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Investment and land-use decision under consideration of uncertainty

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Abstract

Investment and land use decisions pre-determine the distribution of other farm resources and thus constitute core farm activities. Investments at the farm level often include sunk costs, risks, returns-to-scale, investment options of predefined sizes, and multiple stages of investment. Considering these factors is crucial for improving understanding of the economic incentives and disincentives to invest at the farm level and appropriate design of related policy. However, existing numerical methods of investment analysis fail to capture all the listed factors simultaneously due to explicit or implicit restrictions.

This thesis narrows this methodological gap by developing a numerical method to analyze investment options at the farm level. The method is applied to decision making with regard to investing in a perennial energy crop production system—short-rotation coppice (SRC)—on a representative farm in Germany. The investment option implies all of the attributes listed above. Furthermore, empirical analysis of SRC adoption exclusively for biomass production is relevant in light of increasing renewable energy demand. SRC is characterized by multiple environmental benefits relative to other forms of agriculture and offers a more efficient energy generation option compared to annual bioenergy crops. For a farmer, SRC is advantageous due to low input requirements, potential natural hedging, and broad political support. In addition, timing of SRC biomass production is not predetermined and to some extent flexible, such that there is potential to adjust any decision based on how future conditions evolve. Yet, farmers in the European Union have been reluctant to adopt SRC and the literature provides no clear explanation. The empirical aim of this research is hence to quantify the economic incentives and disincentives for German farmers to adopt SRC under consideration of risk levels and preferences, and to provide relevant policy recommendations.

To simulate SRC introduction at the farm level, I design a stochastic-dynamic model and develop a novel solution approach that combines Monte Carlo simulation, scenario tree reduction, and stochastic programming. A scenario tree reduction technique uses draws obtained with Monte Carlo simulation and outputs a scenario tree, which is then combined with a farm-level model. Restrictive assumptions commonly made in the literature are relaxed. In particular, a farmer can either decide to introduce SRC immediately or else postpone the decision; also, coppicing intervals and the total lifetime of SRC plantation are flexible. Potential adoption of SRC is formulated as an American compound option, where planting, each coppicing or biomass harvest, and final reconversion back to annual crop production are stages of the compound option. SRC competes for limited farm resources with annual crop production, while returns from both SRC and annual crops are stochastic. The outcome hence includes not only optimal timing, but also optimal scale of SRC introduction. Risk aversion is introduced using the concept of stochastic dominance. The method developed and demonstrated here is transparent, allows relaxing assumptions, and does not hamper computational capacity. It is a rather general instrument for the analysis of long-term investment options under conditions of uncertainty and risk preferences, and hence is of interest far beyond the specific context described in this case study.

Empirical results demonstrate that SRC cannot compete with annual crop production under current market conditions and that individual farmers wait for a certain trigger or state-of-nature in order to adopt SRC. A risk-averse farmer might decide to introduce SRC earlier, though at a smaller scale, in order to take advantage of the potential natural hedging effect. The results indicate that some level of risk is associated with increased SRC introduction due to the benefits associated with the managerial flexibility inherent to SRC cultivation. In particular, flexible timing with respect to establishment, coppicing, and final reconversion allows farmers to exploit positive risks and mitigate negative ones. In this regard, policy instruments intended to reduce or eliminate risk associated with SRC cultivation were found to be inefficient. In contrast, currently implemented policies that help reduce the sunk costs and opportunity costs of SRC introduction are more efficient at promoting adoption, although the results suggest that such instruments need to be modified in order to be more effective, because otherwise farmers are more likely to postpone making decisions about SRC introduction. The empirical results of the ex-ante analysis conducted here should serve as a basis for higher level analyses and related policy recommendations.

Keywords: Farm-level simulation modelling; technology adoption; real options; American compound option; stochastic programming; risk analysis; risk preferences; risk perception; perennial energy crop.

Zusammenfassung

Entscheidungen über Investitionen und Landnutzung beeinflussen die zukünftige Allokation von Betriebsressourcen und sind daher eine zentrale Aufgabe im landwirtschaftlichen Betrieb. Investitionen in der Landwirtschaft umfassen versunkene Kosten, Risiken, Skalenerträgen, nicht teilbare Investitionsmöglichkeiten und mehrstufige Investitionsentscheidungen. Für ein besseres Verständnis der Anreize für Investitionen sowie zur Ableitung geeigneter Politikmaßnahmen müssen diese Faktoren daher berücksichtigt werden, doch numerische Methoden der Investitionsanalyse scheitern aufgrund expliziter und impliziter Restriktionen, diese in Gänze zu erfassen.

Eins der Ziele der vorliegenden Dissertation ist es, diese methodische Lücke zu schließen. Dafür wird ein neuartiger numerischer Ansatz zur Investitionsanalyse entwickelt und für die Analyse einer Investitionsentscheidung eines landwirtschaftlichen Betriebs in Deutschland bezüglich mehrjähriger Energiepflanzen auf Kurzumtriebsplantagen (KUP) verwendet. KUP, welche alle zuvor genannten Charakteristika aufweisen, werden ausschließlich zur Gewinnung von Biomasse verwendet und sind daher angesichts des steigenden Energiebedarfs von besonderer Bedeutung. KUP bieten dabei in vielerlei Hinsicht Vorteile für die Umwelt und ermöglichen eine effizientere Energieerzeugung als einjährige Energiepflanzen. Für den Landwirt ist eine solche Investition aufgrund des geringen Faktoreinsatzes, als potenzieller natürlicher Risikoabsicherung und wegen ihrer politischen Unterstützung vorteilhaft. Des Weiteren erlaubt der Anbau mit KUP eine hohe zeitliche Flexibilität und ermöglicht dem Landwirt so eine Anpassung seiner Entscheidungen in Abhängigkeit der eingetretenen Umweltzustände. Dennoch wird die KUP bisher nur zurückhaltend in der EU eingesetzt, und die Fachliteratur zeigt kein eindeutiges Bild. Das empirische Ziel dieser Dissertation ist es daher, die ökonomischen Anreize deutscher Landwirte bezüglich des Einsatzes der KUP unter Beachtung von Risiko und Risikopräferenzen zu quantifizieren und politische Empfehlungen zu erarbeiten.

Für die Simulation der Entscheidung eines Ackerbaubetriebs über die Investition in KUP entwerfe ich ein stochastisch-dynamisches Modell und entwickele einen neuartigen Lösungsansatz, der Monte-Carlo-Simulationstechniken, Verkleinerung von Szenariobäumen und stochastischer Programmierung kombiniert. Die Monte-Carlo-Ziehungen dienen als Basis für einen Szenariobaum, der bis zu der gewünschten Anzahl den Blättern verkleinert und mit dem Modell auf der Ebene eines

Landwirtschaftsbetriebs kombiniert wird. Dies erlaubt es, die dem Modell zu Grunde liegenden Annahmen zu reduzieren. So kann im Modell der Landwirt sofort in die KUP investieren, oder aber die Entscheidung verschieben; auch Ernterhythmus und Abschlusskahlschlag sind flexibel. Die potenzielle Nutzung der KUP ist als zusammengesetzte Amerikanische Option modelliert, wobei Anbau, jede Ernte und Abschlusskahlschlag jeweils eine Option darstellen. Die Betriebsressourcen werden zwischen den KUP und den vorhandenen Ackerkulturen aufgeteilt, dabei sind die Rendite der KUP und der vorhandenen Ackerkulturen stochastisch. Das Modell zielt daher nicht nur auf die optimale zeitliche Planung, sondern auch auf den optimalen Umfang der KUP-Einführung ab. Risikoaversion wird mittels stochastischer Dominanz abgebildet. Der zur Lösung dieses Modells neu entwickelte Ansatz ist transparent und erlaubt die Lockerung restriktiver Annahmen ohne zusätzlichen Rechenaufwand. Die vorgeschlagene Methode kann darüber hinaus vielseitig für die Analyse von langfristigen Investitionen unter Betrachtung von Risiko eingesetzt werden und ist daher über die Fallstudie hinaus von Interesse.

Die empirischen Ergebnisse zeigen, dass KUP unter den aktuellen Marktbedingungen nicht konkurrenzfähig gegenüber konventionellen Ackerkulturen sind, und Landwirte auf einen Trigger-Umweltzustand warten bevor sie investieren. Des Weiteren wird gezeigt, dass ein risikoaverser Landwirt die KUP zwar früher, jedoch in kleinerem Umfang anbauen sollte, um die potenzielle natürliche Risikoabsicherung zu nutzen. Risiko stellte sich dabei als vorteilhaft heraus, weil die Flexibilität von Anbau, Ernte und Kahlschlag es erlauben, positive Risiken ausnutzen und negative Risiken zu lindern. Demzufolge sind Politikmaßnahmen zur Risikoreduktion ineffektiv. Aktuelle Politikmaßnahmen, welche auf Kostensenkung abzielen und sowohl versunkene als auch Opportunitätskosten berücksichtigen, sind zwar deutlich effektiver, benötigen jedoch Korrekturen, da sonst ein späterer KUP-Anbau unterstützt wird. Die vorliegenden empirischen Ergebnisse können als Basis für Analysen auf oberen Ebenen und für Politikempfehlungen dienen.

Schlagwörter: Simulationsmodell auf einzelbetrieblicher Ebene; Einführung von Technologie; Realoptionsanalyse; Amerikanische zusammengesetzte Option; stochastische Programmierung; Risikoanalyse; Risikopräferenz; Risikowahrnehmung; mehrjährige Energiepflanzen.

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Abbreviations and symbols

ABM	Arithmetic Brownian motion
BAU	Business as usual
BMEL	Bundesministerium für Ernährung und Landwirtschaft (Ger.; Eng. - Federal Ministry of Food and Agriculture)
BMWi	Bundesministerium für Wirtschaft und Energie (Ger.; Eng. - Federal Ministry for Economic Affairs and Energy)
CAP	Common agricultural policy
CAPRI	Common agricultural policy regionalized impact
DESTATIS	Statistische Bundesamt (Ger.; Eng. – Federal Statistical Office)
DM	Dry matter yields
€	Euro
ECB	European Central Bank
ECN	Energy Research Centre of the Netherlands
EEG	Erneuerbare-Energien-Gesetz (Ger.; Eng. - German Renewable Energy Act)
EFA	Ecological Focus Area
ETI	Brandenburgische Energie Technologie Initiative (Ger.; Eng. - Brandenburg Energy Technology Initiative)
EU	European Union
FNR	Fachagentur Nachwachsende Rohstoffe e.V. (Ger.; Eng. - Agency of Renewable Resources)
FSD	First-order stochastic dominance

FVH	Fachverband Holzenergie (Ger.; Eng. – Wood Energy Trade Association)
GAMS	General Algebraic Modeling System
GBM	Geometric Brownian motion
GHG	Greenhouse gas
GIS	Geographic Information System
GUI	Graphical User Interface
h	Hour
ha	Hectare
IBM	International Business Machines Corporation
IRENA	International Renewable Energy Agency
ISSD	Inverse second-order stochastic dominance
KTBL	Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (Ger.; Eng. - Board of trustees for Technology and Building in Agriculture)
km^2	Square kilometer
LSMC	Least Squares Monte Carlo
MLU-MV	Ministerium für Landwirtschaft und Umwelt des Landes Mecklenburg-Vorpommern (Ger.; Eng. - Ministry of Agriculture and the Environment of the State of Mecklenburg-Western Pomerania)
MOTAD	Minimization of total absolute deviations
MRP	Mean-reverting process
NER	Net energy ratio
NPV	Net present value

ROA	Real options approach
SRC	Short rotation coppice
SSD	Second-order stochastic dominance
StatA-MV	Statistisches Amt des Landes Mecklenburg-Vorpommern (Ger.; Eng. - Statistical office of the State of Mecklenburg-Western Pomerania)
t	Tonne
UK	United Kingdom
USA	United States of America
y	Year

Chapter 1

Introduction and overview of the thesis

1.1. Problem background

Investments and land-use decisions pre-determine the distribution of other farm resources and thus constitute core farm activities. The classical net present value (NPV) approach to investment analysis has been criticized for placing decisions in a "now-or-never" context and ignoring investment irreversibility (Regan et al. 2015, p. 145). In this regard, the alternative real options approach (ROA) takes into account the possibility to postpone or subsequently adjust investments and is considered a more appropriate approach (*ibid.*). Despite the explanatory advantage of ROA over the classical NPV approach, characteristics of actual large-scale investment projects often fail to fit well with the explicitly or implicitly inherent restrictions of existing numerical real options valuation methods (Trigeorgis and Reuer 2017). Complexity is induced by sunk costs, risks, returns-to-scale, investment options of predefined sizes, and multiple stages of investing. A case study of the adoption of a perennial energy crop production system on an arable farm in Germany is featured as an illustrative example of a large-scale complex investment option.

Worldwide, biomass energy is considered a crucial component of targeted renewable energy portfolios (IRENA 2017, pp. 64–67) due to its dispatchability (i.e., the ability to produce and store energy when and where it is needed) (Thiffault et al. 2016, p. 174). Perennial energy crops, and in particular sustainable biomass energy production systems such as short-rotation coppice (SRC) have gained interest since the oil crisis of the mid-1970s (Guidi and Labrecque 2013, p. 424) and remain relevant in light of increasing energy demand, particularly increasing demand for renewable energy. Compared to annual energy crops, perennials are advantageous in multiple dimensions, including greenhouse gas (GHG) emission reduction (Lewandowski 2015, p.35), soil erosion reduction (Rokwood 2014, pp. 5–6; Adams and Lindegaard 2016, fig. 1), and increasing soil fertility (Tolbert et al. 2002, p. 105). The estimated net energy ratio[1] (NER) of SRC using willow species ranges between 9.900 (Keoleian and Volk 2005, p. 395) and 52.000 (Heller et al. 2003, p. 160), compared to 2.100–2.600 for maize used for bioenergy production (Eder et al. 2009, p. 718) and 0.313–0.341 for coal (Keoleian and Volk 2005, p. 395). Moreover, SRC is suitable for soils of variable productivity and thus can be planted on marginal lands unsuitable for other crops (Bringezu et al. 2010, p. 76). Lindegaard et al. (2016, p. 5) provide a comprehensive overview of the advantages of SRC and its market in the European Union (EU).

Due to positive environmental effects and efficient bioenergy generation from SRC systems, there have been a number of regional and national policies implemented to support SRC production. Lindegaard et al. (2016) provide an overview of the history of policy support of SRC in the EU. Current policy instruments intended to promote perennial energy crops can be classified as: (i) cross-sector instruments, including quotas and taxes on fossil energy sources (Mitchell 2000); (ii) investment in research (Witzel and Finger 2016; Bacovsky et al. 2016); and (iii) farm-level instruments. The latter category includes establishment subsidies (e.g., as currently practiced in Germany and Sweden, and in the past in Ireland, Poland, and the United Kingdom) (Lindegaard et al. 2016, p. 2); or qualifying land under SRC as suitable for

[1] Net energy ratio is calculated as energy output divided by the amount of fossil energy required for production (Keoleian and Volk 2005, p. 386). Consequently, the higher the NER the more efficient energy generation is.

"Ecological Focus Area" (EFA)[2] requirements (e.g., as in France, Germany, the Netherlands, Italy and other European countries) (Hart 2015, p. 5).

Different species, varieties, and clones can be cultivated using SRC, including willow (*Salix* spp.), poplar (*Populus* spp.), black locust (*Robinia pseudoacacia L.*), and alder (*Alnus* spp.) (Dimitriou and Rutz 2015, pp. 21–28). Once planted with fast-growing trees, SRC systems can be coppiced several times without replanting. Planting of SRC systems might occur in either March/April or September/October; coppicing is performed in November-March at intervals of at least two years (KTBL 2012). Planting and coppicing activities are usually outsourced (Musshoff 2012). There are several harvest methods with different costs that depend on the desired end product and harvest interval. The common end product in Germany—wood chips (Keutmann et al. 2016, p. 315)—typically involves a harvest interval of two to five years (KTBL 2012). The last harvest should take place at approximately 20 years due to legal restrictions. For instance, in Germany, reconversion of land under SRC back to annual crop production is legally complicated if SRC has been cultivated for longer than 20 years (Federal Forests Act 1975). An extensive overview of SRC cultivation and management practices can be found in Nassi O Di Nasso et al. (2010), KTBL (2012), and Dimitriou and Rutz (2015). There are multiple uses for wood chips, including usage in small- and large-scale heating systems and power plants, processing into pellets, and supplying material for biorefinery processes (Dimitriou and Rutz 2015, p. 62).

To this end, SRC seems attractive for farmers due to low or zero labor input requirements and existing policy support. Although SRC binds land resources for a long term period, it also allows flexible time management, meaning that a farmer can exercise planting, coppicing, and final reconversion back to annual crops depending on future conditions. Nevertheless, farmers are often reluctant to adopt SRC. For instance, in Germany (von Wühlisch 2016; Parra-López et al. 2017, p. 784); Scotland (Warren et al. 2016); Sweden (Dimitriou et al. 2011); and Spain (Parra-López et al. 2017, p. 786) SRC adoption rates are much lower than anticipated. In Sweden approximately

[2] According to the latest Common Agricultural Policy (CAP) reform, large arable farms are required to manage 5% of their land as "Ecological Focus Areas" (EFA), which SRC partially qualifies as.

130–160 km^2 of SRC are currently cultivated, representing the largest area among the EU countries (Mola-Yudego and González-Olabarria 2010). In the UK around 100 km^2 are currently dedicated to energy crops, including SRC and *Miscanthus* spp. production systems, while estimated land capacity for biomass energy production is 9,300–36,300 km^2 (DECC 2013, p. 28). The existing policy support indicates the social aim to encourage SRC adoption. This thesis does not analyze the validity or relevance of the social aim, but rather contributes to its achievement and seeks to quantify farm-level incentives and disincentives to adopt SRC under conditions of uncertainty. In particular, a simulation model based on ROA is designed and valuated. Restrictive assumptions typically made in the literature are relaxed, disabling existing real option valuation methods. Hence, a novel solution approach that combines Monte Carlo simulation, scenario tree reduction, and stochastic programming was developed.

1.2. State of the art

Farm-level decisions regarding SRC adoption are tempered by the fact that it represents a long-term investment option. Yet, the literature provides ambiguous conclusions with respect to the profitability of such investments. Out of 37 relevant studies, 43% report economic viability of SRC; 19% report economic disadvantages; and 38% mixed results (Hauk et al. 2014). The diversity of these conclusions can be explained not only by the different contexts and assumptions made among individual studies, but also by the different theoretical frameworks applied which are discussed below. In the following assessment, the focus is restricted to quantitative investment analysis. Most of the qualitative research efforts on SRC cultivation are based on farm surveys (Smith et al. 2011; Glithero et al. 2013). These have revealed that SRC adoption at the farm level is determined by individual characteristics of the farmer (e.g., attitudes, gender, and work status); farm characteristics (e.g., size of the farm, land use, soil quality, availability of required machinery); as well as characteristics of individual investment options (e.g., required costs and schedule of cash flows). Allen et al. (2014, p. iv) point out that the major factors influencing SRC adoption are economic ones. In particular, costs of planting and harvesting, being irreversible and accounting for about 66% of total costs (Lowthe-Thomas et al. 2010), have the greatest impact on farmer's willingness to adopt SRC. Due to currently observed reluctance of farmers to adopt SRC and hence lack of required data, the focus of the thesis is further restricted to simulation models, leaving empirical econometric models out.

1.2.1. Risk-neutral farm-level investment analysis

Classical investment theory has been most frequently used to analyze the economy of SRC cultivation (Lothner et al. 1986; Strauss et al. 1988; Gandorfer et al. 2011; Schweier and Becker 2013). These research efforts are mainly devoted to the North American countries (Lothner 1991; McKenney et al. 2011) and Europe (Bergez et al. 1991; Ericsson et al. 2006; Gasol et al. 2010), including Germany (Kroeber et al. 2008; Schweier and Becker 2013). Since the approach doesn't allow postponing the decision to adopt SRC (i.e., assuming that implementation of SRC is only possible on a "now-or-never" basis and hence overestimating conversion triggers) (Wolbert-Haverkamp and Musshoff 2014, p. 164), its relevance for the analysis of SRC adoption is highly questionable.

The ROA is often portrayed as taking into account the possibility of postponing investment decisions. More generally, it acknowledges flexibility in future management, depending on how the decision environment evolves, where waiting to adopt SRC is just one option. The ROA is favored over the classical deterministic analysis for investment projects in agriculture, especially in the presence of production and market risk, since farmers can adjust their management to future states-of-nature. Should, for instance, output prices increase or decrease, farmers might adjust their crop portfolio, herd sizes, planned investments or even terminate their operations. Moreover, in reality farmers consider the potential for future flexibility when making investment decisions. Hence, considering future flexibility not only contributes to a better understanding of farm-level decisions, but also typically leads to different and often more plausible economic indicators of interest, such as the expected NPV and its distribution, when investment projects are considered. There are different types of real options defined in the literature, yet, SRC adoption is usually modelled as a (compound) American option, meaning that the option (or each stage of the option if compound) can be exercised at any time point prior to the expiration date[3] or never exercised (Cetinkaya and Thiele 2014).

Valuation of a (compound) American option is far from trivial. Closed-form solutions to real option problems (Black and Scholes 1973; Geske and Johnson 1984) are elegant from a scholarly perspective, but often require assumptions (e.g., about stochastic processes) that are too restrictive for complex real-world examples. Moreover, large investment projects in agriculture typically lead to manifold changes in the way farms are managed. An extension of a farm operation not only requires physical capital, but also has effects on farm production and input use, which in turn require expansion of farm endowments or changes in management. Without considering these consequences, an accurate evaluation of the investment project is not feasible. In this regard, a numerical method is likely to yield better results (Fig 1.1). In what follows, the focus is on the methods of approximating stochastic processes, since methods approximating differential equations were initially designed and are well suited for the valuation of simple European options (Regan et al. 2015, p. 146).

[3] Compare with a European option that can be exercised at the expiration date only or never exercised.

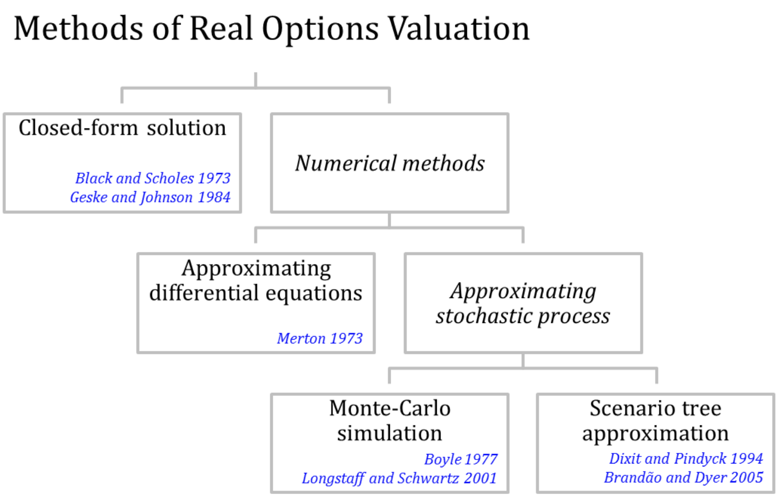

Figure 1.1. Classification of real options valuation methods

Source: based on Cetinkaya and Thiele (2014, p. 12)

Although there are numerous examples of valuating real options for different types of investment problems with methods for approximating stochastic processes (Sagastizábal 2012; Beraldi et al. 2013; Feng and Ryan 2013; Alonso-Ayuso et al. 2014; Simoglou et al. 2014; Tee et al. 2014; van Ackooij and Sagastizábal 2014), its application for the analysis of farm-level adoption of a perennial energy crop or related production system is rather limited. Song et al. (2011) simulated switching from soy production to perennial switchgrass on a representative farm in the USA. The model is based on the real options approach and solved using stochastic programming. However, the analysis is performed on an area basis, meaning that farm-level constraints and requirements are not considered. The same restrictive assumption is made by Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014). Both studies analyzed introducing SRC poplar production on a representative farm in northern Germany. Option valuation is performed using Monte Carlo simulation. Both models are designed on an area basis and assume fixed coppicing intervals. In addition, Musshoff (2012) assumes a fixed plantation lifetime, hence converting a potential compound option into a simple American option. Such restrictive assumptions are also made beyond the analysis of investments in perennial energy crops and related production systems. In particular, a binomial (Guthrie 2009) or trinomial scenario tree is usually involved for the sake of simplicity (Flaten and Lien 2007; Alonso-Ayuso et al. 2014). Since such scenario trees explode in values and the number of leaves as time horizons increase, the number of time periods are restricted (e.g., by aggregating the time periods down to the desired number) (Bartolini and Viaggi 2012; Feng and Ryan 2013). To this end, in order to improve on previous economic assessments of SRC and capture on-farm interaction of SRC with other activities, this thesis seeks to develop a model based on real options and simultaneously relax common restrictive assumptions.

1.2.2. Introducing risk preferences and considering subjective risk perception

An option value to wait also exists under risk neutrality, since postponing a decision might increase overall returns regardless of risk preferences (Dixit and Pindyck 1994, p. 153); risk neutrality is therefore a common assumption in existing real options applications (Wossink and Gardebroek 2006; Wang and Tang 2010; Song et al. 2011). Yet, many empirical studies found that farmers in Europe are risk-averse (e.g., Menapace et al. 2013; Meraner and Finger 2017).

The literature provides examples of different methods of introducing risk preferences into stochastic programming that vary according to the underlying assumptions about risk and risk preferences. Musshoff (2012) and Wolbert-Haverkamp and Musshoff (2014) introduce risk preferences using a risk-adjusted discount rate. This is a rather straightforward method; however for a proper evaluation the discount rate should be re-adjusted each time period, as risk decreases when approaching the leaves of the scenario tree. In addition, different risk-adjusted discount rates should be applied to farm activities of variable risk (Brandão and Dyer 2005; Finger 2016). The expected utility approach, based on the von Neumann-Morgestern utility function, is another option. An analytical solution is provided by Henderson and Hobson (2002) and Hugonnier and Morellec (2007); application to farm optimization can be found in Hardaker et al. (1988). Yet, the approach requires very strong assumptions, such as formulating a risk utility function or estimating a risk aversion coefficient. Another approach is the concept of stochastic dominance, which is also based on maximization of expected utility without requiring its explicit formulation. In particular, first-order stochastic dominance (FSD) only requires that the underlying von Neumann-Morgestern utility function be monotonic; second-order stochastic dominance (SSD) additionally requires it to be concave (i.e., that a decision maker is risk-averse). Pure FSD and SSD methods might substantially undermine computational efficiency, since they require introducing a number of additional binary variables into the model (Gollmer et al. 2007; 2008). In order to overcome these technical issues, some approaches that imply relaxed stochastic dominance were proposed (Dentcheva and Ruszczynski 2003; 2006). Mean-variance analysis[4], initiated by Markowitz (1952), minimizes risk (i.e., variance) for a given expected outcome, or maximizes the expected outcome for a given variance. The approach requires the underlying utility function to be quadratic (Tauer 1983, p. 606) and is consistent with SSD if the risk measure (e.g., returns) is normally distributed (Krokhmal et al. 2011, p. 52). Non-linearity might quickly lead to a computationally challenging model. In order to gain a computational advantage, a linear version—minimization of total absolute deviations (MOTAD)—has been proposed by Hazell (1971), which is consistent with mean-variance analysis and hence with SSD, if the risk measure is normally distributed. Robison and Brake (1979) examine the application of the mean-variance approach in a farm context.

Finally, another class of approaches differentiates between positive and negative risks. These include safety first (Roy 1952; Telser 1955), the minimax approach (Dupačová 1966), lower partial moments (Fleten et al. 2002), and conditional Value-at-Risk—one of the most popular approaches in the literature (Kaya et al. 2011; Lim et al. 2011; Beraldi et al. 2013; Homem-de-Mello and Pagnoncelli 2016). Those models relax the continuity assumption of the underlying utility function. For instance, conditional Value-at-Risk is defined as the expected value of losses below a threshold (Rockafellar and Uryasev 2000). The main challenge, however, is to choose an appropriate threshold (i.e., setting up criteria to distinguish downside risk).

In contrast to risk preferences, the significance of subjective risk level of an investment option has barely been studied (Meijer et al. 2015) and the few existing findings are ambiguous (Jain et al. 2015; Trujillo-Barrera et al. 2016; van Winsen et al. 2016). The literature on the joint effect of risk preferences and subjective risk perception is even more limited. Yet, subjective risk perception often differs from objective risk levels of the investment project

[4] Also known as the modern portfolio theory.

derived ex-post (Liu 2013; Menapace et al. 2013; Bocquého et al. 2014), especially for a novel investment option, like SRC, whose risk might be hard to determine due to a lack of experience and related knowledge (Bougherara et al. 2017, p. 803). A decision maker, however, behaves according to her subjective beliefs (Savage 1972; Marra et al. 2003; Karni 2006).

1.3. Research questions

Based on the literature review, the following gaps have been identified. First, the existing empirical results of investment analysis of SRC are controversial and do not explain the observed reluctance of German farmers towards SRC adoption. Second, although real options is favored over the classical deterministic analysis in terms of explanatory power, existing models simulating SRC adoption at the farm level based on real options are limited due to implicit or explicit restrictions. At the same time, relaxing the commonly made restrictive assumptions hampers the existing real options valuation methods. Finally, introducing risk aversion into a real option model is in line with the empirical results of farmers' risk preferences in Europe, but often either requires further assumptions or leads to a computationally challenging model.

The research aim is thus twofold. The empirical research aim is to assess SRC as a farm-level investment option and provide policy recommendation for SRC promotion. In particular, it includes analysis of farm-level decisions regarding SRC cultivation, coppicing, and reconversion to annual crops, including consideration of risk preferences; and quantification of required market interventions in order to promote SRC cultivation. The methodological aim is to develop a numerical method to analyze such complex investment options at the farm level. To this end, the following research questions and sub-questions are addressed:

Q1: Can SRC compete with other crops and production systems under consideration of risks and farm constraints?

Q1.1. How to capture competition between SRC and other crops and production systems for limited on-farm resources, including environmental requirements, in a stochastic environment?

Q1.2. How to capture potential economies of scale implied by SRC cultivation?

Q1.3. How to solve compound American real options, considering the total number of stages (i.e., the number of intermediate coppicing and overall time horizon or lifetime of SRC plantations), as decision variables?

Q1.4. How do observed stochastic variable values influence optimal decisions regarding the timing and scale of SRC adoption?

Q2: What policy instruments are most effective in promoting SRC adoption at the farm level?

Q2.1. What is the capacity of a policy instrument in terms of additional SRC bioenergy production?

Q2.2. How much governmental cost does a policy instrument require relative to additional bioenergy production?

Q2.3. What benefits or losses to individual farmers does a policy instrument imply?

Q2.4. How does a policy instrument affect optimal timing of SRC adoption?

Q3: How consideration of (subjective) risk levels and risk preferences influence farm-level decisions regarding SRC adoption?

Q3.1. How can risk preferences be accounted for in stochastic programming making limited behavioral assumptions?

Q3.2. How do risk preferences affect optimal scale of SRC adoption?

Q3.3. How do risk preferences affect optimal timing of SRC adoption?

Q3.4. How does (subjective) risk perception affect the optimal scale of SRC adoption?

Q3.5. How does (subjective) risk perception affect optimal timing of SRC adoption?

1.4. Contribution

The research questions listed above are answered using a farm-level model based on real options and solved with a combination of Monte Carlo simulation and stochastic programming. The model allows introduction of multiple risks and risk preferences, as well as considering economy of scale, farm-level resource endowments, and other restrictions. It solves for optimal timing and scale of SRC adoption and quantifies interactions between SRC and other farm activities. The complete model and all related documentation are available in Spiegel et al. (2017) (also see Annex 1). A description and development of the model, as well as different analyses are described in Chapters 2–4 and Conclusions are drawn in Chapter 5.

First, the focus is on solving a compound American option employing a combined stochastic programming, Monte Carlo simulation, and scenario tree reduction technique (Chapter 2). The proposed approach can be summarized into four main steps. First, the decision variables of the problem are defined. Second, the relations among these decision variables are established and combined into a deterministic programming model. Third, based on an appropriate distribution for stochastic parameter(s), Monte Carlo simulation scenarios are run, and a reduced scenario tree is constructed by employing a scenario tree reduction technique. A scenario tree reduction technique[5] picks representative nodes and assigns probabilities to them, approximately capturing the distribution in the original tree[6]. Graphically, one could imagine the algorithm as lumping together neighboring nodes and branches in the tree to bigger ones, where the thickness represents probability mass. At the final step, stochastic programming is employed for the real options valuation outputting both optimal timing and the depth of exercising options (Q1.1, Q1.3). Farmer decisions regarding SRC adoption are formulated as a compound American option, where planting, intermediate harvests, and final

[5] There exist different methods of generating a scenario tree; all of them can be summarized as aggregating nodes and stages, and trimming or refining trees.

[6] In the model designed the thesis, the original scenario tree is the one constructed with the Monte Carlo simulation.

reconversion are the option stages, such that the total number of stages and the total time horizon are decision variables (Q1.3). Other decision variables include optimal timing and scale of SRC systems and harvests. An individual farmer is assumed to maximize expected NPV under two types of constraints: resources endowments and environmental requirements. Limited resources—land and labor—are distributed between SRC, two types of annual crops, and set-aside land; the latter being introduced in order to fulfill EFA requirements (Q1.1). Economy of scale related to SRC is captured by a harvest cost function that differentiates between fixed (per farm), quasi-fixed (per hectare harvested), and variable (per tonne of harvested biomass) costs (Q1.2). For the sake of simplicity, risk neutrality and one stochastic process (i.e., SRC biomass price) are assumed, while other parameters are deterministic. A sensitivity analysis is conducted with respect to the observed price of SRC biomass (Q1.4). The results show that SRC cannot compete with annual crops under current market conditions (Q1). A risk-neutral farmer neither rejects this option, nor invests immediately, but rather postpones a decision and behaves in response to evolving conditions subject to stochastic variables.

The model is further elaborated and a comprehensive policy analysis is performed (Chapter 3). In particular, annual crops are characterized with assumptions about stochastic gross margins that are correlated with stochastic SRC biomass prices. As a result, the model captures multiple risks, and any farmer decisions imply stochastic returns. Four farm-level policy instruments of different intensities intended to support SRC introduction are selected for analysis. Two of the policy instruments—a planting subsidy for SRC and a higher EFA coefficient for land under SRC management—are selected because they have been recently implemented in the study region (MLU-MV 2015; Lindegaard et al. 2016). A planting subsidy reduces sunk costs related to SRC adoption; while a higher EFA coefficient reduces competition for land between SRC and other farm activities, since less land under SRC is required to fulfill the environmental requirements. The other two policy instruments—a guaranteed price and a price floor for SRC biomass—are selected because they address risk, which is argued to be one of the major factors limiting SRC adoption among farmers (Hauk et al. 2014; Wolbert-Haverkamp and Musshoff 2014). A guaranteed price completely eliminates risk associated with SRC cultivation, such that the government assumes risk from market price fluctuations. In contrast, a price floor only cuts the downside price risk and is applied if market price falls below the price floor level. The policy instruments are assessed based on four metrics: effect on bioenergy production (Q2.1), governmental costs required (Q2.2), effects on farmer income (Q2.3), and efficiency of transformation of governmental costs into additional farm income. In general, the results show that SRC bioenergy requires much less governmental support than other renewable energy sources, and hence is economically viable. The results also indicate that recently implemented policy instruments—a planting subsidy for SRC and a higher EFA coefficient for land under SRC management—seem most promising, although neither eliminates incentives to postpone SRC adoption and thus should be modified in order to stimulate earlier SRC introduction (Q2, Q2.4). In contrast, a guaranteed price and a price floor perform much worse and might even have negative effects on SRC adoption, since removing risk eliminates or significantly reduces the benefit of managerial flexibility. The two policy instruments hence encourage earlier or even immediate SRC introduction (Q2.4), but at a lower scale. To this end, risk is found to be beneficial for the expected scales of SRC adoption, and further analysis targets risk, the level of risk, and risk preferences.

Risk preferences are captured by inverse second-order stochastic dominance (ISSD) introduced as an additional constraint (Chapter 4). The stochastic dominance approach is inviting because it requires minimal behavioral assumptions, in particular it requires a farmer to be risk-averse (Q3.1). The final distribution of NPVs before and after SRC introduction is taken as a risk measure. The observed farm portfolio (i.e., before SRC introduction), is assumed to imply tolerable risk and a new portfolio with SRC must dominate the observed benchmark in order to be adopted. The model allows comparisons between a risk-neutral decision and a risk-averse one, and hence quantifies the effect of the latter. Also, a sensitivity analysis is conducted with respect to parameters of the stochastic process for SRC biomass price in order to observe the effect of (subjective) risk levels perceived by farmers, which is especially important for new farm activities due to lack of data and experience (Bougherara et al. 2017, p. 803). For the employed case study, risk aversion is found to negatively affect scale (Q3.2) and positively affect timing (Q3.3) of SRC adoption. In contrast, increasing risk level has a positive effect on scale (Q3.4) and a negative effect at low levels and positive effect at higher levels on timing (Q3.5) of SRC adoption. Hence, a risk-neutral farmer perceiving SRC as a very risky option (with equal respect to positive and negative risks) tends to implement a larger area of SRC earlier, yet not immediately. For a risk-averse farmer expected scale is lower, but SRC would be introduced even earlier (Q3).

1.5. References

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Chapter 2

Monte Carlo simulation and stochastic programming for real options valuation in perennial energy crop cultivation*

Abstract

There are two prominent approaches for the valuation of an American option if a closed-form solution is not available: stochastic simulation based on a binomial (or trinomial) scenario tree and Monte Carlo simulation. In practice, however, real options are rarely independent; and neither method excels in the valuation of compound American options subject to variability of resource endowments and returns-to-scale, as well as investment options of predefined sizes. We present a valuation approach based on Monte Carlo simulation, scenario tree reduction, and stochastic programming that is especially advantageous for real options where not only timing, but also scale and interactions among constraints and alternatives determine value. We illustrate the approach with a case study featuring investment options regarding the adoption, harvest, and conversion of perennial biomass energy production systems.

Keywords: Investment analysis; compound option; American option; farming investment decision; bioenergy.

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2.1. Introduction

In the absence of a closed-form solution, real options are valued using numerical methods. In the case of simple European options valuation is often performed with the Black-Scholes-Merton model (Merton 1973). There are two prominent approaches for the valuation of American options: stochastic simulation based on a binomial (or trinomial) scenario tree (Cox et al. 1979; Trigeorgis 1991) and Monte Carlo simulation (Boyle 1977), including the computationally more efficient Least Squares Monte Carlo (LSMC) simulation method (Longstaff and Schwartz 2001). A binomial (or trinomial) scenario tree is an intuitive and generic approach, however, it suffers from the curse of dimensionality and leads to branches with exploding values or values close to zero already under rather conservative assumptions about variance at the nodes (Lander and Pinches, 1998, pp. 545–546), limiting its applicability to compound options and long time horizons. Although LSMC deals with compound options efficiently, it is often criticized for sensitivity to the choice of functional form in the regression step (Stentoft 2004, p. 136), especially if the dimension increases (Bouchard and Warin 2012, p. 216).

Characteristics of actual large-scale investment projects often fail to fit well with the explicitly or implicitly inherent restrictions of existing numerical real options valuation methods. In this paper we consider investment projects involving compound American real options and/or competition among activities for (quasi-) scarce resources. Returns-to-scale or investment options of predefined sizes can also be considered. Examples include investments in indivisible assets, investments characterized by a high share of transaction or other (quasi-) fixed costs, as well as investments of (quasi-) scarce resources with competing uses. In order to better capture the complexity of actual large-scale investment projects, we propose an alternative numerical valuation method that combines and benefits of scenario tree and Monte Carlo simulation methods.

We propose an approach that applies a scenario tree reduction technique to the outcome of a Monte Carlo simulation. This controls for dimensionality and obtains an advanced scenario tree that enters stochastic programming, which then values real options. In contrast to LSMC this approach does not approximate fitted payoffs and hence the optimal investment decision with one function. Instead we consider the fragmented distribution of self-contained expected payoffs. Real options theory for the analysis of agricultural investment projects has gained interest (Wossink and

Gardebroek 2006; Hinrichs et al. 2008; Hill 2010), but existing empirical applications are rather limited. In order to illustrate this approach and demonstrate its applicability to a complex real-world example, we chose an agricultural economics case study featuring an investment analysis of perennial energy crop cultivation in Germany. The case study depicts a situation where not only timing, but also investment scale and interactions among alternatives are relevant due to competition for resources.

The remainder of this paper is organized as follows. Section 2 provides a methodological background of option valuation and identifies the gaps addressed by the proposed approach. Section 3 provides a general description of the approach. Section 4 illustrates the approach as applied to a case study. Section 5 presents core empirical findings from the case study to demonstrate the results provided the approach. Section 6 discusses further application potential for the proposed approach. Section 7 presents our conclusions.

2.2. State of the art

Lander and Pinches (1998) distinguish the main reasons why practitioners are reluctant to employ real options valuation for investment analyses. First, existing models and real options valuation methods can seem obscure and difficult to follow. Second, restrictive assumptions are often required in order to be able to solve a model. Below we address these two issues while summarizing the major existing real options valuation methods.

Analytical solutions for real options valuation (Black and Scholes 1973; Geske and Johnson 1984) are elegant from a scholarly perspective, but are often deemed inappropriate for practical application due to restrictive assumptions required (e.g., regarding stochastic processes). If such is the case, a numerical method must be employed instead (Trigeorgis 1996; Regan et al. 2015). Cetinkaya and Thiele (2014, p. 12) distinguish between methods that approximate the underlying stochastic process and methods that approximate partial differential equations (see, overview of latter in Trigeorgis [1996]). The most well-known method that approximates partial differential equations—the Black-Scholes-Merton model (Merton 1973)—was initially designed and is well suited for the valuation of simple European options (Regan et al. 2015, p. 146). In contrast, compound American options are typically valued by approximating stochastic process methods. They can further be divided between Monte Carlo simulation (Boyle 1977), including the computationally more efficient LSMC method (Longstaff and Schwartz 2001), and scenario tree approximation.

Scenario tree approximation usually implies either a binomial lattice or a binomial scenario tree (Brandão and Dyer 2005; Smith 2005). An (approximate) optimal value for options depicted by the constructed scenario tree or lattice is then found by dynamic programming (Dixit and Pindyck 1994, pp. 140–147; Guthrie 2009, pp. 88–92). Programming approaches are widely used to analyze investment decisions in a quantitative and relatively transparent way, including stochastic programming applications (Brandes et al. 1980; Haigh and Holt 2002). Examples of real options valuation with stochastic programming include, energy economics (Sagastizábal 2012; Feng and Ryan 2013; Simoglou et al. 2014; van Ackooij and Sagastizábal 2014), managing project portfolios (Beraldi et al. 2013), and natural resource extraction (Alonso-Ayuso et al. 2014). One of the main disadvantages of scenario tree approximation is that a tree can quickly become unsolvable in terms of computational capacity as the number of time periods increases (Lander and Pinches 1998, pp. 545–546), since a binomial lattice requires $\left[{}^{n(n+1)}/_{2}\right]$, and a binomial tree requires 2^n final leaves for n time periods. Furthermore, development of stochastic parameters in a binomial tree with chained relative ups and downs in each node can lead to unrealistic values after a few points in time, since the already rather conservative assumptions about variance at any node can imply exploding branches.

The alternative LSMC method evolves from the core finding that optimal strategy is determined by the conditional expectations of the value of postponing the exercise of an option; and that these conditional expectations can be estimated using simulation results (Longstaff and Schwartz 2001, p. 114). Thus, the method consists of the following three steps: (i) simulation of the payoffs of exercising the option in every time period and keeping it in previous periods; (ii) regression of those payoffs using least squares; and (iii) specification of the optimal strategy based on estimated regression and fitted payoffs. LSMC is considered highly powerful for the valuation of American options and is widely used in the literature (Sabour and Poulin 2006; Abadie and Chamorro 2009; Zhu and Fan 2011). One disadvantage of the LSMC method is that a functional form must be assumed for estimation of the Lagrangian and can be crucial for determining optimal strategy (Stentoft 2004, p. 136). Although follow-up papers have addressed this issue (Rogers 2002; Haugh and Kogan 2004; Létourneau and Stentoft 2014), to date there is no general payoff independent choice algorithm that also works for higher dimensional problems (Bouchard and Warin 2012, p. 216). Accordingly, there is room for alternative methods, especially methods that are able to relax otherwise necessarily restrictive assumptions, which is the motivation for our proposed approach.

Another reason why real option theory is not applied identified by Lander and Pinches (1998) is that existing valuation methods fail to adequately capture the complexity of real-world investment projects. We focus on large investment projects that typically not only involve compound real options, but also compete for (quasi-) scarce resources. This implies that (changes in) returns to inputs and possible management adjustments resulting from resource reallocation also need to be considered. These interactions among endowment constraints and alternative activities are especially crucial in the context of returns-to-scale and/or a set of investment options of predefined sizes (i.e., binary decision variables). In such cases, both the timing and scale of exercising an option are at issue: such as investments in indivisible assets, investments characterized by a high share of transaction or other (quasi-) fixed costs, and investments that affect availability dynamics of resources for which there are competing uses. None of the methods discussed above are well suited for these problem conditions for different reasons. The Black-Scholes-Merton model is not appropriate for valuing compound American options. Due to the curse of dimensionality, a binomial scenario tree hampers valuation of compound options, particularly over a long time horizon. LSMC impedes the choice of Lagrangian function under high dimensionality and requires solving with a programming model for each single fitted payoff if interactions among constraints and alternative activities are considered, which threatens its computational efficiency. Our alternative approach is particularly relevant if alternative activities, returns-to-scale, indivisible assets, and resource endowments and other constraints are jointly considered.

For illustrative purposes we employ a case study based on biomass energy production in Germany featuring agricultural investment characterized by limited resources, returns-to-scale, and predefined sizes of available investment options. Our example refers to farm-level decisions regarding the adoption, harvest and conversion of perennial energy crop production in the context of farm constraints and alternative activities. The application of real options in agricultural economics is rather limited, especially in terms of investment analysis of perennial energy crop production; the dominant approach in the literature is the classical net present value (NPV) method (Lothner et al., 1986; Strauss et al., 1988;

Gandorfer et al., 2011; Schweier and Becker, 2013). The few existing models based on real options have either considered perennial energy crop cultivation as a stand-alone investment option (Frey et al. 2013), or the (partly) killed managerial flexibility it allows for (Bartolini and Viaggi 2012), or both (Song et al., 2011; Musshoff, 2012; Wolbert-Haverkamp and Musshoff, 2014). As discussed previously, these restrictive assumptions were made in order to gain tractability and computational efficiency.

2.3. General methodology

The approach we propose includes four main steps. First, we define the (state contingent) decision variables of the problem and available (compound) real options. Second, we define the relationships (i.e., equations and constraints) among the decision variables, including lagged relationships between time points, and combine them into a programming model. Hence the first two steps design a deterministic mixed-integer linear programming model. Integers, including binaries, enable differentiation among investment options with predefined sizes; non-linearity allows the model to reflect returns-to-scale. In the second step we also define the payoff function (e.g., NPV) subject to constraints, including resource endowments. Third, we introduce different future outcomes (states) and related state contingent decision variables. In order to convert the deterministic version into a stochastic programming equivalent, four additional elements are added: (i) the decision variables are provided an additional index for the decision node (i.e., state); (ii) an ancestor matrix is introduced to reflect the order of nodes in the decision tree; (iii) outcomes for the stochastic parameters for each state are defined; and (iv) the probabilities for each node are assigned. In particular, we choose a distribution to account for uncertainty with respect to parameter(s), create Monte Carlo scenarios, and construct from them a reduced scenario tree with probabilities, using a scenario tree reduction technique. Finally, we employ stochastic programming for the valuation of real options.

There are several important details in the third step concerning how the outcomes and related probabilities are constructed. First we assume distributions for the stochastic components and run Monte Carlo simulations that result in a large scenario tree that is not solvable numerically due to the curse of dimensionality. We reduce the size of the tree without losing too much information about the underlying distributions by employing the tree reduction and construction algorithm of Heitsch and Römisch (2008). Similar to a Gaussian quadrature, which describes a probability density function with few characteristic values and their probability mass, this algorithm picks representative nodes and assigns probabilities to capture the approximate distribution in original trees.[7] The algorithm can be depicted graphically as lumping together neighboring nodes and branches in the tree into bigger ones, where the thickness represents probability mass. In particular, we opt to use a pre-defined number of final leaves and hence pre-determine the number of equations and variables in the model, letting the algorithm decide which nodes to maintain. There is no well-established approach to determine the optimal number of leaves. The choice, however, should reflect a tradeoff between accuracy and solution time: more leaves lead to higher precision in outcomes while increasing the solution time substantially (Dupačová et al. 2000, p. 30). The extreme case of a small number of leaves is the classical NPV approach, with one leaf only and no incentive to postpone. Adding a single leaf converts the problem into real options and might create incentives to postpone exercising an option. Also note that the number of leaves has differential influence on model outcomes. In particular, it might be very hard to stabilize integer variables within a certain range of accuracy. We suggest proceeding as follows: (1) choose the model's "main result variable," (2) determine an appropriate degree of deviation for this variable, (3) run a sensitivity analysis with an increasing number of leaves and observe the effect on this variable, and (4) stop increasing tree size once the variable stabilizes within the deviation level.

Our approach allows the assumption of any risk attitude. However, deviating from risk neutrality and using a risk-adjusted discount rate require re-adjusting the discount rate for every time period, as the risk decreases approaching the final scenario tree leaves (Brandão and Dyer 2005). In addition, different risk-adjusted discount rates should be applied to farm activities that involve different risk ((Brandão and Dyer 2005; Finger 2016).

[7] Basically, all methods of generating a scenario tree can be summarized as aggregating nodes and stages, and trimming or refining trees (Klaassen 1998; Consigli and Dempster 1998; Frauendorfer and Marohn 1998; Dempster and Thompson 1999; Dempster 2006). A practical advantage of the method developed by Heitsch and Römisch (2008) is a GAMS tool, SCENRED2, based on the method.

We solve the model described above with stochastic programming using standard Java libraries[8] for Monte Carlo simulations: GAMS 24.3; a tree construction tool SCENRED2 (GAMS 2015); and an optimization solver, CPLEX (IBM 2016). The computational speed can be increased by employing a multi-core processor. Additional techniques for improving computational efficiency for such large-scale mixed-integer stochastic problems are available (Escudero et al. 2012).

2.4. Empirical application

For illustrative purposes we value investment decisions in perennial energy crop production, specifically short-rotation coppice (SRC) poplar production systems that involve timing, adoption scale, harvest and conversion decisions. The selected case study features the complexities discussed above: it involves compound American options of predefined sizes in the context of limited resources, returns-to-scale, and alternative activities. The main case study characteristics are summarized in Table 2.1.

Under SRC management fast growing trees are coppiced within relatively short intervals—typically between two and five years—for energy production. SRC plantations can be harvested multiple times over a period of up to 20 years. A large share of the costs are sunk in plantation establishment: typically about 2/3 of SRC production system costs are associated with planting and final conversion (Lowthe-Thomas et al. 2010). Relative to alternative land uses, SRC is characterized by low-input production (Faasch and Patenaude 2012); planting and harvesting are usually outsourced to a contractor, minimizing or eliminating the need for on-farm labor (Musshoff 2012, p. 77). In Germany, land use competition between SRC and other land uses has been reduced under the latest Common Agricultural Policy reform, which requires large arable farms to manage 5% of farmland as “Ecological

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[8] The use of Java is mostly motivated by the fact that we store the generated simulations along with the ancestor matrix to describe the node structure efficiently in the proprietary data format GDX (of GAMS) to avoid costly computations.

Focus Areas" (EFA), which SRC partially qualifies as[9] (in Germany one unit of land under SRC management is equivalent to 0.3 of an equal area of set-aside for EFA purposes) (BMEL 2015).

During the lifetime of a plantation, farmers face (at minimum) biomass price uncertainty. While the same might hold true for alternative land uses, the ability to adjust the land-use composition and management intensity on an annual basis might substantially reduce subjective risk to individual farmers (Di Falco and Perrings 2003). We consider SRC management to involve compound American options, where planting, each intermediate harvest, and final conversion to alternative land uses are the option stages. Due to stage-contingent inter-harvest periods ranging between two and five years and the maximum plantation lifetime, the total number of stages is flexible, not predetermined. As a consequence, the sooner each stage is exercised, the more available stages there are overall.

The model data (Appendix 2.1) are from SRC poplar production systems in northern Germany (Musshoff 2012; Faasch and Patenaude 2012; Wolbert-Haverkamp 2012). Relative to average conditions in Germany the region is characterized by low soil quality and precipitation, and thus generally low returns from annual crops. The limited productivity increases the attractiveness of uncommon land-use options such as SRC management. According to (Schuler et al. 2014, p. 69) over 90% of agricultural lands in this region are suitable for SRC management.

In order to model competition for farm resources such as land and labor, we consider two relevant alternative crops for the case study region—winter wheat and winter rapeseed—of which the former is more labor intensive and has a higher gross margin per hectare. Finally, we consider set-asides as an alternative means of fulfilling EFA requirements to SRC systems.

We consider pre-defined plantation sizes because farmers would typically convert existing plots of some other land use to SRC plantation. Assuming total land endowment of 100 ha, we consider three potentially

[9] We consider two options to meet the EFA requirements in our model: set-aside land (i.e., fallow land) and SRC (for a description of other options see BMEL [2015]).

convertible plot sizes[10] of 10 ha, 20 ha, and 40 ha, providing eight possible plantation size combinations from 0 to 70 ha. Each plot is characterized by three core decision variables over the simulation horizon: (1) land-use decisions: whether or not a plot is used for SRC or one of the three alternative activities; (2) SRC harvesting decisions: whether or not SRC plots are harvested in the current year; and (3) the decision of whether or not to convert to an alternative land use.[11]

Revenues from an SRC plantation are linked to harvest decisions, which are based on the interactions among biomass growth and harvest cost functions. Biomass growth is represented by a linear function of available yields and—in combination with the harvest decision for the previous year—provides current yields. The harvest cost function considers transaction costs for outsourcing labor, field-level transport costs, harvest costs, post-harvest fertilization costs, and costs of drying and storing harvested biomass. In order to capture economies of scale with respect to harvest activities, we distinguish among (a) at farm (fixed); (b) per plot (quasi-fixed); and (c) per tonne (t) of harvested biomass (variable) costs as follows:

$$HC = 66.75 + 272.13 \cdot L + 10.67 \cdot Y \tag{2.1}$$

where HC represents total harvest related costs in euro (€); L is the area of land harvested in hectares (ha); and Y is harvested yield in tonnes of dry matter (t).

Considering different harvest intervals allows the plantation to store biomass, such that temporal arbitrage can be applied: a farmer might allow trees to continue growing if biomass prices are low and expected to increase in the future, increasing future harvestable volumes. Moreover, since we specify fixed and quasi-fixed harvest costs, the total harvest cost per tonne of

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[10] Initially four plots and 11 combinations from 0 to 100 ha are assumed, hence covering all available land. Tests reveal that the optimal total area under SRC is always below 40 ha, therefore we restrict ourselves to three plots as described in the text in order to decrease the number of variables and thereby gain computational efficiency.

[11] Conversion can be exercised only in combination with harvest. Costs of conversion include harvest and clear-cutting costs.

dry matter declines over time elapsed since planting or the preceding harvest; between two and five year intervals are considered in the case study.

Table 2.1. Summary of the main case study characteristics

Characteristics of an actual large-scale investment project	Expressed in the case-study via
Compound American option	Short-rotation coppice plantation with initial planting (can be postponed by 3 years), intermediate harvests after 2–5 years from previous stage (i.e., planting or harvesting), and final conversion to alternative land use (maximum 20 years post planting and exercised only in combination with harvest)
Stochastic component	Biomass price (i.e., price for short-rotation coppice output)
Sunk costs	Planting costs, harvest related costs, and final conversion costs
Predefined investment sizes	Predefined land plots for potential conversion to short-rotation coppice plantation
Opportunity costs	Annual production systems, specifically two annual crop options with different inputs (i.e., land and labor) and outputs (i.e., gross margins)
Returns-to-scale	Harvest costs including costs (a) on farm (fixed), (b) per hectare (quasi-fixed), and (c) per tonne of harvested biomass (variable)
Resource endowments	Land and labor: both are assumed to be limited without possibility for expansion
Policy constraints	An “Ecological Focus Area” representing 5% of farmland area must be left fallow or converted to short-rotation coppice plantation (SRC is recognized in the model as equivalent to fallow land with a coefficient of 0.3)

After setting up the mixed integer programming model[12] that maximizes NPV, risk is introduced into the model. We assume a natural logarithm for the SRC output price to follow a mean-reverting process (MRP), specifically an Ornstein-Uhlenbeck process (Musshoff 2012; de Oliveira et al. 2014). After 10,000 Monte Carlo simulation runs for output prices we apply scenario tree reduction. In order to determine the optimal number of leaves we choose the expected area under SRC as the main result and stabilize it within 10% of the expected area under SRC under 500 leaves (see Appendix 2.2 for sensitivity analysis results). We found 100 leaves to be a good tradeoff between accuracy and speed. For the sake of clarity in our analysis we use a risk-neutral decision maker and discount rate.

Additionally we run two types of sensitivity analyses. First, we quantify the difference between the real options and classical NPV approach. For the latter, we force the farmer to make decisions on planting, harvesting and conversion immediately based on expected biomass output price (i.e., we switch from a stochastic to deterministic model). The stochastic process for biomass price stays the same. Second, we analyze the influence of the observed biomass price on farmer decision making. In particular, we shift the constructed scenario tree up and down in parallel keeping all the other parameters constant. In the supplementary material provided in association with this paper we include a Graphical User Interface that allows straightforward changes to the initial parameters, the GAMS code to run the model, and the mathematical representation of the model.

2.5. Empirical results

The results of our sensitivity analysis with respect to the difference between the real options and the classical NPV approach are consistent with theory: the planting trigger under the classical NPV approach is lower than when based on real options. Specifically, under a now or never decision scenario a farmer would convert some land to SRC plantation immediately at a biomass price of

[12] The deterministic model is beyond the focus of this paper, therefore we only present major points that are relevant for the proposed approach (see the supplementary material provided for greater detail).

48 € t^{-1}, which is 5% below our baseline scenario. To the contrary, our real options approach finds a positive option value for postponing SRC adoption at that price, which matches the observed reluctance of farmers in Germany to adopt SRC under current prices (Bemmann and Knust 2010; Allen et al. 2014). In contrast, Musshoff (2012) reported that immediate planting of SRC was profitable under a real option application assuming the same stochastic process for biomass price. We presume that our higher investment trigger is due to consideration of more aspects of a real-world investment context, such as full managerial flexibility in SRC cultivation and alternative land uses that compete for resources. Further detail is provided in the supplementary material for interested readers.

The results of the sensitivity analysis with respect to the observed biomass price (i.e., the starting value of the scenario tree) are shown in Fig. 2.1. Under the observed biomass price of 50 € t^{-1} (i.e., baseline scenario) there is a chance that farmers will not choose to adopt SRC production (the sum of probabilities is below 100%). If a SRC plantation is established, the probability that SRC will be implemented is 23% in the second and third years, and 41% in the fourth year. A breakdown by investment scale is beyond the scope of the information presented in Fig. 2.1: if an SRC plantation is established in the second year under the baseline scenario, 87% of the SRC plantations would be 10 ha and the remaining 13% would be 20 ha. Intuitively, the (expected) area under SRC increases as biomass prices increase (blue line in Fig. 2.1). The same sensitivity analysis can be performed for every stage of the compound option, such as for harvest and land use conversion decisions at any time point.

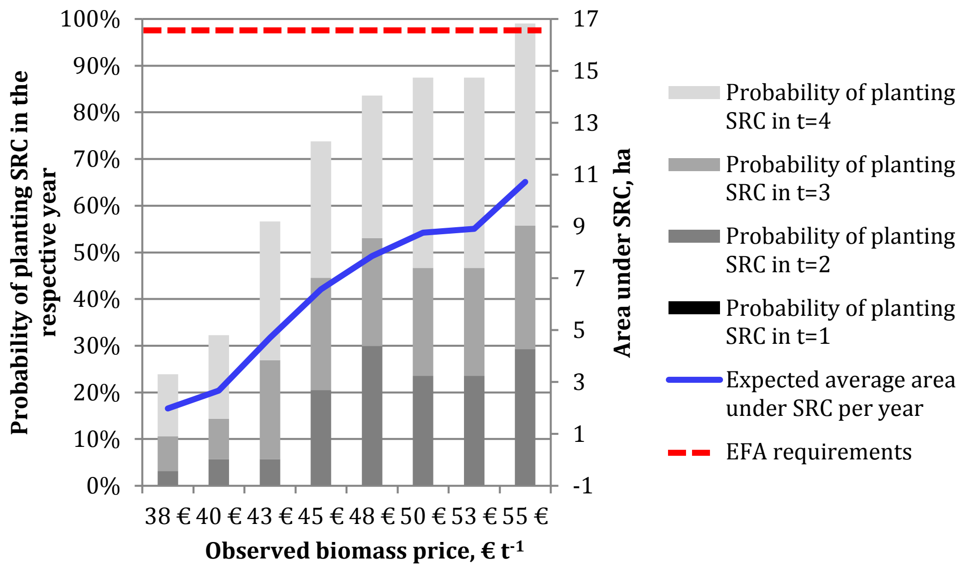

Figure 2.1. Sensitivity analysis with respect to biomass output price for short-rotation coppice (SRC) planting decisions based on the real options approach.

The EFA requirements are not fulfilled with SRC only under the presented scenarios. The interrupted red line in Fig. 2.1, which is always above the expected area under SRC, indicates the area of SRC needed to satisfy EFA requirements. This indicates that the policy measure is not fully exploited; under the scenarios considered SRC is not competitive with alternative land uses. Ignoring policy measures and opportunity costs would have obscured this result.

The relative competiveness of SRC management in our analysis considers redistribution of resources among alternative land uses as an investment consequence. On the one hand, more land under SRC is required for EFA compared to set-asides, as one hectare of SRC is equivalent 0.3 ha of set aside for EFA purposes. On the other hand, labor requirements of SRC are lower than for alternative land uses. Thus, converting area under productive land uses to SRC allows an increasing labor share for more intensively managed crops with a higher gross margin per hectare (wheat) on remaining farm area and thus dampens the impact of competition for space (Fig. 2.2).[13] A similar result can be found if we assume that any freed labor is employed off-farm. Due to this effect, the investment trigger is lowered relative to a simpler model where only competition for land is considered. This outcome is only possible by taking into account alternatives, policy measures and constraints. To this end, our empirical results are consistent with the observed reluctance of farmers in Germany to convert existing land uses to SRC systems under current market and policy conditions and reveal additional information on SRC adoption incentives.

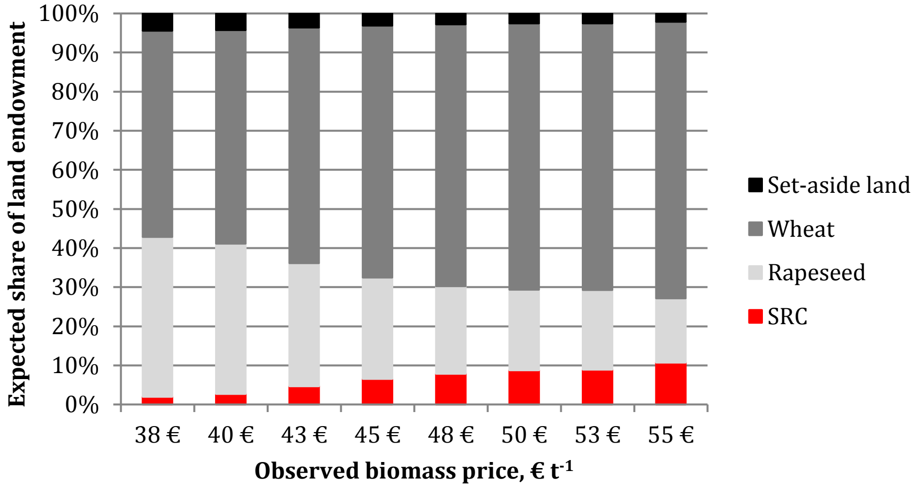

Figure 2.2. Expected land distribution (annual mean) between alternative farm activities under different starting (observed) values of the scenario tree (based on the real options approach).

2.6. Discussion

The proposed approach provides a method for detailed investment analysis, including the timing and depth of exercising every stage of the compound

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[13] Fig. 2.2 illustrates the expected mean land distribution over the simulation period. Although SRC is expected to be implemented (e.g., under baseline conditions when observed biomass price is equal to 50 € t^{-1}), it is not planted immediately.

option. Timing is represented by the optimal investment behavior at each given node of the scenario tree, as well as at the subsequent nodes with assigned probabilities and conditional to antecedents. Depth is expressed in fractional units or—if investment options of predefined sizes are considered—as the exercised subset of all available options. At each node of the scenario tree the value to postpone can be evaluated by comparing expected payoffs with and without temporal flexibility (i.e., payoffs based on real options and the classical NPV approach). The approach also reveals additional incentives (or disincentives) to invest that were previously obscured by restricted assumptions, such as interactions among alternatives and their influence on investment behavior. In particular, it allows adjustment of alternatives or other management changes related to exercising an option.

For clarity we presented a simplified farm model that can be improved by adding more alternatives and constraints. Multiple risks, including mutual correlation, can be assumed with the scenario tree characterized by a vector of simulated values in each node. Alternatively, several stochastic parameters can be combined into a single composite risk, as in some existing models (Flaten and Lien 2007; Bartolini and Viaggi 2012; Beraldi et al. 2013). Risk preferences can also be considered; the simplest way would be to introduce a risk utility function.

Further empirical analysis can be done in different directions. Investment triggers can be determined by conducting sensitivity analyses with respect to any model parameter as a potential trigger. Modifying the respective parameter stepwise would determine intervals within which the investment decision changes to exercising the option immediately, defining the true investment trigger within this interval. The smaller the sensitivity analysis steps, the narrower the range that encompasses the true investment trigger. Our approach allows for stepwise relaxation of assumptions and hence quantifying their influence on investment behavior. A comprehensive policy analysis can be performed, either for measures that directly affect investment options or else the alternatives, resource endowments, and/or other constraints. Such analyses would reveal both direct and indirect effects of policy measures due to resource redistribution among alternatives and other management changes. If risk preferences are considered, a risk analysis can be conducted.

Our approach offers multiple methodological advances. It overcomes the curse of dimensionality of a binomial (trinomial) scenario tree. The constructed asymmetric scenario tree reflects the underlying distribution, while values are not exploding and the number of leaves is restricted. In contrast to LSMC, our approach can be applied efficiently to problems of greater complexity. Once resource endowments and other constraints are considered the LSMC requires a numerical method to solve each Monte Carlo path backwards for each stage, starting from the last one. If the size of the investment project is a decision variable as well, the LSMC requires an additional sensitivity analysis with respect to project size. Generating payoffs for all potential combinations of exercising time points and Monte Carlo runs can be numerically demanding if a programming approach is needed, a process that must be programmed as well. Once it becomes necessary to use a programming approach to determine the NPV of a single Monte Carlo run, potentially conditional of exercising an option at a pre-determined stage. We find it more straightforward to use stochastic programming directly. Instead of approximating the payoff matrix with a regression function as in LSMC, we approximate the Monte Carlo fan based on tree reduction, which is more transparent. Furthermore, as our case study demonstrates, the approach is rather general. It is able to value complex compound options, such as choosing the best combination from a portfolio of different investments that interact or problems where the number of stages is not pre-determined. There are no restrictive methodological requirements associated with our approach. Indeed, any underlying stochastic process can be assumed as long as it is possible to run Monte Carlo simulations and construct a reduced scenario tree. The number of stages is not limited either, unless the relationships between stages cannot be captured with equations. The time horizon is a model parameter and its choice is not restricted. European options can be valued using our approach in a similar way as an American option. Our approach is suitable for comprehensive sensitivity, policy and risk analyses, while representing outcomes in a transparent and intuitive manner.

There are three issues that deserve additional attention. First, an exploding stochastic process cannot be assumed, since a Monte Carlo simulation might quickly lead to unrealistic values. For instance, Geometric Brownian Motion and Arithmetic Brownian Motion—common assumptions used in the literature for estimating stochastic biomass price (Kallio et al. 2012; Di Corato et al. 2013)—explode by simulating over multiple time periods. Since such simulation values are not plausible, this limitation refers to the assumption itself, rather than the approach. Another issue that requires further research is the choice of leaf number. As mentioned above, there is no well-established procedure to determine optimal leaf number. Finally, the appropriate risk-adjusted discount rate applied to a scenario tree should differ from the risk-adjusted discount rate applied to the underlying asset, because a tree does not correctly represent the underlying volatility (Lander and Pinches 1998, p. 553). In addition and as mentioned above, trees are characterized by decreasing risk approaching the leaves. Therefore research could explore methods for determining the appropriate risk-adjusted discount rate for a scenario tree.

2.7. Conclusion

The existing methods of real options valuation fail to capture the complexity of large, real-world investment projects consistently. This limitation leads to reluctance to employ real options theory for investment analysis. In this paper we present a numerical method for the valuation of real (compound American) options that combines and benefits from an intuitive scenario tree approach and LSMC—two well-known approaches for the valuation of American options. Our approach overcomes the curse of dimensionality, does not require additional assumptions about the functional form of the Lagrangian, and ensures computational efficiency by restricting the solution domain. In addition, our approach and the results obtained are very straightforward and comprehensible.

The proposed approach can be summarized in four main steps. First, define the decision variables of the problem. Second, establish the relations among these decision variables, including lagged relations between time points, and combine them into a deterministic programming model. Third, choose an appropriate distribution for stochastic parameter(s), run Monte Carlo simulation scenarios and construct a reduced scenario tree with probabilities from them by employing a scenario tree reduction technique. Finally, employ stochastic programming for the real options valuation step. The results obtained consider both timing and the depth of exercising options. Timing is represented by the optimal investment decision at each given node of the scenario tree and at subsequent nodes with assigned probabilities. Depth is reflected by the optimal scale of exercising an option, taking into account opportunity costs, returns-to-scale, resource endowments, and other constraints. Our approach is also suitable for comprehensive sensitivity, policy and risk analyses, while representing outcomes in a transparent and intuitive way.

We illustrate the approach in a case study context of biomass energy production using SRC management in Germany, demonstrating valuation of the options to adopt, harvest, and conversion of perennial energy crop systems at the farm-level. The empirical model differs from existing investment analyses of perennial energy crop cultivation by a number of simultaneously relaxed assumptions. In particular, we allow full flexibility in planting and harvesting, consider alternative land uses, as well as consider resource endowments and other constraints. The empirical results from the model are consistent with both real options theory and the observed reluctance among farmers in Germany to adopt the cultivation of perennial energy crops. Due to relaxed assumptions, we obtain more plausible results and reveal additional incentives for perennial energy crop cultivation, in particular the redistribution of resources among alternatives. The proposed model can be further improved by considering a greater number of alternative activities and farm constraints, as well as by the introduction of multiple risks and risk preferences. Our approach can be employed in various applications, being especially advantageous for real options valuation, where not only timing, but also the scale and interactions among constraints and alternatives matter.

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2.9. Appendices

Appendix 2.1.

Table 2.2. Data and model parameters

Parameter	Units	Assumed value
	Short-Rotation Coppice	
Labor requirements	Hours per hectare (h ha^{-1})	0.00
Planting costs	Euro per hectare (€ ha^{-1})	2,875.00
Biomass growth function		
Multiplier for last year's biomass	-	1.54
Constant increase per year	Tonnes per hectare (t ha^{-1})	6.68
Harvesting costs		
Fixed costs at farm level	€	66.75
Quasi-fixed costs per hectare	€ ha^{-1}	272.13
Variable costs, depending on	€ t^{-1}	10.67

harvest quantity		
MRP for logarithmic output price ($\ln P_t$)		
Starting value	-	3.92
Mean value	-	3.92
Speed of reversion	-	0.22
Variance of Wiener process	-	0.22
Reconversion costs	€ ha^{-1}	1,400.00
Tree density	ha^{-1}	9,000.00
Other farm activities		
Net annual cash flow from traditional land use		
Winter wheat	€ ha^{-1}	537.15
Winter rapeseed	€ ha^{-1}	460.64
Set-aside	€ ha^{-1}	–50.00
Labor requirements[14]		
Winter wheat	h ha^{-1}	5.32
Winter rapeseed	h ha^{-1}	4.16
Set-aside	h ha^{-1}	1.00
Farm characteristics		
Land area	ha	100.00
Labor availability[15]	h	455.00
Real risk-free discount rate	%	3.87

Sources: Faasch and Patenaude (2012); Musshoff (2012); Pecenka and Hoffmann (2012); Schweier and Becker (2012); Wolbert-Haverkamp (2012); KTBL (2012); StatA-MV (2016)

Two elements of parameterization deserve further attention. First, take the yield function from Ali (2009), introduce some required parameters and

[14] Only includes field work, excluding work associated with management, which is assumed to be limited per farm and hence has no effect on resource distribution.

[15] Based on the assumption that initially 47.5% of land area is devoted to winter wheat, 47.5% to winter rapeseed, and 5% is set-aside. This composition excludes management and off-farm work; both of which are assumed to be limited at the farm level and hence have no effect on resource distribution.

regress a linear function for biomass stock that depends on previous year's stock. Second, based on Schweier and Becker (2012) and Pecenka and Hoffmann (2012) we derive harvest costs separated by (a) farm level (fixed) costs and (b) per hectare (quasi-fixed) costs, plus (c) costs per metric tonne of harvested biomass (variable), in order to consider economy of scale.

Appendix 2.2.

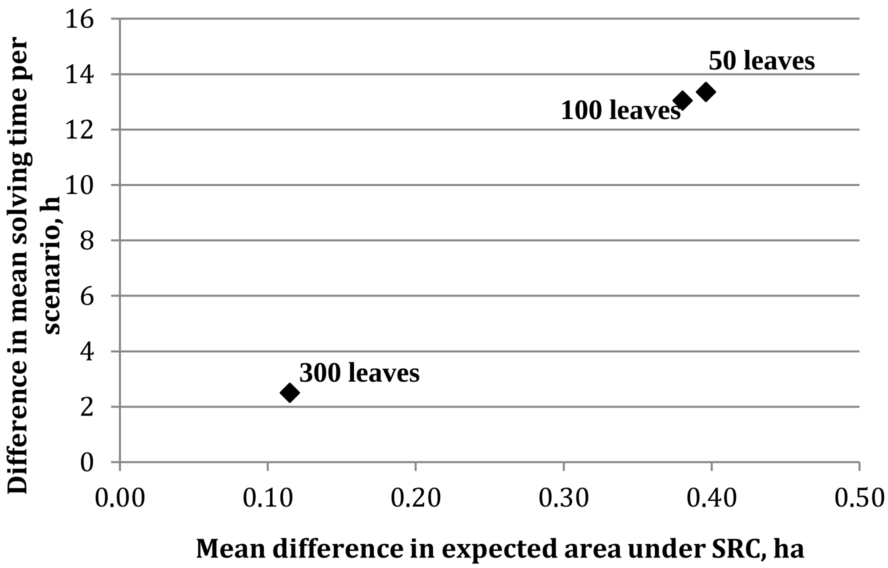

Figure 2.3. Comparison of solving time (for seven price scenarios) and mean expected area under SRC between a model with 500 leaves and models with fewer scenario tree leaves. Solving time for each price scenario is restricted to 20 hours.

Chapter 3

Policy analysis of perennial energy crop cultivation at the farm level: short rotation coppice (SRC) in Germany*

Abstract

Perennial energy crop production methods such as short rotation coppice (SRC) have gained interest among farmers and policy makers. SRC is characterized by rapid biomass production, low inputs, and high managerial flexibility. SRC plantations also provide environmental advantages relative to annual crop production and contribute to the transition towards renewable energy. Yet, the combination of high sunk costs and high uncertainty hampers SRC adoption among farmers. Policy instruments currently implemented to foster SRC adoption exhibit limited success. In this paper we assess the performance of different policy measures intended to stimulate SRC adoption in terms of efficiency and farm-level effects, taking into account related uncertainty. We use a combination of stochastic programming and the real options approach in our model featuring SRC poplar cultivation in Germany. We analyze four policy measures intended to foster SRC adoption: an establishment subsidy, a price floor, a guaranteed price, and increasing the "Ecological Focus Area" (EFA) value for SRC systems within the European Union Common Agricultural Policy. Our results indicate that a guaranteed price can stimulate immediate SRC adoption; however, it is inferior to the

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other instruments in other dimensions. An establishment subsidy as recently implemented in the study area might incentivize farmers to adopt SRC by contributing substantially to farm income, but should be modified because it may encourage postponement of SRC adoption. Increasing the EFA coefficient and a price floor are more efficient measures in terms of governmental expenditures, while having limited positive effects on bioenergy produced.

Keywords: Biomass; policy regulation; real options; stochastic programming; uncertainty.

3.1. Introduction

In light of increasing global energy demand and concerns about greenhouse gas contributions to climate change, renewable energy sources are becoming increasingly important, including bioenergy sources (Rose et al. 2014). In the European Union (EU) the demand for biomass energy is expected to increase by 19.8% by 2020 (IRENA 2017, p. 64–67) in order to meet renewable energy targets. The largest share of this increase is expected to be satisfied with solid biomass, including woody biomass (Scarlat et al. 2015, Fig. 4). A major advantage of biomass energy over solar and wind is its dispatchability (i.e., the ability to produce energy resources when and where they are necessary) (Thiffault et al. 2016, p. 174). Biomass is therefore considered to be a major contributor to balancing renewable energy supply and demand in emerging energy systems that rely heavily on solar and wind power (Tafarte et al. 2015). In the EU the transition process towards increased production and use of renewable energy sources is strongly supported by policy. Existing biomass energy programs focused on traditional annual crops such as maize or rapeseed, however, have considerable environmental and financial costs (Britz and Hertel 2011; Britz and Delzeit 2013). In contrast, short rotation coppice (SRC) offers a more environmentally friendly and economic means to source woody biomass. Ebers et al. (2016, p. 68) distinguish between socio-economic, ecological, and environmental advantages of woody biomass production. Perennial crop production via SRC is characterized by reduced soil erosion and increased biodiversity and overall landscape diversity relative to annual energy crops (Rokwood 2014, pp. 5–6; Adams and Lindegaard 2016, Fig. 1). Due to its positive effects on soil fertility, Tolbert et al. (2002, p. 105) suggest that SRC could be applied to increase yields of subsequently cultivated crops. In addition, SRC is considered carbon neutral because the amount of atmospheric carbon assimilated during growth is converted to energy (Heller et al. 2003, p. 154; Kern et al. 2010, p. 1458); with poplar (*Populus* spp.) and willow (*Salix* spp.) being the most efficient carbon sinks among SRC tree species (Adler et al. 2007, p. 682). Moreover, SRC is suitable for a spectrum of soils in terms of productivity, including marginal soils (Bringezu 2010, p. 76), which can reduce competition with the production of annual crops and related food and feed production trade-offs (Don et al. 2012, p. 387). Once established with fast growing trees, SRC systems can be coppiced several times at intervals between two and five years (for wood chip production) before clear cutting at approximately 20 years when they can be replaced with annual crops (Federal Forests Act 1975). Farmers can adjust the timing of SRC harvests to market and farm conditions, such as harvesting during winter when on-farm labor resources are more available and thus avoid competition for farm labor resources with other activities (Faasch and Patenaude 2012).

Studies in Scotland (Warren et al. 2016), Germany (Musshoff 2012; Schweier and Becker 2013; Kostrova et al. 2016), Sweden (Dimitriou et al. 2011), and Latvia (Abolina and Luzadis 2015) have shown that farmers are often reluctant to adopt SRC despite its many advantages. In Germany SRC is practiced on only about 50–70 km^2 (Bemmann and Knust 2010; von Wühlisch 2016; FVH 2017) out of over 20,000 km^2 of potential production area (Aust et al. 2014). In the UK approximately 100 km^2 are currently dedicated to energy crop production out of an estimated range of 9,300–36,300 km^2 of suitable land (DECC 2013, p. 28). Considerable profit uncertainties due to volatile energy (i.e., woody biomass output) prices combined with high establishment and subsequent reconversion (i.e., sunk) costs have been identified as the major obstacles to SRC adoption (Hauk et al. 2014; Wolbert-Haverkamp and Musshoff 2014).

In order to increase the adoption of perennial bioenergy crop production using practices such as SRC, a large set of policy instruments have been proposed and discussed (Mola-Yudego and Aronsson 2008; Faasch and Patenaude 2012; Hauk et al. 2014; Witzel and Finger 2016). Existing policy instruments supporting SRC and the production of other perennial bioenergy crops (e.g., switchgrass [*Panicum virgatum*] and *Miscanthus* spp.), as well as more general policy measures intended to reduce uncertainty that inhibits farmer investment in perennial biomass energy production can be classified into: (i) cross-sector instruments such as taxation or quotas for fossil energy use (Mitchell 2000), (ii) investment in research and development (Witzel and Finger 2016), and (iii) farm-level policy measures. It is argued that policies intended to increase the competitiveness of SRC over alternative land uses, and reducing risk burden could facilitate SRC adoption (Rokwood 2014; Abolina and Luzadis 2015; Adams and Lindegaard 2016). To the best of our knowledge, however, a structured comparison of different policy instruments with regard to their performance (e.g., related governmental expenditures), outcome (e.g., energy output), and farm-level effects (e.g., income) considering uncertainty does not exist. We attempt to fill this research gap by using a farm-level analysis that assesses different policy approaches intended to increase SRC adoption. Our normative analysis focuses on farm-level policy instruments and provides policy makers with the necessary basis for subsequent analysis at greater scales and across sectors. We simulate and assess policy interventions on a typical farm in northern Germany, a highly suitable region for SRC cultivation and an area where there is considerable interest in fostering SRC adoption among policy makers. We analyze four relevant policy measures: (i) environmental requirements within the Common Agricultural Policy (CAP) of the EU (Lindegaard et al. 2016) (which favors SRC over conventional annual crops), (ii) SRC establishment subsidies (which were recently introduced in our study area) (MLU-MV 2015), and (iii) guaranteed prices (Mitchell et al. 2006; Feil et al. 2013) and (iv) price floors (Feil et al. 2012) for SRC biomass. We incorporate the importance of risks for farmer investment decisions relevant to SRC adoption using a combination of the real option approach and stochastic programming. Our framework allows analysis and comparison of policies effects across various dimensions, including additional bioenergy production, governmental expenditures, and farmer income (Crabbé and Leroy 2012, p. 5).

3.2. Methodology and Data

3.2.1. Characteristics of SRC and the resulting simulation model

SRC is a long-term management option for the production and harvest of woody biomass from fast growing tree species. Due to its long-term nature SRC binds land resources for a much longer time period than most alternative land uses; although SRC plantations can be clear-cut at any time, triggering sunk costs and thus partial irreversibility of investments made. Unlike annual crops, the establishment and harvest schedule for SRC systems is not predefined and can be adjusted to suit market and farm conditions. Similar to other crop production systems, there is spatial flexibility: a farmer can decide how much land to convert to SRC and later either expand or revert to previous land uses. Therefore, SRC production is characterized by: (i) sunk costs related to establishment and harvest; (ii) temporal and spatial flexibility related to establishment, harvest and reconversion; and (iii) risk throughout SRC production cycles. These three aspects imply the existence of an option value (i.e., potential incentives for a farmer to wait and make investment decisions in response to future states-of-nature (Pindyck 2004, p. 199), which is captured by real options theory. The conceptual advantages of the real options theory over the classical net present value (NPV) approach for analysis of SRC adoption is also supported in the literature (Hauk et al. 2014; Fleten et al. 2016). To date, the real options approach has been employed to analyze policy interventions supporting renewable energy on the national level (Boomsma et al. 2012; Haar and Haar 2017). In contrast, we simulate SRC management decisions under different policy instruments at the farm level.

Our analysis features a farm composed of plots with predefined sizes and a total area of 100 ha. The farmer makes decisions about the management of each plot; essentially whether or not to convert it to SRC. We assume that the area under SRC is not fractional, but rather based on five-hectare increments (i.e., 0, 5, 10, …, 100 ha). Establishment of SRC systems on each plot is considered an option that can either be postponed for a maximum of three years or else never exercised. Harvests can be conducted every two to five years after establishment or the previous harvest. The maximum age of a SRC plantation is 20 years, although reconversion back to annual crops is an option at any time interval after establishment. The total time horizon considered is 24 years (Fig. 3.1). Our model takes into account the full flexibility of SRC management: (i) the ability to postpone a decision to establish SRC plantation on each plot, (ii) the potential to invest in variable sized plantations, (iii) the ability to convert plantations to other land uses before the end of a plantation's production cycle, and (iv) flexibility with respect to harvest intervals.

Resources not used for SRC management can be devoted to other farm activities (as fractional shares). Constraints capture competition for land and labor endowments between SRC and alternative land uses: two annual crops, one of which is more labor intensive and profitable than the other, as well as the options to set-aside land or cultivate short cycle catch crops. The latter two options are introduced to fulfill "Ecological Focus Area" (EFA) requirements according to the latest CAP reform (Zinngrebe et al. 2017). According to this requirement, arable farms must devote 5% of farmland to land uses that qualify towards EFA (BMEL 2015). In order to meet this requirement set-aside land is fully valued (e.g., 1.0) based on area, whereas the area of SRC land or combined catch and annual crop cultivation is valued at a factor of 0.3 (Péer et al. 2016). Catch crops are planted in the winter (Hauk et al. 2014), therefore it is assumed that they do not compete with annual crop production for land and labor resources. Likewise, it is assumed that SRC harvests do not to compete with annual crop production for labor because they take place in winter and are usually outsourced (Musshoff 2012). Fig. 3.1 provides a visual representation of competition among different farm activities in our model over the considered time horizon. A farmer maximizes expected NPV over 24 years subject to three types of constraints: (i) resource endowments, (ii) EFA requirements, and (iii) managerial constraints related to SRC management.

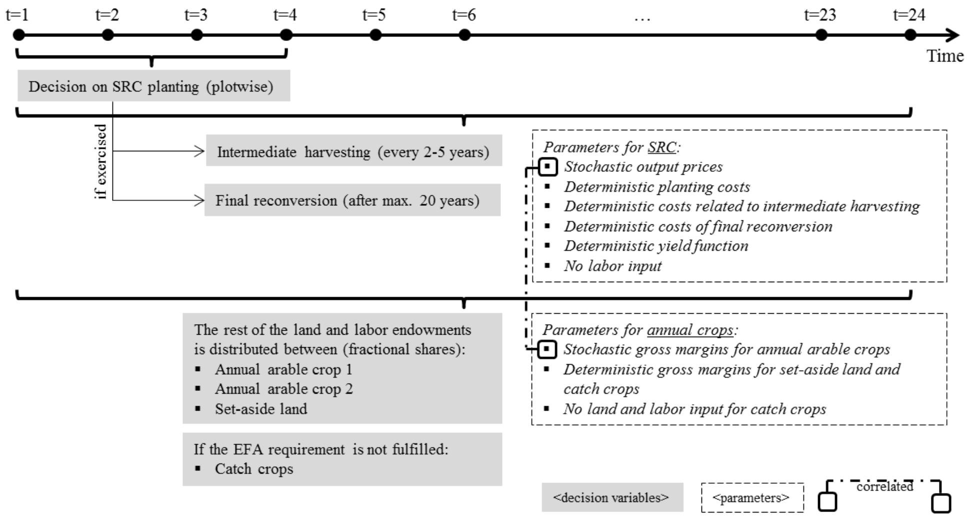

Figure 3.1. Overview of the dynamic farm-level model.

We assume that SRC output prices and annual crop gross margins are stochastic and follow a mean-reverting process (MRP) in logarithmic form. Note that risks related to annual crop production are not specified in detail, but are summarized using a general proxy for stochastic gross margins, which represents the opportunity costs of SRC management. Since a farmer has no flexibility with respect to the harvest of annual crops, further specification of annual crop gross margins or set-aside land would have no influence on farmer behavior. For simplicity and clarity, we only model one stochastic process for the annual crop gross margin based on a single MRP. The simulated level for each node in the scenario tree is then modified with a multiplicative fixed factor for each of the two annual crop options. A correlation coefficient between SRC biomass price and alternative crop gross margins enters the stochastic processes as presented in equation (3.1)

(Schwartz and Smith 2000, p. 896). We consider a correlation between SRC biomass prices and annual crop gross margins due to the fact that global competition for land and other land-use inputs results in correlation of output prices for energy and annual crops (Fritsche et al. 2010; Song et al. 2011, p. 770). In addition, prices for bioenergy crops and the costs of annual crop cultivation are positively correlated because energy prices impact the prices of intermediate inputs such as diesel and agro-chemicals. The correlation coefficient is included as follows:

$$\begin{gathered} dp_t = \mu_{SRC}(\theta_{SRC} - p_t)dt + \sigma_{SRC}dW_t^{SRC} \\ dgm_t = \mu_C(\theta_C - gm_t)dt + \rho\sigma_C dW_t^{SRC} + \sqrt{(1-\rho^2)}\sigma_C dW_t^C \end{gathered} \tag{3.1}$$

where t represents years; SRC stands for short rotation coppice; C is for annual crops; p_t is the natural logarithm of SRC biomass price; gm_t is the natural logarithm of annual crop gross margins; μ_{SRC} and μ_C represent the speed of reversion of the stochastic process; θ_{SRC} and θ_C represent the long-term logarithmic mean SRC biomass price and annual crop gross margin respectively; σ_{SRC} and σ_C are volatilities of logarithmic SRC biomass price and annual crop gross margins respectively; dW_t^{SRC} and dW_t^C are standard independent Brownian motions; and ρ is the correlation coefficient between Brownian motions.

The solution consists of three steps. First, we simulate Monte Carlo draws for the stochastic parameters (i.e., SRC biomass price and annual crop gross margins). The two stochastic processes for each draw yield both a SRC biomass price and an annual crop gross margin that are assigned to the nodes of the scenario tree (Fig. 3.2). Next, we reduce the obtained scenario tree with up to 200 leaves using SCENRED2 (GAMS 2015; Kostrova et al. 2016, pp. 8–9). The scenario tree reduction assigns a probability of occurrence and specific related values for the stochastic SRC biomass price and gross margins of the competing annual crops to each node of the reduced scenario tree. Finally, we solve the resulting stochastic dynamic problem in order to obtain the optimal solution with and without policy intervention (Fig. 3.2). We use a mixed integer programming farm-level model due to various if-then type binary decisions inherent to our problem. In order to avoid introducing non-linearities in addition to binary variables, we do not treat land area under SRC as fractional. The dynamic stochastic programming approach is solved simultaneously over 24 years, considering different potential developments with respect to SRC biomass prices and gross margins of competing crops. The model code and documentation are available online (Spiegel et al. 2017).

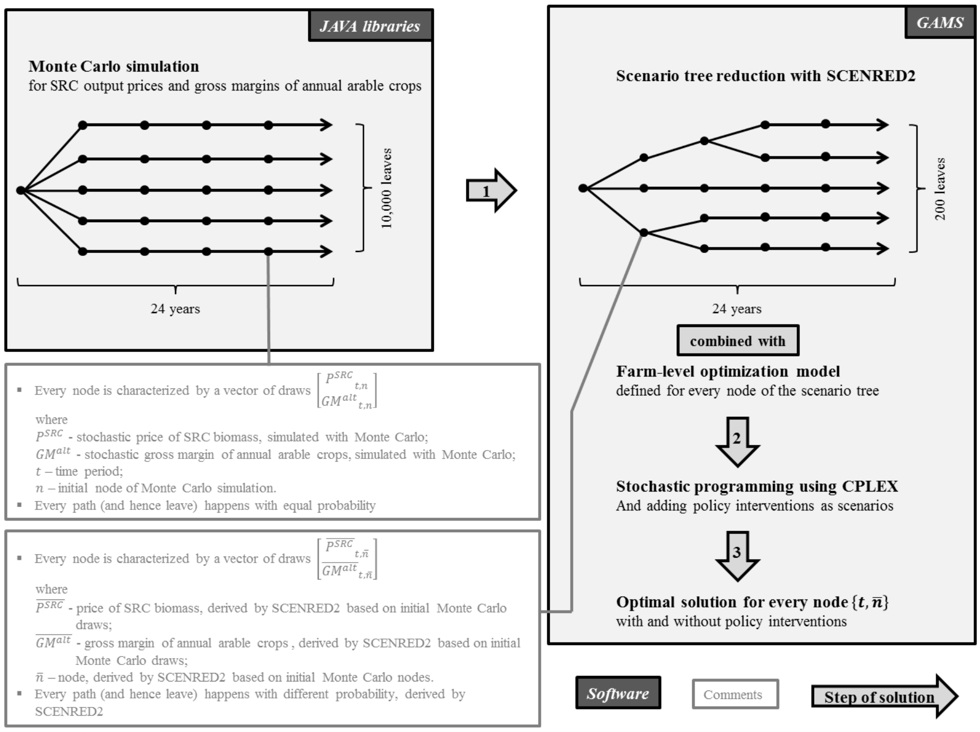

Figure 3.2. Step-by-step solution approach and employed software.

3.2.2. Case study and data

Our case study is based on a typical arable farm in northern Germany. The existing policy framework to support SRC establishment in this region comprises three measures. First, SRC plantations are recognized as agriculture and benefit from direct CAP payments along with annual crop production areas. Direct payments are made to farmers regardless of the agricultural land use and therefore do not influence land-use decisions, so these are not included in the model analysis. Second, although SRC plantations qualify towards EFA requirements, currently the value of land under SRC management in Germany is equal to 0.3 relative to the value of conservation set asides (Péer et al. 2016). Third, since 2015 SRC plantation establishment costs are subsidized with payments of 1,200 € ha^{-1} (Appendix 3.2). While many fast-growing tree species may be used in SRC systems, we focus our analysis on poplars since they are among the most popular SRC species in the EU, particularly in Germany (Hauk et al. 2014, p. 406). The model can easily be adjusted for other trees such as willow species (see Djomo et al. [2011] and Hauk et al. [2014] for economic comparisons of SRC poplar and willow plantations). In Germany the typical end product of SRC biomass is wood chips

(Keutmann et al. 2016, p. 315). We convert harvested SRC biomass values into thermal energy values, assuming a gross calorific value of 16.40 GJ t^{-1} (ECN 2017) and subtract the amount of energy that annual crops would have absorbed if they were cultivated on the same SRC area: 40.00 GJ ha^{-1} y^{-1} (Twidell and Weir 2015) (Appendix 3.1). The calorific value of SRC biomass depends on multiple factors, including; tree genotype (Klasnja et al. 2002; Sabatti et al. 2014), soil quality (Rodrigues et al. 2017), and tree age (Klasnja et al. 2002). In our model settings a different value would lead to multiplicative down- or up-scaling of the outcome without influencing farmer behavior. We also assume that farmers are paid for bioenergy according to dry matter yields (i.e., per tonne as opposed to derived gigajoule) and account for yields in tonnes, therefore, we convert dry matter yields to gigajoules based on model results.

The MRP for SRC biomass prices is adopted from Musshoff (2012). The MRP parameters for annual crop gross margins were estimated using CAPRI model data (CAPRI 2017) on mean gross margins per hectare of arable land in Germany over 1993–2012, following the procedure described in Musshoff and Hirschauer (Musshoff and Hirschauer 2004, pp. 271–273). The two stochastic processes are summarized in Table 3.1 and Appendix 3.1. There are ambiguous findings on the sign and magnitude of correlation between SRC biomass price and annual crop gross margins. Du et al. (2011) quantified the correlation between the volatility of global crude petroleum and wheat and maize prices as 0.07–0.34. Musshoff and Hirschauer (2004) estimated the correlation between the gross margins of non-food rapeseed and other annual crops to range from −0.01 to 0.65. Diekmann et al. (2014) assume a correlation coefficient between the gross margins of *Miscanthus* and wheat of 0.29. We therefore consider both a positive and a negative correlation ρ of ± 0.2 (Eq. 3.1) between the two Brownian motions and compare the results (hereafter referred to as positive and negative correlations). The gross margins obtained from the respective stochastic process enter the model with multiplicative factors of 1.05 for the more profitable crop and 0.95 for the lesser one.

Table 3.1. Parameters of the two stochastic processes.

	Parameters of the mean-reverting process for	
	Natural logarithm of SRC biomass price	Natural logarithm of gross margins of annual crops
Starting value	3.92[a]	6.02[b]
Long-term mean	3.92[a]	6.02[b]
Speed of reversion	0.22	0.32
Standard deviation	0.22	0.28
MRP coefficient for a more labor intensive and profitable crop		1.05
MRP coefficient for a less labor intensive and profitable crop		0.95
Correlation coefficient between MRPs for SRC prices and gross margins of annual annual crops is +/– 0.20		

[a] Equivalent to dry matter price of 50 € t^{-1}

[b] Equivalent to gross margin of 413 € ha^{-1}

Note: Starting values are equal to the long-term mean in order to exclude any possible effect of a trend. Data sources: Musshoff (2012); CAPRI (2017).

The assumed parameters of the model are summarized in Table 3.2 and Appendix 3.1. The gross margins are assumed to be –100 € ha^{-1} for catch crops (de Witte and Latacz-Lohmann 2014, p. 37) and –50 € ha^{-1} for set-aside land (CAPRI 2017). The yield function for SRC biomass follows Ali (2009) as a linear function for biomass stock dependent on the previous year's stock. The harvest cost function includes all costs related to SRC harvests (e.g., additional transaction costs for finding a contractor, fertilization and storage), and is expressed as a sum of farm (fixed), per hectare (quasi-fixed), and per tonne of harvested biomass (variable) costs in order to consider economy of scale (Ali 2009; Schweier and Becker 2012). We apply an annual social discount rate of zero due to the fact that almost zero interest rates are currently available in Germany (ECB 2017) such that governmental expenditures are not discounted. For simplicity and clarity of our analysis, we assume risk neutrality among farmers and use an annual market discount rate of 3.87% y^{-1} (Musshoff 2012). Previous studies suggest that an option value to wait also exists under risk neutrality as investment decisions are time dependent on evolving conditions in order to maximize overall returns (Dixit and Pindyck 1994, p. 153) and risk neutrality is a common assumption in existing real options applications (Dixit and Pindyck 1994; Wossink and Gardebroek 2006;

Song et al. 2011). A frequently used approach for considering risk preferences in dynamic stochastic models is to move from a market-based to a risk-adjusted discount rate (Musshoff 2012; Wolbert-Haverkamp and Musshoff 2014). However, risk varies at each node of the tree in our analysis (e.g., risk decreases approaching the final leaves), such that different risk-adjusted discount rates for each time period and state-of-nature would be needed (Brandão and Dyer 2005; Finger 2016). Also, as the alternatives to SRC are not risk-free, the risk-adjusted discount rates would need to vary according to the endogenously chosen land uses (i.e., for SRC and annual crops) (*ibid.*). Alternatively, risk preferences can be captured by introducing a risk utility function (Ewald and Yang 2008), controlling for conditional value-at-risk (Beraldi et al. 2013), or applying the concept of stochastic dominance (Kuosmanen 2007). Any option requires making additional assumptions, including choice of a risk measure (Kuosmanen 2007; Shapiro 2012; Homem-de-Mello and Pagnoncelli 2016), and might significantly affect computational efficiency.

Table 3.2. Parameters of the model simulation.

Parameters	Units	Assumed values	References
	Short rotation coppice		
Establishment costs	euro per hectare (€ ha^{-1})	2,875.00	Musshoff (2012)
Dry matter growth function			
Multiplier for previous year's biomass	-	1.54	Ali (2009)
Constant increase	tonnes per hectare per year (t ha^{-1} y^{-1})	6.68	Ali (2009)
Costs related to SRC harvests			
Fixed costs a farm level	euro (€)	66.75	Schweier and Becker (2012); Pecenka and Hoffmann (2012)
Quasi-fixed costs for each plot	(€ ha^{-1})	272.13	Schweier and Becker (2012); Pecenka and Hoffmann (2012)

Variable costs, depending on dry matter yields	euro per tonne per hectare (€ t^{-1} ha^{-1})	10.67	Schweier and Becker (2012); Pecenka and Hoffmann (2012)
Reconversion costs	(€ ha^{-1})	1,400.00	Musshoff (2012)
Labor requirements	hours per hectare per year (h ha^{-1} y^{-1})	0.00	Musshoff (2012)
	Annual crops		
Deterministic net annual cash flow (gross margins) from crops recognized as EFA			
Set-aside land (EFA greening coefficient 1.00)	euro per hectare (€ ha^{-1})	–50.00	CAPRI (2017)
Catch crops (EFA greening coefficient 0.30)	euro per hectare (€ ha^{-1})	–100.00	de Witte and Latacz-Lohmann (2014, p.37)
Labor requirements			
A more labor intensive and profitable crop	hours per hectare per year (h ha^{-1} y^{-1})	5.32	KTBL (2012)
A less labor intensive and profitable crop	(h ha^{-1} y^{-1})	4.16	KTBL (2012)
Set-aside land	(h ha^{-1} y^{-1})	1.00	KTBL (2012)
Catch crops	(h ha^{-1} y^{-1})	0.00	KTBL (2012)
	Farm characteristics		
Land endowment	(ha)	100.00*	
Step for adjusting SRC plantation (i.e., size of smallest plot)	(ha)	5.00*	
Labor endowment	hours per year (h y^{-1})	500.00*	
Real risk-free discount rate	percent per year (% y^{-1})	3.87	Musshoff (2012)
Social discount rate	(% y^{-1})	0.00	ECB (2017)

Note: *data are based on own assumptions (Appendix 3.1).

3.2.3. *Policy scenarios*

In our analysis we compare four policy instruments for promoting SRC adoption at different intensities (Table 3.3, Appendix 3.2) to a business-as-usual (BAU) scenario where only the currently implemented EFA weighting coefficient of 0.3 (Péer et al. 2016) is applied. Two of the policies—introducing an establishment subsidy and increasing the EFA weighting coefficient—are chosen because they already exist and are proposed in literature (MLU-MV 2015; Lindegaard et al. 2016). The remaining two policies—a price floor and a guaranteed price for SRC biomass—address SRC market risk, considered a major barrier to SRC adoption (Mitchell et al. 2006; Feil et al. 2012; 2013), and have been used to promote renewable energy production in the EU (Bakhtyar et al. 2017). Based on theoretical considerations and the existing literature, the policy instruments are expected to impact SRC adoption as follows. Increasing the EFA weighting coefficient should mitigate competition for land between SRC and annual crops, therefore lowering the opportunity costs of SRC systems (Dixit and Pindyck 1994, p. 346). An SRC establishment subsidy decreases the sunk costs of the investment (Dixit and Pindyck 1994, pp. 33–35). A price floor increases the expected price of SRC biomass by removing downside risk (Feil and Musshoff 2013). Additionally, a guaranteed price removes upside risks related to the price of SRC biomass and leaves the annual crop gross margins as stochastic variables in the model. This decreases incentives to delay implementation and renders the model more similar to a classical NPV approach. The stochastic annual crop gross margins impact the opportunity costs of land and labor, and thus create a potentially positive option value related to SRC cultivation (Dixit and Pindyck 1994, pp. 38–39).

Table 3.3. Policy instruments, intensities and related governmental expenditures chosen for the analysis.

		Intensities	Governmental expenditures	Schedule of policy support
BAU	EFA weighting coefficient, (0;1)	0.3	-	-
Policy interventions	Increasing the EFA weighting coefficient, (0;1)	0.5; 0.7; 1.0	-	-
	Planting subsidy, euro per hectare (€ ha^{-1})	500; 1,000; 1,200; 1,500	Establishment subsidy multiplied by land area devoted to SRC	Paid once SRC established
	Guaranteed SRC dry matter price, euro per ton (€ t^{-1})	50; 55; 60	Difference between guaranteed price and market price multiplied by harvested SRC biomass	Paid for each harvest
	Price floor for SRC biomass (€ t^{-1})	40; 45; 50	If the difference between price floor and market price is positive, this difference is multiplied by harvested SRC biomass dry matter	Paid for each harvest if market price falls below price floor

Note: BAU = business-as-usual (baseline scenario); EFA = Ecological Focus Area

The EFA weighting coefficient considers a range starting from the currently granted factor of 0.3 under the BAU to a maximum of 1.0 (i.e., to a point where one hectare of SRC production would be treated equally to one hectare of set-aside land). For the different subsidy levels, we focus our assumptions on recently implemented support measures in the case study region. Specifically, if the total SRC establishment investment exceeds 7,500 €, up to 40% and a maximum of 10 ha are subsidized at a rate of 1,200 € ha^{-1} per farm (MLU-MV 2015) (Appendix 3.2). For simplicity we ignore any existing requirements and constraints for the establishment subsidy, but consider different subsidy levels. A guaranteed price as a supportive policy instrument only makes sense at or above the long-term mean SRC dry matter price used in the Monte Carlo analysis (50 € t^{-1}), therefore, we have chosen 50 €, 55 €, and 60 € t^{-1} as subsidy levels. Similarly, in order for a price floor to reduce downside risk it should be below the expected mean, therefore, we have considered 40 €, 45 €, and 50 € t^{-1} in our analysis.

We assess the policy instruments based on the metrics proposed by Crabbé and Leroy (Crabbé and Leroy 2012, p. 5): (i) policy performance (expressed by associated governmental expenditures); and (ii) policy outcome (expressed by additional biomass produced at the farm level). In addition, we assess: (iii) the effect on farm income, and (iv) how efficiently the governmental expenditures are transformed into additional farm income. The production of SRC biomass and farm income are simulated directly by the model, governmental expenditures are calculated as follows: the establishment subsidy granted per hectare is multiplied by the area converted to SRC; the amount of harvested SRC biomass is multiplied in each state-of-nature and year by the difference between the price floor and the market price, if the latter undercuts the price floor. The latter condition is dropped for a guaranteed price such that expenditures at each node and in sum might be positive or negative. Finally, we assume no governmental expenditures for changing the EFA weighting coefficient. Appendix 3.2 provides further details, including mathematical representation of governmental costs.

The effect on farm income is calculated as a difference in the NPV of (i) the overall farm with a policy instrument in place and (ii) under the BAU scenario. The ratio between the absolute change in farm income and governmental expenditures provides the policy instrument's transfer efficiency (i.e., how much farm income is generated from each euro of governmental expenditures).

3.3. Results

In the BAU scenario, assuming a positive correlation of 0.2 between the price of SRC biomass and annual crop gross margins, a farmer is expected to implement SRC on 5.6 ha (Appendix 3.3). The implementation of SRC is not exercised immediately, but rather once market conditions are attractive enough to justify the investment (i.e., in later time periods when the highest expected net returns can be generated). The probability of implementing SRC is 60.8% in the first three years after the initial time period. Postponing the decision to implement SRC in order to benefit from new information on prices and gross margins reflects a positive option value.

Results under both the BAU and policy scenarios are not overly sensitive with respect to the correlation coefficient between SRC biomass price and annual crop gross margins (Fig. 3.3). However, under a negative correlation coefficient SRC is a better risk hedging strategy and thus creates slightly greater incentives for SRC and higher farm income (BAU scenario results in Appendix 3.3). Consequently, a guaranteed price, which reduces the hedging effect, performs much worse under a negative correlation relative to the BAU scenario (Fig. 3.3).

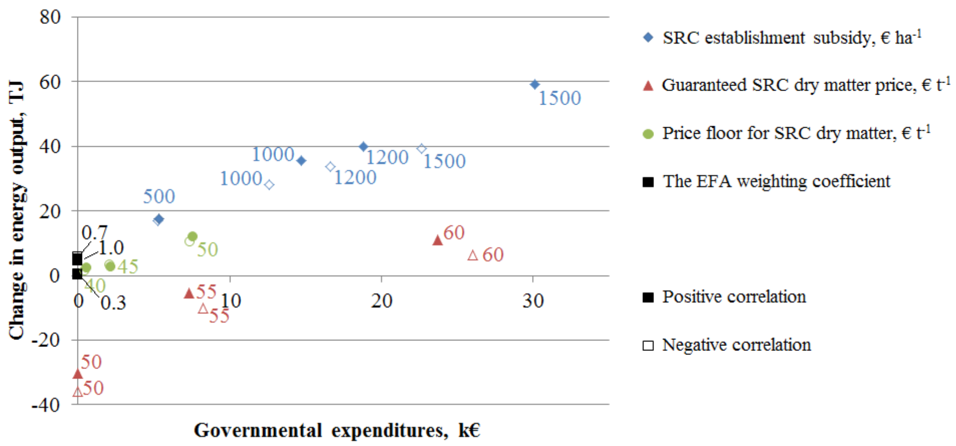

Figure 3.3. Efficiency of different policy instruments in terms of expected mean changes in energy production and governmental expenditures.

Note: TJ represents Terajoules; k€ represents one thousand euro; € ha^{-1} represents euro per hectare; and € t^{-1} represents euro per tonne. Values indicate change relative to the business-as-usual scenario, assuming positive or negative correlation between biomass prices and agricultural crop gross margins. The intensity of the policy instruments (Table 3.3) is indicated next to the corresponding points.

Our results reveal that the performance of a policy instrument is dependent on its intensity and varies by metric. An establishment subsidy leads to the highest expected mean absolute increase in thermal energy produced from biomass, while a guaranteed SRC dry matter price floor of 50 € or 55 € t^{-1} reduces expected energy production (Fig. 3.3). The latter can be explained by the elimination of stochasticity with respect to biomass price, substantially reducing managerial flexibility to adjust SRC plantation and harvests according to states-of-nature. While a guaranteed price might seem to be the least efficient incentive, it is the only policy instrument that stimulates immediate SRC implementation because it reduces incentives to postpone. The effects on thermal energy production of both higher EFA coefficients and a price floor are rather limited (Fig. 3.3). The limited impact of increasing the coefficient may be due to the fact that the total EFA requirement for individual farms is only 5%. Accordingly, even the maximal implicit support level for SRC reached with a factor of unity is equivalent to only 5% of SRC land use relative to total farm area. Also, an EFA coefficient value of 1.0 is less efficient than 0.7 in terms of its effect on bioenergy production and land area under SRC (Table 3.4). This is caused by our assumptions on total land endowment and available plots for SRC implementation. Since the smallest plot is assumed to be five hectares, devoting this amount of area alone to SRC fulfills the EFA requirement with a coefficient of 1.0. However, ten hectares of SRC are needed to fulfill the EFA requirement if the coefficient is 0.7, whereas five hectares is insufficient. Therefore, SRC replaces set-aside land to fulfill environmental requirements with the greater EFA coefficient, yet it cannot compete for land resources with annual crops.

With regard to governmental outlays, increasing the EFA coefficient represents a no-cost option. A high SRC establishment subsidy is the most expensive policy instrument; however, a high guaranteed price represents comparable governmental costs, while being much less efficient for increasing bioenergy production. The effect of different policy instruments on bioenergy production is not necessarily positive when risk is considered. As discussed in the example above, guaranteed prices eliminate upside risk, which otherwise can be exploited by farmers based on the possibility of postponing SRC implementation and adjustment of harvest timing. We therefore further compare policy instruments in terms of governmental expenditures per additional GJ of energy produced, distinguishing between positive and negative effects of policy instruments on bioenergy production (Fig. 3.4). The EFA coefficient is not considered because it does not affect costs and a guaranteed SRC dry matter price of 50 € t^{-1} in a situation where SRC is not implemented. Compared to all other instruments and intensity levels, price floors of 40 € and 45 € t^{-1} for SRC dry matter perform best (Fig. 3.4), however, there is a low probability (0.12 and 0.21 respectively) of an increase in energy production. An establishment subsidy of 500 € ha^{-1} requires similar governmental costs per unit increase in energy production, while the probability of success is at least double (0.45). In all of the simulated policy scenarios, less than 2 € GJ^{-1} are spent (Fig. 3.4), which is substantially less than required governmental expenditures according to the German Renewable Energy Act, which stipulates 9.17 € to 77.50 € GJ^{-1} for renewable energy from different sources (BMWi 2017, p. 12).

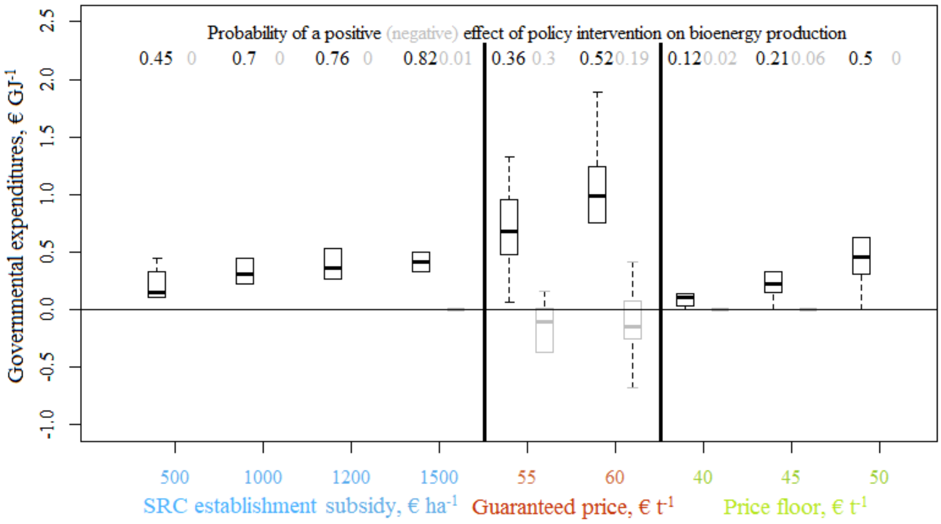

Figure 3.4. Probability of impacts resulting from governmental expenditures on change in energy production assuming positive correlation between biomass price and annual crop gross margins.

Note: € GJ^{-1} represents euro per gigajoule; € ha^{-1} represents euro per hectare; and € t^{-1} represents euro per tonne. For each policy instrument and scenario tree leaf, the total governmental expenditures are divided over the absolute difference in bioenergy production relative to the business-as-usual scenario and are combined with the probability of the leaf occurring. Outliers, defined as points lying outside 1.5·IQR (interquartile range) from the first and third quartiles, are omitted.

A price floor seems advantageous in terms of governmental expenditures, however, it is characterized by comparatively inefficient transformation of those expenditures into additional farm income (Fig. 3.5). Guaranteed biomass price exhibits a similar dynamic. In contrast, an establishment subsidy achieves a transformation efficiency of up to 90% (farmers earn 90 cent for each euro of governmental expenditure). This higher transformation efficiency of the establishment subsidy also reflects the difference between individual and social discount rates. The latter is assumed to be zero such that any future discount factor is unity. An establishment subsidy is paid in the year when SRC is introduced (i.e., between the first and fourth years of the simulation), such that the private discount factor is still close to unity and differs slightly from the social one. Compared to establishment subsidies, price floors and guaranteed prices shift governmental costs and related income increases for farmers in the future with higher private discount factors, such that the difference between social and private discounting alone reduces the transformation efficiency of these policy instruments. This demonstrates that if the private discount rate exceeds the public one, a direct income transfer in the future cannot achieve a transfer efficiency of 100%.

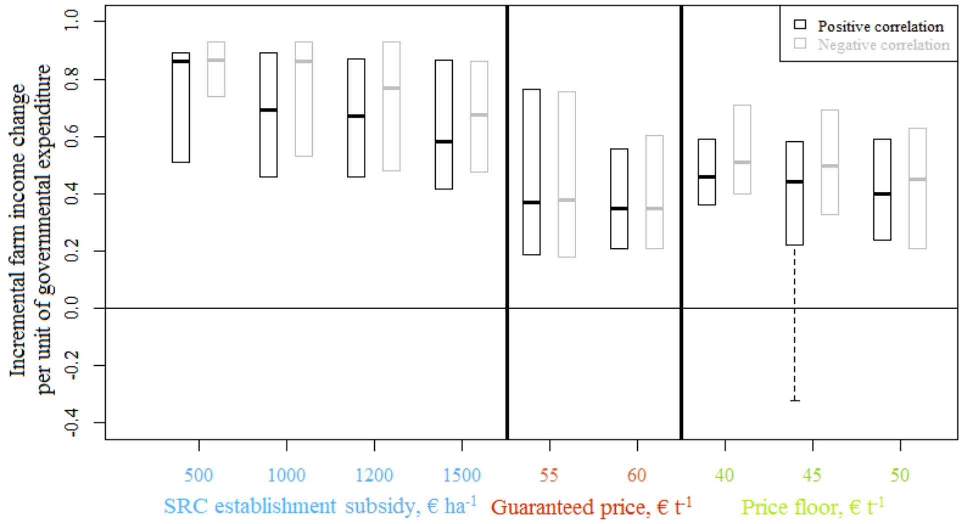

Figure 3.5. Transformation of governmental expenditures into farm income assuming positive or negative correlation between biomass prices and annual crop gross margins.

Note: € ha^{-1} represents euro per hectare and € t^{-1} represents euro per tonne. The model results shown are for intervention effects relative to the business-as-usual scenario. Outliers, defined as the points lying outside 1.5·IQR (interquartile range) from the first and third quartiles, are omitted.

Policy instrument performance based on the different metrics is summarized in Table 3.4. A guaranteed price is the least effective instrument across all metrics, being beneficial only as a stimulus for immediate SRC establishment at high intensities/prices (Appendix 3.3). The other three policy instruments exhibit better performance. Increasing EFA coefficients is attractive from the standpoint that it does not represent additional governmental expenditure, however, its effect on bioenergy production is limited. The price floor option exhibits a similar dynamic. In contrast, establishment subsidy has the greatest effect on SRC implementation and farm income.

Table 3.4. Overview of predicted policy instrument performance assuming a positive correlation between biomass price and annual crop gross margins.

Policy intervention	Intensity	Policy instrument performance (expected values compared with BAU scenario)				
		Effect on bioenergy production (GJ)	Governmental expenditures per GJ increase in bioenergy production (€ GJ^{-1})	Effect on farm income (€)	Farm income increase per euro of governmental expenditures (€)	Change in land area devoted to SRC (ha)
Establishment subsidy (€ ha^{-1})	500	17,689.22	0.20	3,758.82	0.71	3.94
	1,000	35,697.37	0.39	9,116.07	0.66	8.00
	1,200	40,008.32	0.41	11,698.12	0.64	8.93
	1,500	59,152.11	0.44	16,199.09	0.60	13.34
Guaranteed SRC biomass dry matter price, (€ t^{-1})	50	−30,197.50	0.00	−8,441.67	−∞*	−6.73
	55	−5,414.20	0.70	−2,830.71	0.29	−1.21
	60	10,971.94	0.97	2,826.29	0.51	2.45
Price floor for SRC biomass dry matter (€ t^{-1})	40	2,509.05	0.11	110.74	0.78	0.58
	45	2,711.58	0.25	248.55	0.50	0.60
	50	12,073.17	0.48	2,562.49	0.86	2.69
Increasing EFA coefficient	0.5	4,467.72	0.00	3,534.75	+∞**	1.00
	0.7	5,167.49	0.00	6,865.08	+∞**	1.15
	1.0	435.11	0.00	11,584.65	+∞**	0.10

Notes: The results come from a negative (*) or positive (**) change in bioenergy production compared to the business-as-usual scenario results and no governmental expenditures. The best and worst results are highlighted in green and red respectively.

3.4. Policy recommendations

We find that policy instrument efficiency and performance depend on their intensity and vary according to the metric used to assess their impacts. In order to incentivize immediate SRC implementation, a guaranteed biomass price seems to be most effective according to our results, although overall it is the least efficient of the policy instruments evaluated due to a very limited or possibly even negative effect on bioenergy production, while being costly. Similarly, Boomsma et al. (2012) found that a fixed feed-in tariff (i.e., guaranteed price) initiates earlier investment, yet at a lower capacity. A guaranteed price removes upside risk beneficial for SRC cultivation that can be exploited by temporal managerial flexibility. This negative impact of a risk reducing policy instrument might seem counterintuitive as high risk related to SRC cultivation is often discussed in the literature as one of the main obstacles to SRC adoption. Chatalova and Balmann (2017) also conclude that investors might benefit from increasing uncertainty due to the available option to adjust their investment behavior according to states-of-nature. In addition, due to low correlation of SRC and annual crop yield gross margins, Hauk et al. (2017) consider SRC adoption as an efficient risk-reducing strategy; an advantage that is lost under a guaranteed SRC biomass price policy. Uncertainty is only beneficial when there is temporal or spatial flexibility. For example, annual energy crops offer no temporal managerial flexibility and therefore a risk reducing policy instrument would be expected to have a positive impact on their immediate adoption. Indeed, a fixed feed-in tariff (i.e., guaranteed price) for electricity produced from renewable energy sources appears to be a highly relevant instrument to stimulate adoption in Germany (Mitchell et al. 2006; Feil et al. 2013) and the EU (Proskurina et al. 2016). However, the effect of this policy has been found to be cost-inefficient, in particular because feed-in tariffs do not target the cheapest renewable energy sources (Kreuz and Müsgens 2017). In addition, the high costs of the existing policy are charged to final electricity consumers; an intended effect that can foster energy saving measures and help to reduce energy use. In the case of SRC biomass, driving up demand side prices is rather counterproductive because the market needs to be developed in alignment with primary production (Rokwood 2014). Price floors and guaranteed prices also suffer from other disadvantages. Both policies require government agencies to act directly or indirectly as SRC biomass buyers. Furthermore, governmental expenditures for these instruments cannot be planned in advance because the government assumes price risk. The effect of price regulation is sensitive to the way in which it is implemented and adjusted over time, and may trigger undesirable strategic decisions by market actors (Alizamir et al. 2016; Chatalova and Balmann 2017). Finally, such programs must be maintained over the full lifetime of the subsidized plantations, whereas alternative instruments such as an establishment subsidy can be implemented for limited periods.

Based on governmental costs, an increase of the EFA coefficient is superior to the other policy instruments examined, since it does not require funding. Adjustment to the EFA is the only one of the evaluated instruments that avoids increasing competition for land between energy and food production. Opportunity costs of land are crucial for SRC adoption because it requires little farm labor and SRC management activities that require labor can be scheduled during periods when farm labor is more available or else can be outsourced. Increasing the EFA coefficient could provide incentives to convert set-aside land to SRC production, which might have positive effects on several ecosystem services such as biodiversity (Rowe et al. 2011) depending on the scale of SRC operations (Louette et al. 2010) and the initial biodiversity status on the set-asides.

If increased bioenergy production is a priority, then an establishment subsidy is the most promising of the policy instruments. By reducing sunk costs associated with SRC cultivation, which have been identified as a major barrier to adoption, an establishment subsidy also has the greatest positive effect on farm income. This policy instrument is also efficient at transforming governmental expenditures into farm income, while governmental costs are not directly influenced by market price fluctuations and therefore can be forecasted accurately. Although governmental costs required for establishment subsidies are high, the costs of additional bioenergy (as measured in gigajoules) using this instrument are quite moderate, while the probability of a positive effect is considerable (82% in our model) at high subsidy intensities. Superior effectiveness of investment subsidies relative to price floors is consistent with the findings of Feil and Musshoff (2013) and Feil et al. (2012) based on evaluation of policy intervention effectiveness on investment and disinvestment decisions of homogenous firms in a competitive environment. Three issues require special attention for practical implementation of a subsidy. First, recently introduced establishment subsidies in our study region imply a set of restrictions (Appendix 3.2) that would limit the positive effects of this instrument exhibited by the model results. Second, the results suggest that an establishment subsidy does not eliminate incentives to postpone SRC adoption. A temporally limited establishment subsidy and/or a first-come-first-serve eligibility basis would increase the costs of postponement and likely stimulate more immediate SRC adoption. Furthermore, a first-come-first-serve eligibility basis allows policy makers to impose limits on related governmental expenditures. Third, an establishment subsidy may be more effective if implemented in combination with other policy instruments. For instance, establishment costs of perennial energy crops were subsidized during 2000–2013 in the UK, yet the budget was underspent and the intended target was not achieved (Adams and Lindegaard 2016, pp. 195–196). The lack of policy support in addition to the subsidy scheme was revealed to be the main reason for this failure; in particular, no infrastructural support was provided and opportunity costs were very high (*ibid.*). Combining an establishment subsidy with a higher EFA coefficient to lower opportunity costs could mitigate the latter problem. As for infrastructure development, successful SRC policies often require coordinated action at regional scales (Rokwood 2014), particularly for ensuring investment in harvesting equipment and biomass processing facilities. The different potential supply chain actors may become trapped in a 'prisoner's dilemma' as postponement can be the optimal strategy for all actors. For example, farmers might prefer not to invest in SRC systems because they lack both partners to market their products and contractors to harvest their plantations. On the other hand, a regionalized establishment subsidy might catalyze the development of local supply chains.

In the case of our study area, we recommend increasing the EFA coefficient and modifying the recently implemented establishment subsidy by either restricting availability to a limited period or area, or restricting eligibility on a first-come-first-serve basis. Our model results demonstrate that promoting SRC cultivation can require much less governmental expenditure than other renewable energy sources subsidized under the German Renewable Energy Act (e.g., biogas, solar, wind energy) (BMWi 2017, p. 12). Our findings improve understanding of farm-level decisions regarding SRC adoption and inform related policy analysis at larger scales. Additional issues related to the practical implementation of policy support of SRC systems deserve further research. A farm-level policy instrument might indirectly affect other economic agents and industries (e.g., food or pulp and paper industries) (Scarlat et al. 2015, p. 983). Policy makers should be aware of potential negative effects of policy instruments, including technical inefficiency and moral hazard (Rizov et al. 2013, pp. 539–540). Furthermore, any policy instrument intended to stimulate bioenergy production should be implemented consistently in order to achieve long-term effects (White et al. 2013) because frequent changes or excessive policy instruments can undermine public confidence and might hamper efficiency due to increased complexity (Ebers et al. 2016). In particular, our model can be scaled up and effects on other markets and agents can be integrated, which would permit investigation of direct and indirect policy impacts. Risk preferences can also be introduced in the model.

3.5. Conclusion

Increasing the use of woody biomass energy resources and related production systems, including SRC, is crucial for reaching EU renewable energy targets (Scarlat et al. 2015; Hauk et al. 2017). Due to its advantages over the production of annual energy crops such as maize, SRC offers a promising means of sourcing bioenergy, especially on marginal lands. Some of these advantages are environmental, including carbon neutrality and positive biodiversity impacts. However, to date SRC adoption among farmers is quite limited due to high sunk costs related to plantation establishment, harvest, and the final reconversion of SRC systems back to annual crop production, as well as due to risk over the course of SRC plantation cycles (Hauk et al. 2014; Wolbert-Haverkamp and Musshoff 2014). Taking these perspectives into account, we analyze the performance of a range of policy instruments intended to incentivize SRC adoption at the farm level based on the following metrics: increase in bioenergy production, effect on farm income, and governmental expenditures. In particular, we modeled a typical northern Germany farm based on real options considering the redistribution of limited resources in order to implement SRC under different policy instrument support: (i) an establishment subsidy, (ii) a guaranteed biomass price, (iii) a biomass price floor, and (iv) an increase of the EFA value of SRC systems. The model settings allow individual farmers to postpone SRC introduction, to adjust the land area converted to SRC, and to vary harvest intervals in response to stochastic variables—SRC biomass price and annual crop gross margins. We solve the model with a combination of Monte Carlo simulation, a scenario tree reduction technique, and stochastic programming.

Our methodological contribution to policy development is twofold. We demonstrated that considering all competing farm activities and limited resources is crucial for capturing direct and indirect effects of a policy instrument on farm resource redistribution. In particular, analysis of increasing the EFA value of SRC systems is only possible in this context, since this policy instrument reduces SRC opportunity costs. We also demonstrate that a policy analysis for long-term investment decisions with temporal and spatial flexibility under consideration of all possible states-of-nature reveals additional effects of policy instruments on investment behavior. In our example, a guaranteed SRC biomass price exhibits poor overall performance because it eliminates both positive and negative risks, and thus any possible advantages of postponement or adjusting decisions based on states-of-nature. The empirical model results suggest that price floors and guaranteed prices for biomass are not promising policy measures, whereas establishment subsidies and increasing the EFA value of SRC systems could be more effective at increasing woody biomass energy production and transforming governmental expenditures to farm income. However, in our study area SRC establishment subsidies should be offered on a first-come-first-serve basis or for a limited period to avoid incentivizing postponement of SRC implementation at the farm level.

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3.7. Appendices

Appendix 3.1. Model parameters

Establishment and reconversion costs related to SRC biomass production

Establishment (2,875 € ha^{-1}) and reconversion (1,400 € ha^{-1}) costs were adopted from Musshoff (2012). Additional SRC establishment and reconversion costs were found in the literature cited in Table 3.5.

Table 3.5. SRC plantation establishment and reconversion costs.

Establishment costs (€ ha^{-1})	Reference	Reconversion costs (€ ha^{-1})	Reference
2,316.38	Kroeber et al. (2008)	2,072.50	Faasch and Patenaude (2012)
2,255.00–3,223.00	Strohm et al. (2012)	960.00–3,200.00	Strohm et al. (2012)
3,199.92	Wolbert-Haverkamp (2012)	1,800.00	Schweier and Becker (2013)
2,380.00–3,223.00	ETI (2013)	1,121.00	Wolbert-Haverkamp and Musshoff (2014)
2,736.00	Wolbert-Haverkamp and Musshoff (2014)		

SRC biomass growth function and biomass harvest costs

The following yield function was adapted from Ali (2009):

$$Y = 2.27 \cdot (-0.1133 \cdot 10^{-8} \cdot D^2 + 0.254 \cdot 10^{-4} \cdot D + 0.028) \cdot (1.569 \cdot HI + 0.4 \cdot 10^{-3} \cdot PT \cdot SQI - \frac{23.198 \cdot Temp}{W})^{(0.34 \cdot 10^{-8} \cdot D^2 - 0.501 \cdot 10^{-4} \cdot D + 2.614)} \tag{3.2}$$

where Y represents dry matter yields, D is the density of trees per hectare; HI is the intermediate harvesting interval (2, 3, 4, or 5 years); PT is the mean sum of precipitation in May and June (mm); SQI is a soil quality index value; $Temp$ is the mean temperature from April through July (°C); and W represents available ground water capacity (mm). All variables except for intermediate harvesting interval (HI) were fixed at the levels presented in Table 3.6.

All the variables except for intermediate harvesting interval (HI [2, 3, 4, or 5 years]) were fixed on the following levels:

Table 3.6. Parameters of the yield function and assumed values

Variables	Description	Values	References
D	density of trees per hectare	9,000	Musshoff (2012)
PT	mean sum of precipitation in May and June (mm)	106.27	Based on precipitation recorded for May and June (1995–2015) in Mecklenburg, Germany (WetterOnline 2016)
SQI	soil quality index	35	Musshoff (2012)
$Temp$	mean temperature from April through July (°C)	14.51	Mean of daily mean temperatures (minimum and maximum) for April through July (1995–2015) in Mecklenburg, Germany (WetterOnline 2016)
W	available ground water capacity (mm)	220.00	Musshoff (2012)

Then we fitted the obtained values to a linear function of available biomass in the previous year:

$$Y = 1.651 \cdot Y_{-1} + 3.962 \quad (3.3)$$

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

We assume that harvest related costs include: (i) transportation and labor costs based on the distance from the farm to the field, expressed as fixed costs per farm; (ii) transportation and labor costs based on harvested area; and (iii) transportation and labor costs are based on harvested biomass (Schweier and Becker 2012). Summarizing the costs provided by Schweier and Becker (2012) and Pecenka and Hoffmann (2012), we derived the following harvest cost function:

$$HC = 66.75 + 272.13 \cdot L + 10.67 \cdot L \cdot Y \quad (3.4)$$

where HC are the total harvest costs in euro; L is the land area harvested in hectares; and Y represents dry matter yields in tonnes per hectare. The formula requires an additional assumption about a transportation distance. Pecenka and Hoffmann (2012) report a distance between 5 km and 200 km. We assumed a transportation distance of 25 km. The assumptions described above result in the biomass and harvest cost based on the harvest intervals and land areas under SRC present in Table 3.7.

Mean SRC harvest costs per tonne of dry matter (€ t^{-1}) range from 24 to nearly 41 euro: 24 (Musshoff 2012); 28.85 (Kroeber et al. 2008); 32 (Wolbert-Haverkamp and Musshoff 2014); 30.28–39.00 (Strohm et al. 2012); 40.8 (Faasch and Patenaude 2012).

Table 3.7. SRC biomass yields and harvest costs based on harvest interval and land area.

	Land area under SRC (ha)	**Harvest interval (years)**			
		2	**3**	**4**	**5**
Dry matter yields (t ha^{-1})	any	10.503	21.302	39.133	68.571
Harvest costs (€ ha^{-1})	1	450.95 (42.94)	566.17 (26.58)	756.43 (19.33)	1,070.53 (15.61)

Value per tonne of dry matter in parentheses (€ t^{-1})	10	390.87 (37.22)	506.10 (23.76)	696.35 (17.79)	1,010.46 (14.74)
	30	386.42 (36.79)	501.65 (23.55)	691.90 (17.68)	1,006.01 (14.67)
	50	385.53 (36.71)	500.76 (23.51)	691.01 (17.66)	1,005.12 (14.66)

Stochastic processes for SRC biomass price and annual crop gross margins

We assume that the natural logarithm of SRC biomass price and annual crop gross margins follows an Ornstein-Uhlenbeck MRP (Nicolato and Venardos [2003] and Pérez-Abreu [2010] provide an Ornstein-Uhlenbeck process overview). This choice is motivated by the assumption that individual farmers act as a 'price-taker' in a market where the price fluctuates around a constant long-term mean value due to market forces, for example, under assumptions of no monopolistic power (Metcalf and Hassett 1995, p. 1472) and/or constant technology (Song et al. 2011, p. 775). The formula of an MRP is as follows (Dixit and Pindyck 1994, p. 74):

$$dx = \eta(\dot{x} - x)dt + \sigma dz \tag{3.5}$$

where x is a stochastic variable; $\dot{x}$ is the "normal" or mean value of x (to which x tends to revert); dx is the change in x; dt represents the time interval; $\eta > 0$ is the speed of reversion; $\sigma > 0$ represents variance; and dz is the increment of a Wiener process.

The MRP for SRC biomass prices is adopted from Musshoff (2012). The parameters of the MRP for alternative crops gross margins were estimated using data from the CAPRI (2017) model on gross margins of an average hectare of arable land in Germany over 1993–2012, following the procedure described in Musshoff and Hirschauer (2004, pp. 271–273). For both stochastic processes the starting values are set equal to the long-term mean in order to exclude any possible effect of a trend over time. Opportunity costs of SRC plantations (€ ha^{-1}) vary according to soil quality, values found for Germany include 549 € ha^{-1} (Wolbert-Haverkamp 2012) and a range of 230–710 € ha^{-1} (Faasch and Patenaude 2012).

Deterministic net annual cash flow (gross margins) from crops that qualify towards EFA requirements

The costs of cultivating catch crops depend on farm activities prior to planting and vary from 40 € to 140 € ha^{-1} (de Witte and Latacz-Lohmann 2014, p. 37). In our model we assume the costs of cultivating catch crops to be 100 € ha^{-1}. The gross margin of set-aside land (–50 € ha^{-1}) is the mean of net revenues for set aside and fallow land over 1991–2012 (CAPRI 2017).

Labor requirements and endowments

Labor requirements only include fieldwork, management is assumed to be limited and therefore have no effect on resource distribution at the farm level.

Land endowment

The total land endowment of 100 ha used in the model facilitates straightforward interpretation of the outcomes (land area devoted to different land uses can be directly transformed into proportions of the total area). The farm size is representative for northern Germany. For example, the average size of an agricultural holding in the North German states of Mecklenburg-Western Pomerania, Lower Saxony and Schleswig-Holstein was 89.85 ha in 2017 (DESTATIS 2017).

Energy absorbed by crops

We used the gross calorific value of SRC yields for wood chips derived from poplar (*Populus* spp.) (ECN 2017). Twidell and Weir (2015, chap. 9.6.3) provide mean values of energy absorbed by food crops, including: maize (77 GJ ha^{-1} y^{-1}), wheat (50 GJ ha^{-1} y^{-1}), soy (20 GJ ha^{-1} y^{-1}), and rapeseed (60 GJ ha^{-1} y^{-1}). The authors point out that the values vary according to soil and climate conditions. Since our study region is characterized by comparatively unfavorable conditions for annual crops, we assume a moderate value of 40 GJ ha^{-1} y^{-1}.

Appendix 3.2. Policy instruments chosen for the analysis

Increasing the EFA value of land under SRC management

"Greening" was introduced in 2015 as a part of the EU CAP. Zinngrebe et al. (2017) provide a comprehensive overview and analysis of the EFA system in Germany. They conclude that the EFA weighting coefficients are chosen based on administrative, technical, and economic considerations rather than ecological or social ones.

Establishment subsidy

Subsidies for establishing SRC plantations were introduced in Germany in 2015 in some states (Baden-Württemberg, Brandenburg, Berlin, Mecklenburg-Western Pomerania, North Rhine-Westphalia, and Thuringia) (FNR 2017). The subsidy is 1,200 € ha^{-1} with a minimum of 7,500 € total per farm and a maximum of 40% of total establishment costs. The physical requirements for the subsidy include a maximum of 10 ha per farm, a minimum density of 3,000 trees per hectare, and a minimum period of 12 years before reconversion of plantation areas to other land uses (FNR 2017). For the sake of simplicity we ignore additional establishment subsidy requirements and constraints in Germany and analyze four establishment subsidy levels instead (500 €, 1,000 €, 1,200 €, and 1,500 € per hectare). Countries that provide subsidies for SRC plantation establishment and maintenance include Ireland, Poland, and Sweden (Lindegaard et al. 2016).

Price floor and guaranteed price

The difference between a price floor and a guaranteed price is that the former eliminates downside price risk only, while the latter eliminates price risk in both directions. A price floor is applied once the observed market price falls below it. In contrast, guaranteed price is applied continuously and the government assumes both positive and negative risk of market price fluctuations.

Currently, no farm-level price regulations exist for SRC biomass in Germany. However, in many countries, including Germany, Spain, Switzerland, and the USA, a feed-in tariff system is applied to electricity produced from renewable sources (Ebers et al. 2016; FNR 2013). For example, the current feed-in tariff level for electricity from biomass in Germany ranges 5.71–13.32 cent kWh^{-1} depending on rated capacity (EEG 2017, sec. 42). The policy has an indirect effect on farmer decisions related to biomass production through the price that an electricity producer is willing to pay for biomass.

Governmental expenditures

At each node of the scenario tree, governmental expenditures are determined using equation (3.6). Total governmental costs are the sum of governmental costs at each node weighted by the respective probabilities of the nodes.

$$
\begin{gathered}
GC_{EFA} = 0 \\
GC_S = S \cdot L_{plant} \\
GC_{p\_min} = \max[p_{min} - p_{market}; 0] \cdot L \cdot Y \\
GC_{p\_fix} = \left(p_{fix} - p_{market}\right) \cdot L \cdot Y
\end{gathered} \tag{3.6}
$$

where GC_{EFA} represents governmental expenditures for increasing the EFA coefficient in euro; GC_S represents governmental expenditures for an establishment subsidy in euro; GC_{p_min} represents governmental expenditures for a price floor in euro; GC_{p_fix} represents governmental expenditures for guaranteed price in euro; S is the establishment subsidy value in euro per hectare; L_{plant} represents the land area on which SRC is established in hectares; L is the land area under SRC to be harvested in hectares; Y is the dry matter yield harvested in tonnes per hectare; p_{market} is the observed market price of SRC dry matter yields in euro per tonne; p_{min} is the price floor for SRC biomass in euro per tonne; and p_{fix} is the guaranteed price for SRC biomass in euro per tonne. Time and node indices are omitted for simplicity. Only a fully guaranteed price can generate additional government income if the market price exceeds the fixed price. Also, timing of governmental outlays varies: an establishment subsidy triggers cost at the time of establishment, a price floor and guaranteed price are set in the year a plot is harvested.

Appendix 3.3. Model results overview

Table 3.8. Overview of the model results assuming that the correlation coefficient between SRC biomass prices and annual crop gross margins is equal to +0.2.

	Policy intervention													
	BAU	Establishment subsidy (€ ha⁻¹)				Guaranteed price (€ t⁻¹)			Price floor (€ t⁻¹)			Increasing EFA coefficient		
		500	1,000	1,200	1,500	50	55	60	40	45	50	0.5	0.7	1.0
Farm income (net present value over 24 years) (1,000s €)														
Maximum	932.431	967.189	1,001.946	1,015.849	1,036.704	856.853	856.771	860.971	932.431	932.431	932.431	932.431	932.431	932.431
Expected	643.002	646.761	652.118	654.700	659.201	634.561	640.172	645.829	643.113	643.251	645.565	646.537	649.867	654.587
Minimum	500.708	500.708	502.589	502.589	502.589	500.708	509.937	511.988	500.708	500.708	503.513	502.589	503.602	508.843
Probability of SRC adoption														
Immediately	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
In one year	0.19	0.27	0.34	0.37	0.47	0.00	0.00	0.00	0.25	0.30	0.38	0.29	0.43	0.48
In two years	0.21	0.32	0.30	0.32	0.29	0.00	0.00	0.00	0.18	0.16	0.28	0.26	0.30	0.29
In three years	0.21	0.22	0.25	0.25	0.21	0.00	0.00	0.00	0.26	0.26	0.34	0.26	0.25	0.21
Never	0.39	0.19	0.11	0.06	0.03	1.00	0.00	0.00	0.31	0.28	0.00	0.19	0.01	0.02
Land under SRC (ha)														
Maximum	75.00	75.00	75.00	75.00	75.00	0.00	15.00	15.00	75.00	75.00	75.00	75.00	75.00	75.00
Expected	5.61	8.90	12.24	13.04	16.60	0.00	4.60	7.65	6.08	6.11	7.85	6.44	6.57	5.69
Minimum	0.00	0.00	0.00	0.00	5.00	0.00	5.00	5.00	0.00	0.00	5.00	0.00	0.00	0.00

	SRC bioenergy production (GJ)													
Maximum	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91	0.00	67,884.98	67,884.98	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91
Expected	30,466.78	48,313.74	66,484.29	70,832.32	90,152.39	0.00	25,004.30	41,536.56	32,998.89	33,202.54	42,647.61	34,974.34	35,680.35	30,905.77
Minimum	0.00	0.00	0.00	0.00	16,971.25	0.00	22,628.33	22,628.33	0.00	0.00	22,628.33	0.00	0.00	0.00
	Change in bioenergy production compared with BAU (including energy absorbed by annual crops) (GJ)													
Expected	-	17,689.22	35,697.37	40,008.32	59,152.11	−30,197.50	−5,414.20	10,971.94	2,509.05	2,711.58	12,073.17	4,467.72	5,167.49	435.11
	Age of SRC plantation (years)													
Expected	20.00	20.00	19.98	19.98	19.91	0.00	20.00	20.00	19.92	20.00	20.00	20.00	20.00	20.00
	Expected area under alternative crops (ha)													
More profitable annual crop	83.93	83.79	81.71	81.77	78.68	80.01	89.86	88.12	84.59	84.96	87.42	86.17	88.34	87.22
Less profitable annual crop	8.79	6.03	5.00	4.21	3.83	17.21	4.53	3.60	7.81	7.48	3.79	6.19	4.12	6.53
Set-aside	1.67	1.27	1.05	0.98	0.89	2.79	1.00	0.63	1.53	1.45	0.94	1.19	0.97	0.55
Catch crops	6.83	6.42	6.05	5.66	5.44	7.38	8.74	6.90	6.84	7.06	7.06	4.32	2.78	1.16
	Total governmental expenditures (€)													
Maximum	0.00	37,500.00	75,000.00	90,000.00	112,500.00	0.00	74,993.40	99,825.67	9,935.02	17,620.94	43,334.95	0.00	0.00	0.00
Expected	0.00	5,337.75	14,735.50	18,795.00	30,104.25	0.00	7323.19	23,672.29	592.38	2,118.48	7,549.51	0.00	0.00	0.00
Minimum	0.00	0.00	0.00	0.00	7,500.00	0.00	−42,384.29	−91,348.48	0.00	0.00	0.00	0.00	0.00	0.00
	Governmental expenditures per GJ of increase in bioenergy production compared to BAU (only states-of-nature with increase in bioenergy included) (€ GJ^{-1})													
Maximum	-	0.45	0.89	1.07	1.00	0.00	1.33	1.89	0.39	0.70	1.18	-	-	-
Expected	-	0.20	0.39	0.41	0.44	0.00	0.70	0.97	0.11	0.25	0.48	-	-	-
Minimum	-	0.11	0.22	0.27	0.33	0.00	−0.05	−1.13	0.00	0.00	0.00	-	-	-

Table 3.9. Overview of the model results assuming that the correlation coefficient between SRC biomass prices and annual crop gross margins is equal to –0.2.

	Policy intervention													
	BAU	Establishment subsidy (€ ha⁻¹)				Guaranteed price (€ t⁻¹)			Price floor (€ t⁻¹)			Increasing EFA coefficient		
		500	1,000	1,200	1,500	50	55	60	40	45	50	0.5	0.7	1.0
Farm income (net present value over 24 years) (1000s €)														
Maximum	830.556	862.941	895.327	908.281	927.712	832.519	833.697	837.897	830.556	830.556	831.752	835.066	835.066	851.629
Expected	643.462	647.205	652.233	654.884	658.771	636.230	641.841	647.701	643.290	644.439	646.115	647.490	650.052	655.820
Minimum	497.914	497.914	493.233	494.092	495.381	495.122	502.246	516.402	497.914	496.994	500.742	492.957	496.976	503.370
Probability of SRC adoption														
Immediately	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
In one year	0.23	0.20	0.30	0.35	0.35	0.00	0.00	0.00	0.20	0.23	0.43	0.25	0.36	0.42
In two years	0.20	0.29	0.28	0.30	0.32	0.00	0.00	0.00	0.22	0.25	0.26	0.30	0.32	0.34
In three years	0.27	0.25	0.27	0.30	0.28	0.00	0.00	0.00	0.29	0.34	0.30	0.33	0.32	0.22
Never	0.31	0.25	0.14	0.04	0.06	1.00	0.00	0.00	0.29	0.17	0.01	0.13	0.00	0.02
Land under SRC (ha)														
Maximum	75.00	75.00	75.00	75.00	75.00	0.00	15.00	15.00	75.00	75.00	75.00	75.00	75.00	75.00
Expected	5.98	8.73	10.50	11.53	12.56	0.00	4.80	7.90	6.24	6.50	7.97	7.09	7.20	6.25
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	5.00	5.00	0.00	0.00	0.00	0.00	5.00	0.00
SRC bioenergy production (GJ)														
Maximum	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91	0.00	67,884.98	67,884.98	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91	339,424.91
Expected	32,498.80	47,415.40	57,032.44	62,642.00	68,232.33	0.00	26,045.20	42,916.89	33,867.82	35,303.58	43,273.85	38,486.26	39,101.75	33,915.34

Minimum	0.00	0.00	0.00	0.00	0.00	0.00	22,628.33	22,628.33	0.00	0.00	0.00	0.00	22,628.33	0.00
Change in bioenergy production compared with BAU (including energy absorbed by annual crops) (GJ)														
Expected	-	14,750.91	24,179.95	29,747.53	35,147.42	−32,180.86	−6,354.62	10,380.74	1,346.89	2,783.74	10,676.90	5,957.26	6,570.35	1,435.39
Age of SRC plantation (years)														
Expected	20.00	20.00	20.00	19.97	19.99	0.00	20.00	20.00	19.93	19.96	19.91	20.00	19.97	20.00
Expected area under alternative crops (ha)														
More profitable annual crop	84.63	82.92	82.98	83.49	82.41	80.20	89.79	87.97	84.77	86.09	86.99	86.54	87.97	86.99
Less profitable annual crop	7.78	6.88	5.24	3.99	4.04	16.94	4.44	3.52	7.44	6.08	4.04	5.21	3.82	6.15
Set-aside	1.60	1.47	1.28	0.98	0.99	2.86	0.98	0.61	1.56	1.34	1.00	1.17	1.01	0.62
Catch crops	7.21	6.68	6.24	6.13	5.56	7.14	8.61	6.73	7.15	7.40	7.33	4.22	2.62	0.90
Total governmental expenditures (€)														
Maximum	0.00	37,500.00	75,000.00	90,000.00	112,500.00	0.00	83,059.97	105,891.24	8,076.75	16,771.97	32,327.14	0.00	0.00	0.00
Expected	0.00	5,238.50	12,602.00	16,624.20	22,622.25	0.00	8,210.59	25,989.43	442.85	2,079.53	7,392.52	0.00	0.00	0.00
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	−38,837.36	−50,795.99	0.00	0.00	0.00	0.00	0.00	0.00
Governmental expenditures per 1 GJ of increase in bioenergy production compared with BAU (only states-of-nature with increase in bioenergy included) (€ GJ^{-1})														
Maximum	-	0.33	0.67	0.81	1.01	0.00	106.68	115.14	4.44	4.88	1.16	-	-	-
Expected	-	0.21	0.36	0.40	0.49	0.00	2.81	3.26	0.31	0.27	0.43	-	-	-
Minimum	-	0.11	0.22	0.27	0.33	0.00	−127.78	−0.51	0.00	0.00	0.00	-	-	-

Chapter 4

Risk, risk aversion and agricultural technology adoption—a combination of real options and stochastic dominance*

Abstract

We propose a novel approach to capture risk and risk aversion for agricultural technology adoption by integrating second order stochastic dominance in a farm-level model based on real options. We employ an illustrative case study of perennial energy crop adoption. In our example, we find that risk aversion leads to smaller and earlier adoption of a new technology; in contrast, higher subjective risk levels increase the expected scale and at first slow down but later accelerate adoption. These effects would be obscured if technology adoption is considered as standing alone or as a now-or-never decision.

Keywords: Risk preferences; farm-level investment decision; stochastic programming; short rotation coppice.

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4.1. Introduction

Decisions about the adoption of new technologies are of crucial relevance for farm success (Blandford and Hill 2006, p. 43; Kumar and Joshi 2014). The literature proposes expected revenues (Trujillo-Barrera et al. 2016), opportunity costs (White et al. 2005), resource endowments (Affholder et al. 2010; Grabowski and Kerr 2014), risk preferences (Liu 2013), and risk perception (Marra et al. 2003; Liu 2013) as key determinants of technology adoption. Research of the joint effects of these factors on optimal timing and the scale of technology adoption is still limited (Meijer et al. 2015). To account for the essential role of risk, real option theory provides a powerful framework to analyze investment based technology adoption decisions at the farm level (Wossink and Gardebroek 2006; Hinrichs et al. 2008; Hill 2010; Maart-Noelck and Musshoff 2013). Moreover, farm-level programming approaches are widely used tools for detailed farm management analysis as they allow reflecting resource endowments or economies of scale as inherent issues in farm-level analyses.

In this study we propose a novel farm-level modeling approach that allows simultaneous analysis and quantification of the effects of these determinants. In particular, we embed the concept of stochastic dominance into the real options framework and demonstrate with an empirical example how (subjective) risk levels and risk preferences can be reflected. Our approach solves for both optimal timing and scale of technology adoption.

Changing the timing and scale of a farm level investment typically impacts both expected returns and their distribution by affecting production or associated risks. The latter have been found to have a significant influence on technology adoption (Marra et al. 2003; Liu 2013). Different approaches have been proposed to incorporate risk in farm-level programming approaches (Krokhmal et al. 2011; Homem-de-Mello and Pagnoncelli 2016), but most are not well suited to stochastic dynamic programming. Furthermore, the popular mean-variance based approaches or their variants, such as MOTAD[16] or Target MOTAD, require a risk aversion coefficient, which

[16] Minimization Of Total Absolute Deviations (MOTAD) is a linear version proposed by Hazell (1971) of mean-variance analysis (Markowitz 1952). Mean-variance analysis in general minimizes the risk (i.e., variance) for a given expected outcome or maximizes the expected

is empirically difficult to determine and scale dependent. We therefore employ the concept of stochastic dominance, which we consider inviting as it requires limited assumptions on risk preferences and can be efficiently incorporated into stochastic programming (Nie et al. 2012). Specifically, a set of additional constraints ensures that a new technology is only adapted at a scale (or not at all) at which it stochastically dominates a given risk benchmark with respect to farm production activities. Subjective perception risks are crucial determinants of technology adoption, which is emphasized in the case of a lack of knowledge and experience concerning new technologies (Marra et al. 2003; Ghadim 2003; Karni 2006). We consider this aspect by conducting a sensitivity analysis with respect to risk level associated with a new technology.

To illustrate our modeling approach, we employ a case study of introducing short-rotation coppice (SRC) biomass energy production systems as a new technology on a typical arable farm in northern Germany. Establishing an SRC plantation with a typical production cycle of approximately 20 years represents significant sunk costs for planting, coppicing, and final reconversion to an alternative land use. It binds land for a longer period than other land uses and competes with annual crops for limited farm resources (e.g., land). Both SRC and annual crop agriculture imply stochastic returns; with the latter constituting an observed benchmark. The case study thus encompasses the elements mentioned above as inherent for investment-based technology adoption in agriculture and shows how to quantify the effects of (subjective) risk level and risk preferences of timing and scale of adoption.

4.2. Literature and theoretical background

In the presence of production, market, institutional, and technological risks (Sunding and Zilberman 2001), irreversible investments and sunk costs, the real options approach is increasingly favored over the classical NPV approach for modelling farm-level investment decisions, including technology adoption

outcome for a given variance; and is consistent with second-order stochastic dominance applied here if the risk measure (e.g., returns) is normally distributed (Krokhmal et al. 2011, p. 52).

(Wossink and Gardebroek 2006; Hinrichs et al. 2008; Hill 2010; Kuminoff and Wossink 2010; Maart-Noelck and Musshoff 2013). It captures the option value (i.e., the possibility to postpone a decision or timing flexibility) or later adjusts it (scale flexibility) depending on how future conditions evolve. The real options approach can be incorporated into a farm-level programming approach based on stochastic programming where risk is captured by a scenario tree (Beraldi et al. 2013; Alonso-Ayuso et al. 2014; Simoglou et al. 2014). Most applications still use binomial scenario trees or lattices (Schulmerich 2010; Beraldi et al. 2013; Alonso-Ayuso et al. 2014) where model size increases exponentially 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; Kostrova et al. 2016).

The real options approach can be applied under different assumptions with regard to risk preferences, as a positive option value might exist regardless of risk attitude: any decision maker aims to maximize overall returns and takes into account possible development of stochastic variables (Dixit and Pindyck 1994, p. 153). Yet, risk preferences might influence the timing and scale of optimal decision making and therefore are relevant for analyzing technology adoption (Marra et al. 2003; Liu 2013). Empirical results highlight that with respect to European agriculture, farmers tend to be risk-averse (Menapace et al. 2013; Meraner and Finger 2017), such that we consider it in our stochastic dynamic programming approach. Homem-de-Mello and Pagnoncelli (2016) provide a comprehensive overview of approaches for introducing risk aversion into stochastic programming. Based on their evaluation, we consider stochastic dominance as especially suitable because it is consistent with the expected utility hypothesis (Chavas 2004, chap. 5), but does not require a fully specified utility function. In particular, second-order stochastic dominance (SSD) only requires the underlying von Neumann-Morgenstern utility function to be monotone and concave (i.e., in the case of a risk-averse decision maker). So, a random variable B is SSD over 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 the one of A, (i.e., $\mathbb{E}[u(B)] \geq \mathbb{E}[u(A)]$) (Dentcheva and Ruszczyński 2006, p. 298). 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, p. 57):

$$B \succcurlyeq_{(2)} A \quad \Leftrightarrow \quad \sum_x [(F_A(x) - F_B(x)) \cdot (x_{+1} - x) \mid x \leq z] \geq 0 \quad \forall z \tag{4.1}$$

where 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 of x higher than x.

Introducing SSD as a constraint into an optimization model, however, substantially increases computational complexity, since it requires introducing additional binary variables (Gollmer et al. 2007; 2008). To advance in this regard, alternative (approximate) formulations of stochastic dominance are proposed. 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 by a risk measure, which in turns depends on decision variables; hence the number of variables, as well as required solution time increase substantially. This limitation can be overcome if intervals over the cumulative probability are defined rather than over realizations of a risk measure, an approach termed inverse second order stochastic dominance (ISSD) (Ogryczak and Ruszczynski 2002; Dentcheva and Ruszczyński 2006; Rudolf and Ruszczyński 2008). Examples of introducing (I)SSD constraints into optimization models are still limited and can be found in financial applications (El Karoui and Meziou 2006; Roman et al. 2006; Luedtke 2008; Nie et al. 2012), however, to the best of our knowledge no applications to agricultural investment problems exist.

For a probability space $(\Omega, \Lambda, \mathbb{P})$ we first introduce the following definitions (Ogryczak and Ruszczynski 2002, p. 66):

$$\begin{cases} F^{(-2)}(x; p) = p \cdot \mathbb{E}\{x | x \leq \eta\} \\ \qquad p = \mathbb{P}\{x \leq \eta\} \end{cases} \tag{4.2}$$

where $F^{(-2)}: \mathbb{R} \rightarrow \overline{\mathbb{R}}$ is the second quantile function[17]; $\mathbb{E}\{\cdot\}$ is an expectation operator; $x \in \mathbb{R}$ are realizations of a random variable; and $\eta \epsilon \mathbb{R}$ is the so-called

[17] Hereinafter $\mathbb{R}$ remains for the set of real numbers and $\mathbb{N}$ for the set of natural numbers.

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, p. 66):

$$
\begin{aligned}
B \succcurlyeq_{(2)} A \quad \Leftrightarrow \quad & \frac{F_B^{(-2)}(x;p)}{p} \geq \frac{F_A^{(-2)}(x;p)}{p} \quad \Leftrightarrow \\
\Leftrightarrow \quad & \mathbb{E}_B\{x|x \leq \eta\} \geq \mathbb{E}_A\{x|x \leq \eta\} \quad \forall p = \mathbb{P}\{x \leq \eta\} \\
& \in (0;1]
\end{aligned}
\tag{4.3}
$$

The approach does not require ordering realizations x; for each p the target value η is defined and all $x \leq \eta$ are multiplied with the respective probabilities to define $\mathbb{E}\{x|x \leq \eta\}$ without being ordered. We define stochastic returns of a farm under the benchmark farm program as A, then characterize the tolerable risk to a particular farmer; and define B as returns under a new technology that should stochastically dominate that benchmark A in order to be adopted. Hence, 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 is. The optimization problem then appears as follows:

$$
\begin{aligned}
\max \quad & f(x) \\
\text{subject to} \quad & \begin{cases} \mathbb{E}_B\{x|x \leq \eta\} \geq \mathbb{E}_A\{x|x \leq \eta\} \mid \eta : p_i = \mathbb{P}\{x \leq \eta\} \\ p_1 = {}^1\!/_N \\ p_{i+1} = p_i + {}^1\!/_N \end{cases} \\
& \forall i = \{1,2,\ldots,N\} \\
& x \epsilon C
\end{aligned}
\tag{4.4}
$$

where $f(x) \colon \mathbb{R} \rightarrow \overline{\mathbb{R}}$ is the objective function and set C represents further constraints for decision variable x (i.e., resource endowment constraints).

The literature indicates that more risk-averse decision makers tend to adopt a new technology at smaller scales (Liu 2013; Trujillo-Barrera et al. 2016; van Winsen et al. 2016). Indeed, while a risk-neutral farmer would maximize the expected returns without controlling for implied risk, a risk-averse farmer can either replicate the optimum chosen by a risk-neutral farmer or opt for lower risk associated with a smaller scale of adoption and lower expected returns. The effect of risk aversion on timing depends on risk associated with opportunity costs (i.e., returns if not investing). If the returns from alternative resource allocations are risk-free, then risk aversion leads to postponed investment (Hugonnier and Morellec 2007). If opportunity costs are also stochastic and correlated with the investment option to be exercised (as in our settings), then there is a potential opportunity for hedging that a more risk-averse decision maker is more willing to exploit by investing earlier (Henderson and Hobson 2002; Truong and Trück 2016; Chronopoulos and Lumbreras 2017). Therefore we hypothesize that risk aversion leads to smaller scale (*H1*) and earlier adoption on average (*H2*).

Measuring risk levels of stochastic returns at different time points is far from trivial. In a farm household context without off-farm income, yearly profit withdrawals as the main objective variables of a particular farmer are clearly driven mainly by stochastic returns on farming operations; but their risk level can be managed by additional instruments such as the timing of larger household expenditures or short-term loans (see de Mey et al. [2016] for holistic analysis of risk behavior). The latter instruments are very difficult to observe. Additionally, the computational speed would be significantly hampered if we control for ISSD at each time period, while introducing factors such as short-term loans as additional decision variables. In this regard, it is relatively common to use the distribution of the NPV to assess risk level of an investment project (Abadi et al. 1999) instead of considering the distribution of cash inflows and outflows in each year. Conceptually, this implies that an agent would only consider the distribution of her (discounted) terminal wealth after the lifetime of a project. The literature suggests use of a normative portfolio characterized by a tolerable distribution of a risk measure (Bailey 1992; Kuosmanen 2007) if alternatives are evaluated. In the farm context, a farmer's observed production activities and related risk measures can be considered as such a benchmark (Musshoff and Hirschauer 2007). Hence, NPV generated under consideration of a new technology should stochastically dominate that benchmark in order to be realized.

Subjective risk perception often differs from objective risk levels of the investment project derived ex-post (Liu 2013; Menapace et al. 2013; Bocquého et al. 2014), while a decision maker behaves according to her subjective beliefs (Savage 1972; Marra et al. 2003; Karni 2006). The expected utility hypothesis overlaps here with competing prospect theory; the latter capturing subjective probabilities by weighting probability (Bocquého et al. 2014, p. 137). Empirical research identifies a number of factors that affect subjective 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). Subjective risk level is especially relevant for a new technology, whose risk might be hard to determine due to a lack of experience and related knowledge (Bougherara et al. 2017, p. 803). This uncertainty might even be tagged as risk ambiguity (i.e., inability to formulate subjective probabilities) (Barham et al. 2014; Bougherara et al. 2017). The significance of subjective risk level of technology adoption has barely been studied (Meijer et al. 2015) and 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 increases both the option value and the trigger price that should be reached in order to initiate investment (Dixit and Pindyck 1994, p. 192; Hugonnier and Morellec 2007). In contrast, zero volatility would convert the problem into a classical NPV approach without incentive to postpone. We thus hypothesize that subjective overestimation of risk imposed by a new technology increases the negative effect of risk aversion on scale (*H3*) and decreases its positive effect on the timing (*H4*) of technology adoption (Trujillo-Barrera et al. 2016).

4.3. Case study and the resulting farm-level model

As an illustrative example of technology adoption in farming, we consider introducing a perennial energy crop production system (SRC) on a typical arable farm in northern Germany. Establishing a SRC plantation requires high sunk costs (Lowthe-Thomas et al. 2010); yet, once established, an SRC plantation has a lifetime of approximately 20 years, during which it can be coppiced several times without being replanted. During the long lifetime of an SRC plantation, there is (at least) uncertainty in SRC biomass prices. SRC competes with annual crop production for land resources at the farm level, yet SRC establishment and harvesting are usually outsourced, such that little or no farm labor is required (Musshoff 2012, p. 77). The combination of uncertainty, high sunk costs, and the possibility to postpone the adoption decision and to adjust the scale of SRC implementation motivates an option value (i.e., a value of postponing and acquiring more information prior to making a decision) (Pindyck 2004).

SRC adoption has been analyzed using real options (Song et al. 2011; Bartolini and Viaggi 2012; Frey et al. 2013; Kostrova et al. 2016) under risk aversion by introducing a risk-adjusted discount rate (Musshoff 2012; Wolbert-Haverkamp and Musshoff 2014). We expand these models in the following dimensions. First, we consider SRC and evaluate the option value in a farm-level context, capturing interactions with annual crops based on competition for fixed resources. We therefore simulate both optimal timing and scale of technology adoption. Second, we assume that currently observed shares of annual crops constitute a portfolio with stochastic returns (i.e., a farmer reallocates resources within this portfolio and SRC), with both entailing risk. Next, based on empirical results for German farmers (Meraner and Finger 2017) we assume risk-aversion and introduce risk preferences based on ISSD (i.e., without specifying a risk utility function or risk premium or making further restrictive assumptions). Finally, we analyze the effect of subjective risk perception on SRC adoption by changing the risk level associated with SRC.

The currently observed production activities consist of four types of land uses: production of two types of annual crops, one of which is more profitable, but also more labor-intensive than the other, as well as set-aside land and catch crops. A farmer is assumed to be a price-taker. Annual crops are characterized by stochastic gross margins, while set-aside land and catch crops are modeled with deterministic costs and introduced to consider the Ecological Focus Area (EFA) requirement[18]. Two scarce on-farm resources (land [100 ha] and labor [500 hours per year—h y^{-1}]) are allocated among farm activities in fractional shares. A particular farmer considers introducing SRC immediately or within the next three years. A SRC plantation can be coppiced every five years over a period of up to 20 years and afterwards must be clear-cut, although earlier reconversion to other land uses is possible. The time horizon of our model is hence 24 years: a maximum of four years for possible SRC introduction added to the maximal plantation lifetime of 20 years. 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). Economic considerations of introducing SRC are the following. On one hand, SRC requires significant and irreversible investments for establishment and final reconversion (Table 4.1) and binds land resources

[18] According to the Common Agricultural Policy (CAP) introduced with the latest reform, large farms must devote 5% of their land area to land uses serve environmental purposes; with each hectare under catch crops being equivalent to 0.3 ha of set-aside land (EFA) in Germany (BMEL 2015; Péer et al. 2016).

for a long time period, while SRC biomass price is assumed to be stochastic. On the other hand, land under SRC also qualifies for EFA with a coefficient of 0.3 (BMEL 2015; Péer et al. 2016), while no labor input is required as SRC cultivation and harvest are based on contracted services (Musshoff 2012). Accordingly, labor previously used on a plot now devoted to SRC can be reallocated to more profitable and labor-intensive annual crop production. 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. These variables are captured in the SRC harvest cost function:

$$HC = 66.75 + 272.13 \cdot L + 10.67 \cdot L \cdot Y \tag{4.5}$$

where HC represents the total costs related to harvest (€); L is the land area to be harvested; and Y is biomass to be harvested in tonnes of dry matter yield per hectare (t). 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). We use an individual annual discount rate of 3.87% y^{-1} (Musshoff 2012). Appendix 4.1 provides more information on the model parameters. In summary, our model maximizes NPV at each leaf of the scenario tree conditional to risk expectations—$f(\cdot)$ in Eq.4.4—and subject to resource endowments and EFA regulation (C in Eq.4.4), as well as to ISSD constraints.

Table 4.1. Input requirements and returns of alternative farm activities

Parameter	Value	Source
	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 4.2*	
Costs related to harvest	*Defined according to Eq. 4.5*	
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 (2012)
Labor requirements for a less profitable crop	4.16 h ha^{-1} y^{-1}	KTBL (2012)

Gross margins of annual crops	*Stochastic, see Table 4.2*	
Land uses recognized as Ecological Focus Area		
Labor requirements for set-aside land	1.00 h ha^{-1} y^{-1}	KTBL (2012)
Labor requirements for catch crops	0.00 h ha^{-1} y^{-1}	KTBL (2012)
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)

We assume that the natural logarithm of each stochastic variable follows a mean-reverting process (MRP). An MRP is characterized by a long-term mean, speed of reversion, and variance (Dixit and Pindyck 1994, p. 74):

$$dy = \theta(\dot{y} - y)dt + \sigma dz \qquad (4.6)$$

where y is a stochastic variable; $\dot{y}$ is a long-term mean of y to which y tends to revert; dy represents a change in y; dt is a time interval; $\theta > 0$ is the speed of reversion; $\sigma > 0$ is variance; and dz is an increment of a Wiener process. We estimate the parameters of the MRP for annual crops using data on gross margins of an average hectare of arable land in Germany over 1993–2012 from the CAPRI (2017) model following the procedure described in Musshoff and Hirschauer (2004, pp. 271–273). Appendix 4.1 provides more details on the estimation of the MRP. The MRP for SRC biomass prices is adopted from 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). Thus, we assume a zero correlation coefficient between the two stochastic variables. This reflects the fact that gross margins of SRC and annual crops are not driven by similar market and climatic conditions. In contrast, we assume that the gross margins of the two annual crops are perfectly correlated. We hence use one MRP for gross margins and then adjust the draw at each node of the scenario tree with multiplicative coefficients (Table 4.2) to derive gross margin levels.

Table 4.2. (Objective) Parameters of stochastic processes.

Parameter	Value	Source
Mean-reverting process for natural logarithm of SRC biomass price		
Starting value	3.92[ac]	
Long-term mean	3.92[a]	Musshoff (2012)
Speed of reversion	0.22	Musshoff (2012)
Standard deviation	0.28	Musshoff (2012)
Correlation coefficient with the other stochastic process	0.00[d]	
Mean-reverting process for natural logarithm of gross margins of annual crops		
Starting value	6.02[bc]	
Long-term mean	6.02[b]	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[e]	
Multiplicative coefficient for a less labor-intensive and less profitable crop	0.95[e]	

[a] Is equal to ca.50 euro per tonne of dry matter yield (€ t^{-1}).

[b] Is equal to 413 euro per hectare (€ ha^{-1}).

[c] The starting values are set up equal to the long-term mean in order to exclude any possible effect of a trend.

[d] The assumptions is based on ambiguous evidences in the literature about sign and magnitude of the correlation (Musshoff and Hirschauer 2004; Du et al. 2011; Diekmann, et al. 2014).

[e] The multiplicative coefficients are assumed for draws converted back from natural logarithm into euro per hectare.

We solve the mixed-integer model with stochastic programming. We represent uncertainty using a scenario tree, which we construct by running a Monte Carlo simulation with 10,000 draws and then employ a scenario tree reduction technique following Heitsch and Römisch (2008) to obtain a scenario tree with 200 leaves[19]. The algorithm allows control over the number of leaves, keeping the values assigned to each node within a certain plausible range and hence gaining a computational advantage. Since there are several stochastic variables in the model—gross margins of annual crops and SRC biomass price—a vector of values is assigned to each node of the scenario tree. Under the assumption of risk neutrality the model output is the optimal decision with respect to SRC for each node of the tree conditional to decisions made prior to the node and conditional to the possible follow-up scenarios (Fig. 4.1). In order to quantify the effect of risk aversion we introduce risk aversion by means of ISSD and then compare the results with and without risk preferences. In particular, we consider the final distribution of NPVs as a measure of portfolio risk levels and use the currently observed behavior as the benchmark for tolerable risk. The additional ISSD constraints ensure (approximately) that the final distribution of NPVs under consideration of SRC second-order stochastically dominates the distribution of NPVs under the observed crop production activities. We set N equal to 100 and thus consider 100 intervals[20] with a 1%-step (Eq. 4.4), which should render the impact of the approximation negligible. The model, as well as all the related documentation, is publicly available in Spiegel et al. (2017).

[19] The number of leaves in reduced scenario tree is a model parameter and can be adjusted. Its choice is a tradeoff between accuracy and execution time. 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.

[20] Similar to 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 is an acceptable tradeoff between accuracy and execution time.

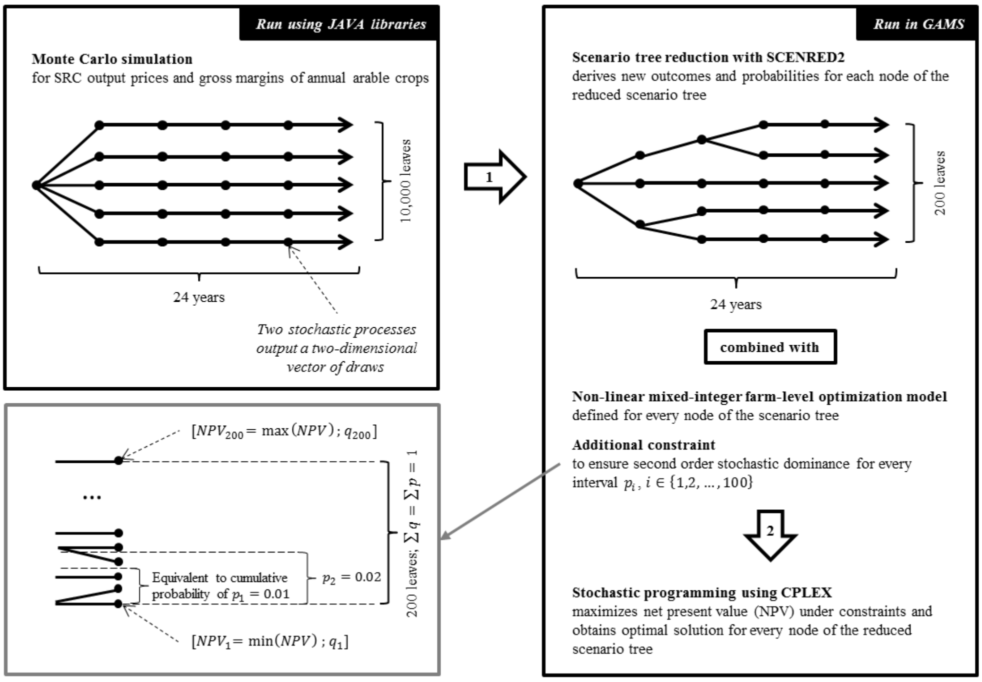

Figure 4.1. Schematic representation of the solution approach

In order to capture the subjective risk levels associated with SRC, we conduct a sensitivity analysis, making stepwise changes to the standard deviation and speed of reversion of the stochastic process for SRC biomass price, while the draws of the other stochastic process (i.e., the gross margins of annual crops) are obtained once and fixed. The higher the standard deviation and the lower the speed of reversion, the more volatile the stochastic process is, reaching a broader range of possible values and reverting at a slower pace back to the long-term mean. Note that neither the long-term mean nor the expected mean SRC biomass price in each year are affected in the sensitivity analysis. Consequently, results under a now-or-never risk-neutral decision (i.e., the classical risk-neutral NPV approach) would not change.

4.4. Results

The key results without considering risk aversion and under objective risk perception are presented in Table 4.3. Note that introducing SRC immediately (i.e., in $t = 1$) is not optimal (i.e., an option value exists). Accordingly, the investment decision is postponed and exercised later or not at all depending on how future conditions evolve. We find that in approximately 40% of the simulated cases that SRC would be never introduced. The expected area under SRC is 7.97 ha, which is not enough to fulfill the EFA requirement, and hence set-aside land and catch crops are remain in the farm portfolio. As argued above, since SRC requires no labor input, a farmer reallocates labor resources to a more profitable and more labor-intensive crop. This interaction of a new technology with other farm activities and reallocation of resources would have obscured analysis of technology adoption as a stand-alone investment.

Table 4.3. Comparison of business-as-usual scenario and introduction of short rotation coppice (SRC) with no ISSD constraint and under objective risk perception.

	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

As our stochastic dynamic optimization setting under risk neutrality introduces SRC on some of the future scenarios, the expected NPV must increase compared to the benchmark, however, we also find substantially higher risk. Indeed, a visual analysis immediately reveals that NPV with SRC simulated under risk neutrality (i.e., without the ISSD constraints) cannot stochastically dominate the BAU scenario: its lowest NPV realization undercuts the lowest one under the BAU scenario (compare black and red solid curves in Fig. 4.2). Introduction of the ISSD constraints and thus requiring SSD for new farm activities turns the NPV distribution function with SRC in a counterclockwise direction, cutting the left-hand-side tail (black dashed curve in Fig. 4.2).

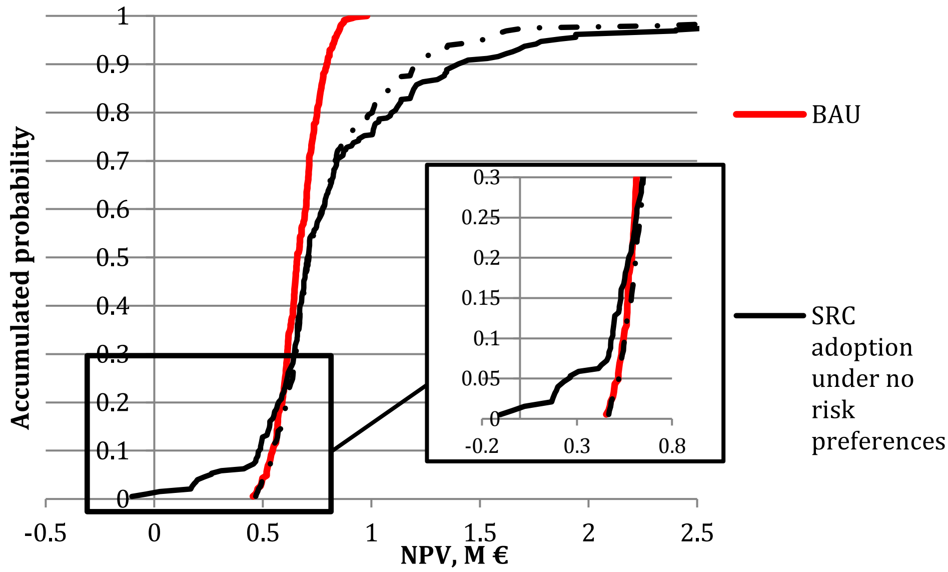

Figure 4.2. Effect of risk preferences on the distribution of NPVs compared with the business-as-usual scenario (BAU).

Note: standard deviation and speed of reversion of logarithmic SRC biomass price are 1.00 and 0.22 respectively.

We now demonstrate the effect of risk aversion and subjective risk levels on the scale of technology adoption (i.e., expected area under SRC). Fig. 4.3 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 indeed leads to a smaller expected area under SRC, which is consistent with *H1*. Since the ISSD constraints cut off the lower tail of NPV distribution, no SRC adoption is possible in those leaves where it would be realized under risk neutrality, and hence the overall expected scale of SRC adoption is reduced. In contrast, *H3* is rejected in our example. Our results show that a higher (subjective) risk level leads to a larger expected area under SRC, even for a risk-averse decision maker. This is explained by managerial flexibility regarding the scale of investment: a farmer exploits the opportunity of investing in a larger SRC plantation when prices are high and vice versa. Due to that managerial flexibility, a part of the scenario tree with low SRC prices is cut off, since SRC is only adopted if the price exceeds a certain threshold. Higher (subjective) risk levels increase the spread of the scenario tree without changing the expected mean. It thus creates a larger area where SRC is not realized and the gross margins of alternative crops generate farm income, 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 adaption, increases at higher (subjective) risk levels for both risk-neutral and risk-averse decision makers, even though the respective trigger price increases. However, this effect of increasing risk levels is dampened by risk aversion, especially when adjusting the speed of reversion: the expected scale of SRC adaption decreases under risk aversion (Fig. 4.3).

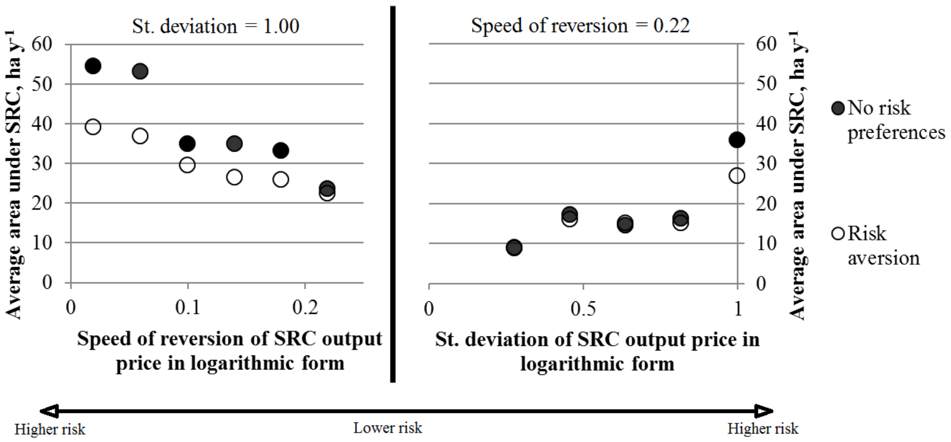

Figure 4.3. Effect of increasing subjective risk levels of short rotation coppice (SRC) biomass output prices on the expected area under SRC.

Next we address the hypotheses *H2* and *H4*. Our results reveal a U-parabolic relationship between (subjective) risk levels of SRC and incentives for earlier SRC introduction (Fig. 4.4). Lower standard deviation values provide limited incentives to postpone SRC introduction by eliminating risk and the related option value (i.e., the decision problem moves towards a classical NPV analysis). As discussed above, higher standard deviation values increase the chance of reaching the trigger price on the nodes and thus again limit incentives to postpone. A similar U-parabolic relationship can be observed between (subjective) SRC risk levels and the probability of never adopting SRC: there is a level of risk that implies the highest probability of never adopting SRC (Fig. 4.4). Hence, *H4* is confirmed in our settings for lower levels of risk and rejected for greater ones. Comparing the timing of SRC introduction in the case of risk-neutral (wider bars in Fig. 4.4) and risk-averse (narrower bars in Fig. 4.4) decision makers, we observe that risk aversion might lead to earlier SRC introduction. This is caused by the hedging effect between the uncorrelated stochastic returns of annual crops and SRC exploited by a risk-averse decision maker. A risk-averse farmer is predicted to introduce SRC earlier in order to reduce overall farm risk, although on average they adopt a smaller area of SRC compared to a risk-neutral farmer. This effect would have been 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 is highest at mid standard deviation values, while it is not apparent at higher and lower values (Fig. 4.4). As risk levels decrease there is no incentive to postpone adoption regardless of risk preferences. When risk levels increase a trigger price is reached sooner that stimulates SRC adoption. Thus we cannot reject *H2*.

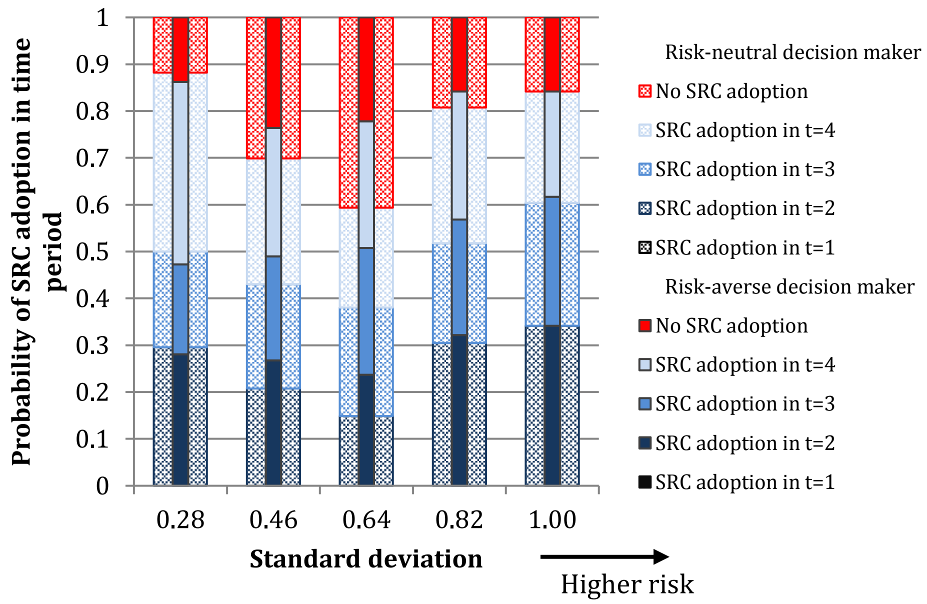

Figure 4.4. Effects of increasing standard deviation values of logarithmic SRC biomass price on timing of SRC introduction with and without risk preferences.

Note: speed of reversion of logarithmic SRC biomass price is 0.22.

To this end, a decision maker perceiving SRC as a high risk option (equally with respect to positive and negative risks) tends to introduce a larger area of SRC earlier, yet not immediately. Hence, a respective trigger price has to be reached (i.e., observed) in order to initiate SRC introduction; otherwise an investment decision will be postponed forever. Furthermore, the negative effect of risk aversion on scale of adoption increases as subjective risk levels increase. The major findings are presented in Table 4.4.

Table 4.4. Summary of the major findings and check of hypotheses

		Effect on	
		Scale of technology adoption	**Timing of technology adoption**
Factor	**Risk aversion**	Negative (*H1* not rejected)	Neutral/positive (*H2* not rejected)
	Higher risk level	Positive (*H3* rejected)	First negative, then positive (*H4* not rejected)

4.5. Discussion and conclusion

Understanding farmer motives with respect to technology adoption is crucial for forecasting and the development of efficient policies. We develop a dynamic farm-level model where returns both to the current farm activities and a new investment-based activity are stochastic. Our approach simulates the effects of (subjective) risk levels and risk preferences on both timing and scale of technology adoption and considers interactions among different farm activities based on competition for limited resources, but also based on hedging. We illustrate our approach by analyzing the introduction of SRC on a typical arable farm in northern Germany.

Our results demonstrate that risk aversion negatively affects the scale of technology adoption, which 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 and reduces probability of no adoption as expected, although 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 stimulates earlier investment in climate change adaptation projects that are intended to reduce risk. This result can be explained by higher incentives of a risk-averse farmer to exploit the natural hedging effect of diversifying with novel and established activities. The lower the correlation coefficient between both activities, the higher the potential effect of natural hedging. Consequently, the effect of risk aversion on timing of technology adoption might be different or obscured in other settings (i.e., if a new technology implies perfectly correlated returns with established alternatives or if technology adoption is analyzed under different assumptions such as stand-alone).

Although the findings of previous studies suggest that risk and subjective risk perception of farmers are relevant, especially with respect to new technologies, such findings are ambiguous regarding the effect of both on technology adoption. Our results show that due to managerial flexibility, higher (subjective) risk levels lead to greater mean scales of technology adoption, which is, however, dampened by risk aversion. The treatment of risks and risk levels in our analysis implies consideration of both positive and negative risks. Only considering downside risk might provide additional insight, but requires a different type of sensitivity analysis where a negative drift would need to be introduced in the stochastic process, while the ISSD constraints would only capture a predetermined part of the distribution. Risk perception defined this way would lead to a lower scale of technology adoption. We therefore emphasize that the definition of risk perception requires special attention when applying the methods we propose.

As for the timing of technology adoption, we observe a U-parabolic effect: with increased risk levels, a farmer first tends to postpone or even reject technology adoption, and then to adopt earlier. However, the U-parabolic relationship is smoothed by risk aversion. Hence, if a farmer perceives a technology as a low risk option, they would tend to adopt sooner, but at a smaller scale on average. In contrast, perceiving a technology as high risk, a farmer would also tend to adopt earlier, but at a larger scale. This result is consistent with Chatalova and Balmann (2017), who also found that uncertainty might be beneficial due to possibility to adjust behavior depending on states-of-nature.

This study might serve as a basis for future research in multiple dimensions. First, the model can be further specified (e.g., controlling for annual volatility in returns), and expanded to other farm-level decisions. Second, different policy instruments to promote SRC could be analyzed under variable risk preferences. Furthermore, learning algorithms might be incorporated (Guthrie 2009). The model and all of the related documentation to facilitate further research are provided in Spiegel et al. (2017).

4.6. References

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4.7. Appendices

Appendix 4.1. Assumed values of the parameters of the model

SRC biomass growth function

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

$$\begin{aligned} Y = 2.27 \cdot (-0.1133 \cdot 10^{-8} \cdot D^2 + 0.254 \cdot 10^{-4} \cdot D \\ + 0.028) \cdot (1.569 \cdot HI + 0.4 \cdot 10^{-3} \cdot PT \cdot SQI \\ - \frac{23.198 \cdot Temp}{W})^{(0.34 \cdot 10^{-8} \cdot D^2 - 0.501 \cdot 10^{-4} \cdot D + 2.614)} \end{aligned} \tag{4.7}$$

Where Y represents dry matter yields (t ha^{-1}); D stays for density of trees (ha^{-1}); HI is possible intermediate harvesting interval: 2, 3, 4, or 5 (y); PT is average sum 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 interval between harvests (Table 4.5.) and fitted the obtained values to a linear function of available biomass in the previous year:

$$Y = 1.651 \cdot Y_{-1} + 3.962 \tag{4.8}$$

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

Table 4.5. Parameters of the yield function and assumed values

Variables	Description	Values	References
D	density of trees, ha^{-1}	9,000	Musshoff (2012)
PT	average sum 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)
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)
W	available groundwater capacity, mm	220	Musshoff (2012)

The model hence allows adjusting the interval between harvests or even transforming it into a decision variable. In the latter case, tests revealed that a 5-year interval is usually the optimal one. In this regard, we used a fixed 5-year interval between harvests, in order to increase computational speed.

Comparison of model parameters with the evidences from the literature

Table 4.6. Comparison of model parameters with the evidences 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	–140.00–(–40.00)	de Witte and Latacz-Lohmann (2014, p.37)

Resources endowments

Labor endowment and labor requirements include only fieldwork and exclude management work, which is assumed to be fixed per farm and hence has no effect on resource distribution. The total land endowment of 100 ha is representative for northern Germany: for instance, in the federal state Mecklenburg-Western Pomerania 20% of agricultural farms operated on an area of 50 to 200 ha (StatA-MV 2016).

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):

Table 4.7. 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	

The Dickey-Fuller test implies non stationary. However, we follow economic considerations and assume a stationary mean-reverting process (MRP), motivating by the assumption of a farmer being price-taker in a market where the price fluctuates around a constant long-term level due to market forces (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).

Chapter 5

Conclusion

5.1. Summary of the major results

Investment and land-use decisions pre-determine the distribution of other farm resources and thus constitute core farm activities. Real-world large-scale investment projects at the farm level are often highly complex due to sunk costs, risks, returns-to-scale, investment options of predefined sizes, and multiple stages of investment. Considering those factors is crucial for improving understanding of the economic incentives and disincentives to invest at the farm level and appropriate design of related policy. However, existing numerical methods of investment analysis fail to capture complexity due to explicit or implicit restrictions. The thesis narrows the gap and develops a numerical method to analyze complex investment options at the farm level. An illustrative example of such a complex investment decision is the introduction of a perennial energy crop and related production systems at the farm level. Perennial energy crops, in particular SRC, have gained interest among both farmers and policy makers due to their multiple environmental benefits, more efficient energy generation, and low input requirements. Yet despite political support, European farmers are reluctant to adopt SRC on a large scale. This thesis quantifies economic incentives and disincentives of SRC adoption at the farm level under consideration of risks and risk preferences.

Returning to the research questions posed at the beginning of this thesis, results indicate that SRC cannot compete with other crops under current market conditions (Q1). Competition between SRC and other crops for limited on-farm resources, including environmental requirements and economy of scale, is captured in a mixed-integer non-linear farm-level model (Q1.1; Q1.2). Decisions regarding SRC adoption are formulated as a compound American real option, where the total number of stages (i.e., the number of intermediate harvests) is a decision variable, bounded from above as well. The model is solved with a combination of Monte Carlo simulation, a scenario tree reduction technique, and stochastic programming (Q1.3). The approach requires limited restricting assumptions and allows valuation of compound American option under consideration of economy of scale, predefined investment scales, resource endowments, and other farm-level constraints. As hypothesized, a sensitivity analysis with respect to observed SRC biomass price reveals that an increase in the price leads to earlier adoption at larger scales (Q1.4). Such an analysis allows finding the trigger price (i.e., a price that stimulates immediate SRC adoption).

A follow-up policy analysis clearly supports the recently implemented planting subsidy and suggests combining it with increased EFA value (Q2). Although both policies lead to earlier SRC adoption, they do not stimulate immediate SRC introduction and hence should be adjusted accordingly (e.g., implemented in a limited quantity) (Q2.4). In contrast, a guaranteed SRC biomass price encourages immediate SRC adoption (Q2.4) smaller scales. In general, it is concluded that policy instruments supporting SRC at the farm level require much less governmental expenditures per additional bioenergy produced than current policy instruments supporting other renewable energy initiatives (Q2.2). As for the scale of SRC adoption, the most effective policy instrument considered—a planting subsidy of 1,500 € ha^{-1}—leads to an increase in produced bioenergy by approximately 200%, although some policy instruments (e.g., low intensities of guaranteed price) lead to a reduction in bioenergy production (Q2.1). The majority of the considered policy instruments lead to an increase in expected farm income and hence are also beneficial for farmers (Q2.3).

Deviating from risk-neutrality of a farmer affects optimal behavior. Since many studies indicate that farmers in Europe are risk-averse, the concept of second-order stochastic dominance is employed (Q3.1). The approach is attractive as it requires limited behavioral assumptions and allows solving a real options approach under risk preferences in a consistent manner. In particular, new farm portfolios containing SRC cultivation should outperform currently observed portfolios in order to be adopted. Our case study reveals that risk aversion leads to earlier SRC adoption at smaller scales (Q3.2; Q3.3). This result is valid unless returns from SRC and other annual crops are perfectly correlated (i.e., natural hedging is possible). Furthermore, the effect of (subjective) risk perception implied by SRC is tested. In our case study, higher (subjective) risk level stimulates earlier SRC adoption at larger scales (Q3.4; Q3.5). Two assumptions are crucial for this result. First, greater risk levels are assumed to be symmetrical (i.e., implied for both positive and negative risks). In this regard, only positive risks extended with increasing risk levels can be exploited if there is managerial flexibility (i.e., the ability to adjust behavior according to future conditions exists). Hence, managerial flexibility is the other crucial assumption.

The effects of selected factors influencing SRC adoption analyzed in the study are summarized in Table 5.1. While observed SRC biomass price and opportunity and sunk costs act in a coherent manner, risk aversion and lower levels of (subjective) risk imply a conflict between timing and scale, initiating either later adoption at larger scales or earlier adoption at smaller scales (Table 5.1). This raises a question about what should be preferred by a social planner: earlier SRC adoption or adoption at larger scales.

Table 5.1. Summary of the main factors and their influence on expected timing and scale of SRC adoption

	Timing[1]	Scale[2]
Observed SRC biomass price	-	+
Opportunity costs	+	-
Sunk costs	+	-
(Subjective) risk level	+ → - [3]	+
Risk aversion	-	-

[1] For timing: "+" = later adoption; "-" = earlier adoption
[2] For scale: "+" = larger scale; "-" = smaller scale
[3] Positive for lower levels and negative for higher levels

Another question refers to adjustability of the factors determining SRC adoption. If observed biomass price, costs, and (subjective) risk levels can be affected in a relatively straightforward manner by different policy instruments (Chapter 3), changing risk aversion is more complex, since the literature provides ambiguous evidence for the stability of risk preferences (Baucells and Villasís 2010; Chuang and Schechter 2015) and hence the capacity of policy instruments to affect them.

The methodology proposed here is a rather general instrument for the analysis of long-term investments under uncertainty and hence is of interest far beyond our case study. It allows relaxing restrictive assumptions, while computational capacity is not hampered, and both the approach and the outcomes are transparent. Empirical results shed light on farm-level incentives and disincentives to adopt perennial energy crop production systems, analyze necessary policy support for promoting adoption, and quantify potential biomass capacity supplied with SRC.

5.2. Policy recommendations

The existing policy support for SRC production systems clearly indicates the social aim to encourage SRC adoption. This thesis does not aim to analyze the validity or relevance of the social aim, but rather contributes to its achievement. In particular, a number of policy recommendations for the case study area have been defined.

The first policy recommendation refers to much less governmental expenditure required for promoting SRC cultivation, compared with other renewable energy sources (e.g., biogas, solar, wind energy). Hence, supporting SRC production systems as a source of renewable energy is economically justified.

Second, optimization of political support of SRC production systems represents a trade-off between different dimensions and requires defining the social preferences first. In particular, it has been revealed that if increased bioenergy production is a priority, then an establishment subsidy is most promising. Based on governmental costs, an increase of the EFA coefficient is superior to other policy instruments. In order to incentivize immediate SRC implementation, a guaranteed biomass price is most effective, yet having a very limited or possibly even negative effect on bioenergy production, while being costly. Chapter 4 additionally concludes that increasing risk at high levels is beneficial for both timing and scale of SRC adoption, meaning that SRC is established earlier and at a larger scale, while increasing risk at low levels imply a conflict between timing and scale. Note that uncertainty is only beneficial when (i) there is temporal or spatial flexibility; and (ii) the perceived positive risk is at least as high as the negative one. In this regard, a price floor performs better, than a guaranteed price, since a price floor reduces the negative risk only. Yet, both risk reducing policies should be maintained for a longer time period and require government agencies to (partly) overtake the price risk leading to stochastic governmental expenditures. This, again, raises a question of social preferences and available resources to promote SRC adoption.

Finally, development of markets and infrastructure is crucial for encouraging SRC adoption. The fail of the UK system to support of perennial energy crops in 2000–2013 due to, among others, no infrastructural support is an illustrative example. Successful SRC policies should ensure investment in harvesting equipment and biomass processing facilities, in order to avoid a 'prisoner's dilemma'. For example, farmers might prefer not to invest in SRC systems because they lack both partners to market their products and contractors to harvest their plantations.

5.3. Outlook and future research

There are a number of factors whose effects on the timing and scale of SRC adoption can also be quantified using the model developed here. These include discount rate, biomass yields, managerial flexibility, economy of scale, and length of the time horizon. Further stochastic processes can be incorporated (e.g., for harvest costs or biomass yields). The model and all related documentation are available (Spiegel et al. 2017; see also Annex 1) in order to facilitate further application. Yet, some issues go beyond the model and require further research.

In terms of empirical research, the influence of SRC adoption on other markets (including food, pulp and paper, and energy markets) should be investigated with respect to price formation and resource distribution. In particular, the model presented here can be scaled up, and other industries can be integrated. The model can also be extended and reproduced for different agents. This would allow investigation of interaction among farmers or with other market actors (e.g., capturing strategic behavior or learning processes). Furthermore, environmental benefits of SRC—so far not directly considered in the model—can be expressed in monetary terms and taken into account, especially for policy analysis. Furthermore, transaction costs for both farmers and policy makers can be introduced. For a farmer, these might include finding a contractor or learning new practices; for a policy maker this might include costs for implementing and maintaining a particular policy instrument, as well as costs of control and analysis. Other instruments of risk management can also be introduced (e.g., insurance, futures, or off-farm diversification) (Huirne et al. 2000; Hardaker et al. 2015); although risk-averse farmers have been found to prefer on-farm risk management strategies (Menapace et al. 2016; Meraner and Finger 2017). Finally, as mentioned above, social preferences regarding the timing and scale of SRC adoption and required governmental costs should be investigated further, as well as possibility of affecting risk preferences. All of these would allow not only evaluating consequences of SRC adoption, but also determining potential capacity and optimal levels of political support for SRC.

There is also abundant room for further methodological research. As mentioned above, there are no well-established approaches for determining the optimal number of leaves in a reduced scenario tree and the optimal number of intervals for an ISSD constraint. Also, exploding stochastic processes cannot be assumed as a basis for a scenario tree; these include popular processes in the literature such as geometric and arithmetic Brownian motions (Di Corato et al. 2013; Wolbert-Haverkamp and Musshoff 2014). Using the methods developed here, such stochastic processes used for long time horizons would produce implausibly large or small values. Next, further research is needed to develop methods for differentiating between different levels of risk aversion or to assume a risk-loving decision maker. Finally, further research might investigate how to consider rolling time horizons (e.g., if SRC introduction can be postponed for an infinite number of time periods).

5.4. References

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Annex 1. Documentation of the stochastic dynamic optimization model*

Abstract

The stochastic dynamic optimization model documented in here simulates decisions of an arable farm with respect to long-term investment based on a compound American option. The implemented application is an investment in short-rotation coppice (SRC). SRC uses fast-growing trees that, once they are set-up, are coppiced several times and finally cleared-up. Time and scale of SRC introduction, intermediate harvest quantities, and final reconversion are flexible and constitute decision variables along with cropping shares for competing crops. A farmer distributes limited resources, i.e. land and labor, to SRC and competing annual crops. This decision is based on the maximization of the expected NPV under constraints related to policy obligation capturing ecological requirements. The price of SRC biomass and gross margins of annual crops are assumed to stochastic and captured by a stochastic process, but these prices can also be included as deterministic components. The costs of harvests are depicted by a function capturing economies of scale. Moreover, the farmer represented in the model can be assumed as risk-neutral or risk-averse. The model quantifies optimal time and scale of SRC cultivation and allows conducting policy and risk analyses.

Keywords: Real option; stochastic programming; investment analysis; risk analysis; policy analysis; short-rotation coppice; scenario tree reduction; Monte-Carlo simulation

* The documentation, accomplished with the codes and user interface, was published as 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).

A.1.1. General settings

We assume an arable farm with the following land-use options: (1) two types of annual arable crops, one of which is more profitable and more labor intensive, than the other one; (2) set-aside land; and (3) catch crops. The two latter land-uses are introduced as alternatives to fulfill ecological requirements. Under the latest Common Agricultural Policy reform large arable farms are required to manage 5% of farmland as "Ecological Focus Areas" (EFA). Here, set-aside land is recognized with a coefficient of 1.00, and area under catch crops – with coefficient of 0.30, meaning that each hectare of catch crops is equivalent to 0.30 hectare of EFA (Péer et al. 2016). A farmer is assumed to be a price taker. Annual crops are characterized by gross margins and required labor input per hectare. Gross margins of set-aside land and catch crops are assumed to be deterministic, while gross margins of the two arable crops are assumed to be stochastic and perfectly correlated with each other. We capture the resulting distribution of gross margins with a single mean-reverting process (MRP) in logarithmic form, and then apply a multiplicative factor to each draw obtained with the stochastic process. The MRP is defined as usual (Dixit and Pindyck 1994, p.74):

$$dgm_t = \mu_{arable}(\theta_{arable} - gm_t)dt + \sigma_{arable} dW_t^{arable} \qquad \text{(A.1.1)}$$

where $t \in \{1,2,\dots,T\}$ is a set of time periods; gm_t is natural logarithm of gross margin of arable crops [per year (y^{-1})]; θ_{arable} is a "normal", or average, level of gross margin of arable crops, to which gm_t tends to revert [y^{-1}]; dgm_t is a change in gm_t; dt is a time interval; $\mu_{arable} > 0$ is a speed of reversion; $\sigma_{arable} > 0$ is a variance; and dW_t^{arable} is an increment of a Wiener process.

A farmer allocates limited resources, i.e. land and labor, to different farm activities in order to maximize the expected net present value (NPV) as defined below:

$$E[NPV] = \sum_{t=1}^{T} \sum_{c} \frac{E[GM_{t,c}] \cdot L_{t,c}}{(1+i)^t} \qquad \text{(A.1.2)}$$

where $E[\cdot]$ represents expectation operator; $GM_{t,c}$ stays for gross margin of a land use option c in time period t [in euros per hectare per year (€ ha^{-1} y^{-1})]; $L_{t,c}$ stays for fractional land area dedicated to a land use option c in time period t [in hectares per year (ha y^{-1})]; i is an annual discount rate [% y^{-1}]; and

c includes arable crop 1 ($c = arable1$), arable crop 2 ($c = arable2$), set-aside land ($c = setaside$), and catch crops ($c = catch$).

While the expectation operator for gross margins of set-aside land and catch crops can be omitted in Eq.A.1.2 as they are deterministic, for arable crops it can be derived as follows:

$$\begin{aligned} E\left[GM_{t,c=arable1}\right] &= E\left[\widetilde{GM}_t\right] \cdot \tau_{arable1} \\ E\left[GM_{t,c=arable2}\right] &= E\left[\widetilde{GM}_t\right] \cdot \tau_{arable2} \end{aligned} \qquad \text{(A.1.3)}$$

where $E\left[\widetilde{GM}_t\right]$ is a draw obtained with a single stochastic process for gross margins [€ ha^{-1} y^{-1}]; $\tau_{arable1}$ and $\tau_{arable2}$ are multiplicative factors.

The expected NPV defined in Eq.A.1.2 is maximized subject to the following constraints:

1. *Resource endowments*

We use fixed input-output coefficients to depict competition for land and labor resources at given farm-level endowments:

$$\sum_c \bar{a}_{c,i} \cdot L_{t,c} \leq \bar{b}_{t,i} \quad \forall i \quad \forall t \qquad \text{(A.1.4)}$$

where 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 crop or land use [ha y^{-1}].

2. *Policy constraints*

Compliance with the 5% "Ecological Focus Area" land-use requirement is ensured as follows:

$$L_{t,c=setaside} + 0.3 \cdot L_{t,c=catch} \geq 0.05 \cdot \bar{b}_{t,i=land} \qquad \text{(A.1.5)}$$

where $L_{c=setaside}$ and $L_{c=catch}$ represent area of set aside land and area under catch crops respectively [ha y^{-1}]; and $\bar{b}_{i=land}$ is the total land endowment [ha y^{-1}].

A farmer considers introducing a perennial energy crop, in our example short rotation coppice (SRC), which is characterized by a stochastic price for harvested biomass. In particular, SRC biomass price is assumed to follow a

MRP in logarithmic form, and both MRPs – for gross margins of arable crops and for SRC biomass price – are assumed to be correlated. The correlation coefficient enters stochastic processes as follows:

$$dp_t = \mu_{SRC}(\theta_{SRC} - p_t)dt + \sigma_{SRC}dW_t^{SRC}$$

$$dgm_t = \mu_{arable}(\theta_{arable} - gm_t)dt + \rho\sigma_{arable}dW_t^{SRC} + \sqrt{(1-\rho^2)}\sigma_{arable}dW_t^{arable} \tag{A.1.6}$$

where t is the time period; SRC indicates short rotation coppice; index $arable$ indicates both arable crops; p_t is natural logarithm of 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.

While the land devoted to annual crops can be flexibly adjusted from year to year, SRC as a perennial is set up once for a longer time period, during which it can be coppiced several times without being replanted. Planting of SRC can be postponed; intermediate coppicing is also flexible and usually exercised every 2-5 years. Finally, plantation can be clear cut and reconverted back to annual crops, and the total lifetime of a plantation is not predefined, though restricted from above (by 20 years in our settings). On top, the area to be dedicated to SRC can also be adjusted. We assume that a farmer manages different plots for which he whether to convert each to SRC or not. Once introduced, SRC triggers sunk costs, namely costs for planting and final reconversion. Due to risks, managerial flexibility, and sunk costs associated with SRC, there might exist a positive option value, i.e. an incentive to postpone decision and observe how the stochastic variables evolve. A farmer hence does not decide about SRC now or never based on expectations, but rather optimizes over the overall time horizon taking into account possible development of the stochastic variables and sunk costs linked to SRC. The problem is solved based on stochastic programming (SP) where uncertainty is captured by a scenario tree. We first describe the decision problem in a deterministic set-up, and then add stochasticity converting it into a SP problem.

We assume the following function for available SRC biomass at the end of year t, depending on the decision to harvest decision in the current year t and the available biomass in the previous time period t-1:

$$stock_{t,p} + harvQuant_{t,p} = stock_{t,p} \cdot \overline{gwl} + S_p \cdot \overline{gwc} \qquad \text{(A.1.7)}$$

where $stock_{t,p}$ is standing biomass in time period t on land plot p, [in tonnes of dry matter yields per year (t y^{-1})]; $p \in \{p_1, p_2, \dots, p_M\}$ $harvQuant_{t,p}$ is the amount of biomass harvested in time period t on plot p [t y^{-1}]; $\overline{gwl}$ is a growth multiplier based on biomass stock in the previous time period; $\overline{gwc}$ is a growth constant depicting yearly biomass growth independent from previous biomass values [t ha^{-1} y^{-1}]; S_p is size of plot p [ha y^{-1}].

Note that we assume that partial harvesting is not possible. Eq.A.1.7 hence yields at the end of year t either a biomass stock, which captures the additional growth in that year given last year's stock, or a zero; in the latter case biomass stock is harvested at the end of year t.

The linkage between the decision to harvest in a specific year and harvested biomass is reflected by a binary indicator inequality and a maximal bound:

$$harvQuant_{t,p} \geq harvest_{t,p} \cdot \overline{minHarvQuant_p} \qquad \text{(A.1.8)}$$

$$harvQuant_{t,p} \leq \overline{maxHarvQuant_p} \qquad \text{(A.1.9)}$$

where $harvest_{t,p}$ indicates whether a plot is harvested (=1) or not (=0); $\overline{minHarvQuant_p}$ is a constant that defines the minimal harvest quantity [t y^{-1}]; and $\overline{maxHarvQuant_p}$ is a constant that defines the maximal harvest quantity [t y^{-1}].

Maximal harvest quantities after the plantation has grown for a number of years can be calculated using the biomass growth function. These data can be introduced in the two equations above to ensure minimal and maximal waiting times between harvests. Harvesting the standing biomass only partly is not considered feasible; therefore an additional equation ensures that standing stock from the previous year is completely removed with each harvest:

$$stock_{t,p} \leq (1 - harvest_{t,p}) \cdot \overline{maxHarvQuant_p} \qquad \text{(A.1.10)}$$

A similar equation ensures that biomass is available and grows, only if the respective plot is devoted to SRC:

$$stock_{t,p} \leq src_{t,p} \cdot \overline{maxHarvQuant_p} \tag{A.1.11}$$

where $src_{t,p}$ is a binary variable indicating that a plot is managed under SRC (=1) or not (=0) in time period t.

Maximal plantation lifetime is depicted by a year counter combined with an upper bound:

$$age_{t,p} = age_{t-1,p} + src_{t,p} \tag{A.1.12}$$

$$age_{t,p} \leq \overline{maxage} \tag{A.1.13}$$

where $age_{t,p}$ is a natural variable reflecting plantation age [y]; and $\overline{maxage}$ is a constant plantation age upper bound [y].

Finally, two equations linked to either a positive change in SRC on a plot (0 in t-1 to 1 in t) or reconversion costs linked to negative change (1 in t-1 to 0 int) are used to describe set-up costs:

$$iniCost_{t,p} \geq \left(src_{t,p} - src_{t-1,p}\right) \cdot \overline{costIni} \cdot S_p \tag{A.1.14}$$

$$reconvCost_{t,p} \geq \left(src_{t-1,p} - src_{t,p}\right) \cdot \overline{costReconv} \cdot S_p \tag{A.1.15}$$

where $iniCost_{t,p}$ represents the actual set-up costs per plot [€ y^{-1}]; $\overline{costIni}$ is a coefficient for set-up costs [€ ha^{-1} y^{-1}]; $reconvCost_{t,p}$ represents actual reconversion costs per plot [€ y^{-1}]; and $\overline{costReconv}$ is a coefficient for reconversion costs [€ ha^{-1} y^{-1}].

The equations for set-up and reconversion costs also implicitly ensure that a plot is permanently managed under SRC during the entire rotation period. We capture all costs associated with intermediate coppicing in one function and assume that there is possible economy of scale associated with harvest, accounting for the fixed costs of bringing harvesting machinery to a plot (accounts for own harvesting or execution by a contractor). More specifically, we differentiate between total harvest costs per farm (fixed costs), harvest costs per hectare (quasi-fixed costs), and harvest costs per metric ton of harvested biomass (variable costs):

$$TotalHarvCost_t \geq [\overline{harvCostFixed} + \sum_p [\overline{harvCostPlot} \cdot S_p + \overline{harvCostYield} \cdot stock_{t,p}]] \cdot harvest_{t,p} \qquad \text{(A.1.16)}$$

where $TotalHarvCost_t$ captures total costs on farm associated with harvest of SRC [€ y^{-1}]; $\overline{harvCostFixed}$ represents fixed harvest costs [€ y^{-1}]; $\overline{harvCostPlot}$ represents quasi-fixed harvest costs [€ ha^{-1} y^{-1}]; and $\overline{harvCostYield}$ represents variable costs [€ t^{-1} y^{-1}].

The equations above jointly define a deterministic programming model where neither different future outcomes (stages) nor stage contingent decision variables are depicted. In order to convert this deterministic version into a SP equivalent, four additional elements are needed. First, decision variables need to carry an additional index for the node of the scenario tree (i.e., stage). Second, an ancestor matrix reflecting the order of nodes in the scenario tree must be introduced. The matrix is used everywhere where a lag operator ($t - 1$) is found in the equations above. Next, stochastic parameter outcomes for each stage need to be defined and finally, the probabilities for each node should be assigned.

The objective function defined in Eq.A.1.2 is defined in the SP set-up as follows:

$$E[NPV] = \sum_{path} [\pi_{path} \cdot NPV_{path}] = \sum_{path} [\pi_{path} \cdot \sum_{t=1}^{T} \left[\sum_c \frac{GM_{(t,n),c} \cdot L_{(t,n),c}}{(1+i)^t} + \sum_p \frac{-iniCost_{(t,n),p} + P_{(t,n)}^{SRC} \cdot harvQuant_{(t,n),p} - reconvCost_{(t,n),p}}{(1+i)^t} + \frac{-TotalHarvCost_{(t,n)}}{(1+i)^t} \right]] \qquad \text{(A.1.17)}$$

where π_{path}stays for probability of each path; $\sum_{path} \pi_{path} = 1$; and (t, n) is a combination of time period and node of the scenario tree assigned to each path.

The expected NPV defined in Eq.A.1.17 is maximized subject to the following constraints that are also modified compared with Eq.A.1.4-5 (time and nodes indices are left out for simplicity):

1. *Land resource endowments*

$$\bar{a}_{SRC,i} \cdot L_{t,SRC} + \sum_{c} \bar{a}_{c,i} \cdot L_{t,c} \leq \bar{b}_{t,i} \quad \forall i \tag{A.1.18}$$

where $\bar{a}_{SRC,i}$ represents inputs requirements for SRC [ha^{-1} y^{-1}]; and L_{SRC} indicates the area dedicated to SRC [ha y^{-1}].

2. *Policy constraints*

$$\begin{aligned} L_{t,c=setaside} + 0.3 \cdot L_{t,c=catch} + greenCoef_{SRC} \cdot L_{t,SRC} \\ \geq 0.05 \cdot \bar{b}_{t,i=land} \end{aligned} \tag{A.1.19}$$

where $greenCoef_{SRC}$ is the EFA weighting coefficient for SRC.

As mentioned above, the model is solved as a SP problem. The required scenario tree contains hence a vector of two draws for two stochastic processes and is constructed in two steps. First, Monte-Carlo draws for both stochastic processes are obtained, resulting in a huge scenario tree with independent equally probable paths. Then a scenario tree reduction technique SCENRED2 (GAMS 2015) merges selected paths and calculates new probabilities and outcomes for each node to construct a reduced scenario tree. The number of Monte-Carlo draws and the number of leaves in the reduced scenario tree are parameters of the model to be specified. For further details of the solution process, see Kostrova et al. (2016).

A.1.2. Sensitivity, risk, and policy analyses

The model allows conducting different types of analysis with sensitivity, risk, and policy analyses being the major ones.

I. *Sensitivity analysis*

It is possible to run a sensitivity analysis with respect to any parameter of the model. One type of sensitivity analysis is already programmed and can be run straightforward: sensitivity analysis with respect to draws for SRC biomass price in the scenario tree. In particular, each draw for SRC biomass price would be shifted parallel up- or downwards by multiplying with a given coefficient. See "Using Graphical User Interface" for further details. An example of such a sensitivity analysis is presented by Kostrova et al. (2016).

II. Risk analysis

There are two ways to introduce risk aversion of a farmer into the model: (i) using a risk-adjusted discount rate; and (ii) introducing an additional constraint of second order stochastic dominance of distribution of NPVs after SRC adoption over initial distribution of NPVs before SRC was adopted (ISSD constraint). If a risk-adjusted discount rate is involved, it would be used in the objective function (Eq.A.1.17). SSD is captured by additional ISSD constraints which approximate over a set of predefined intervals of cumulated distribution; the smaller the intervals the more accurate the approximation is:

$$\begin{aligned} &\max \quad \textstyle\sum_{path}[\pi_{path} \cdot NPV_{path}(x)] \\ &\text{subject to} \quad \begin{cases} \mathbb{E}_{+SRC}\{x|x \leq \eta\} \geq \mathbb{E}_{NoSRC}\{x|x \leq \eta\} \mid \eta: q_i = \mathbb{P}\{x \leq \eta\} \\ q_1 = {}^{1}/_{N} \\ q_{i+1} = q_i + {}^{1}/_{N} \end{cases} \qquad \text{(A.1.20)} \\ &\forall i = \{1,2,\dots,N\} \\ &x \in \tilde{X} \end{aligned}$$

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 q_i is a set of predefined intervals of cumulated distribution; and set $\tilde{X}$ represents further constraints for decision variable x, i.e. resource endowments and environmental requirements.

The number of intervals N can be set up directly via Graphical User Interface (GUI). There it is also possible to restrict the number of used intervals, such that only the lowest ones would be used. It allows controlling for downside risk only.

III. Policy analysis

Four policy instruments supporting SRC are programmed and can be included via the GUI: a planting subsidy, increasing the EFA coefficient for SRC, and a guaranteed price as well as a price floor for SRC biomass. The difference between a guaranteed price and a price floor is that a farmer gets the former always, regardless of the observed market price of SRC biomass; while a price floor is paid only if the market price falls below the floor level. A guaranteed price might hence generate additional governmental income if the market price is above that guaranteed level. Timing of governmental outlays differs: a planting subsidy triggers cost at the time at set-up, a price floor and guaranteed price - in years where a plot is harvested. The outcome of a model run includes governmental costs of each policy instrument. They are determined at each node of the scenario tree as follows. The total governmental costs are the sum of governmental costs at each node weighted by the respective probabilities of the nodes.

$$\begin{gathered} GC_{EFA} = 0 \\ GC_{Sub} = Sub \cdot L_{SRC} \\ GC_{p\_min} = \max[P_{min} - P_{market}; 0] \cdot \sum_{p} harvQuant_p \\ GC_{p\_fix} = \left(P_{fix} - P_{market}\right) \cdot \sum_{p} harvQuant_p \end{gathered} \tag{A.1.21}$$

where GC_{EFA} determines governmental costs for increasing the EFA weighting coefficient [€ y^{-1}]; GC_{Sub} determines governmental costs for planting subsidy [€ y^{-1}]; GC_{p_min} determines for governmental costs for price floor [€ y^{-1}]; GC_{p_fix} determines governmental costs for guaranteed price [€ y^{-1}]; Sub stays for intensity of planting subsidy [€ ha^{-1} y^{-1}]; L_{SRC} indicates land area devoted to SRC establishment [ha y^{-1}]; $harvQuant_p$ indicates dry matter biomass yields to be harvested on plot p [t y^{-1}]; P_{market} indicates observed market price of SRC dry matter yields [€ t^{-1}]; p_{min} stays for price floor for SRC biomass [€ t^{-1}]; and p_{fix} determines guaranteed price of SRC biomass [€ t^{-1}]. Time and node indices are omitted for simplicity.

Whether a policy instrument should be considered and in what intensity can be adjusted directly in GUI (see details below). An example of such a policy analysis is presented by Spiegel et al. (2018).

A.1.3. Data and parameters

Default parameters are chosen for a typical arable farm in Northern Germany based on the literature. The major ones are presented below.

Table A.1.1. Parameters of the model, their default values and references

Parameters	**Units**	**Assumed values**	**References**
	Short rotation coppice (SRC)		
Planting costs	euro per hectare (€ ha^{-1} y^{-1})	2875.00	Musshoff (2012)
Dry matter growth function			
Multiplier for last year's biomass	-	1.54	Ali (2009)
Constant increase	tonnes per hectare per year (t ha^{-1} y^{-1})	6.68	Ali (2009)
Costs related to harvesting of SRC			
Fixed costs a farm level	€ y^{-1}	66.75	Schweier and Becker (2012); Pecenka and Hoffmann (2012)
Quasi-fixed costs for each plot	€ ha^{-1} y^{-1}	272.13	Schweier and Becker (2012); Pecenka and Hoffmann (2012)
Variable costs, depending on harvested quantity of dry matter yields	€ t^{-1} y^{-1}	10.67	Schweier and Becker (2012); Pecenka and Hoffmann (2012)
Reconversion costs	€ ha^{-1} y^{-1}	1400.00	Musshoff (2012)
Labor requirements	hours per hectare per year (h ha^{-1} y^{-1})	0.00	Musshoff (2012)
	Annual crops		
Deterministic net annual cash flow (gross margins) from crops recognized as Ecological Focus Area (EFA)			
Set-aside land	€ ha^{-1} y^{-1}	-50.00	CAPRI (2017)

Catch crops	€ ha^{-1} y^{-1}	-100.00	de Witte and Latacz-Lohmann (2014, p.37)
Labor requirements			
A more labor intensive and more profitable crop	h ha^{-1} y^{-1}	5.32	KTBL (2012)
A less labor intensive and less profitable crop	h ha^{-1} y^{-1}	4.16	KTBL (2012)
Set-aside land	h ha^{-1} y^{-1}	1.00	KTBL (2012)
Catch crops	h ha^{-1} y^{-1}	0.00	KTBL (2012)
Stochastic processes			
Mean-reverting process for SRC biomass price in logarithmic form			
Starting value	y^{-1}	3.92[21]	
Long-term mean	y^{-1}	3.92	Musshoff (2012)
Speed of reversion		0.22	Musshoff (2012)
Standard deviation		0.22	Musshoff (2012)
Mean-reverting process for gross margins of arable crops in logarithmic form			
Starting value	y^{-1}	6.02[22]	
Long-term mean	y^{-1}	6.02	CAPRI (2017)
Speed of reversion		0.32	CAPRI (2017)
Standard deviation		0.28	CAPRI (2017)
Gross margin multiplier for more profitable and more labor-intensive crop		1.05	
Gross margin multiplier for less profitable and less labor-intensive crop		0.95	

[21] Set up equal to the long-term mean, in order to exclude any possible effect of a trend.

[22] Set up equal to the long-term mean, in order to exclude any possible effect of a trend.

Farm characteristics			
Land endowment	ha y^{-1}	100.00	
Step for adjusting SRC plantation (i.e. the size of the smallest plot)	ha	5.00	
Labor endowment	h y^{-1}	500.00	
Real risk-free discount rate	% y^{-1}	3.87	Musshoff (2012)
Risk-adjusted discount rate	% y^{-1}	8.87	Musshoff (2012)
Policy support for SRC			
EFA weighting coefficient for SRC		0.30	Péer et al. (2016)
Planting subsidy for SRC	€ ha^{-1} y^{-1}	1200.00	MLU-MV (2015)
Social discount rate	% y^{-1}	0.00	ECB (2017)

A.1.4. Using Graphical User Interface (GUI)

The model can be set-up and run based on a GUI. For a proper functioning of the GUI, the following guidelines should be followed: (i) download the complete folder and save it as a single folder (hereinafter “MainFolder”); (ii) do not shift anything within MainFolder; (iii) do not rename anything in MainFolder; (iv) ensure that the directory path of MainFolder contains no space; (v) ensure that the folder containing GAMS files, including GAMS licenses, is in the same parent folder as MainFolder; and (vi) create a new folder in the same parent folder as MainFolder and name it “results”. The GUI can be opened with the Windows batch commend file “srcPA.bat” in the folder “GUI”. A window with six tabs each containing a number of settings will open. They are explained below.

Table A.1.2. Model setups that can be adjusted using the graphical user interface.

Label	Range	Description
		Model setup
Simulation control		
Scenario description	Text up to 100 symbols[23]	This will be included into the name of the file containing the results.
Monte carlo draws	true/false	If <true> new draws for stochastic variables will be obtained. Option <false> might be advantageous for different types of analysis to ensure a proper comparison of different scenarios.
Tree generation	true/false	If <true> the scenario tree will be constructed based on the latest Mon-Carlo draws. Advantageous in conducting sensitivity analysis with respect to parameters of stochastic processes with or without drawing the stochastic component. If <false> the latest scenario tree will be used, even if new Monte-Carlo draws are obtained.
Risk modelling	None, ISSD	If <None> no stochastic dominance constraint is included. If additionally a market-based discount rate is used, a farmer is assumed to be risk-neutral. If <ISSD> an ISSD-constraint is involved.
Use risk adjusted discount rate	true/false	Another way to consider risk preferences is to use a risk-adjusted discount rate.
Solve according to the real options	true/false	If <true> a decision on SRC introduction can be postponed and will be made based on states-of-nature.
Solve according to the classical NPV	true/false	If <true> a decision on SRC introduction must be made now or never, based on expectations of stochastic variables.

[23] Range can be adjusted in the file "srcPA.xml" containing code for GUI.

SRC timing		
Minimum harvest period	A natural number between 2 and 5	Determines the minimum time period (in years) between planting or latest harvest and following harvest or final clear-up
Maximum harvest period	A natural number between 2 and 5	Determines the maximum time period (in years) between planting or latest harvest and following harvest or final clear-up
Minimum age of plantation	A natural number between 2 and 25	Determines the minimum time period (in years) between planting and final clear-up
Maximum age of plantation	A natural number between 10 and 25	Determines the maximum time period (in years) between planting and final clear-up
Simulation length	A natural number between 20 and 30	Indirectly determines the maximum time period (in years) to postpone SRC planting, which is determined as "Simulation length" minus "Maximum age of plantation".
Price scenarios		
Minimum price multiplier	Between 0.50 and 1.20 with a 0.05-step	Determines the lowest multiplier for sensitivity analysis with respect to SRC biomass price
Maximum price multiplier	Between 0.70 and 2.50 with a 0.05-step	Determines the highest multiplier for sensitivity analysis with respect to SRC biomass price
Number of scenarios	A natural number between 1 and 20	Indirectly determines the step of sensitivity analysis with respect to SRC biomass price, equally distributing the required number of scenarios between the minimum and maximum price multipliers.
Risk parameters		
Number of intervals	A natural number between 0 and 1000	Number of intervals for an ISSD-constraint. Used only if Risk modelling is <ISSD>
Number of used intervals	A natural number between 0 and 1000	If lower, than Number of intervals, then ISSD-constraint is applied only to the indicated quantity of the lowest intervals. Check therefore conditional value-at-risk for downside risk.
		MIP
MIP accuracy		
Absolute	Between 0 and 100 with a 10-step	Required for mixed-integer programming (MIP). Refers to a difference in objective value, i.e. expected NPV, between the

Relative in %	Between 0 and 10 with a 0.01-step	reference non-integer solution and an integer solution found under the current iteration. The solution process is stopped, once the either absolute or relative accuracy is achieved.
Limits		
Max solution time in minutes for each solve	A natural number between 1 and 120	Restricts the maximal solution for each MIP solve
Max # of repeated solves when the time limit exceeded	A natural number between 1 and 5	Restricts the maximal repeated attempts to solve the MIP
Algorithm		
MIP algorithm	GUROBI, CPLEX, CPLEXD	MIP solver used
Use NEOS server via KESTREL	true/false	Remote solving on NEOS solver
Tuning	On, Off, Use old tuning results	Use automated tuning, should be normally be switched off
Use manual priorities	On, Off	Uses branching priorities programmed in the code, should be normally switched off
Use old results as starting point	true/false	An option to accelerate solution process. Iterating starts with the results obtained previously.
ReloadFile	<GDX-file name>	Refers to a GDX-file containing the results that should be used as a starting point
Stochastic processes		
Start price	Between 50 and 100 with a 0.1-step	Refers to a currently observed value of the first stochastic process (in our case: SRC biomass price). Natural logarithm of this value enters the stochastic process to proceed with Monte-Carlo draws.
Mean price	Between 50 and 100 with a 0.1-step	Natural logarithm of this value enters the first stochastic process to proceed with Monte-Carlo draws.
St.deviation of Wiener process 1	Between 0.00 and 1.00 with a 0.01-step	Enters the first stochastic process. Kills stochasticity if set up equal to 0. The higher the value the more volatile the respective stochastic variable is.

Speed of mean reversion 1	Between 0.00 and 1.00 with a 0.01-step	Enters the first stochastic process. The higher the value the less volatile the respective stochastic value is, since it faster reverts to the long-term mean.
Start gross margin	Between 100 and 1000 with a 0.01-step	Refers to a currently observed value of the other stochastic process (in our case: gross margins of arable crops). Natural logarithm of this value enters the stochastic process to proceed with Monte-Carlo draws.
Mean gross margin	Between 100 and 1000 with a 0.01-step	Natural logarithm of this value enters the other stochastic process to proceed with Monte-Carlo draws.
St.deviation of Wiener process 2	Between 0.00 and 1.00 with a 0.01-step	Enters the other stochastic process. Kills stochasticity if set up equal to 0. The higher the value the more volatile the respective stochastic variable is.
Speed of mean reversion 2	Between 0.00 and 1.00 with a 0.01-step	Enters the other stochastic process. The higher the value the less volatile the respective stochastic value is, since it faster reverts to the long-term mean.
Correlation coefficient	Between -1.00 and 1.00 with a 0.01-step	Correlation coefficient between two Brownian motions
GM multiplier for less labor intensive crop	Between 0.00 and 2.00 with a 0.01-step	Each draw of the second stochastic process (for gross margins) will be multiplied by this coefficient and the resulting value enters the optimization model as a gross margin of a less labor intensive crop
GM multiplier for more labor intensive crop	Between 0.00 and 2.00 with a 0.01-step	Each draw of the second stochastic process (for gross margins) will be multiplied by this coefficient and the resulting value enters the optimization model as a gross margin of a more labor intensive crop
Number of original scenarios	Between 100 and 50’000 with a 100-step	Number of required Monte-Carlo draws
Number of final reduced leaves	A natural number between 10 and 2’000	Number of required leaves for reduced scenario tree
Model parameters		
SRC Growth		
Constant of biomass growth function	Between 3.000 and 5.000 with a 0.001-step	If no harvest is exercised: an increase in SRC biomass regardless of available biomass in the previous time period.

Multiplier of biomass growth function	Between 1.000 and 2.000 with a 0.001-step	If no harvest is exercised: an increase in SRC biomass depending on available biomass in the previous time period.
Harvest cost		
Per tonne	Between 5.00 and 15.00 with a 0.01-step	Costs occur once harvest is exercised and depend on total harvested SRC biomass (variable costs).
Per hectare	Between 100.00 and 400.00 with a 0.01-step	Costs occur once harvest is exercised and depend on total harvested area under SRC and do not depend on harvested SRC biomass (quasi-fixed costs).
Per farm	Between 10.00 and 100.00 with a 0.01-step	Costs occur once harvest is exercised and depend neither on total harvested area under SRC nor on harvested SRC biomass (fixed costs).
Set-up and reconversion		
Set-up cost	A natural number between 1000 and 5000	Costs per hectare of planted SRC. Occur once a plot is converted into SRC.
Reconversion cost	A natural number between 1000 and 5000	Costs per hectare of cleared-up SRC. Occur once a plot is converted back to annual crops: either if earlier reconversion is exercised or if the maximum lifetime of SRC plantation is reached.
Discount rates		
Market based	Between 0.00 and 15.00 with a 0.01-step	Risk-neutral discount rate base only on expectations and opportunities on market.
Risk adjusted	Between 0.00 and 15.00 with a 0.01-step	Should be equal to a sum of a market-based discount rate and a risk premium.
Social	Between 0.00 and 15.00 with a 0.01-step	Required for discounting governmental costs
Policy analysis		
Subsidy for SRC planting		
Planting subsidy per ha	A natural number between 0 and 3000	This amount will be subtracted from planting costs per hectare

Price floor for SRC output		
Apply minimum price of SRC output	true/false	If <true> the price floor defined below is applied.
Minimum price of SRC output	A natural number between 0 and 100	If a simulated SRC biomass price falls below this level, the government covers the difference and a farmer gets the defined minimum price.
Guaranteed price of SRC output		
Apply guaranteed price of SRC output	true/false	If <true> the guaranteed price defined below is applied.
Guaranteed price of SRC output	A natural number between 0 and 100	A farmer gets this price for SRC biomass regardless of how the market price evolves. The difference (both positive and negative) between this guaranteed price and simulated market price constitutes the governmental expenditures.
Greening coefficient		
Greening coefficient for SRC	Between 0.00 and 1.00 with a 0.05-step	It is assumed that a farmer has to dedicate 5% of his total land endowment to ecological purpose – Ecological Focus Area (EFA). This requirement can be fulfilled with set-aside land (coefficient 1.00 means that each hectare of set-aside land is recognized as 1.00 hectare of EFA); catch crops (coefficient 0.30 means that each hectare of catch crops is recognized as 0.30 hectare of EFA); or SRC (coefficient defined here).
GAMS		
Listing		
Print GAMS code to listing	onListing, offListing	Adds the GAMS code to the listing file
Symbol list	onSymList, offSymList	Shows the lists of parameters, equations and variables used
Symbol list with cross references	onSymxRef, offSymxRef	Same as above, with indication where the symbols are used
Solve outputs		
Solution printing	Suppress, Overview, Variables and equations, Full output	Option for the model listings

Limrow	0, 10, 100, 1000, 10000	Number of entries for each equation shown in the listing for each solve, should be set to zero for production runs
Limcol	0, 10, 100, 1000, 10000	Number of entries for each variable shown in the listing for each solve, should be set to zero for production runs

Having set up, the button “Start GAMS” should be pressed and the window should not be closed until the model is solved.

A.1.5. Working with GAMS code

In order to modify anything beyond what captured in GUI, one should refer to the GAMS code directly. It can be found under the name “GAMSCode.gms”. Saved modifications will be automatically considered in the next run. If the file is renamed, GUI code should be adjusted accordingly.

A.1.6. Reading outcomes of the model

The outcomes are saved in the folder “results”. The name of the GDX-file includes the name of scenario, risk preferences, managerial flexibility, as well as policy instruments involved. In the file the main results are in the tabs “p_res” and “p_res_leaves” containing descriptive statistics of the results and full results for each leave of the reduced scenario tree respectively. Scenario “noScr” stays for business-as-usual scenario, when no SRC is cultivated. Results under “p_res_leaves” also include the respective probability of each leaf. Scenarios “scen1”, “scen2”,… refer to introduction of SRC under different price scenarios (currently observed price of SRC biomass).

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Annex 2. Co-authors' statement

Co-author statement

related to the PhD thesis of Alisa Spiegel

Paper title	Publication outlet	List of authors
Monte Carlo simulation and stochastic programming for real options valuation in perennial energy crop cultivation	Submitted to the *European Journal of Operational Research* (currently in the first round of review)	Alisa Spiegel, Wolfgang Britz, Utkur Djanibekov, Robert Finger
Policy analysis of perennial energy crop cultivation at the farm level: short rotation coppice (SRC) in Germany	Published in *Biomass and Bioenergy* 110 (2018) pp. 41–56	Alisa Spiegel, Wolfgang Britz, Utkur Djanibekov, Robert Finger
Risk, risk aversion and agricultural technology adoption—a combination of real options and stochastic dominance	Submitted to the *European Review of Agricultural Economics* (currently under major revision)	Alisa Spiegel, Wolfgang Britz, Robert Finger

The undersigned co-authors hereby confirm that Alisa Spiegel has made the major contribution to the papers.

Prof. Dr. Robert Finger	Zürich, 04.04.18 place, date	[redacted]
PD Dr. Wolfgang Britz	Bonn, 4.4.18 place, date	[redacted]
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