insurance demand. Expected utility theory has been the dominant approach for decades, but has been recently extended/generalized to include an additional dimension of risk, so-called ambiguity or compound risk aversion in the context of basis risk for index-based insurance. Focusing on the "compound-lottery" nature of index-based products, Elabed et al. (2013), Elabed and Carter (2015), and Belissa, Lensink, and van Asseldonk (2020) show that compound risk aversion or ambiguity aversion depresses the demand for index-based products in the presence of basis risk. Alternatively, Clarke (2016) shows that rational and expected utility maximizers can have low demand for index insurance in the presence of basis risk and Hill, Robles, and Ceballos (2016) find empirical relationships among risk aversion, premiums, and basis risk that are consistent with the predictions from expected utility theory.

p0605 Other research has prescribed a more decided break from expected utility theory. Du, Feng, and Hennessy (2017) show that standard expected utility theory predicts that farms would maximize subsidy when choosing coverage levels and contrasts this with empirical evidence that shows otherwise. Other papers have emphasized alternative shapes of the value function for the decision-maker and their (often subjective) views on the probability distributions over potential outcomes (e.g., Babcock, 2015; Cao, Weersink, & Ferner, 2020; Feng, Du, & Hennessy, 2020; McIntosh, Povel, & Sadoulet, 2019; Serfilippi, Carter, & Guirkinger, 2020).

Motivated by low insurance demand in absence of subsidy, evidence has emerged questioning the underlying assumptions of expected utility theory. Babcock (2015) and Feng et al. (2020) empirically show that the crop insurance choices of US farms are consistent with prospect theory predictions. However, Babcock (2015) also shows that the choices of US farms are only consistent with the reference point specification of crop insurance as a stand-alone investment.

p0610 Premium subsidies have tended to trend upward over time as programs seek to induce enrollment. This trend cannot continue forever and could even regress depending on budgeting priorities, thereby bringing into focus the importance of accurately estimating price (i.e., premium) elasticities of demand, especially in the context of US FCIP (e.g., Goodwin, 1993). Researchers also have attempted to explain low insurance demand by linking it to asymmetric information (e.g., Makki & Somwaru, 2001), which highlights the importance of understanding demand elasticities. Ramirez and Shonkwiler (2017) propose a probabilistic model that explains individual crop insurance decisions explicitly assuming that neither the insured nor the insurer knows the true actuarially fair premiums. Woodard and Yi (2020) highlight the fact that premiums are endogenous to insurance demand and proposes an instrument based on the estimation of the relationship between premium rates and coverage levels.

p0615 Additional research has focused on key features of the program such as subsidies in insurance premiums or administrative and operating costs, and the availability of other government programs.[42] Du, Hennessy, and Feng (2014) find that farms with greater yields and less production risk tend to choose higher insurance coverage, which can be explained by growers seeking to maximize premium subsidy. Growers prefer a marginal increase in the premium subsidy but the private insurers prefer a marginal increase in the A&O subsidy (Pearcy & Smith, 2015). Bulut, Collins, and Zacharias (2012) theoretically show that the optimal insurance level depends on the price and availability of area programs. Ubilava, Barnett, Coble, and Harri (2011) find that Supplemental Revenue Assistance Payments (SURE) program introduced in the 2008 Farm Bill had little impact on optimal crop insurance purchase decisions. Bulut (2017) focus on the expectation of farms on possible *ex post* disaster payments when considering the purchase of crop insurance.

p0620 Field experiments, both hypothetical stated choice and incentivized experiments, also have been utilized extensively to empirically assess the demand for insurance. Willingness-to-pay estimates based on hypothetical choice experiments are either lower than (e.g., Tadesse, Alfnes, Erenstein, & Holden, 2017) or similar to (e.g., Hill, Hoddinott, & Kumar, 2013; McIntosh, Sarris, & Papadopoulos, 2013) actuarially fair premiums. However, actual demands for an index insurance product examined in the same study of McIntosh et al. (2013) were low and had little correlation with the

np0215 [42]In the context of the US FCIP, despite the subsidization, many farms do not choose the highest coverage level. While future researches can shed light on the coverage choices, there are a couple of program features that can lead to observed coverage choices. The premium subsidy rates are smaller for the higher coverage levels or premium rate. Also, the premium rates can be different from the fair premium rates as noted in the earlier section.

stated demands from the hypothetical choice experiment. Using cumulative prospect theory and framed experiments, Visser, Jumare, and Brick (2020) find risk-averse farms are less likely to adopt a new technology whereas bundling the new technology with an insurance scheme encourages loss-averse farms to adopt. In the context of policy incentives for conservation practices, Marenya, Smith, and Nkonya (2014) conduct a framed choice experiment and finds lower demand for an index insurance contract as the incentive for conservation practices. Incentivized experiments have also been utilized in eliciting willingness-to-pay for index insurance (e.g., Hill et al., 2019; Matsuda & Kurosaki, 2019).

p0625 Empirical studies have also focused on the role of basis risk and personal/household characteristics for insurance demand. Mobarak and Rosenzweig (2012) find the negative relationship between the demand for a rainfall index insurance and the distance to rainfall gauges, which suggest the negative impact of the basis risk. Hill et al. (2013) also find a negative relationship as expected, and Elabed et al. (2013) show that this effects increases substantially when compound risk aversion—aversion to a compound lottery—is considered. Elabed and Carter (2015) also show that compound risk aversion reduces potential demand for index insurance by almost 50%. Similarly, McIntosh et al. (2019) use a lab-in-the-field design and find that basis risk plays substantial role in undermining the willingness-to-pay for index insurance. Ward and Makhija (2018) use a hypothetical choice experiment to show that because of basis risk in weather-index insurance farms prefer the bundled product that combines the weather-index insurance and drought-tolerant varieties. Relating to personal characteristics, Cole et al. (2013) provide empirical evidence that the lack of trust, liquidity, and limited salience matter using a randomized controlled trial in India. Similar findings are documented by Karlan, Osei, Osei-Akoto, and Udry (2014) and de Nicola (2015). Belissa, Bulte, Cecchi, Gangopadhyay, and Lensink (2019) use an experiment in Ethiopia to show that liquidity constraints reduce the demand for insurance.

p0630 Recent research has suggested that direct experience with an insurance program and/or learning over time also affects demand. A randomized experiment of Hill et al. (2016) shows that experience matters as previously receiving insurance payouts will increase demand. In the case of rainfall index insurance in India, Bjerge and Trifkovic (2018) find that excessive rainfall in previous years increases demand. A similar finding is documented by Santeramo (2019) from the observational data of Italian farms for their multiperil yield insurance. Bulte, Cecchi, Lensink, Marr, and van Asseldonk (2020) find that the willingness-to-pay for insurance increased when farms experienced the insurance contract through an experiment that offered a free insurance product conditional on adopting certified seed in Kenya. Recently, Cai, de Janvry, and Sadoulet (2020) provide causal estimates of premium subsidies and financial education on the future demand for insurance. Social networks (e.g., Cai, De Janvry, & Sadoulet, 2015), individual characteristics such as age and education level (e.g., Finger & Lehmann, 2012) or financial characteristics (e.g., Enjolras & Sentis, 2011) have also been explored as potential determinants of insurance participation.

p0635 A very challenging aspect of deriving/estimating insurance demand functions is the large number of options that a producer can typically choose among, all of which are essentially substitutes for one another. A producer can often choose among types of insurance (yield vs revenue), and then also the amount of insurance they wish to purchase (coverage level).[43] In addition one must consider how the producer evaluates and ultimately makes a decision on various outcomes of interest and their associated probabilities. Future research that holistically assesses the crop insurance choice among many alternative insurance products and portfolio choices along with different risk perceptions and preferences of the potential insurance participants can stimulate discussion on improving program design. Understanding and distinguishing the roles of risk and time preferences in the insurance demand context is an on-going and active research area (Andreoni & Sprenger, 2012; Casaburi & Willis, 2018). Another important topic that can contribute to the policy discussion is on the welfare consequences of insurance provisions or related behavioral interventions as some findings have suggested that increases in insurance take-up do not necessarily lead to welfare gains (Harrison, Morsink, & Schneider, 2020; Harrison & Ng, 2016).

s0110 6.3 Effects of agricultural insurance

p0640 Combining the optimization conditions for the insurance and input decisions (assuming an interior solution for both[44]) provides insight to the interaction between insurance and production decisions as the solution takes the form

$$E_t[s_{t+1}R_{t+1}] = 1$$

where

$$R_{t+1} = \left(\frac{p_{t+1}F_x + \xi_{t,\ x_t} + \xi_{t,\ \theta_t}}{1 + \pi_{t,x_t} + \pi_{t,\theta_t}} \right). \tag{5}$$

p0645 We can draw several important insights from Eq. (5). The numerator, which is the marginal return with respect to changes in x_t and θ_t, is the sum of three terms: (i) the value of the marginal product, $p_{t+1}F_x$, (ii) the marginal indemnity with respect to the input use, $\xi_{t,\ x_t}$, and (iii) the marginal indemnity with respect to the insurance quantity, $\xi_{t,\ \theta_t}$. The denominator is the sum of the marginal costs of the input use and the insurance quantity. Among the terms in the numerator, $\xi_{t,\ x_t}$ is the "moral hazard" effect because it captures the agent's incentive to adjust *ex post* input levels

np0220 [43] As noted by the recent study of Yu, Sumner, and Lee (2021), relative subsidies and expected returns from different insurance products and coverage levels also play an important role in explaining insurance demand.

np0225 [44] Note that if $\theta_t = 0$, $R_{t+1} = p_{t+1}F_x$ and the optimal input choice is identical to the case in the absence of insurance market. The corner solution cases with $x_t = 0$, which indicate zero production, are unrealistic in this context. More generally, note that the first order conditions imply that the input and insurance choices are jointly determined as emphasized in earlier work (e.g., Babcock & Hennessy, 1996; Horowitz & Lichtenberg, 1993; Ramaswami, 1993; Smith & Goodwin, 1996).

to directly affect indemnity payments. It also highlights one of the key strengths of index insurance products, whereby moral hazard incentives disappear as $\xi_{t,\ x_t} = 0$, i.e., the change in the input does not affect the indemnity.[45]

p0650 Another important insight is on the role of premium subsidies. As the schedule of premium changes, the two derivatives in the denominator, π_{t,x_t} and π_{t,θ_t}, change. These two derivatives represent the direct changes in the marginal cost of additional input and the marginal cost of additional indemnity. For the inputs like acreage, π_{t,x_t} is normally nonzero and can affect the production decision by directly altering the marginal cost.[46] Premium subsidies also can indirectly affect input use through π_{t,θ_t} even if those inputs may not directly influence premiums. Ultimately, the changes in π_{t,x_t} and π_{t,θ_t} affect the expectation of R_{t+1} and the covariance between R_{t+1} and s_{t+1}.

p0655 When an insurance mechanism is available producers are likely to alter on-farm production and investment decisions. Here, we group the effects of agricultural insurance into two categories: the *ex ante* effects and the *ex post* effects. The *ex ante* effects include production or investment decisions that are made before the insurance sign-up such as land use or technology/practice adoption decisions, whereas the *ex post* effects include production or management decisions after the purchase of insurance such as input decisions. We also discuss the indirect effects of the insurance provision and the risk-sharing arrangements.

s0115 *6.3.1* Ex ante *effects*

p0660 The availability of insurance or the subsidy embedded affects production decisions like crop acreage and land use. Claassen, Langpap, and Wu (2017) find a small effect of US crop insurance on conversions of noncropland to cropland whereas studies like Miao, Hennessy, and Feng (2016) and Yu, Smith, and Sumner (2018) find substantial acreage effects of crop insurance. Using simulations, Miao et al. (2016) find that 0.05%–3.3% of cropland would not have been converted from grassland had premium subsidies not existed. More recently, exploiting US crop insurance policy changes, Yu et al. (2018) find that a 10% increase in the premium subsidy causes a 0.43% increase in the acreage of a crop. The empirical analysis of Hill et al. (2019) from a randomized controlled trial in Bangladesh documents the positive impact of insurance on the planted area of high-value crops. A theoretical discussion on how the availability and subsidy structure of crop insurance affect crop choices has been provided by Yu and Sumner (2018). On the contrary, Stoeffler, Carter, Guirkinger, and Gelade (2021) find no significant impact of insurance on cotton production, which emphasizes the fact that the insurance impacts depend on the structure of the market. Turvey (2012) highlights that the type of insurance and the level of subsidy offered affects crop

np0230 [45]Note that the inputs like acreage, which can be reflected in the premium through $\pi_{t,\ x_t}$, can still affect the indemnity. More importantly, it still can affect the input decision by changing the stochastic discount factor, s_{t+1}, and through the covariance between s_{t+1} and R_{t+1}.

np0235 [46]Many *ex post* inputs have $\pi_{t,x_t} = 0$ as it is difficult to incorporate the production effects of those inputs in the premium rates. Yet, the changes in the schedule of premium still can indirectly influence the use of those inputs indirectly via nonzero π_{t,θ_t}.

production. In addition to the impacts on the acreage, Connor and Katchova (2020) show that an increase in crop insurance participation increases the downside risk of yield for corn and soybeans, possibly because of crop expansion to marginal lands.

p0665 Providing insurance can also affect investment decisions as in the US context crop insurance has been found to effect technology adoption (e.g., Woodard, Pavlista, Schnitkey, Burgener, & Ward, 2012), conservation practices (e.g., Schoengold, Ding, & Headlee, 2015), productivity (e.g., Cornaggia, 2013), and marketing contracts (e.g., Du, Ifft, et al., 2015). The literature has also focused on the potential roles of index-based insurance products in developing countries as providing risk management tools can encourage investment in high-risk and high-return activities.[47] de Nicola (2015) uses a dynamic stochastic model to show that weather insurance can promote the adoption of more productive but riskier seeds. Karlan et al. (2014) show that having insurance leads to more production of and investment in high-risk and high-return crops with a randomized experiment in Ghana. Cai (2016) uses a natural experiment and finds that the provision of agricultural insurance in China increased production and borrowing. Similarly, a randomized experiment in China shows that the greater insurance coverage leads to more production (Cai, Chen, Fang, & Zhou, 2014).

s0120 *6.3.2* Ex post *effects*

p0670 Here, we focus on behavior after insurance sign-up (i.e., within season) and explore studies that examine possible moral hazard effects of insurance. While there have been theoretical studies and discussion linking insurance to input use (e.g., Ramaswami, 1993) and empirical studies to test the theoretical predictions (e.g., Babcock & Hennessy, 1996; Horowitz & Lichtenberg, 1993; Smith & Goodwin, 1996), the recent study of Weber, Key, and O'Donoghue (2016) shows that federal crop insurance has little impact on production and input use. However, Annan and Schlenker (2015) argue that crop insurance provides a disincentive to climate change adaptation. Also, crop insurance can reduce the likelihood of farm exits and disinvestment (Kim, Yu, & Pendell, 2020), which is in line with the findings of Key, Prager, and Burns (2018) that crop insurance reduced income volatility of US farms. Risk-reduction effects of crop insurance differs by crop production pattern (Woodard, Sherrick, & Schnitkey, 2010).

p0675 Several studies explore the features of the US crop insurance program that promote moral hazard behavior such as prevented planting (e.g., Kim & Kim, 2018; Wu, Goodwin, & Coble, 2020) or fraudulent claims (e.g., Park, Goodwin, Zheng, & Rejesus, 2020) whereas others investigate the program features that incentive to reduce moral hazard such as the Actual Production History (e.g., Mieno, Walters, & Fulginiti, 2018). Incentives for moral hazard behavior depends on the contract design (e.g., Mieno et al., 2018) and the technological environment (e.g., Yu & Hendricks, 2020). Theoretically, Mieno et al. (2018) show that endogenous production history, which determines the insurance trigger and the premium rate of the contract, affects decision-making and can reduce the incentives for moral hazard. A stylized model of Yu and Hendricks (2020) examines the role of greater information on crop

np0240 [47]We discuss the effect of insurance on credit in Section 6.4.

conditions in input use decisions for insured and uninsured farms and shows that moral hazard incentives can decrease in the long run in response to an improvement in forecast accuracy. Carriquiry and Osgood (2012) provide a theoretical foundation on how forecast and index insurance can interact and affect production. He, Zheng, Rejesus, and Yorobe (2020) find that corn farmers in the Philippines using cost-of-production insurance used a greater amount of chemical inputs (e.g., fertilizers and total chemical expenditure). An Indonesian example of Fadhliani, Luckstead, and Wailes (2019) indicates that the expected yield has fallen due to the provision of a multiperil crop insurance policy suggesting possible moral hazard.

p0680 The low program costs and the inherent ability of index insurance to mitigate moral hazard concerns have given it a prominent focus in the development community. For example, Chantarat, Mude, Barrett, and Carter (2013) propose an index-based insurance product for livestock in Kenya to reduce mortality risk. Contract designs and financial environments are crucial for index insurance to work as an effective development tool (e.g., Carter, de Janvry, Sadoulet, & Sarris, 2017; Carter, Cheng, & Sarris, 2016). Insurance for smallholders in developing countries is also considered as an *ex post* coping tool. For example, recent empirical studies indicate that there are positive impacts of index insurance on coping with shocks (e.g., Bertram-Huemmer & Kraehnert, 2018; Janzen & Carter, 2019).

s0125 6.3.3 Indirect effects

p0685 Insurance provision or creating risk-sharing networks can also have indirect effects, especially in developing countries. For example, credit lenders can benefit from insurance provision as shown by Miranda and Gonzalez-Vega (2011) or can reduce interest rates, which can further stimulate saving and technology adoption (Farrin & Miranda, 2015). Santos, Pacheco, Santos, and Levin (2021) show that the interaction between risk-sharing and index insurance participation brings a social coordination problem. Delpierre, Verheyden, and Weynants (2016) describe the case when introducing risk-sharing reinforces inequality. Also, risk-sharing arrangements based on kinship can induce free-riding behaviors and reduce the adoption of other risk-mitigation strategies (Di Falco & Bulte, 2013).

s0130 6.4 Credit constraint and risk management

p0690 Credit markets play an important role in agricultural risk management. Here, we focus on "net borrowers" as savings are a type of investment asset modeled in Section 5.3.[48] Specifying $\chi_t = -B_t$ where $B_t \geq 0$ is the amount borrowed and $h(\cdot) = \kappa_{t+1}(\cdot) \geq 0$ as the repayment function, we have

np0245 [48]In modeling savings decision, ξ does not depend on the realization of stochastic variables. If we consider lending decisions, ξ would depend on the state of the borrower. While this type of (informal) lending decisions can be important, especially in the context of informal risk-sharing arrangements, we will focus on borrowing decisions in this subsection. Note that the lending decisions can be modeled by extending Model (2).

$$V(W_t) = \max_{x_t, B_t \geq 0} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})] \tag{6}$$

subject to

$$W_t = x_t - B_t + m_t, \quad W_{t+1} = p_{t+1}F(x_t, \epsilon_{t+1}) - \kappa_{t+1}(B_t, K; r_{t+1}, p_{t+1}, \epsilon_{t+1}),$$

and

$$B_t \leq \bar{B}(K).$$

Here K is the amount of collateral, r_{t+1} is the interest rate (which may be a function of the collateral), and $\overline{B}(K)$ is the credit limit faced by the agent. For simplicity, we assume that the level of collateral K is exogenous. The repayment function is given by

$$\kappa_{t+1}(B_t, K; r_{t+1}, p_{t+1}, \epsilon_{t+1}) = \begin{cases} K & \text{if one defaults} \\ (1 + r_{t+1})B_t & \text{otherwise} \end{cases}$$

which will be driven by price and production risks since they can influence the default decisions.

p0695 It is interesting to study credit decisions as a standalone problem, but we also extend the model to consider interactions with insurance decisions in which the model becomes

$$V(W_t) = \max_{x_t, B_t, \theta_t \geq 0} \quad U(m_t) + E_t[V_{t+1}(W_{t+1})] \tag{7}$$

subject to

$$W_t = x_t - B_t + \pi_t(\theta_t, x_t) + m_t,$$

$$W_{t+1} = p_{t+1}F(x_t, \epsilon_{t+1}) - \kappa_{t+1}(B_t, \theta_t, K; r_{t+1}, p_{t+1}, \epsilon_{t+1}) + \xi_t(\theta_t, x_t; p_{t+1}, \epsilon_{t+1}),$$

and

$$B_t \leq \bar{B}(K, \theta_{t+1})$$

where the interest rate, r_{t+1}, and the credit limit, $\overline{B}$, can now be endogenously influenced through the producers insurance choice, θ. Ultimately the extent of this endogeneity will be context dependent as determined by available loan contract design.

p0700 Without deriving the conditions that characterize the optimal choices of x_t, B_t, and θ_t, we can draw useful insights from Model (7). First, from Eq. (3) of Model (2), we can infer that θ_t is more likely to be zero when W_t is small as s_{t+1} becomes smaller. In other words, the liquidity constraint can play an important role in the demand for insurance. A recent study by Casaburi and Willis (2018) show that the liquidity constraint can deter the demand for insurance. Therefore, access to credit can affect the demand for insurance but it will apparently depend on the structure of offered credit contracts.

p0705 On the other hand, availability of insurance can affect credit accessibility particularly through the alleviation of "risk-rationing" (Boucher, Carter, & Guirkinger, 2008).

Relating to the endogeneity of loan terms via insurance decisions mentioned above, offering insurance contracts has been considered as a tool to improve credit accessibility (e.g., Miranda & Gonzalez-Vega, 2011). Carter et al. (2016) provide a theoretical foundation for the effectiveness of standalone insurance and credit-interlinked insurance under different agricultural and financial environments. Giné and Yang (2009) present an experimental result that shows that linking a credit contract with insurance reduces the uptake of the credit contract, a finding consistent with Carter et al. (2016) which emphasize the role of agronomic and financial factors. The interaction between insurance and credit can also be particularly important for smallholders and poor households because the presence of uninsured risks and the lack of credit access can be associated with "poverty traps" (e.g., Carter & Barrett, 2006; Dercon, 1998; Lybbert, Barrett, Desta, & Layne Coppock, 2004).[49] Mishra et al. (2021) find positive effects of both standalone and credit-interlinked insurance on the likelihood of loan approval in Ghana with a larger impact associated with interlinked insurance. However, offering credit-interlinked insurance contracts can face logistical challenges (e.g., Ahmed, McIntosh, & Sarris, 2020).

p0710 Empirical challenges for drawing causal linkages from insurance to credit (or vice versa) exist stemming from the simultaneous nature of the decisions. Motivated by risk-balancing theory (e.g., Featherstone, Moss, Baker, & Preckel, 1988), Ifft, Kuethe, and Morehart (2015) provide empirical evidence on the positive association between the US Federal Crop Insurance Program participation and short-term farm debt which is consistent with the risk-balancing theory and acknowledge the challenge of establishing causality.[50] In the context of a tobacco insurance program in China Cai (2016) shows the positive impact of insurance provision on borrowing by leveraging the natural experimental aspect of the program.

s0135

7 Decision theories, measurement, and estimation

p0715 One of the key components of the stylized model discussed throughout this chapter is the definition of the "utility" function and the probability distribution associated with the outcomes of interest. To emphasize this it is helpful to reconsider our model in a two period setting where decisions in period t are made to generate wealth in period $t+1$, all of which is consumed. More specifically the model is:

$$V(m_t, W_t) = \max_{x_t} \quad u(m_t) + E_t[u(W_{t+1})] \tag{8}$$

subject to $W_t = x_t + m_t$ and $W_{t+1} = F(x_t, \epsilon_{t+1})$. To carry the discussion further and sharpen the illustration, here we assume that ϵ_i denotes both price and production shocks.

np0250 [49]For recent developments in the poverty trap literature, see Barrett, Carter, Chavas, and Carter (2019).
np0255 [50]Note that in Model (7), an increase in the amount of borrowing can be from a change in credit limit $\overline{B}$ or a joint decision of borrowing, insurance, and input uses.

p0720 Here, the valuation of the uncertain outcomes is represented by $E_t[u(W_{t+1})]$, which can be expanded to

$$E_t[u(W_{t+1}(x_t, \epsilon_{t+1}))] = \sum_i^N Prob_t(\epsilon_{i,t+1}) u(W_{t+1}(x_t, \epsilon_{i,t+1})) \qquad (9)$$

where the realization of ϵ_{t+1} is represented by $i = 1, \ldots, N$ states and under the standard expected utility framework, one assumes $u(\cdot)$ to be a von Neumann–Morgenstern utility function and $Prob_t(\epsilon_{t+1})$ are the probabilities associated with the realizations of the production risk. For a fixed set of probabilities, the degree of risk aversion and its influence on the optimal choice of x_t will be dictated by the curvature of $u(\cdot)$.

p0725 Represented by well-known paradoxes such as Allais (1953) (i.e., fails to account for the preference toward "certainty") and Ellsberg (1961) (i.e., fails to account for "ambiguity" aversion), expected utility theory has been subject to the criticism that the empirical observations are not consistent with its theoretical predictions.[51] Simultaneously, either extensions to or alternatives for expected utility have been developed (e.g., Andreoni, Sprenger, et al., 2010; Cerreia-Vioglio, Dillenberger, & Ortoleva, 2015; Hong, 1983; Kahneman & Tversky, 1979; Klibanoff, Marinacci, & Mukerji, 2005; Quiggin, 1982; Tversky & Kahneman, 1992). For a brief summary of these developments, see Chew and Epstein (1989), Buschena and Zilberman (1994), and Starmer (2000).

p0730 The goal of this section is to discuss recent developments in decision theories and their applications to risk management within the agricultural production literature. We first explore the literature that tests, extends, and applies the expected utility framework. We then briefly provide the discussion on state-contingent models and switch our focus to the recent studies that apply (cumulative) prospect theory of Kahneman and Tversky (1979) and Tversky and Kahneman (1992). Finally, we discuss some issues in the measurement and estimation of risk and risk preference parameters and the role of risk preference heterogeneity.

s0140

7.1 Testing, applying, and extending expected utility theory

p0735 Recall that, under the expected utility framework, the valuation of the uncertain outcomes is represented by Eq. (9). To represent the various extensions of the expected utility framework, we rewrite Eq. (9) as:[52]

np0260 [51] Allais paradox and Ellsberg paradox are well-known examples of the violation of the independence axiom of the vNM expected utility theory.

np0265 [52] It is important to note that there exists a trade-off between the generalization of the model (and the flexibility that the model obtains) and the empirical challenges associated with identifying different parameters.

$$E_t[u(W_{t+1}(x_t,\epsilon_{t+1}))] = \sum_{j}^{M} \psi_j \phi\left(\sum_{i}^{N_j} \rho_i^j u(W_{t+1}(x_t,\epsilon_{i,t+1}))\right) \tag{10}$$

where ρ is a (subjective) probability or a decision weight (transformed from the probability) of the outcome $\epsilon_{i,t+1}$, ψ_j is a (subjective) probability of the set of ρ_i^j being "right", and ϕ is a function that represents the ambiguity preference of Klibanoff et al. (2005).[53] Note that the generalized representation of the probability of the outcome $\epsilon_{i,t+1}$ is to represent the generalized expected utility approaches (see Buschena and Zilberman (1994) for the summary) and the ambiguity-related notations ψ_j and ϕ are to represent the ambiguity aversion of Klibanoff et al. (2005). With $\psi_j = 1$ for any j or ϕ being the identity function, Eq. (10) reduces to the expression for the generalized expected utility.

p0740 We can further generalize expression (10) by replacing $u(\cdot)$ with $v(\cdot)$ and allowing $v(\cdot)$ to be nonconcave, nondifferentiable or even discontinuous. Examples of $v(\cdot)$ include the value functions of the prospect theory (Kahneman & Tversky, 1979) and cumulative prospect theory (Tversky & Kahneman, 1992) where $v(\cdot)$ is concave for "gains", i.e., the values above a reference point, and convex for the "losses", i.e., the values below the reference point; and the discontinuous utility function of Andreoni et al. (2010) that allows the discontinuity between degenerate and nondegenerate lotteries.

p0745 While the empirical application of the expected utility theory often leads to reasonable results (e.g., Brick & Visser, 2015; Musshoff, Odening, Schade, Maart-Noelck, & Sandri, 2013; Pope et al., 2011; Serra, Goodwin, & Featherstone, 2011), there has been growing empirical evidence that expected utility theory fails to predict observed behavior of agricultural producers. The literature encompasses empirical evidence from experimental data, which can provide cleaner identifications of the parameters but can be context-dependent or unstable with respect to framing; and from observational data, which can face the empirical challenges in identifying the parameters of interest. The recent study of Bellemare et al. (2020) provides some evidence that expected utility theory does not produce predictions on the output decision under price risk using lab and field experiments. Du et al. (2017) provide predictions of expected utility theory on the crop insurance decisions of US growers and shows that observed patterns are not consistent with those predictions. A calibration study of Just and Peterson (2010) also shows that the degree of the concavity of the utility function needs to be substantially large to have expected utility theory explain the observed input use of Iowa corn growers.[54]

np0270 [53]Note that there are cases when the ambiguity, subjective beliefs, and ambiguity preferences can be only represented by using supports. The scalar representation in Model (10) is a restrictive and special case of modeling the ambiguity preference.

np0275 [54]Note that combining the existing estimates on the risk aversion parameter and the observed behavior from secondary data through the calibration approach resolves the identification issue in estimating risk aversion using observational data.

These findings do not necessarily mean that one cannot utilize the expected utility theory. Then, one important question is to understand when the expected utility fails most and the degree of the "inconsistency". A leading example is Andreoni and Sprenger (2011), which finds that the expected utility theory performs well if one is away from certainty.

p0750 Research has provided empirical evidence that supports alternative generalized expected utility theories. One extension of the expected utility theory with growing empirical attention is ambiguity aversion. Using experimental or structural approaches, studies documented that farms are in general ambiguity averse (e.g., Barham, Chavas, Fitz, Salas, & Schechter, 2014; Belissa et al., 2020; Bougherara, Gassmann, Piet, & Reynaud, 2017; Elabed & Carter, 2015). In the context of assessing demands for index insurance, experimental data in Mali (Bougherara et al., 2017) and Ethiopia (Belissa et al., 2020) show that farms are "compound risk averse," which is a specific form of ambiguity aversion. A choice experiment survey of French farms indicates that farms are ambiguity averse (Bougherara et al., 2017). Barham et al. (2014) find that ambiguity-averse farms are more likely to adopt genetically modified corn as it reduces the ambiguity of pest damages. Another extension of the expected utility theory is to incorporate a "certainty effect" (e.g., Serfilippi et al., 2020). Using a field experiment in Burkina Faso, Serfilippi et al. (2020) show that farms value certainty more than expected utility predicts, and framing the insurance with a premium rebate can increase the demand.

s0145 7.2 State-contingent models

p0755 In the context of modeling farm-level decision-making, there is perhaps no approach further out on the frontier than the nexus of generalized expected utility and state-contingent production. A great reference for introductory material on the state-contingent approach is Chambers and Quiggin (2000), and even though this textbook was published over 20 years ago it is striking how well aware the authors were that any worthwhile innovation in modeling production technology would have to be synergistic with the generalizations of expected utility theories that were becoming more mainstream. With this in mind it becomes clear what the fundamental core concept must be that unites the disparate concepts of risk preferences and production technology in their worldview: states of nature.

p0760 In the previous section we saw that the generalizations of expected utility theory are based on aggregating outcomes, or functions of outcomes, across states of nature $i = 1, \ldots, N$. As noted in Chambers and Quiggin (2000), "a wide variety of generalized expected utility models have been developed since the early 1980s" which is discussed within the context of Examples of Preference Functions in chapter 3.2 of their textbook. They include examples of such functions for the standard cases of risk neutrality, expected utility, and mean variance; but also include a preference function for rank-dependent expected utility. We suspect that this was not by accident, but rather that they knew that the merits of their approach might ultimately depend on its ability to "play nice" with general preference functions that transformed either the probability of a state of nature occurring and/or the utility obtained within that state.[55]

p0765 Ultimately one might argue that the major innovation provided by the state-contingent generalization of production technology is the possibility of substitutions across states of nature, without which the approach collapses back to traditional "output-cubical" technology. Unfortunately empirical applications of the state-contingent approach are few due to a crucial data limitation: observed outputs are associated with a single state of nature. Among these few studies evidence for output-cubical technology is mixed with Chavas (2008) finding empirical support for it using aggregate US farm data while Nauges, O'Donnell, and Quiggin (2011) find evidence rejecting it using Finnish farm-level data.

p0770 One of the major (and crucial) early results provided in Chambers and Quiggin (1998, 2000) showed that standard cost minimization still applied under a state-contingent approach. Essentially, cost functions expanded to include all $y_1, \ldots, y_n$ state-contingent outputs as arguments alongside the usual input prices; in this sense input decisions are made conditional on all possible outcomes. Chambers and Serra (2019) provide a nice discussion on how this result fits in with a broader sequence of approaches, from the early methods that conditioned costs on *ex post* output to the work of Pope and Just (1996, 1998) and Moschini (2001) that proposed approaches based on *ex ante* output.[56] If one conceptualizes a discrete distribution of possible outputs, say a histogram, these *ex ante* approaches essentially conditioned on the first moment of that distribution whereas the state-contingent approach conditions on the full range (support) of possible outcomes; and in this sense it is a more general *ex ante* cost function.

p0775 There are many discussions, applications, and theoretical developments of state-contingent production that are worth mentioning here for the interested reader. Chavas, Chambers, and Pope (2010) place it within the more general historical context of assessing the role of technology and farmers' risk preferences. O'Donnell, Chambers, and Quiggin (2010) use simulation methods to illustrate the type and

np0280 [55]It is interesting to note that "prospect theory" does not appear in the Index of the textbook, so in some sense the authors had a good feeling for what was coming down the road in general but did not see clearly which of the generalized expected utility models would break through in popularity. Ultimately this is probably for the best as it would be a shame if we had to put them on trial for sorcery.

np0285 [56]The general idea within this line of literature is that while observable to the researcher, *ex post* output is not the relevant decision variable for a producer because they make (the vast majority of) input decisions based on an *ex ante* (expectation of) output before the production shock is realized. While theoretically closer to the true decision variable, the downside for researchers is that this expectation of output is unobservable to all but the producer. This shortcoming is very similar in spirit to the problem that utility presents on the consumer side of microeconomics, an insight that LaFrance and Pope (2010) leverage to derive farm factor demands as functions of observable input prices and total variable cost. This parallels the same approach taken on the consumer side in which demand to derive Marshallian demand as a function of prices and income to overcome difficulties that Hicksian demands present in empirical settings when utility is unobservable. Tack, Pope, LaFrance, and Cavazos (2015) provide an empirical implementation of the LaFrance and Pope (2010) approach.

magnitude of empirical errors that can emerge in efficiency analysis as a result of overly restrictive representations of production technologies.[57] O'Donnell and Griffiths (2006) show that fixed and random effects state-contingent production frontiers can be conveniently estimated in a finite mixtures framework, and an empirical application suggests that this approach produces significantly different estimates of elasticities, firm technical efficiencies, and other quantities of economic interest. Both Chambers and Voica (2017) and Chambers and Serra (2019) provide recent examples of theoretical models that are consistent with both generalized expected utility theory and state-contingent production.[58] Finally, in a setting focused on technology adoption and climate risk, Holden and Quiggin (2017) provide what might very well become the template for applied (empirical) research that employs flexible production technology and general risk attitudes by leveraging information from both a field experiment coupled with a farm household survey to estimate a state-contingent production model with cumulative prospect theory preferences.

s0150 ## 7.3 Prospect theory and its applications

p0780 Both prospect theory (Kahneman & Tversky, 1979) and its cumulative counterpart (Tversky & Kahneman, 1992) have gained much attention in the agricultural economics literature. The weight, ρ, in expression (10) is the decision weight and arrives from a transformation of the probability of the outcome; and the "utility" function is replaced with a value function, $v(\cdot)$. More importantly, the outcome is now redefined as gains and losses, which now depend on a reference point. Thus, a prospect theory representation of expression (10) is (with the ambiguity preference function ϕ being the identity function),

$$V = \sum_{i}^{N} \rho_i v(W_{t+1}(x_t, \epsilon_{i,t+1}),\ R_t) \tag{11}$$

where ρ now is the decision weight, and $v(\cdot)$ is the value function that depends on a reference point, R_t.

p0785 The outcome of interest is now the difference between W_{t+1} and R_t. That is, the argument in the value function is now $\Delta = W_{t+1} - R_t$ with the "gains" defined as $\Delta > 0$

np0290 [57]It is important to note that both Data Envelopment Analysis (DEA) and Stochastic Frontier Models (SFM) are relevant and evolving tools for analyzing various topics at the nexus of risk management and agricultural production. We do not detail these approaches in this chapter, and the interested reader is referred to the following resources. Ray (2020) provide a broad overview of the literature on DEA methodology and applications. Mardani, Zavadskas, Streimikiene, Jusoh, and Khoshnoudi (2017) provide a review of DEA models in regards to energy efficiency. Peykani, Mohammadi, Saen, Sadjadi, and Rostamy-Malkhalifeh (2020) review approaches for handling uncertainty in DEA. Kumbhakar, Parmeter, and Zelenyuk (2020a, 2020b) review developments in the econometric estimation of productivity and efficiency surrounding the stochastic frontier model and place an emphasis on highlighting recent research and providing broad coverage.

np0295 [58]It is interesting to note that in these models a wide range of preference structures can be accommodated using their simple notation of $W(m_0, m_1)$ where m_0 is nonrandom consumption in the first period and m_1 is stochastic consumption in the next.

and the "losses" as $\Delta < 0$. To account for the fact that agents are more sensitive to changes in their losses compared to their gains, Kahneman and Tversky (1979) hypothesizes the value function, $v(\cdot)$, to be concave with the gains ($v''(\Delta) < 0$ for $\Delta > 0$) and convex with the losses ($v''(\Delta) > 0$ for $\Delta < 0$).[59] Another key feature of prospect theory is that the decision weight, ρ, is a transformation of the probabilities that overweights small probabilities and underweights larger probabilities. In cumulative prospect theory, Tversky and Kahneman (1992) define the decision weight as the difference in transformed cumulative probabilities between the adjacent outcomes. In sum, the loss aversion, which is represented by different curvatures of the value function in the loss and gain domains, and the decision weights characterize (cumulative) prospect theory.

p0790 Some recent literature has focused on testing and applying prospect theory in the context of agricultural production. Several studies find that its application explains observed behaviors better in various contexts such as crop insurance decisions (e.g., Babcock, 2015; Feng et al., 2020), government program participation (Cao et al., 2020, e.g.,), community-supported agriculture participation (e.g., Zhao & Yue, 2020a), and bioenergy crop production (e.g., Anand, Miao, & Khanna, 2019). A noticeable exception is Harrison, Humphrey, and Verschoor (2010), which finds that about half of the sample behave consistently with expected utility theory. Alternatively, McIntosh et al. (2019) utilize both expected utility and prospect-theory-based approaches to decompose the willingness-to-pay for an index insurance product into the portion that is explained by expected utility theory versus the "behavioral" portion, and show that the latter is greater when the basis risk is small. Recent empirical studies also document that farms are loss averse (e.g., Bocquého, Jacquet, & Reynaud, 2014; Bougherara et al., 2017; Liu & Huang, 2013; Zhao & Yue, 2020b), and subjectively weight probabilities (often overweighting small probabilities) (e.g., Liebenehm & Waibel, 2014; Liu, 2012; Zhao & Yue, 2020b). Also, as the applications of prospect theory become more popular, one should consider that Tonsor (2018) and Babcock (2015) show that specifying the reference point is an important consideration.

s0155 7.4 Measuring and estimating risk and (heterogeneous) risk attitudes

p0795 Here, we focus on empirical issues related to understanding the probabilities of the outcome and the shape of the utility or value function, which dictates risk preference. In the context of Eq. (10), the degree of "risk" depends on the outcome, ϵ, and the associated probability distribution, which is further transformed to ρ. More specifically, we can represent ρ_i^j as

$$\rho_i^j = \rho(\pi_i + \eta_i^j) \tag{12}$$

where π_i is the "objective" probability associated with the outcome ϵ_i; η_i^j is the "error" on the subjective probability for the outcome ϵ_i from the set j (and thus, the subjective

np0300 [59]Note that the first derivative is discontinuous at the reference point.

probability is $\pi_i + \eta_i^j$); and ρ is a transformation function that transforms (subjective) probabilities to decision weights. For example, consider ρ that is convex in π_i (or $\pi_i + \eta_i^j$) for $\pi_i < 0.5$ and concave in π_i for $\pi_i > 0.5$. In that case, the transformation puts smaller weights on "small" probabilities and greater weights on "greater" probabilities. Note that, as described earlier, having $\psi_j = 1$ for any j in Eq. (10) eliminates the role of "ambiguity".

p0800 The second component of Eq. (10) is $u(\cdot)$ or $v(\cdot)$, where $u(\cdot)$ is a usual concave utility function and $v(\cdot)$ is the value function as described in Section 7.3. For example, Tversky and Kahneman (1992) define the value function

$$v(\Delta) = \begin{cases} \Delta^a & \text{if} \quad \Delta \geq 0 \\ -\lambda(-\Delta)^a & \text{if} \quad \Delta < 0 \end{cases} \tag{13}$$

where λ determines the degree of loss aversion, and a defines the curvature of the value function. In sum, the risk attitude is dictated by the shape of $u(\cdot)$ and/or $v(\cdot)$.

p0805 In this section, we first highlight the importance of understanding, measuring, and separating the objective and subjective probabilities, the decision weights (described by Eq. 12), and the preference parameters in $u(\cdot)$ and $v(\cdot)$. We focus on the empirical issues related to elicitation of subjective beliefs and risk preferences, and identification of the different parameters that characterize the risk distribution in production, subjective beliefs and expectations, and the risk preferences. We also discuss the possible correlation between the shape of $u(\cdot)$ or $v(\cdot)$ and other demographic or environmental factors.

p0810 Defining and measuring "risk" is extremely crucial as unclear definitions or measures can lead to contradicting predictions on behavior under risk.[60] The discussion around marginal risk aversion (Chambers, 2016; Just & Lybbert, 2009, 2012) highlights such importance. Understanding and measuring the degree of "riskiness" of agricultural production, i.e., the distribution of ϵ_i, largely depends on estimations of yield and price distributions. As we have discussed in Section 6, we have seen recent innovations on yield and revenue estimation such as a mixture model (e.g., Woodard & Sherrick, 2011), a flexible parametric model (e.g., Zhu et al., 2011), a maximum-entropy approach (e.g., Tack, 2013), Bayesian approaches to incorporate spatial process (e.g., Ker et al., 2016; Park et al., 2019; Ramsey, 2020), or copulas (e.g., Ahmed & Serra, 2015; Bozic et al., 2014; Goodwin & Hungerford, 2015; Ramsey et al., 2019). An alternative approach to measure the degree of "riskiness" is, especially in the context of developing countries and village economies, to focus on changes or volatilities in individual consumption levels. For example, Gaurav (2015) estimates the response of household-level consumption to covariate or idiosyncratic shocks in order to

np0305 [60]Earlier studies such as Antle (1983b), Chambers and Quiggin (2000), Antle (2010), and Kim, Chavas, Barham, and Foltz (2014) highlight the need for more flexible approaches (e.g., higher moments or state-contingent frameworks) than the estimation of mean and variance under the symmetric assumption in estimating and assessing risk.

measure the degree to which individual households are exposed to risk, especially the risk that cannot be insured via risk-sharing arrangements.

p0815 As represented in expression (12), the decision weights can be a function of the subjective probabilities as opposed to the objective probabilities. This often indicates that it can be challenging to separate risk preferences from perceived subjective probabilities or beliefs and/or their possible transformation to some decision weights in a complex setting.[61] In a lab-experiment setting, such as Holt and Laury (2002) and Tanaka, Camerer, and Nguyen (2010), one can assume that the participants perceive the probabilities given to them by the experiments as they are and thus the subjective errors are zero, i.e., $\eta = 0$. The challenge in understanding subjective probabilities is, thus, mostly with field experiments or observational data. Several empirical studies have assessed these subjective probabilities using surveys with different elicitation techniques (e.g Brown, Daigneault, Tjernström, & Zou, 2018; Fezzi, Menapace, & Raffaelli, 2021; Lybbert, Barrett, McPeak, & Luseno, 2007; Turvey, Gao, Nie, Wang, & Kong, 2013). As discussed and empirically tested by Lybbert et al. (2007), one important research topic is to understand how these subjective probabilities or beliefs and expectations are formed and updated. Delavande, Giné, and McKenzie (2011) provide detailed review of this literature and guidelines for eliciting subjective probabilities and expectations.

p0820 Many studies have explored different risk preference elicitation methods. Building on the finding of Dohmen et al. (2011), Roe (2015) uses a survey question that asks respondents to choose from an 11-point scale, assess the distribution of the risk tolerance across different populations, and find farmers are more risk-tolerant than general population but less risk-tolerant than nonfarm business owners. Nielsen, Keil, and Zeller (2013) and Menapace, Colson, and Raffaelli (2016) find that different hypothetical risk elicitation techniques produce different estimates and they are either not correlated or weakly correlated. Moreover, Hellerstein, Higgins, and Horowitz (2013) show that lottery-choice measures of risk aversion do not explain the behaviors under risk. In contrast, Ihli, Chiputwa, and Musshoff (2016) find low inconsistency rates across two elicitation methods. Additionally, Holt and Laury (2002) type (incentivized) lotteries provide reasonable estimates that explain production behavior (Vollmer, Hermann, & Mußhoff, 2017). Franken, Pennings, and Garcia (2014) suggest supplementing with low-cost survey-based measures. More recently, Fezzi et al. (2021) use the observed insurance choices of Italian farmers and survey data of subjective beliefs to estimate risk preferences. By accounting for the subjective beliefs, they find that estimated risk aversion coefficients from the observed choices are in line with previous estimates from lab or field experiments.

p0825 Another important consideration is the possibility that preferences are heterogeneous across groups (e.g., Chiappori, Samphantharak, Schulhofer-Wohl, & Townsend, 2014; Herberich & List, 2012) and distinguishing risk preference from

np0310 [61]Manski (2004) emphasizes the importance of measuring subjective probabilities as observed behaviors can be consistent with many alternative combinations of preferences and expectations or beliefs.

other factors or characteristics is often challenging. For example, separating risk preferences and probability perceptions is difficult (e.g., Just & Just, 2016; Menapace, Colson, & Raffaelli, 2013). Similarly, estimating risk preferences should account for wealth dynamics as risky decisions respond to changes in wealth over time (Lybbert, Just, & Barrett, 2013). Furthermore, several studies provide evidence that risk attitudes or preferences differ across some observable covariates. In a framed high-stakes gamble, Indian farms engage in risk-taking behaviors, and credit constraints and nonconvex production functions are considered to be possible drivers (Maertens, Chari, & Just, 2014). Using structural equation models, Franken, Pennings, and Garcia (2017) find that managerial characteristics indirectly affect marketing behavior through risk attitudes. Although either risk preference depends on some factors or some factors are correlated with risk preference, utilizing proxies for risk preferences in an empirical context requires caution. For example, using wealth as a proxy for risk aversion only works under a very specific condition (Bellemare & Brown, 2010).

s0160 8 Concluding remarks

p0830 The primary goal of this chapter is to provide a useful framework for thinking about various issues in the intersection of risk and agricultural production decisions. As we highlight in the earlier sections, one can treat the modeling approach as a road map to unify, and add structure to, the fragmented segments of the theoretical discussions and empirical evidence in the literature.

p0835 As George Box stated, "all models are wrong, but some are useful." And our model is no different. While we believe that readers can construct a model to serve their purposes from our modeling framework by modifying and extending either each modification presented in various sections or the combination of modifications, some caution is warranted. One should especially be aware of the trade-off between simplicity/tractability versus the degree of "realistic" representations of the problem. We aim for the appropriate degree of this balance and hope that the framework can at least help readers to conceptualize and clarify their economic intuition in various contexts.

p0840 We would like to conclude with the following messages, which are somewhat evident from our modeling framework. First, many of the researchers' variables of interest, which include production, management, and marketing decisions, are determined jointly and simultaneously. It is worth emphasizing this well recognized but often neglected point as overlooking this simultaneity can lead to mistakes such as forming an incorrect research question or mistakenly interpreting correlation as causation. Second, distinguishing *ex ante* risks and *ex post* variability is crucial as farms make decisions in response to the former and the latter is the result of their decisions. Researchers should be careful in distinguishing between these when modeling behavior and estimating empirical relationships. Third, identifying and measuring risk (and the associated subjective beliefs) versus risk preferences is challenging. One can potentially combine experimental and observational data or at least can acknowledge shortcomings of each approach. Finally, empirically identifying the "effects" of interest is challenging because of simultaneity and measurement issues. Potential avenues to overcome this challenge are to explore recent methodological innovations in causal inferences (to tackle confounders due to the simultaneity or unobserved heterogeneity) and to leverage "big data" and machine learning techniques (to mitigate the challenges related to the measurement issues). More importantly, we believe one should start with recognizing the foundations of these empirical challenges via conceptual modeling, which we hope that our modeling framework can play a useful role.

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