Q Open, 2021, **1**, 1–26
https://doi.org/10.1093/qopen/qoab016
Advance access publication date: 22 July 2021
Article

Risk, Risk Aversion, and Agricultural Technology Adoption — A Novel Valuation Method Based on Real Options and Inverse Stochastic Dominance

Alisa Spiegel[1], Wolfgang Britz[1] and Robert Finger[2,*]

[1]Institute for Food and Resource Economics, University of Bonn, Meckenheimer Allee 174, 53115 Bonn, Germany
[2]Agricultural Economics and Policy Group, ETH Zurich, Sonneggstrasse 33, 8092 Zurich, Switzerland
*Corresponding author: E-mail: rofinger@ethz.ch

Received: March 20, 2021. **Accepted:** June 29, 2021

Abstract

Risk and risk preferences belong to the key determinants of investment-based technology adoption in agriculture. We develop and apply a novel approach in which an inverse second order stochastic dominance approach is integrated into a stochastic dynamic farm-level model to quantify the effect of both risk and risk aversion on the timing and scale of agricultural technology adoption. Our illustrative example on short rotation coppice adoption shows that risk aversion leads to technology adoption that takes place earlier, but to a smaller extent. In contrast, higher levels of risk exposure lead to postponed but overall larger adoption. These effects would be obscured if technology adoption is not analyzed in a farm-scale context or considered as a now-or-never decision, the still dominant approach in the literature.

Keywords: Risk preferences, farm-level investment decision, stochastic dynamic programming, inverse stochastic dominance, perennial energy crop

JEL codes: Q1

1 Introduction

Decisions to take up new activities and/or adopt new technologies are of crucial relevance for farm success (Blandford and Hill 2006, p.43; Kumar and Joshi 2014) and reflect production, market, technological and institutional risks as inherent properties of agriculture (e.g. Chavas 2004), as farmers are often risk averse (e.g. Iyer *et al.* 2020). This is confirmed in empirical studies which find risk exposure, risk perception (Marra *et al.* 2003; Liu 2013) and risk preferences (Liu 2013) to be among key determinants for the timing and scale of technology adoption. Thus, all three should be considered in dynamic investment analysis (Iyer *et al.* 2020). Spiegel *et al.* (2018; 2020) demonstrated that stochastic dynamic programming can be efficiently combined with Monte-Carlo simulations of stochastic variables followed by a scenario tree reduction technique to study the effect of risk on timing and scale of technology adoption in the context of a policy analysis. We extend this approach in two directions. First, we explicitly address the risk level based on lack of knowledge and experience as a crucial determinant of technology adoption (Marra *et al.* 2003; Karni 2006) by

conducting sensitivity analysis. Second and more importantly, we relax the assumption of risk neutrality underlying Spiegel *et al.* (2018; 2020) and hence explicitly model the effect of risk preferences on technology adoption.

The frequently used expected risk utility theory (Morgenstern and von Neumann 1953) and prospect theory (Kahneman and Tversky 1979) provide a straightforward way to operationalize (perceived) risk exposure, risk perception and risk preferences to investigate effects of both on optimal scale investment. In particular, they reveal that decision makers with a higher risk aversion tend to adopt a new technology at smaller scales (Liu 2013; Trujillo-Barrera *et al.* 2016; van Winsen *et al.* 2016). Yet, effects of risk and risk preferences on optimal timing remain often unexplored (Meijer *et al.* 2015; van Winsen *et al.* 2016), partly because to date there is no well-established approach to incorporate risk preferences into dynamic investment analysis (Homem-de-Mello and Pagnoncelli 2016). The real option theory provides a powerful framework to analyze optimal timing and scale of investment-based adoption decisions at farm-level (Wossink and Gardebroek 2006; Hinrichs *et al.* 2008; Hill 2010; Maart-Noelck and Musshoff 2013). Furthermore, stochastic dynamic programming is widely used for detailed analysis of managerial decisions as it reflects resource endowments and can account for economies of scale. Different approaches have been proposed to incorporate risk preferences into farm-level stochastic dynamic programming approaches (Krokhmal *et al.* 2011; Homem-de-Mello and Pagnoncelli 2016). However, most of them require a risk aversion coefficient or a risk utility function, which is difficult to determine empirically (see e.g. Charness *et al.* 2013; Just and Just 2016; Iyer *et al.* 2020). Furthermore, the computation of these approaches can become quite demanding if the programming model comprises integers, necessary to capture indivisibilities of specific assets and economies of scale. To cope with this, we employ the concept of second-order stochastic dominance instead, namely partial ordering of alternative stochastic distributions in terms of their superiority for a risk-averse decision maker. We consider this promising as it requires limited assumptions on risk preferences and can be efficiently incorporated into stochastic dynamic programming (Nie *et al.* 2012). Specifically, a set of additional constraints ensures that a new technology or activity is only adopted at a scale (or not at all) at which it stochastically dominates a risk benchmark given by the current farm program. There are a few examples of introducing stochastic dominance constraints into optimization models in financial applications (El Karoui and Meziou 2006; Roman *et al.* 2006; Luedtke 2008; Nie *et al.* 2012). Although these models are concerned with the optimal shares in a portfolio of risky assets, they are not considering resource (inequality) constraints or indivisibilities relevant for farm-scale optimization, which implies different approaches to numerical optimization.

We here contribute to close this gap by developing a novel farm-level stochastic dynamic programming[1] approach that quantifies the effects of risk and risk preferences on optimal scale and timing of investment-based technology adoption. In particular, we embed the concept of inverse stochastic dominance into the real options framework and demonstrate how the proposed approach can reflect risk levels and risk preferences in an empirical example of adopting a new investment-based activity. We call the approach DIASS—Dynamic programming and Inverse Approximated Second-order Stochastic dominance. Using the designed model and applying it to an empirical case study, we test for this specific case whether risk aversion (vis-à-vis risk neutrality) leads to earlier technology adoption at a lower scale. Moreover, we test whether higher associated risk levels ceteris paribus lead to later technology adoption at a lower scale. We also quantify the economic relevance of these effects. Findings underline that the DIASS approach allows to simulate farmers' decisions more precisely and thus to better inform policy makers about expected adoption of targeted investment-based technologies, for instance, regarding contributing to environment protection, animal welfare, or digitalization.

Our case study features introduction of short-rotation coppice (SRC) biomass energy production systems as an investment-based new technology[2] on a typical arable farm in

northern Germany. Setting up an SRC plantation with its typical production cycle of approximately 20 years implies significant sunk costs for planting, coppicing and final reconversion to arable land. Reconversion is considered as the plantation will be otherwise considered legally as a forest, which prevents future re-conversion to arable land and claiming of farming subsidies. SRC binds land for a longer period than other currently observed land uses in that type of farms and competes with annual crops for limited farm resources such as land and labour. Both SRC and annual crops imply stochastic returns; the observed distribution of returns from annual crops constitutes an observed risk benchmark. The case study thus encompasses the elements mentioned above as inherent for investment-based technology adoption in agriculture, such as sunk cost, uncertain future returns, and competition with existing activities. It hence perfectly fits to demonstrate how the effects of risk level and risk preferences on timing and scale of adoption can be quantified and analyzed. To this end, we provide insights in both a generic modelling approach and in a specific case study. The DIASS approach can be applied to any other case study by adjusting the underlying stochastic processes and their mutual correlation, the number of investment and disinvestment decisions considered, or the time horizon. We provide the code, data, all the related documentation, as well as a graphical user interface, in Spiegel *et al.* (2017), in order to facilitate use of the proposed approach for other case studies in and beyond agriculture.

Our results show that risk aversion leads to technology adoption that takes place earlier, but to a smaller extent. In contrast, higher levels of risk exposure lead to postponed but overall larger adoption. These complex interdependencies between risk, risk preference and technology adoption would be obscured if technology adoption is not analyzed in a farm-scale context or considered as a now-or-never decision, i.e. according to the still dominant approach in the literature.

The remainder of this paper is structured as follows. Section 2 introduces the theoretical background (section 2.1), develops the DIASS approach (2.2), and formulates hypotheses (2.3). Section 3 illustrates our approach with a case study. In particular, it presents the general layout of the designed model (3.1), the solution process (3.2), the case study characteristics, including deterministic parameters (3.3), and the stochastic components of the model (3.4). Our empirical results are presented in Section 4. Section 5 concludes.

2 Literature and theoretical background

2.1 State of the art of investment-based technology adoption under consideration of uncertainty and risk attitude

Given the production, market, institutional and technological risks involved in agricultural production (Sunding and Zilberman 2001), plus irreversible investments and sunk costs, the real options approach is increasingly favored over the classical Net Present Value (NPV) approach for modelling farm-level investment decisions, including technology adoption (Wossink and Gardebroek 2006; Hinrichs *et al.* 2008; Hill 2010; Kuminoff and Wossink 2010; Maart-Noelck and Musshoff 2013). The real options approach explicitly considers the option value, or value of waiting, linked to the possibility to postpone decisions (timing flexibility) or to adjust the investment project at a later point in time (scale flexibility), for instance by dis-investing. It can be incorporated into a farm-level programming approach based on stochastic dynamic programming where risk is captured by a scenario tree (Beraldi *et al.* 2013; Alonso-Ayuso *et al.* 2014; Simoglou *et al.* 2014). This is usually based on binomial scenario trees or lattices (Schulmerich 2010; Beraldi *et al.* 2013; Alonso-Ayuso *et al.* 2014) where model size increases quadratically or even exponentially[3] with the number of time points, which limits model complexity and timescale. These restrictions can be partly overcome with more advanced approaches such as Monte Carlo simulation followed by scenario tree reduction (Dempster 2006; Heitsch and Römisch 2008; Spiegel *et al.* 2018, 2020).

The real options approach can be applied under different assumptions with regard to risk preferences. Incentives to postpone a managerial decision, e.g. technology adoption, might exist regardless of risk attitude (Dixit and Pindyck 1994, p.153). Spiegel *et al.* (2018) demonstrated that in the risk-neutral context, decreasing or eliminating a risk might lead to earlier adoption at a lower scale. However, risk preferences can influence the optimal timing and scale of technology adoption as well (Marra *et al.* 2003; Liu 2013). Empirical results highlight that European farmers tend to be risk averse (Menapace *et al.* 2013; Meraner and Finger 2017; Iyer *et al.* 2020). That motivates the development of an approach which combines the real options approach and risk aversion in a programming setting. Literature provides no established approach for this yet (Homem-de-Mello and Pagnoncelli 2016). In the following, we discuss the advantages and disadvantages of the dominant approaches suggested by the literature, namely the expected utility function, using a risk-adjusted discount rate, and the concept of stochastic dominance. We show that they are particularly limited when not only optimal time and scale of technology adoption are considered, but also competition among different farm activities for limited resources.

Introducing and maximizing a utility function is a straightforward approach and often used in empirical applications (Hugonnier and Morellec 2007; Shapiro 2012). Obviously, results are sensitive to functional choice and parameterization, found as empirically challenging (Lence 2009; Crosetto and Filippin 2016). In the context of programming models, expected mean-variance analysis initiated by Markowitz (1952) is common; it optimizes a weighted sum of the expected mean and the variance, namely a quadratic utility function. To avoid quadratic programming, Hazell (1971) suggested minimization of total absolute deviations as a linear approximation of expected mean-variance analysis which is based on absolute deviations from the mean, typically taken solely downside risk into account. These approaches are applied frequently in programming models without state contingency where for each time point (or in the comparative-static case, for an average one) just one combination of decision variables can be chosen. The optimization weights the outcomes from different states based on the risk utility objective. State contingency renders calculations far more demanding, especially if the decision variables are binaries or integers as in our case, since the distribution of average returns per hectare of a crop depends on its endogenously optimized state contingent acreages.

Computational limits can be overcome by maximizing the certainty equivalent instead and using an approximation (e.g. see Henderson and Hobson 2002). The approach requires assuming a coefficient of risk aversion only, rather than formulating a risk utility function. Meyer and Meyer (2005), Gandelman and Hernandez-Murillo (2015) and Iyer *et al.* (2020) provide an overview of levels of relative risk aversion. Stable optimal behavior under different levels of risk aversion requires additional assumptions about the related risk. For instance, Černý (2004) observed a negligible effect only for small and non-skewed associated risk. Kallberg and Ziemba (2013) found that decision makers with a 'similar' absolute risk aversion coefficient select 'similar' portfolios, regardless of the utility function; however, this result applies to normally distributed assets and a short time horizon. Furthermore, the literature on risk aversion usually deals with annual volatility and employs a distribution, rather than a stochastic process (e.g. Chavas and Shi 2015). This automatically implies a potential natural hedging effect when accumulated over years, namely reduction of total risk exposure due to imperfect correlation of multiple stochastic processes. Capturing risk preferences by a Risk-Adjusted Discount Rate represents a conceptually different approach, not affecting computational feasibility. In contrast to a risk-free discount rate, a Risk-Adjusted Discount Rate reflects both the level of risk and the decision maker's attitude towards this risk. Therefore, it should be adjusted as the level of risk changes over time. More specifically, the adjustment would be specific for each farm activity, which is characterized by a different level of risk, and at each node of the scenario tree, since the risk decreases when approaching the leaves of the scenario tree (Brandão and Dyer 2005;

Finger 2016). Furthermore, capturing level of risk and risk aversion by one joint parameter excludes their separate analysis.

Based on these considerations, we regard second-order stochastic dominance (SSD) as a promising option; its application offers new insights on how risk and risk aversion affect the timing and scale of technology adoption at farm-level. While consistent with the expected utility hypothesis (Chavas 2004), SSD only requires the underlying von Neumann-Morgenstern utility function to be monotone and concave featuring the case of a risk averse decision maker. Any risk-averse decision maker should therefore prefer a solution which incorporates a new technology or activity if it is second-order stochastically dominates his current farm program. If adoption at higher scale is riskier than the benchmark, SSD provides a lower limit on the simulated scale of adoption, while solving for the risk neutral case should provide an upper limit (assuming that risk loving can be empirically excluded). The opposite applies if the new technology or activity is less risky. Simulating both cases thus allows defining the band of potential adoption scale and timing under economic rational behavior. Hardaker *et al.* (2004) suggests how to apply SSD to certainty equivalents of stochastic alternatives for a given range of risk aversion coefficients. The method, called stochastic efficiency with respect to a function is a more powerful variation of the stochastic dominance analysis with respect to a function introduced by Meyer (1977). These methods advance in considering a range of risk aversion coefficients simultaneously, but still require assumptions on a risk utility function, like other alternatives described above. Additionally, their direct implementation as constraints in a dynamic programming model with stage consistency would be numerical quite challenging. To this end, ensuring computational feasibility and measuring risk are the two most demanding issues when introducing SSD or related concepts into a farm-level stochastic dynamic programming model. The following sub-section discusses both and proposes solutions.

2.2 Inverse stochastic dominance and stochastic dynamic programming

According to SSD, a random variable B dominates a random variable A (i.e. $B \succcurlyeq_{(2)} A$) if the expected utility $\mathbb{E}[u(\cdot)]$ of B is at least as high as that of A, (i.e. $\mathbb{E}[u(B)] \geq \mathbb{E}[u(A)]$) (Dentcheva and Ruszczyński 2006). In general terms, the condition of SSD for a discrete case can be formulated as follows, as long as the underlying utility function is monotone and concave (Chavas 2004):

$$B \succcurlyeq_{(2)} A \;\Leftrightarrow\; \sum_{x} \left[(F_A(x) - F_B(x)) * (x_{+1} - x) \;\mid x \leq z \right] \;\geq 0 \;\forall z \tag{1}$$

where $\succcurlyeq_{(2)}$ stays for second-order stochastic dominance; A and B are stochastic variables with possible realizations x; F_A and F_B are their cumulative distribution functions; x_{+1} is the minimum possible realization higher than x.

The incorporation of SSD as a constraint into an optimization model will typically imply a substantial increase in computational complexity, since it requires the introduction of additional binary variables (Gollmer *et al.* 2007, 2008). Alternative (approximate) formulations of stochastic dominance are proposed to deal with this. In particular, Dentcheva and Ruszczynski (2003) suggest a relaxation of the SSD constraint, namely defining a finite number of compact intervals of possible realizations and ensuring SSD within all intervals simultaneously. This so-called interval second order stochastic dominance approach requires ordering realizations, which in turn depends on decision variables and leads to a substantial increase in both the number of variables and the required solution time. This limitation can be overcome if intervals are defined over the cumulative probability rather than over realizations (Fig. 1), an approach termed inverse second order stochastic dominance (ISSD) (Ogryczak and Ruszczynski 2002; Dentcheva and Ruszczyński 2006; Rudolf and Ruszczyński 2008). More specifically, for a probability space $(\Omega,\ \Lambda,\ \mathbb{P})$ we first introduce

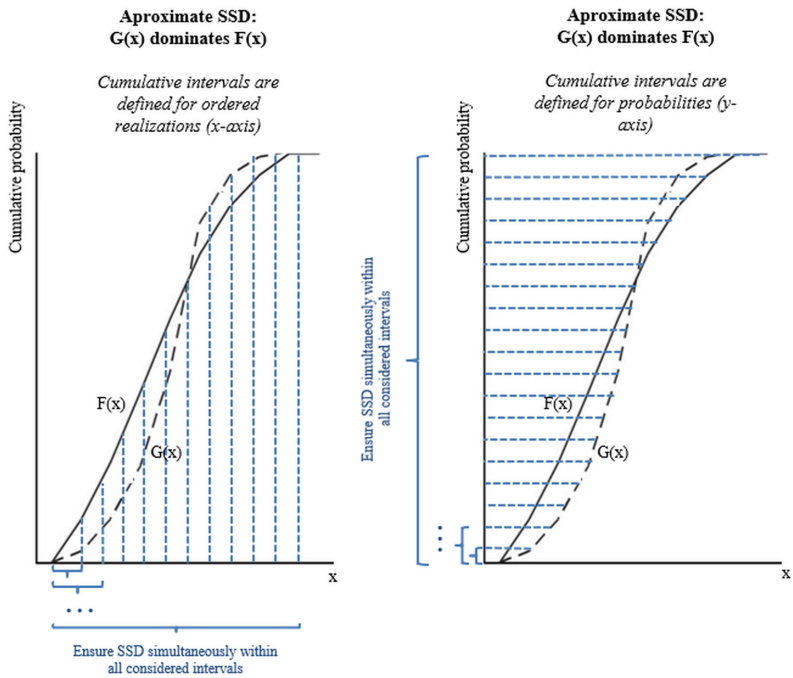

Figure 1. Schematic comparison of approximate second order stochastic dominance (SSD) and inverse SSD

the following definitions (Ogryczak and Ruszczynski 2002):

$$F^{(-2)}\ (x;\, p) = \ p * \mathbb{E}\,\{x|x \leq \eta\}\ \mid p\ =\ \mathbb{P}\,\{x \leq \eta\} \tag{2}$$

where $F^{(-2)}:\ \mathbb{R} \rightarrow \bar{\mathbb{R}}$ is the second quantile function[4]; $\mathbb{E}\{\cdot\}$ is the expectation operator; $x \in \mathbb{R}$ are realizations of a random variable; and $\eta \epsilon \mathbb{R}$ is the so-called target value. It is shown that SSD of B over A is equivalent to the expected realization of B being greater than or equal to the expected realization of B at all intervals p (Ogryczak and Ruszczynski 2002):

$$\begin{aligned} B \succcurlyeq_{(2)} A \ \ &\Leftrightarrow\ \ \frac{F_B^{(-2)}\,(x;\, p)}{p} \geq \frac{F_A^{(-2)}\,(x;\, p)}{p} \\ &\Leftrightarrow\ \ \mathbb{E}_B\,\{x|x \leq \eta\} \geq \mathbb{E}_A\,\{x|x \leq \eta\}\ \ \forall p\ = \mathbb{P}_B\ \ \{x \leq \eta\} \in (0;\, 1] \end{aligned} \tag{3}$$

The approach does not require ordering realizations x beforehand; the target value η is defined for each p and all $x \leq \eta$ are multiplied with the respective probabilities to define $\mathbb{E}\{x|x \leq \eta\}$ without being ordered. We first derive the distribution of returns of a farm under the observed benchmark farm program as A representing a revealed optimal choice given the farmer's risk preferences. Next, we solve for B. More specifically, we determine a program with optimal timing and scale for the new technology or activity under the condition that it (approximately, using ISSD) stochastically second-order dominates the given benchmark A. The original farm program A is comprised in the set of potential solutions B and might be returned as the optimal choice. This happens if there is no stochastically dominating solution involving the new technology or activity. Otherwise, a changed plan B is returned, i.e. the highest expected NPV which is not riskier as the benchmark A as it dominates A (approximately) stochastically in the second order.

Specifically, we define a finite number $N \epsilon \mathbb{N}$ of compact intervals $[0;\ p_i]$ with $i = \{1, 2, \ldots, N\}$; $p_1 = {}^1\!/\!_N$; and $p_{i+1} = p_i + {}^1\!/\!_N$, and ensure the condition (3) for each of them. The narrower the intervals $[0;\ p_i]$, (i.e. the higher the number N), the closer the approximation of ISSD.

Farmers' field-, farm- and household-level decisions are driven by a wide range of factors, such as cognitive ones (perceived costs and benefits), social ones (social norms) and dispositional ones (goals and preferences) (Dessart *et al.* 2019) of which we consider only profits, risk perception and risk preferences. Assuming a farm household context without off-farm income, we take yearly profit withdrawals (net of taxes) as the objective variable, driven by stochastic returns of the farming operations. Measuring related risk levels in each year is challenging. Besides adjustment of the farm's production and investment program as endogenously optimized, yearly withdrawals can be managed by additional instruments, such as adjustments of household expenditures or the use of short-term loans (see de Mey *et al.* 2016 for holistic analysis of farm-household risk behavior). However, these instruments are very difficult to observe. In addition, computational speed would be significantly reduced if we control for ISSD at each time period and at the same time introduce additional decision variables such as short-term loans. It is therefore relatively common to use the distribution of the NPV to assess the risk level of an investment project (Ghadim and Pannell 1999) instead of considering the annual distribution of cash inflows and outflows. This concept implies that an agent only considers the distribution of his/her (discounted) terminal wealth after the lifetime of a project. The literature suggests using a normative portfolio characterized by a tolerable distribution (Bailey 1992; Kuosmanen 2007) if alternatives are evaluated. In the farm context, a farmer's observed production activities and related realizations can be considered as such a benchmark (Musshoff and Hirschauer 2007). We find it straightforward to include the initial farming activity as the benchmark and optimize an alternative one considering the adoption of a new technology, using constraints to ensure that it stochastically dominates the status quo. Assuming that the status-quo is not based on rational behavior obscures the simulation outcome, since differences between the benchmark and the optimal solution would not only reflect the opportunities arising from considering the new technology, but also different behavior.

2.3 Risk analysis and hypotheses

With regard to the effect of risk aversion on the scale of new technologies, literature indicates that higher risk aversion tend to reduce the scale (Liu 2013; Trujillo-Barrera *et al.* 2016; van Winsen *et al.* 2016). This suggests that new technologies are assessed as riskier than those currently in use. The effect of risk aversion on timing reflects the returns if not investing as the opportunity costs associated with the risk. Accordingly, investments are postponed if the returns from alternative resource allocations are viewed as less risky (Hugonnier and Morellec 2007). If opportunity costs are also stochastic and correlated with the investment option to be exercised (as in our settings), there is a potential opportunity for hedging and a risk averse decision maker may be more willing to exploit this by investing earlier (Henderson and Hobson 2002; Truong and Trück 2016; Chronopoulos and Lumbreras 2017). Therefore, we hypothesize that risk aversion leads to a smaller scale and earlier adoption (Table 1).

Previous studies often revealed differences between the ex-ante risk perception of investment projects and actual risk levels derived ex-post (Liu 2013; Menapace *et al.* 2013; Bocquého *et al.* 2014), suggesting that investment decisions are based on subjective beliefs (Savage 1972; Marra *et al.* 2003; Karni 2006). Empirical research identifies a number of factors that affect risk perception, including age (Menapace *et al.* 2013), past experience (Menapace *et al.* 2013), education (Liu 2013), social networks (Kassie *et al.* 2015), as well as risk aversion (Menapace *et al.* 2013; Trujillo-Barrera *et al.* 2016). Perceived risk levels

Table 1. Formulation of the null (H0) and alternative (H1) hypotheses

		Effect on	
		Scale of technology adoption	**Timing of technology adoption**
Factor	**Risk aversion**	H0: Comparing with risk neutrality, risk aversion leads to a lower optimal scale of technology adoption H1: Comparing with risk neutrality, risk aversion leads to the same or a greater optimal scale of technology adoption	H0: Comparing with risk neutrality, risk aversion accelerates technology adoption H1: Comparing with risk neutrality, risk aversion delays or does not affect the timing of technology adoption
	Higher risk level	H0: The higher the risk level the lower the optimal scale of technology adoption H1: Either risk level does not influence the optimal scale of technology adoption or the higher the risk level the greater the optimal scale of technology adoption	H0: The higher the risk level the later technology adoption should be exercised H1: Either risk level does not influence the optimal timing of technology adoption or the higher the risk level the earlier technology adoption should be exercised

are especially relevant in association with new technologies where lack of experience results in uncertainty (Bougherara *et al.* 2017). This uncertainty might even be tagged as risk ambiguity, or inability to formulate subjective probabilities (Barham *et al.* 2014; Bougherara *et al.* 2017). There are hardly any studies addressing the significance of the (perceived) level of risk for technology adoption (Meijer *et al.* 2015). The few existing findings are ambiguous: some argue that it is one of the major determinants (Jain *et al.* 2015; Trujillo-Barrera *et al.* 2016), while others have failed to find any significant effect (van Winsen *et al.* 2016). According to the theory of real options, higher volatility, or a higher perceived risk level, increases both the option value and the trigger price that must be reached in order to initiate investment (Dixit and Pindyck 1994; Hugonnier and Morellec 2007). In contrast, zero perceived risk would convert the problem into a classical NPV approach with no incentive to postpone. Therefore, we hypothesize that a higher perceived risk level of a new technology leads to a smaller scale of technology adoption and postponement (Table 1).

3 Empirical application of the DIASS approach

3.1 General layout

We develop a model based on the stochastic-dynamic programming approach where decision variables are state-contingent. We allow the farmer to introduce a new venture which competes with established activities for (quasi-fixed) resources such as farm land and labor. The adoption of the new activity requires investments subject to indivisibilities of assets and returns to scale. Per unit returns from the new venture are risky and follow a stochastic process, the same applies to established activities. This implies that opportunity costs for the new activity are not known beforehand, but depend on the interaction of the level of adoption and the states of nature. We also assume that the initial farm program before adopting a new technology constitutes an optimal portfolio under the given stochastic returns; it serves as our risk benchmark. With a set of additional constraints, we ensure that a new venture is only adopted at a scale (or not at all) at which it second-order stochastically dominates this benchmark. Furthermore, the decision maker has the flexibility to postpone the adoption of the new activity, motivating the use of a real option approach. To this end,

we assume that the decision about optimal time and scale of a new technology adoption is based on an NPV maximization; subject to existing resource endowments and other farm-level constraints; conditional to possible future developments of stochastic variables; while ISSD constraints approximate inverse second order stochastic dominance over the endogenously simulated distribution of discounted terminal wealth. The optimization problem can then be expressed as follows:

$$\max NPV \qquad (x; z) \tag{4}$$

$$\text{subject to} \begin{cases} \mathbb{E}_B\{NPV(x;\ z)|NPV(x;\ z) \leq \eta\} \geq \mathbb{E}_A\{NPV(x;\ z)|NPV(x;\ z) \leq \eta\} \\ \eta\colon p_i = \mathbb{P}_B\ \{NPV(x;\ z) \leq \eta\} \\ p_i = {}^{i}\!/_{N} \\ \forall i\ = \{1, 2, \ldots,\ N\},\ x \epsilon C \end{cases}$$

where $NPV(x;\ z)\colon \mathbb{R} \rightarrow \bar{\mathbb{R}}$ is objective function; $z \in \mathbb{R}$ are realizations of a random variable; $N \epsilon \mathbb{N}$ is a finite number of compact intervals $[0;\ p_i]$ with $i\ = \{1, 2, \ldots,\ N\}$; and set C represents further constraints for decision variable x, for instance, resource endowment constraints.

Some consequences of these assumptions are worthy of closer consideration. First, we apply ISSD to compare distributions of terminal wealth of two portfolios of risky farm activities rather than single activities. This allows considering interaction and correlation between separate activities, including risk mitigating effects of not perfectly correlated stochastic variables such as profits from different crops, i.e. a natural hedge. Second, a joint parallel shift of resulting NPV distributions under A and B scenarios does not affect the outcome of (I)SSD such that we can ignore levels and changes in costs and benefits independent of the farm's activity portfolio, for instance, fixed management costs, direct payments or other sources of household income. This is an advantage of ISSD since such fixed costs and benefits and their stochastic distribution would need to be specified if different levels of risk aversion were considered. It reflects that ISSD is not based on the specification of a risk utility function and does not require a risk-adjusted discount rate when discounting cash flows related to investments with a differing degree of risk or to different nodes of the scenario tree (Brandão and Dyer 2005; Finger 2016).

3.2 Solution process

The mixed-integer model is solved with stochastic dynamic programming by using a scenario tree to represent uncertainty with a predetermined number of $\bar{D}$ leaves. This tree stems from first running a Monte Carlo simulation with $D = 10{,}000$ draws and subsequently reducing the resulting tree to the desired size by applying a scenario tree reduction technique according to Heitsch and Römisch (2008).[5] This allows control over overall model size, while keeping the values assigned to each node within a certain plausible range and hence gaining a computational advantage. Since there are multiple stochastic variables in the model, a vector of values is assigned to each node of the scenario tree. The optimal decision with respect to technology adoption for each node of the tree is conditional to decisions made prior to this node and the possible follow-up scenarios (Fig. 2).

The effect of risk aversion is quantified by adding the ISSD constraints to the model, and then comparing resulting outcomes without these constraints, namely the risk-neutral case. As mentioned, we measure risk levels based on the final distribution of NPVs and use the currently observed behavior as the benchmark for tolerable risk. The additional ISSD constraints ensure (approximately) that, giving due consideration to the new activity, the distribution of NPVs under the benchmark is dominated second-order stochastically by the final distribution of NPVs (Fig. 2).

We conduct a sensitivity analysis to capture different risk levels associated with technology adoption by considering different parameters of the related stochastic process (Fig. 2),

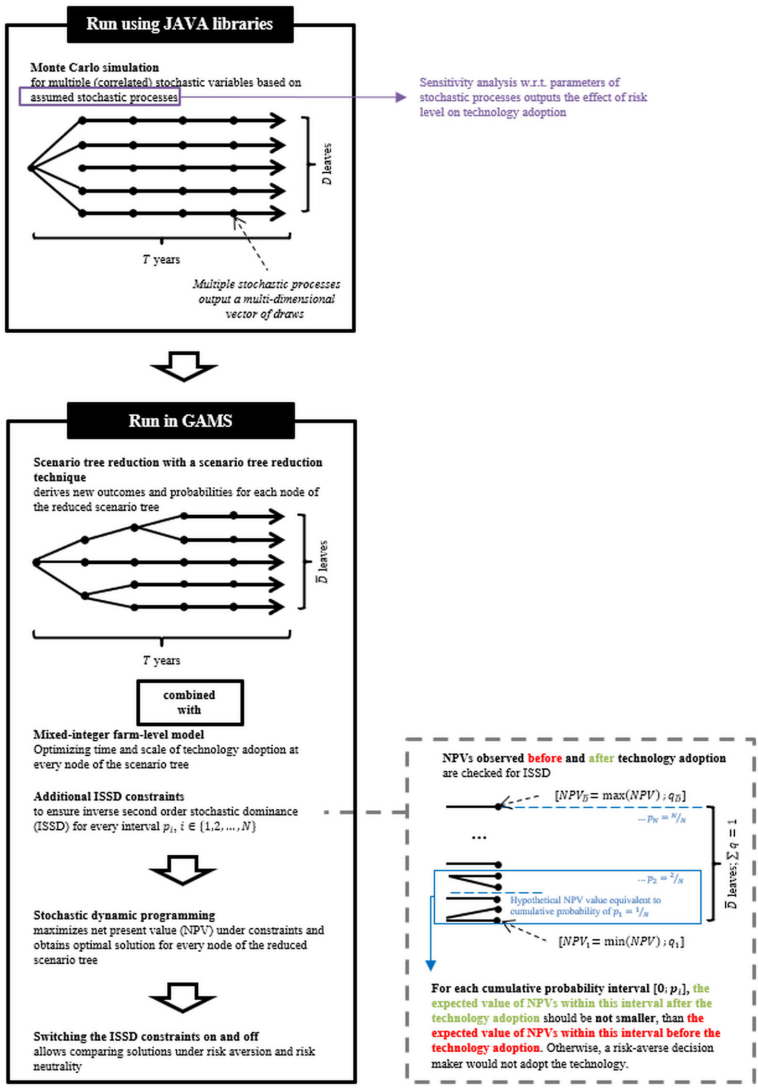

Figure 2. Schematic representation of the solution approach.

however without changing its long-term mean nor the expected mean in each year. Consequently, results under a now-or-never risk neutral decision (or the classical risk neutral NPV approach) would not change. Draws of the other stochastic processes which relate to the activities present at the farm prior to technology adoption are obtained once and fixed.

3.3 Case study and model specification

We illustrate the DIASS approach using the example of potential introduction of a perennial energy crop production system (SRC) on an arable farm. Setting up an SRC plantation is an investment with high sunk costs (Lowthe-Thomas *et al.* 2010). Once established, the plantation has a lifetime of approximately two decades, during which it can be coppiced several times without being replanted. Volatile and hard to forecast prices of fossil fuels,

which SRC biomass substitutes for heating purposes, imply that also future SRC biomass prices are highly uncertain.

The combination of uncertainty, high sunk costs plus the possibility to postpone the adoption decision and to adjust the scale of SRC implementation generates an option value (or a value of postponing implementation and acquiring more information prior to making a decision) (Pindyck 2004). SRC adoption has been analyzed using real options under risk neutrality (Song *et al.* 2011; Bartolini and Viaggi 2012; Frey *et al.* 2013; Spiegel *et al.* 2018, 2020) and under risk aversion by introducing a risk-adjusted discount rate (Musshoff 2012; Wolbert-Haverkamp and Musshoff 2014). Empirical results for German farmers (Meraner and Finger 2017) suggest risk aversion, here depicted by ISSD as a new methodological approach. Compared to previous studies, we analyze additionally the effect of different risk levels on the timing and scale of SRC introduction by changing the risk level associated with SRC. Equally, we compare timing and scale of SRC adoption between risk neutral and risk-averse farmers by switching the ISSD constraints on and off.

We evaluate the option value of SRC in a farm-level context, capturing interactions with annual crops based on competition for land and labor as fixed resources which are allocated among farm activities in fractional shares. The currently observed production activities considered for the benchmark comprise the production of two types of annual crops, one of which is more profitable, but also more labor-intensive (for instance, winter wheat compared to rapeseed), as well as set-aside land and catch crops. The two annual crops are characterized by gross margins following a stochastic process, while set-aside land and catch crops are modeled with deterministic costs and introduced to fulfill the Ecological Focus Area requirement,[6] to which SRC contributes in Germany with a coefficient of 0.3 (BMEL 2015; Pe'er at al. 2016). SRC competes with annual crop production for land resources, while the setting up and harvesting of SRC are usually outsourced, so that little or no farm labor is required (Musshoff 2012). Economic considerations of introducing SRC are thus as follows. On the one hand, SRC requires significant and irreversible investments for establishment and final reconversion and binds land for a long time, while its price is assumed to be stochastic. On the other hand, SRC reduces the amount of idling land or catch crops required for the Ecological Focus Area requirement, while labor is saved due to use of contracted services (Musshoff 2012). Consequently, labor previously used on a plot now devoted to SRC can be reallocated to the more profitable and labor-intensive annual crop.

In our setting, the farmer considers introducing SRC immediately or within the next three years. He can coppice a SRC plantation every five years over a period of up to 20 years after which it must be clear-cut, although earlier reconversion to other land uses (dis-investment) is possible. This leads to time horizon of 24 years: a maximum of four years for possible SRC introduction plus the 20 years of maximum plantation lifetime. Decision on SRC adoption are based on maximizing the expected NPV, calculated from the NPV at each leaf of the constructed scenario tree and the attached probability, conditional on risk expectations and subject to constraints:

$$\begin{aligned}\mathbb{E}[NPV] &= \sum_{path}[q_{path} * NPV_{path}] \\ &= \sum_{path}\Bigg[q_{path}\sum_{t=1}^{T}\Bigg[\sum_{c}\frac{GM_{(t,n),c} * L_{(t,n),c}}{(1+i)^t} + \frac{PR^{SRC}_{(t,n)} * harvQuant_{(t,n)}}{(1+i)^t} \\ &\quad + \frac{-iniCost_{(t,n)} - TotalHarvCost_{(t,n)} - reconvCost_{(t,n)}}{(1+i)^t}\Bigg]\Bigg] \qquad (5)\end{aligned}$$

where $(t,\ n)$ is a combination of time period and node of the scenario tree assigned to each path; q_{path} stands for probability of each path; $\sum_{path} q_{path} = 1$; $GM_{(t,n),c}$ is gross margin of a land use option c in time period t [euros per hectare per year, € ha^{-1} y^{-1}]; $L_{t,c}$ is fractional land area dedicated to a land use option c in time period t [ha y^{-1}]; c includes arable crop 1 ($c = arable1$), arable crop 2 ($c = arable2$), set-aside land ($c = setaside$), and catch crops ($c = catch$); $PR^{SRC}_{(t,\ n)}$ is biomass output price [euros per tonne of dry matter yields, € t^{-1}]; $harvQuant_t$ is the amount of biomass harvested [t y^{-1}]; $iniCost_{t,p}$ represents the actual set-up costs [€ y^{-1}]; $TotalHarvCost_t$ captures total costs on farm associated with harvest of SRC [€ y^{-1}]; $reconvCost_{t,p}$ represents actual reconversion costs [€ y^{-1}]; i is an annual discount rate [per cent y^{-1}]. The expected NPV defined in Eq. 5 is maximized subject to the following constraints (nodes indices are left out for simplicity):

Resource endowments

$$\bar{a}_{SRC,i} * L_{t,SRC} + \sum_c \bar{a}_{c,i} * L_{t,c} \leq \bar{b}_{t,i}\ \forall i \tag{6}$$

where $\bar{a}_{SRC,i}$ represents input requirements for SRC [ha^{-1} y^{-1}]; L_{SRC} indicates the area dedicated to SRC [ha y^{-1}]; i represents inputs including land ($i = land$) and labor ($i = labor$); $\bar{a}_{c,i}$ denotes fixed input-output coefficients [ha^{-1} y^{-1}]; $\bar{b}_{t,i}$ describes farm-level resource endowments [y^{-1}]; and $L_{t,c}$ indicates the area dedicated to the production of each annual crop [ha y^{-1}].

Policy constraints

$$L_{t,c\ =\ setaside} + 0.3 * L_{t,c\ =\ catch} + greenCoef_{SRC} * L_{t,SRC} \geq 0.05 * \bar{b}_{t,i\ =\ land} \tag{7}$$

where $greenCoef_{SRC}$ is the ecological focus area weighting coefficient for SRC.

ISSD constraints

$$\begin{cases} \mathbb{E}_{+SRC}\{x|x \leq \eta\} \geq \mathbb{E}_{NoSRC}\{x|x \leq \eta\} \mid \eta{:}p_i = \mathbb{P}_{+}SRC\{x \leq \eta\} \\ p_i = i/N \\ \forall i = \{1, 2, \ldots, N\}, x \in C \end{cases} \tag{8}$$

where x is a set of decision variables; $+SRC$ and $NoSRC$ denote scenarios after and before SRC adoption respectively; $\mathbb{P}\{x \leq \eta\}$ denotes cumulative probability of η; set p_i is a set of predefined intervals of cumulated distribution.

As explained below, various relationships in the model need integer variables. Thus, in order to avoid a mixed non-linear integer programming problem, we keep the model linear by pre-defining plots of certain sizes to be potentially converted into SRC plantation in 5-hectare increments (i.e. providing 0, 5, 10, ..., 100 ha of SRC plantation). Each plot can be converted to SRC, coppiced, or clear-cut independently from the others, but partial coppicing on an individual plot is not possible. Two equations linked to either a positive (0 in t-1 to 1 in t) or a negative (1 in t-1 to 0 in t) change in SRC on a plot are used to describe set-up and reconversion costs respectively (nodes indices are left out for simplicity):

$$iniCost_{t,pl} \geq \left(src_{t,pl} - src_{t-1,pl}\right) * \overline{costIni} * S_{pl} \tag{9}$$

$$reconvCost_{t,pl} \geq \left(src_{t-1,pl} - src_{t,pl}\right) * \overline{costReconv} * S_{pl} \tag{10}$$

where index pl refers to a plot; $\overline{costIni}$ is a coefficient for set-up costs [€ ha^{-1} y^{-1}]; $\overline{costReconv}$ is a coefficient for reconversion costs [€ ha^{-1} y^{-1}]; $src_{t,\ pl}$ is a binary variable indicating that a plot is managed under SRC (= 1) or not (= 0) in time period t; S_{pl} is size of plot pl [ha y^{-1}]. Maximum plantation lifetime is depicted by a year counter combined with an upper bound (nodes indices are left out for simplicity):

$$age_{t,pl} = age_{t-1,pl} + src_{t,pl} \tag{11}$$

Table 2. Input requirements and returns of alternative farm activities

Parameter	Value	Source
General farm characteristics		
Land endowment	100 ha	
Labor endowment	500 hours per year (h y^{-1})	
Real risk-free discount rate	3.87% y^{-1}	Musshoff (2012)
Short rotation coppice		
Planting costs	2,875.00€ ha^{-1}	Musshoff (2012)
Biomass yields every five years	68.57 t ha^{-1}	Ali (2009)
Price of biomass yields	*Stochastic, see Table 3*	
Costs related to harvest	*Defined according to* Eq. 13	
Fixed costs	66.75€ y^{-1}	Based on Pecenka and Hoffmann (2012) and Schweier and Becker (2012)
Quasi-fixed costs	272.13€ ha^{-1} y^{-1}	
Variable costs	10.67€ t^{-1} y^{-1}	
Final clear-cut costs	1,400.00€ ha^{-1}	Musshoff (2012)
Annual crops		
Labor requirements for a more profitable crop	5.32 h ha^{-1} y^{-1}	KTBL (2016)
Labor requirements for a less profitable crop	4.16 h ha^{-1} y^{-1}	KTBL (2016)
Gross margins of annual crops	*Stochastic, see Table 3*	
Land uses recognized as Ecological Focus Area		
Labor requirements for set-aside land	1.00 h ha^{-1} y^{-1}	KTBL (2016)
Labor requirements for catch crops	0.00 h ha^{-1} y^{-1}	KTBL (2016)
Gross margin of set-aside land	–50.00 h ha^{-1} y^{-1}	CAPRI (2017)
Gross margin of catch crops	–100.00 h ha^{-1} y^{-1}	de Witte and Latacz-Lohmann (2014, p.37)

$$age_{t,pl} \leq \overline{maxage} \tag{12}$$

where $age_{t,pl}$ is an integer variable reflecting plantation age [y]; and $\overline{maxage}$ is a constant plantation age upper bound [y]. We also assume economies of scale related to SRC, for instance related to transaction costs of finding a contractor or transport costs of harvest equipment. In particular, we differentiate between fixed costs at the farm level, quasi-fixed costs per each plot harvested and variable costs per tonne of dry matter harvested (Pecenka and Hoffmann 2012; Schweier and Becker 2012) (nodes indices are left out for simplicity):

$$TotalHarvCost_t \geq \left[\overline{harvCostFixed} + \sum_p \left[\overline{harvCostPlot} * S_{pl} + \overline{harvCostYield} * stock_{t,pl}\right]\right] * harvest_{t,pl} \tag{13}$$

where $\overline{harvCostFixed}$ represents fixed harvest costs [€ y^{-1}]; $\overline{harvCostPlot}$ represents quasi-fixed harvest costs [€ ha^{-1} y^{-1}]; $\overline{harvCostYield}$ represents variable costs [€ t^{-1} y^{-1}]; $stock_{t,pl}$ is standing biomass in time period t on land plot pl, [t y^{-1}]; $harvest_{t,pl}$ indicates whether a plot is harvested (= 1) or not (= 0).

The deterministic parameters, capturing conditions in northern Germany, are derived from the literature (Table 2). Appendix A provides further details and also compares our data assumptions with similar ones from the literature.

Table 3. Estimated parameters of stochastic processes based on historical observations

Parameter	Value	Source
Mean-reverting process for natural logarithm of SRC biomass price		
Starting value	3.92[a], ca.50 euro per tonne of dry matter yield (€ t^{-1})	
Long-term mean	3.92	Musshoff (2012)
Speed of reversion	0.22	Musshoff (2012)
Standard deviation	0.28	Musshoff (2012)
Correlation coefficient with the other stochastic process	0.00[b]	
Mean-reverting process for natural logarithm of gross margins of annual crops		
Starting value	6.02[a], equal to 413 euro per hectare (€ ha^{-1})	
Long-term mean	6.02	CAPRI (2017), own estimation
Speed of reversion	0.32	CAPRI (2017), own estimation
Standard deviation	0.28	CAPRI (2017), own estimation
Multiplicative coefficient for a more labor-intensive and more profitable crop	1.05[c]	
Multiplicative coefficient for a less labor-intensive and less profitable crop	0.95[c]	

[a] Starting value are stet equal to the long term mean to exclude any possible effect of a trend
[b] The assumption is based on ambiguous evidence in the literature about sign and magnitude of the correlation (Musshoff and Hirschauer 2004; Du *et al.* 2011; Diekmann *et al.* 2014).
[c] Multiplicative coefficients are assumed for draws converted back from natural logarithm into euro per hectare

3.4 Stochastic component

We assume that the natural logarithm of each stochastic variable follows a mean-reverting process. This choice is based on the premise that the farmer is a price-taker in an environment where market forces cause prices and gross margins to fluctuate around constant long-term levels, for instance, under the assumption that there is no monopolistic power (Metcalf and Hassett 1995) and/or technology is constant (Song *et al.* 2011). An mean-reverting process is characterized by a long-term mean, speed of reversion and standard deviation (Dixit and Pindyck 1994). We estimate the parameters of the process for annual crops using data[7] on gross margins of an average hectare of arable land in Germany between 1993–2012 from the CAPRI (2017) model data base following the procedure described in Musshoff and Hirschauer (2004). Appendix B provides more details on this estimation. The process for SRC biomass prices is based on Musshoff (2012).

The literature provides ambiguous evidence regarding the correlation coefficient between SRC biomass price and annual crop gross margins (Musshoff and Hirschauer 2004; Du *et al.* 2011; Diekmann *et al.* 2014), while the effect of the coefficient on farmers' behavior has been found to be limited (Spiegel *et al.* 2018). This lets us assume a zero correlation between the biomass price and annual crop gross margins, reflecting that gross margins of SRC and annual crops are not driven by similar market and climatic influences. In contrast, we assume that the gross margins of the two annual crops are perfectly correlated. Therefore, we use one process for both gross margins and then adjust the draw at each node of the scenario tree

Table 4. Comparison of business-as-usual scenario and introduction of short rotation coppice (SRC) under risk neutrality and baseline risk levels

	Business-as-usual (no SRC)	SRC introduction without an ISSD constraint
Probability of introducing SRC (%)		
In $t = 1$	-	0.00
In $t = 2$	-	15.66
In $t = 3$	-	24.01
In $t = 4$	-	20.90
Never	-	39.43
Mean area (ha y^{-1})	-	
SRC	-	7.97
More profitable annual crop	80.16	81.36
Less profitable annual crop	17.00	8.97
Set-aside land	2.84	1.70
Catch crop	7.19	6.69
Expected net present value, (1000s €)	641.31	655.28

with multiplicative coefficients to derive gross margin levels (see Table 3). The correlation coefficient enters stochastic processes as follows:

$$d\ pr_t = \mu_{SRC}\ (\theta_{SRC} - pr_t)\, dt + \sigma_{SRC} dW_t^{SRC}$$

$$d\ gm_t = \mu_{annual}\ (\theta_{annual} - gm_t)\, dt + \rho\sigma_{annual} dW_t^{SRC} + \sqrt{(1-\rho^2)}\sigma_{annual} dW_t^{annual} \quad (14)$$

where t is the time period; SRC indicates short rotation coppice; index $annual$ indicates both arable crops; pr_t is the natural logarithm for the price of SRC biomass; μ_{SRC} is speed of reversion of the stochastic process for SRC biomass price; θ_{SRC} is long-term logarithmic average price of SRC biomass; σ_{SRC} is standard deviation of logarithmic SRC biomass price; dW_t^{SRC} is standard Brownian motion independent from dW_t^{arable}; ρ is correlation coefficient between two Brownian motions.

Further research might specify the alternative portfolio in greater detail, including different correlation coefficients between gross margins of annual crops. The DIASS approach does not imply any restrictions in this regard, but it is beyond the scope of our illustrative purposes.

We obtain $D = 10,000$ draws (see Fig. 2) from the Monte Carlo simulation. In order to select the number of leaves in the reduced scenario tree, we performed multiple runs of the model gradually increasing the number of leaves and noticed that the expected area under SRC stabilizes beginning at 200 leaves ($\bar{D} = 200$ on Fig. 2). For ISSD constraints, we consider 100 intervals[8] with a 1 per cent-step ($N = 100$ in Fig. 2 and in Eq. 8), which should render the impact of the approximation negligible. We performed the risk analysis by gradually increasing the standard deviation and decreasing the speed of reversion in the stochastic process for the SRC output price. The higher the standard deviation and the lower the speed of reversion, the more volatile the stochastic process becomes, reaching a higher spread and reverting to the long-term mean more slowly.

4 Results

The key results under risk neutrality and baseline risk levels are presented in Table 4. Note that introducing SRC immediately (in $t = 1$) is not optimal, meaning that an option value exists even for a risk-neutral farmer. Accordingly, the investment decision is postponed and

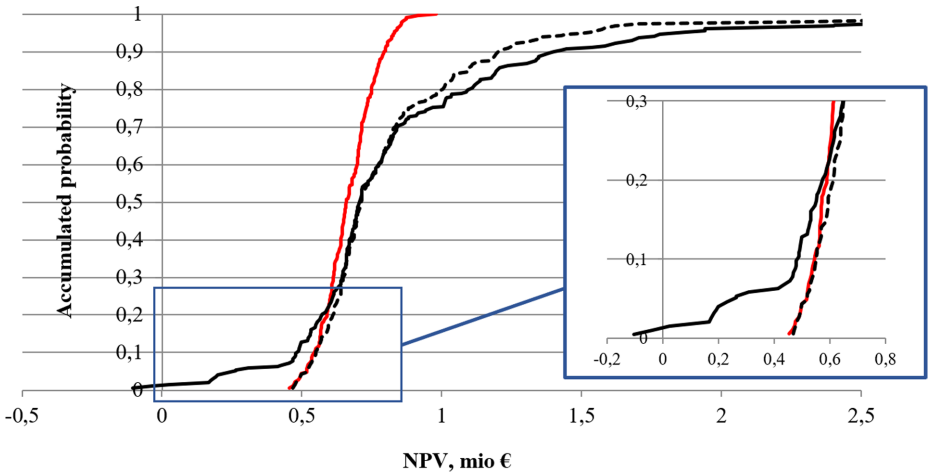

Figure 3. Effect of risk preferences on the distribution of NPVs compared with the benchmark (BAU). Note: standard deviation and speed of reversion of logarithmic SRC biomass price are 1.00 and 0.22 respectively.

exercised later, or not at all, depending on future developments. In 39.43 per cent of the simulated cases, we find that SRC would never be introduced. The expected area under SRC is 7.97 ha, which mainly stems from substituting the less profitable crop. This level of SRC is not sufficient to fulfill the Ecological Focus Area requirement (16.67 ha would be required given the total land endowment of 100 ha) and thus set-aside land and catch crops remain in the farm portfolio (1.70 ha and 6.69 ha respectively).

As argued above, SRC requires no labor input. Thus, if SRC is introduced, a farmer reallocates labor to the more labor-intensive and more profitable crop (compare 80.16 ha and 81.36 ha after introduction of SRC). This reallocation of resources creates an additional incentive for adoption, which would be neglected when the technology adoption would be analyzed as a stand-alone investment and not in the farm context. The optimization under risk neutrality introduces SRC in some scenarios, such that the expected NPV must increase compared to the benchmark. However, this also implies substantially higher risk as seen in Fig. 3. The distribution of NPVs with SRC simulated under risk neutrality (i.e. without the ISSD constraints, black solid curve) does not stochastically dominate the benchmark (red curve): its lowest NPV realization undercuts the lowest one in the benchmark. Enforcing SSD by introducing the ISSD constraints turns the NPV distribution function with SRC in a counterclockwise direction, cutting the left-hand-side tail (black dashed curve). That also reduces the probability of larger NPVs compared to the higher adoption rates of SRC under the risk neutral case, underlining the tradeoff between a higher mean and a higher risk.

We now demonstrate the effect of risk aversion and changes in risk levels on the scale of technology adoption (i.e. the expected acreage of the farm under SRC). Fig. 4 combines the effects of adjusting the standard deviation and mean of reversion of the stochastic process for the SRC biomass price with and without the ISSD constraints. Our analysis shows that risk aversion (under the ISSD constraint) does indeed lead to a smaller expected area under SRC, which is consistent with the null hypothesis. Indeed, many white dots (risk aversion) on Fig. 4 lie substantially below the respective black dots (risk neutrality). The ISSD constraints cut off the lower tail of NPV distribution as discussed above such that no SRC adoption is observed in some leaves where it would be realized under risk neutrality. This reduces the overall expected scale of SRC adoption. These differences can reach up to 20

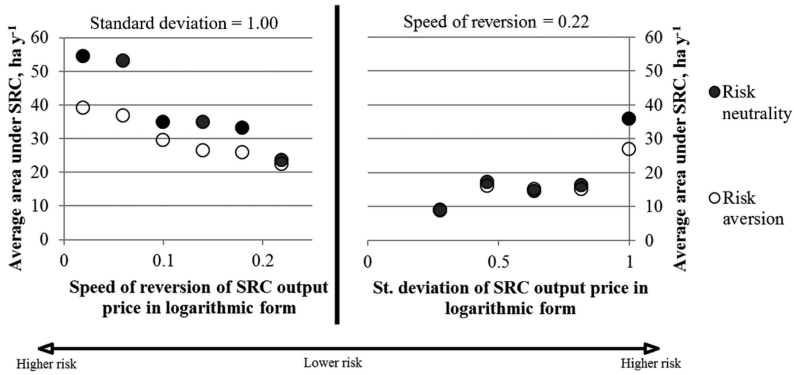

Figure 4. Effect of increasing risk levels of short rotation coppice (SRC) biomass output prices on the expected area under SRC.

hectares or around 50 per cent for the extreme cases, and are found to react more sensitive to changes in the speed of reversion.

In contrast, the null hypothesis on the effect of higher risk levels on optimal scale is rejected in our example. Results show that even for a risk averse decision maker, a higher risk level leads to a larger expected area under SRC. This is explained by managerial flexibility regarding the scale of investment depicted by state contingency: a farmer exploits the opportunity of investing in a larger SRC plantation when prices are high and vice versa. This managerial flexibility cuts off a part of the scenario tree with low SRC prices, since SRC is only adopted if the price exceeds a certain threshold. Due to the set-up of the sensitivity analysis, higher risk levels increase the spread of the scenario tree without changing the expected mean. This not only creates a larger area where SRC is not realized and farm income stems from the established annual crops, only, but also shifts up the expected SRC price for the nodes where the threshold price is exceeded, which triggers a larger scale of the investment project for these nodes. In our application, the expected mean area under SRC, which measures the scale of adoption, increases at higher risk levels for both risk neutral and risk-averse decision makers, even though the respective trigger price increases. For instance, the expected mean area under SRC for a risk-neutral decision maker increases from around 22 to 54 hectares when decreasing speed of reversion from 0.22 to 0.02. However, this effect of increasing risk levels is smoothed by risk-aversion, especially when adjusting the speed of reversion (Fig. 4).

Next, our results reveal a U-parabolic relationship between risk levels of SRC and incentives for earlier SRC introduction (Fig. 5). Lower standard deviation values limit incentives to postpone SRC introduction by reducing risk and the related option value, reflecting that the decision problem moves towards a classical NPV analysis. A similar U-parabolic relationship can be observed between SRC risk levels and the probability that SRC will never be adopted: there is a level of risk that implies the highest probability of never adopting SRC, which can be quantified using our approach (for instance, in our application it is associated with the standard deviation of around 0.64 on the left-hand side of Fig. 5). Therefore, the null hypothesis is confirmed in our settings for lower levels of risk and rejected for greater ones.

A comparison of the timing of SRC introduction in the case of risk neutral and risk averse decision makers (Fig. 5) reveals that risk aversion might lead to earlier SRC introduction (for instance, for standard deviation of 0.64 the probability of adopting in the second year increases from 13 per cent to 22 per cent when risk aversion is considered). This is due to the fact that risk averse decision makers exploit the hedging effect between the uncor-

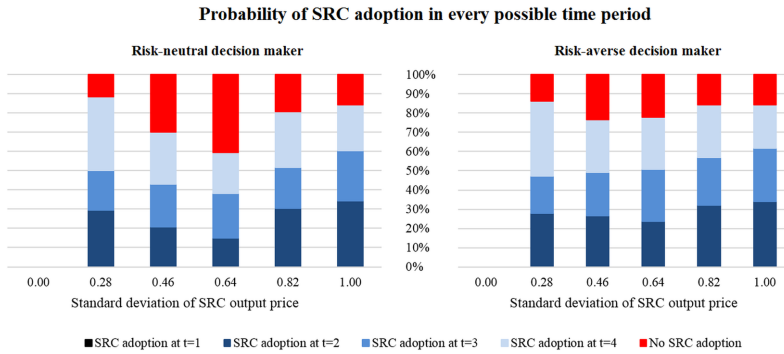

Figure 5. Effects of increasing standard deviation values of logarithmic SRC biomass price on timing of SRC introduction with and without risk preferences. Note: speed of reversion of logarithmic SRC biomass price is 0.22.

Table 5. Summary of the major findings and check of hypotheses

		Effect on	
		Scale of technology adoption	**Timing of technology adoption**
Factor	**Risk aversion**	Comparing with risk neutrality, risk aversion leads to a lower optimal scale of technology adoption (*H0* cannot be rejected)	Comparing with risk neutrality, risk aversion has no effect on/accelerates technology adoption (*H0* cannot be rejected)
	Higher risk level	The higher the risk aversion the higher the optimal scale of technology adoption (*H0* rejected)	Up to a certain risk level, the higher the risk level the later technology adoption should be exercised. Starting from a certain risk level, the higher the risk level the sooner technology adoption should be exercised. (*H0* cannot be rejected for low risk levels; *H0* rejected for high risk levels)

related stochastic returns of annual crops and SRC. A risk averse farmer is predicted to introduce SRC earlier in order to reduce overall farm risk, although on average the area of SRC adopted is smaller compared to a risk neutral farmer. This effect would be obscured if the alternative land use portfolio is assumed to be deterministic or if technology adoption is considered stand-alone. The effect of risk preferences on timing of SRC adoption is highest at mid standard deviation values (e.g. standard deviation of 0.64, Fig. 5). Regardless of risk preferences, there is no incentive to postpone adoption for low levels of risk. Increasing risk levels imply that a trigger price that stimulates SRC adoption is reached sooner. In contrast, SRC adoption is not attractive for very high-risk levels. Therefore, we cannot reject the null hypothesis.

A decision maker who perceives SRC as quite risky (implying larger deviations of its price below and above expectation levels) tends to commit a larger area to SRC earlier, but not immediately. A respective trigger price must be reached in order to initiate SRC introduction, otherwise an investment decision will be postponed indefinitely. Furthermore, the negative effect of risk aversion on the scale of adoption rises as risk levels increase. The major findings are presented in Table 5.

5 Discussion and conclusion

The development of efficient policies and forecasting of targets demands a well-informed understanding of farmers' motives with respect to technology adoption. However, the analysis of joint effects of explanatory factors on technology adoption is still limited, especially with regard to risk and risk preferences (Meijer *et al.* 2015; van Winsen *et al.* 2016). In addition, the available literature provides no established approach to separately consider the effects of risk levels and risk preferences on timing and scale of technology adoption at farm level, while also considering interactions among different farm activities generated by competition for limited resources. We address this gap by proposing a novel approach based on stochastic dynamic programming and inverse second order stochastic dominance. The approach requires a limited number of empirical assumptions and does not threaten computational capacity, but considers consistently expected utility theory. The proposed approach can be used to analyze adoption of any investment-based technology. Our illustrative example involves short rotation coppice adoption. The resulting stochastic dynamic farm-level model is characterized by stochastic returns on both the current farm activities and a new investment-based activity, and considers farm-level resource endowments and returns-to-scale.

Our empirical results demonstrate that higher risk aversion leads to lower optimal scale of technology adoption. This is consistent with previous research findings (Liu 2013; Trujillo-Barrera *et al.* 2016; van Winsen *et al.* 2016). We also find that risk aversion accelerates technology adoption. The effect is not apparent at very low or very high risk levels in our case study. A similar result was obtained by Truong and Trück (2016), who found that risk aversion encourages earlier investment in those climate change adaptation projects that are designed to reduce risk. Our results can be explained by the fact that the incentives are higher for a risk averse farmer to exploit the natural hedging effect of diversification, by adding novel to the established activities. The lower (or even the more negative) the correlation coefficient between both activities, the higher is the potential effect of natural hedging. Consequently, the effect of risk aversion on the timing of technology adoption might be different or obscured in other settings, especially if technology adoption is analyzed under different assumptions that do not imply natural hedging, such as stand-alone.

The findings of previous studies suggest that farmers' risk perception is relevant, especially with respect to new technologies. However, these findings are ambiguous regarding their effect on technology adoption. Our results show that due to managerial flexibility, higher risk levels lead to greater scales of technology adoption to exploit upside risk, which is, however, mitigated by risk aversion. The treatment of risks and risk levels in our analysis implies consideration of both positive and negative deviations from expectations. A study of the downside risk alone might provide additional insights, but requires a different type of sensitivity analysis where a negative drift would have to be introduced in the stochastic process, while the inverse second order stochastic dominance constraints would only capture a predetermined part of the distribution. Higher risks defined this way would lead to a lower scale of technology adoption. Therefore, we emphasize that the definition of risk perception requires special attention when applying the DIASS approach proposed here. We observe a U-parabolic effect for the timing of technology adoption: with increased risk levels, a farmer first tends to postpone or even reject technology adoption, and then to adopt it earlier. The proposed approach allows quantifying the risk levels associated with the lowest incentives to adopt a new technology. However, the U-parabolic relationship is smoothed by risk aversion. Consequently, if a technology is perceived as a low risk option, a farmer would tend to adopt it sooner, but on a smaller average scale. In contrast, if a technology is viewed as a high risk, a farmer would also tend to adopt earlier and on a larger scale.

Two issues regarding our empirical findings are worth mentioning. Firstly, the results can only be applied to an investment-based technology adoption that implies a potential option

value. In this regard, three characteristics of technology adoption must be present simultaneously: (i) sunk costs; (ii) risk; and (iii) the possibility to postpone adoption. Secondly, the DIASS approach does not allow for a close-form analytical solution. Therefore, our findings cannot be generalized. The DIASS approach and the model presented here can be further specified and expanded to other farm-level decisions. The model and all the related documentation are provided in Spiegel *et al.* (2017) to facilitate further development and application.

The DIASS approach is subject to the following limitations. Firstly, it does not allow any differentiation between varying levels of risk aversion. This exceeded the scope of our study. If the purpose is to differentiate between levels of risk aversion, the certainty equivalent approach could be used instead of inverse second order stochastic dominance, but it must be borne in mind that this involves another limitation, namely computational feasibility. Finally, we explicitly assume that the constructed scenario tree is assigned to the farmer and fixed. It would be more realistic to assume a process of learning for the true scenario tree and adjust behavior accordingly. However, stochastic dynamic programming does not provide any established approach to consider learning processes (Sunding and Zilberman 2001; Guthrie 2009). Further methodological research can address these limitations.

End Notes

1. In the following we use the term 'stochastic dynamic programming' to emphasize that we refer to a long-term problem and solve for an optimal steady-state decision, in contrast to stochastic programming that provides a transient solution (King and Wallace 2012).
2. We consider SRC as an agronomic innovation (i.e. a new farm management practice), based on the definition by Sunding and Zilberman (2001).
3. Note that a binomial lattice requires $[{}^{n(n+1)}/_{2}]$, and a binomial tree -2^n final leaves for n time periods.
4. In the following, $\mathbb{N}$ remains for the set of natural numbers, $\mathbb{R}$ for the set of real numbers, and $\bar{\mathbb{R}}$ for the set of real numbers extended by positive infinity and negative infinity ($\bar{\mathbb{R}} = \mathbb{R} \cup \{-\infty, +\infty\}$).
5. The number of leaves on a reduced scenario tree is a model parameter and can be adjusted. Its choice is a tradeoff between accuracy and execution time.
6. According to the Common Agricultural Policy, large farms must allocate 5 per cent of their land area to land uses devoted to environmental purposes; each hectare under catch crops is equivalent to 0.3 ha of set-aside land in Germany (BMEL 2015; Pe'er *et al.* 2016).
7. Stationarity required for an mean reverting process can only be identified for long time data series (Pindyck and Rubinfeld 1997). Since there are no long time series of sufficiently lengthy duration, as in our example, the choice of a stochastic process must be supported by theoretical considerations, rather than statistical tests. (Dixit and Pindyck 1994). Therefore, some researchers argue for this process, because it allows a long term equilibrium level accompanied by temporal fluctuations that is plausible for many economic variables (Musshoff 2012).
8. As with the number of leaves in a reduced scenario tree, the number of intervals is also a model parameter. Tests with an increasing number of intervals reveal that 100 intervals are an acceptable tradeoff between accuracy and execution time.

Data availability statement

The data and the code underlying this article are available in the Research Collection of ETH Zurich at https://doi.org/10.3929/ethz-b-000219189.

References

Abadi Gadim A.K. and Pannell D.J. (1999). A conceptual framework of adoption of an agricultural innovation. *Agricultural Economics*, 21: 145–54.

Ali W. (2009). *Modelling of biomass production potential of poplar in short rotation plantations on agricultural lands of Saxony, Germany*. Doctoral thesis at Technische Universität Dresden. Available at: http://nbn-resolving.de/urn:nbn:de:bsz:14-ds-1237199867841-24821 (Last access: 18.02.2018).

Alonso-Ayuso A., Carvallo F., Escudero L.F., Guignard M., Pi J., Puranmalka R. and Weintraub A. (2014). Medium range optimization of copper extraction planning under uncertainty in future copper prices. *European Journal of Operational Research*, 233: 711–26.

Bailey J.V. (1992). Are manager universes acceptable performance benchmarks? *The Journal of Portfolio Management*, 18: 9–13.

Barham B.L., Chavas J.-P., Fitz D., Salas V.R. and Schechter L. (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior & Organization*, 97 (January): 204–18.

Bartolini F. and Viaggi D. (2012). An analysis of policy scenario effects on the adoption of energy production on the farm: A case study in Emilia, Romagna (Italy). *Energy Policy*, Renewable Energy in China, 51 (December): 454–64.

Beraldi P., Violi A., De Simone F., Costabile M., Massabò I. and Russo E. (2013). A multistage stochastic programming approach for capital budgeting problems under uncertainty. *IMA Journal of Management Mathematics*, 24: 89–110.

Blandford D. and Hill B. (2006). *Policy Reform and Adjustment in the Agricultural Sectors of Developed Countries*. CABI Pub, Oxfordshire, Cambridge.

BMEL—Bundesministerium für Ernährung und Landwirtschaft (2015). *EU-Agrarpolitik - FAQ zur Agrarreform und der nationalen Umsetzung*. Available at: http://www.bmel.de/DE/Landwirtschaft/Agrarpolitik/_Texte/GAP-FAQs.html (Last access: 18.02.2018).

Bocquého G., Jacquet F. and Reynaud A. (2014). Expected utility or prospect theory maximisers? Assessing farmers' risk behaviour from field-experiment data. *European Review of Agricultural Economics*, 41: 135–72.

Bougherara D., Gassmann X., Piet L. and Reynaud A. (2017). Structural estimation of farmers' risk and ambiguity preferences: a field experiment. *European Review of Agricultural Economics*, 44: 782–808.

Brandão L.E. and Dyer J.S. (2005). Decision analysis and real options: A discrete time approach to real option valuation. *Annals of Operations Research*, 135: 21–39.

CAPRI—Common Agricultural Policy Regional Impact Analysis. (2017). Model documentation. Available at: http://www.capri-model.org/dokuwiki/doku.php?id=start (Last access: 25.01.2017).

Černý A. (2004). *Mathematical Techniques in Finance: Tools for Incomplete Markets*. Princeton, NJ: Princeton University Press.

Charness G., Gneezy U. and Imas A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization*, 87: 43–51.

Chavas J.-P. (2004). *Risk Analysis in Theory and Practice*. Elsevier Academic Press, San Francisco.

Chavas J.-P. and Shi G. (2015). An economic analysis of risk, management, and agricultural technology. *Journal of Agricultural and Resource Economics*, 40: 63–79.

Chronopoulos M. and Lumbreras S. (2017). Optimal regime switching under risk aversion and uncertainty. *European Journal of Operational Research*, 256: 543–55.

Crosetto P. and Filippin A. (2016). A theoretical and experimental appraisal of four risk elicitation methods. *Experimental Economics*, 19: 613.

de Mey Y., Wauters E., Schmid D., Lips M., Vancauteren M. and Van Passel S. (2016). Farm household risk balancing: empirical evidence from Switzerland. *European Review of Agricultural Economics*, 43: 637–62.

de Witte T. and Latacz-Lohmann U. (2014). *Was kostet das Greening? Topagrar*, 4/2014.

Dempster M.A.H. (2006). Sequential importance sampling algorithms for dynamic stochastic programming. *Journal of Mathematical Sciences*, 133: 1422–44.

Dentcheva D. and Ruszczynski A. (2003). Optimization with stochastic dominance constraints. *SIAM Journal on Optimization*, 14: 548–66.

Dentcheva D. and Ruszczyński A. (2006). Inverse stochastic dominance constraints and rank dependent expected utility theory. *Mathematical Programming*, 108: 297–311.

Dessart F.J., Barreiro-Hurlé J. and van Bavel R., (2019). Behavioural factors affecting the adoption of sustainable farming practices: a policy-oriented review. *European Review of Agricultural Economics*, 46: 417–71.

Diekmann A., Wolbert-Haverkamp M. and Musshoff O. (2014). *Die Bewertung der Umstellung einer einjährigen Ackerkultur auf den Anbau von Miscanthus: eine Anwendung des Realoptionsansatzes*. Working Paper. Available at: https://www.econstor.eu/handle/10419/97613 (Last access: 18.02.2018).

Dixit A.K. and Pindyck R.S. (1994). *Investment Under Uncertainty*. Princeton University Press, Princeton.
Du X., Yu C.L. and Hayes D.J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: a Bayesian analysis. *Energy Economics*, 33: 497–503.
El Karoui N. and Meziou A. (2006). Constrained optimization with respect to stochastic dominance: application to portfolio insurance. *Mathematical Finance*, 16: 103–17.
ETI—Brandenburgischen Energie Technologie Initiative. (2013). *Energieholz aus Kurzumtriebsplantagen*. Available at: http://www.eti-brandenburg.de/news/news-einzelseite/article/energieholz/ (Last access: 18.02.2018).
Faasch R.J. and Patenaude G. (2012). The economics of short rotation coppice in Germany. *Biomass and Bioenergy*, 45 (October): 27–40.
Finger R. (2016). Assessment of uncertain returns from investment in short rotation coppice using risk adjusted discount rates. *Biomass and Bioenergy*, 85: 320–6
Frey G.E., Mercer D.E., Cubbage F.W. and Abt R.C. (2013). A real options model to assess the role of flexibility in forestry and agroforestry adoption and disadoption in the Lower Mississippi Alluvial Valley. *Agricultural Economics*, 44: 73–91.
Gandelman N. and Hernandez-Murillo R. (2015). Risk Aversion at the Country Level. *Review*, 97: 53—66. Available at: https://ssrn.com/abstract=2646134 (Last access: 24.10.2018).
Gollmer R., Gotzes U. and Schultz R. (2007). Second-order stochastic dominance constraints induced by mixed-integer linear recourse. *Stochastic Programming E-print Series (SPEPS)* 2007 (June). Available at: http://edoc.hu-berlin.de/docviews/abstract.php?id=27962 (Last access: 08.02.2018).
Gollmer R., Neise F. and Schultz R. (2008). Stochastic programs with first-order dominance constraints induced by mixed-integer linear recourse. *SIAM Journal on Optimization*, 19: 552–71.
Guthrie G. (2009). *Real Options in Theory and Practice*. Oxford, UK: Oxford University Press.
Hardaker J. B., Richardson J. W., Lien G. and Schumann K. D. (2004). Stochastic efficiency analysis with risk aversion bounds: a simplified approach. *The Australian Journal of Agricultural and Resource Economics*, 48: 253–70.
Hazell P.B.R. (1971). A linear alternative to quadratic and semivariance programming for farm planning under uncertainty. *American Journal of Agricultural Economics*, 53: 53–62.
Heitsch H. and Römisch W. (2009). Scenario tree reduction for multistage stochastic programs. *Computational Management Science*, 6: 117–33.
Henderson V. and Hobson D.G. (2002). Real options with constant relative risk aversion. *Journal of Economic Dynamics and Control*, 27: 329–55.
Hill R.V. (2010). Investment and abandonment behavior of rural households: an empirical investigation. *American Journal of Agricultural Economics*, 92: 1065–86.
Hinrichs J., Musshoff O. and Odening M. (2008). Economic hysteresis in hog production. *Applied Economics*, 40: 333–40.
Homem-de-Mello T. and Pagnoncelli B.K. (2016). Risk aversion in multistage stochastic programming: A modeling and algorithmic perspective. *European Journal of Operational Research*, 249: 188–99.
Hugonnier J. and Morellec E. (2007). *Real options and risk aversion. Swiss Finance Institute Research Paper Series*, 2007 (September).
Iyer P., Bozzola M., Hirsch S., Meraner M. and Finger. R. (2020). Measuring farmer risk preferences in Europe: a systematic review. *Journal of Agricultural Economics*, 71: 3–26.
Jain M., Naeem S., Orlove B., Modi V. and DeFries R.S. (2015). Understanding the causes and consequences of differential decision-making in adaptation research: adapting to a delayed monsoon onset in Gujarat, India. *Global Environmental Change*, 31 (March): 98–109.
Just D. R. and Just R. E. (2016). Empirical identification of behavioral choice models under risk. *American Journal of Agricultural Economics*, 98: 1181–94.
Kahneman D. and Tversky A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, 47: 263–91.
Kallberg J.G. and Ziemba W.T. (2013). Comparison of alternative utility functions in portfolio selection problems. In: MacLeanm, L.C., Ziemba, W.T. (Eds.): *Handbook of the Fundamentals of Financial Decision Making*. World Scientific Publishing Co. Pte. Ltd., Singapore.
Karni E. (2006). Subjective expected utility theory without states of the world. *Journal of Mathematical Economics*, 42:3, 325–42.
Kassie M., Teklewold H., Jaleta M., Marenya P. and Erenstein O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in Eastern and Southern Africa. *Land Use Policy*, 42: 400–11.

King A.J. and Wallace S.W. (2012). *Modeling with Stochastic Programming*. Springer Science & Business Media, New York.

Kroeber M., Hank K., Heinrich J. and Wagner P. (2008). *Ermittlung der Wirtschaftlichkeit der Energieholzanbaua in Kurzumbetriebslantagen - Risikoanalyse mit Hilfe der Monte-Carlo-Simulation*. Paper prepared for presentation at the 48th GEWISOLA Conference, Bonn, Germany, September 24. Available at: http://core.ac.uk/download/pdf/6570052.pdf (Last access: 08.02.2018)

Krokhmal P., Zabarankin M. and Uryasev S. (2011). Modeling and optimization of risk. *Surveys in Operations Research and Management Science*, 16: 49–66.

KTBL—Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (2016). *Energiepflanzen : Daten für die Planung des Energiepflanzenanbaus* 2nd ed., KTBL, Darmstadt.

Kumar P. and Joshi P.K. (2014). Input subsidy versus farm technology — which is more important for agricultural development? *Agricultural Economics Research Review*, 27: 1–18.

Kuminoff N.V. and Wossink A. (2010). Why isn't more US farmland organic? *Journal of Agricultural Economics*, 61: 240–58.

Kuosmanen T. (2007). Performance measurement and best-practice benchmarking of mutual funds: combining stochastic dominance criteria with data envelopment analysis. *Journal of Productivity Analysis*, 28: 71–86.

Lence S.H. (2009). Joint estimation of risk preferences and technology: flexible utility or futility? *American Journal of Agricultural Economics*, 91: 581–98

Liu E.M. (2013). Time to change what to sow: risk preferences and technology adoption decisions of cotton farmers in China. *Review of Economics and Statistics*, 95: 1386–403.

Lowthe-Thomas S.C., Slater F.M. and Randerson P.F. (2010). Reducing the establishment costs of short rotation willow coppice (SRC)—A trial of a novel layflat planting system at an upland site in Mid-Wales. *Biomass and Bioenergy*, 34: 677–86.

Luedtke J. (2008). New formulations for optimization under stochastic dominance constraints. *SIAM Journal on Optimization*, 19: 1433–50.

Maart-Noelck S.C. and Musshoff O. (2013). Investing today or tomorrow? An experimental approach to farmers' decision behavior. *Journal of Agricultural Economics*, 64: 295–318.

Markowitz H. (1952). Portfolio selection. *The Journal of Finance*, 7: 77–91.

Marra M., Pannell D.J. and Abadi Ghadim A. (2003). The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: where are we on the learning curve? *Agricultural Systems*, 75: 215–34.

Meijer S.S., Catacutan D., Ajayi O.C., Sileshi G.W. and Nieuwenhuis M. (2015). The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in Sub-Saharan Africa. *International Journal of Agricultural Sustainability*, 13 40–54.

Menapace L., Colson G. and Raffaelli R. (2013). Risk aversion, subjective beliefs, and farmer risk management strategies. *American Journal of Agricultural Economics*, 95: 384–9.

Meraner M. and Finger R. (2017). Risk perceptions, preferences and management strategies: evidence from a case study using German livestock farmers. *Journal of Risk Research*, (July): 1–26.

Metcalf G.E. and Hassett K.A. (1995). Investment under alternative return assumptions comparing random walks and mean reversion. *Journal of Economic Dynamics and Control*, 19: 1471–88.

Meyer J. (1977). Choice among distributions. *Journal of Economic Theory*, 14: 326.

Meyer D.J. and Meyer J. (2005). Relative Risk Aversion: What Do We Know? *Journal of Risk and Uncertainty*, 31: 243–62.

Morgenstern O. and von Neumann J. (1953). *Theory of games and economic behavior*. Princeton university press.

Musshoff O. (2012). Growing short rotation coppice on agricultural land in Germany: a real options approach. *Biomass and Bioenergy*, 41 (June): 73–85.

Musshoff O. and Hirschauer N. (2004). Optimization under uncertainty with stochastic simulation and genetic algorithms – case study for a crop farm in Brandenburg. *Agrarwirtschaft*, 53: 264–79.

———. (2007). What benefits are to be derived from improved farm program planning approaches? – The role of time series models and stochastic optimization. *Agricultural Systems*, 95: 11–27.

Nie Y., Wu X. and Homem-de-Mello T. (2012). Optimal path problems with second-order stochastic dominance constraints. *Networks and Spatial Economics*, 12: 561–87.

Ogryczak W. and Ruszczynski A. (2002). Dual stochastic dominance and related mean-risk models. *SIAM Journal on Optimization*, 13: 60–78.

Pecenka R. and Hoffmann T. (2012). Harvest technology for short rotation coppices and costs of harvest, transport and storage. *Agronomy Research*, 13: 361–71.

Pe'er G., Zinngrebe Y., Hauck J., Schindler S., Dittrich A., Zingg S., Tscharntke T., Oppermann R., Sutcliffe L.M.E., Sirami C., Schmidt J., Hoyer C., Schleyer C. and Lakner S. (2017). Adding some green to the greening: improving the EU's ecological focus areas for biodiversity and farmers. *Conservation Letters*, 10: 517–30.

Pindyck R.S. (2004); Irreversibility, uncertainty, and investment. In Schwartz, E.S., Trigeorgis, L. (eds.): *Real Options and Investment Under Uncertainty: Classical Readings and Recent Contributions*. MIT Press, London.

Roman D., Darby-Dowman K. and Mitra G. (2006). Portfolio construction based on stochastic dominance and target return distributions. *Mathematical Programming*, 108: 541–69.

Rudolf G. and Ruszczyński A. (2008). Optimization problems with second order stochastic dominance constraints: duality, compact formulations, and cut generation methods. *SIAM Journal on Optimization*, 19: 1326–43.

Savage L.J. (1972). *The Foundations of Statistics*. 2nd ed. Dover Publications, New York.

Schulmerich M. (2010). Real options in theory and practice. In Schulmerich, M. (ed.): *Real Options Valuation*. Springer, Berlin, Heidelberg.

Schweier J. and Becker G. (2012). New Holland forage harvester's productivity in short rotation coppice: evaluation of field studies from a German perspective. *International Journal of Forest Engineering*, 23: 82–8.

———. (2013). Economics of poplar short rotation coppice plantations on marginal land in Germany. *Biomass and Bioenergy*, 59: 494–502.

Shapiro A. (2012). Minimax and Risk Averse Multistage Stochastic Programming. *European Journal of Operational Research*, Feature Clusters, 219: 719–26.

Simoglou C.K., Kardakos E.G., Bakirtzis E.A., Chatzigiannis D.I., Vagropoulos S.I., Ntomaris A.V., Biskas P.N., Gigantidou A., Thalassinakis E.J., Bakirtizis A.G. and Catalão J.P.S. (2014). An advanced model for the efficient and reliable short-term operation of insular electricity networks with high renewable energy sources penetration. *Renewable and Sustainable Energy Reviews*, 38 (October): 415–27.

Song F., Zhao J. and Swinton S.M. (2011). Switching to perennial energy crops under uncertainty and costly reversibility. *American Journal of Agricultural Economics*, 93: 768–83.

Spiegel A., Britz W. and Finger R. (2017). *A real-option farm-level model on investment in perennial energy crops under risk considerations*. Model documentation. Available at: https://doi.org/10.3929/ethz-b-000219189 (Last access: 08.02.2018).

Spiegel A., Britz W., Djanibekov U. and Finger R. (2018). Policy analysis of perennial energy crop cultivation at the farm level: Short rotation coppice (SRC) in Germany. *Biomass and Bioenergy*, 110: 41–56.

Spiegel A., Britz W., Djanibekov U. and Finger R. (2020). Stochastic-dynamic modelling of farm-level investments under uncertainty. *Environmental Modelling & Software*, 127, 104656.

StatA-MV—Statistisches Amt Mecklenburg-Vorpommern. (2016). *Statistic database*. Available at: http://www.statistik-mv.de/cms2/STAM_prod/STAM/de/ep/Regionaldaten%2c_Datenbanken/index.jsp (Last access: 02.08.2016).

Strohm K., Schweinle J., Liesebach M., Osterburg B., Rödl A., Baum S., Nieberg H., Bolte A. and Walter K. (2012). Kurzumtriebsplantagen aus ökologischer und ökonomischer Sicht. *Arbeitsberichte aus der vTI-Agrarökonomie* 06.

Sunding D. and Zilberman D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. In Hermalin, B., Weisbach, M. (eds.): *Handbook of Agricultural Economics*, Volume 1A. Elsevier, Amsterdam.

Trujillo-Barrera A., Pennings J.M.E. and Hofenk D. (2016). Understanding producers' motives for adopting sustainable practices: the role of expected rewards, risk perception and risk tolerance. *European Review of Agricultural Economics*, 43: 359–82.

Truong C. and Trück S. (2016). It's not now or never: implications of investment timing and risk aversion on climate adaptation to extreme events. *European Journal of Operational Research*, 253: 856–68.

van Winsen F., de Mey Y., Lauwers L., van Passel S., Vancauteren M. and Wauters E. (2016). Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. *Journal of Risk Research*, 19: 56–78.

WetterOnline. (2016). Database. Available at: http://www.wetteronline.de (Last access: 09.12.2015).

Wolbert-Haverkamp M. (2012). Miscanthus und Pappelplantagen im Kurzumtrieb als Alternative zum klassischen Ackerbau — eine Risikoanalyse mittels Monte-Carlo Simulation. *Berichte über Landwirtschaft*, 90: 302–16.
Wolbert-Haverkamp M. and Musshoff O. (2014). Are short rotation coppices an economically interesting form of land use? A real options analysis. *Land Use Policy*, 38 (May): 163–74.
Wossink A. and Gardebroek C. (2006). Environmental policy uncertainty and marketable permit systems: the Dutch phosphate quota program. *American Journal of Agricultural Economics*, 88: 16–27.

Appendix A: Assumed values of deterministic parameters of the model

SRC biomass growth function

We adapted the following yield function from Ali (2009):

$$Y = 2.27 * \left(-0.1133 * 10^{-8} * Dens^2 + 0.254 * 10^{-4} * Dens + 0.028\right)$$
$$* \left(1.569 * HI + 0.4 * 10^{-3} * PT * SQI - \frac{23.198 * Temp}{W}\right)^{\left(0.34 * 10^{-8} * Dens^2 - 0.501 * 10^{-4} * Dens + 2.614\right)} \quad \text{(A1)}$$

where Y represents dry matter yields (t ha^{-1}); *Dens* stands for density of trees (ha^{-1}); *HI* is possible intermediate harvesting interval: 2, 3, 4, or 5 (y); *PT* is average amount of precipitation in May-June (mm); *SQI* is soil quality index; *Temp* is average temperature in April–July (°C); and *W* is available ground water capacity (mm). We fixed all the variables except for the interval between harvests (Table A1) and fitted the values obtained to a linear function of available biomass in the previous year:

$$Y = 1.651 * Y_{-1} + 3.962 \quad \text{(A2)}$$

where Y_{-1} represents dry matter yields in the previous year (t ha^{-1}).

The model allows the interval between harvests to be adjusted or even transformed into a decision variable. In the latter case, tests revealed that a 5-year interval is usually the best. We used a fixed 5-year interval between harvests, in order to increase computational speed.

Comparison of model parameters with the evidence from the literature

Labor endowment and labor requirements only cover fieldwork and exclude management work, which is assumed to be fixed per farm and thus has no effect on resource distribution. The total land endowment of 100 ha is representative for northern Germany: for instance, in

Table A1. Parameters of the yield function and assumed values

Variables	Description	Values	References
Dens	density of trees, ha^{-1}	9,000	Musshoff (2012)
PT	average amount of precipitation in May and June, mm	106.27	The sum of mean averages Precipitation in May and June in the region Meckl. Seen (1995–2015) (WetterOnline, 2016)
SQI	soil quality index	35	Musshoff (2012)
Temp	average temperature in April–July,°C	14.51	Mean of average temperatures (the highest and the lowest during the day) in April–July in the region Meckl. Seen (1995–2015) (WetterOnline, 2016)
W	available groundwater capacity, mm	220	Musshoff (2012)

Table A2. Comparison of model parameters with the evidence from the literature

Parameter	Assumed value	Values found in the literature	Reference
SRC planting costs, € ha^{-1}	2,875.00	2,316.38	Kroeber *et al.* (2008)
		2,255.00–3,223.00	Strohm *et al.* (2012)
		3,199.92	Wolbert-Haverkamp (2012)
		2,380.00–3,223.00	ETI (2013)
		2,736.00	Wolbert-Haverkamp and Musshoff (2014)
Reconversion costs, € ha^{-1}	1,400.00	2,072.50	Faasch and Patenaude (2012)
		960.00–3,200.00	Strohm *et al.* (2012)
		1,800.00	Schweier and Becker (2013)
		1,121.00	Wolbert-Haverkamp and Musshoff (2014)
Gross margins of catch crops, € ha^{-1} y^{-1}	−100.00	–	de Witte and Latacz-Lohmann (2014, p.37)
		140.00−(−40.00)	

the federal state Mecklenburg-Western Pomerania 20 per cent of agricultural farms operated on an area of 50 to 200 ha (StatA-MV 2016).

Appendix B: Estimation of a mean reverting process for gross margins of annual crops

The following data for gross margins of arable land were used CAPRI (2017):

The Dickey-Fuller test implies non-stationary. However, we allow for economic considerations and assume a stationary mean-reverting process (MRP), based on the assumption that a farmer is price-taker in an environment where market forces cause the gross margins to fluctuate around a constant long-term level (Metcalf and Hassett 1995, p.1472) and/or constant technology (Song *et al.* 2011, p.775). We derive parameters of the MRP following the procedure and formulas described in Musshoff and Hirschauer (2004).

Table B1. Gross margins and their natural logarithms used for estimation of stochastic process for gross margins of annual crops

Year	1993	1994	1995	1996	1997	1998	1999
Gross margins (GM), € ha^{-1}	277.90	287.88	268.23	360.32	348.16	339.33	312.84
Natural logarithm of GM	5.63	5.66	5.59	5.89	5.85	5.83	5.75
Year	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
Gross margins (GM), € ha^{-1}	281.46	356.42	268.33	237.25	355.15	268.85	312.25
Natural logarithm of GM	5.64	5.88	5.59	5.47	5.87	5.59	5.74
Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	
Gross margins (GM), € ha^{-1}	588.97	516.79	379.15	518.40	680.44	662.92	
Natural logarithm of GM	6.38	6.25	5.94	6.25	6.52	6.50	