Adoption of perennial crops and behavioral risk preferences. An empirical investigation among French farmers. *

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Abstract

We mix survey and experimental data to investigate the impact of individual risk preferences on the adoption of perennial energy crops by French farmers in the prospect theory framework. Our results demonstrate that farmers' degree of loss aversion and probability weighting matter in the adoption decision. The effect of loss aversion is highly dependent on farmers' reference level, which may be related to land type or farm history, while the effect of probability weighting is highly dependent on land type only. We find that the more loss averse the farmer, and the more weighted the extreme events, the lower the probability of adoption on high-potential land. We also show that farm characteristics are relevant factors: a higher share of low-profitability land drives adoption up whereas cattle breeding tends to hamper adoption.

Keywords: innovation, non-expected utility decision models, miscanthus, marginal land, biomass

JEL Codes: C34; Q16; Q12

1 Introduction

Today, agriculture faces new challenges, namely ensuring food security in quality, supplying raw material for non-food purpose, and respecting the environment. In this context, perennial crops have received lately a renewed attention (Glover et al., 2010; Schulte et al., 2006; Atwell et al., 2010). Indeed, perennials have advantages over annuals in providing at the same time high yields and important environmental benefits. Due to longer growing seasons and deeper rooting depths, they exhibit a high water and light-use efficiency, while their great root mass has positive effects on soil quality and stability as well as on carbon sequestration (Hansen et al., 2004; Brandão et al., 2011). Permanent coverage was also shown to benefit to wildlife (Bellamy et al., 2009; Semere and Slater, 2007). Moreover, perennial crops require few field operations and chemical inputs, which explains their good energy and greenhouse gas balance (McLaughlin and Walsh, 1998; St Clair et al., 2008). These features are particularly valuable where resources are limited.

Perennial crops can be used both for food and non-food purpose. The attention has particularly focused on non-food crops because of the strategic and environmental interest of replacing petroleum-based products, and especially on perennial energy crops because of the huge volume and value at stake.

However, the issue of the competition of perennial energy crops with food crops for land and water resources is strongly debated. It will raise more and more sharply while food needs are increasing and chemically intensive farming is diminishing (Smith and Moore, 2010). Moreover, direct and indirect land-use change induced by the expansion of energy crops can result in carbon debt and biodiversity loss if land with high carbon stock and high biodiversity value is to be altered (Havlík et al., 2011). Thus, a careful investigation of factors driving farmers' willingness to grow perennial crops is needed to quantify the potential food and non-food biomass supply, assess the ensuing economic and environmental outcomes, and identify relevant policy designs.

A growing number of authors has conducted investigations to explain why farmers include perennial crops in their farming systems. Farm-level cost studies are by far the most numerous, especially those concerned with perennial energy crops (e.g., Downing and Graham (1996), Duffy and Nanhou (2002), Monti et al. (2007) for switchgrass and Styles et al. (2008), Smeets et al. (2009) for miscanthus). They provide break-even output prices according to different input price, yield and discounting scenarios. They generally conclude that perennial crops can be competitive with traditional annual crops only under restrictive conditions. Some authors also developed whole-farm economic analyses to take into account competition for farm resources. For instance, Byrne et al. (2010) and Bell et al. (2008) focused on the value of perennial wheat in Australian dryland agricultural systems. Bathgate and Pannell (2002) studied lucerne adoption in the context of on-farm salinity prevention in Australia. Sherrington and Moran's (2010) study is a recent application to willow short-rotation coppice and miscanthus in the United Kingdom. A few researchers also led field surveys to investigate a wider range of factors (e.g., Jensen et al. (2007), Villamil et al. (2008) , Qualls et al. (2012) on switchgrass and miscanthus in the United States, and Roos et al. (2000), Sherrington et al. (2008), Rämö et al. (2009) on short-rotation coppice and miscanthus in northern Europe). Common factors identified as influencing the adoption of perennial crops include profitability, farm size, human capital (age, eduction, moral and social concerns), resource and technical constraints, access to information, triability.

Surprisingly, risk issues have been largely overlooked in the aforementioned studies. As noted by Feder et al. (1985), and later by Marra et al. (2003), there is a general lack of individual adoption studies that have adequately addressed the role of risk, probably due to the difficulties in observing and measuring risk. However, risk factors have been repeatedly shown to be key elements in understanding the process of innovation adoption in many contexts (e.g., Koundouri et al., 2006; Serra et al., 2008; Just and Zilberman, 1983; Abadi Ghadim et al., 2005) and, as such, they are expected to be also relevant in the case of perennial crops. In addition, because it takes several years before return on investment is positive, the long-term profitability of perennial crops is particularly uncertain to farmers (Sherrington et al., 2008; Villamil et al., 2008; Pannell, 2001b). Indeed, the economic and legal environment is highly variable over time, whereas up-front costs can be quite large.

Furthermore, perennial energy crops raise some new interesting issues for risk analysis. First, perennial energy crops are usually sold under production contracts which guarantee a long-term output price (Alexander et al., 2012; Bocquého and Jacquet, 2010), and thus considerably decrease perceived risk. Second, despite those contracts, production or market accidents such as an establishment failure or a counterparty failure do exist, and can result in extreme income losses. In their survey of northern American farmers, Smith et al. (2011) reported that the risk of unsuccessful establishment was one of the most important perceived barriers to growing perennial energy crops.

Third, the resistance of perennial species makes them relatively profitable and unrisky compared to annual crops and pastures if growing conditions are poor. On the contrary, in good growing conditions, perennial energy crops are expected to be less profitable than traditional land uses. Thus, crop location is important when comparing the attractiveness of perennial energy crops with competing land uses.

There are two noteworthy exceptions to the scarcity of risk analyses applied to perennial energy crops. Bocquého and Jacquet (2010) is one of them. The authors built a stochastic farm model to quantify the effect of price risk and farmers' risk preferences on the extent of miscanthus and switchgrass adoption in French cereal farms. They showed with an expected utility approach that diversification effects, especially if the long-term price of the perennial crop is guaranteed by a production contract, can be powerful incentives to adoption. Song et al. (2011) is the second exception. Using a real option framework, they studied the patterns of land conversion into and out of perennial energy crops over time. Applying their model to switchgrass in the United States, they highlighted the significant option value of delaying land conversion to reduce uncertainty, even when a static net present value threshold is passed. However, the value of these two studies is mainly normative.

The aim of this paper is to clarify the relationship between adoption of perennial energy crops and farmers' risk preferences. We also test the effect of other farm and farmer characteristics on the adoption decision. The empirical analysis is based on a cross-sectional sample of French farmers. We make three contributions to the adoption literature. First, we mix survey data with experimental preference data. The survey data include a wide range of farm and farmer characteristics which are used as explanatory variables along with the experimental measures of preferences. By resorting to experimental data, we avoid the hypothetical bias inherent to most empirical adoption studies which rely on stated data when incorporating some preference measure (Cardenas and Carpenter, 2007). [1] We also believe our results to be more accurate than those from other studies on the adoption of perennial energy crops because we rely on an observed adoption decision. [2]

Second, we extend the usual risk studies based on the standard expected utility (EU) framework to

[1] Studies mixing survey and experimental data are rather uncommon in agricultural economics. The seminal paper by Binswanger (1980) is an early attempt to explain farming decisions with experimental risk-aversion measures. Liu and Huang (2013), Barham et al. (2011), Bauer et al. (2012), and Nguyen and Leung (2009) are other recent examples relative to farmers' decision making.

[2] To our knowledge, Roos et al. (2000) is the only previous study analyzing an actual adoption decision regarding perennial energy crops.

take into account loss aversion and extreme events. Under EU theory, farmers value perennial based on objective probabilities. However, faced with unfavorable extreme events, they may have a more complex behavior, similar to the predictions of Tversky and Kahneman's (1992) prospect theory (PT). PT has been widely applied in the financial literature, but seldom in the agricultural literature.

Third, we contrast adoption on regular land and low-profitability land. Because farmers may value perennial energy crops relative to the *status quo*, they may perceive them as a sure income loss compared to annual crops on land where growing conditions are favorable, and a sure income gain on land where growing conditions are unfavorable. As farmers are risk-seeking for losses and more sensitive to losses than gains (Bocquého et al., 2014), they may be more reluctant to allocate regular land to perennial energy crops than forecasted by EU theory. PT also accommodates this kind of reference-dependent behavior.

Shedding light on how risk preferences affect the adoption of perennial crops may help the processing industry to propose efficient contracts to secure the supply. It may also give governments insights about how public incentives could be designed to make perennial crops a credible and sustainable biomass source for non-food purpose.

This paper is organized as follows. In Section 2, we present the PT framework guiding our analysis. In Section 3, we describe the land allocation model underlying the adoption decision. The data are described in Section 4. In Section 5, we specify the empirical adoption models. The results are presented in Section 6. Section 7 concludes and highlights policy implications.

2 Theoretical background: prospect theory for risky choices

In the field of agricultural economics, and notably in adoption studies, risky decisions have been mostly analyzed in the light of von Neumann and Morgenstern's (1947) EU (e.g., Feder and O'Mara, 1981; Just and Zilberman, 1988), a standard rational choice theory. On the contrary, our empirical strategy is based on predictions drawn from a behavioral decision model. Indeed, since the pioneering work by Simon (1955, 1956) introducing the concept of bounded rationality, it is recognized that cognitive, emotional and social biases strongly influence behavior, leading to changing and unstable preference functions. Behavioral models adapt traditional normative models of decision making by explicitly incorporating the systematic errors made by decision makers. Such descriptive models have been repeatedly shown to better account for observed behavior than standard rational approaches. In this section, we describe the main features of Tversky and Kahneman's (1992) PT, a behavioral model which proved to convincingly depict risk preferences.

In this framework, agents are assumed to make choices so as to maximize a *prospective value*. Four features distinguish cumulative PT from EU theory.

- First, decision makers view outcomes as *changes in wealth* rather than absolute wealth levels (decision makers' assets are integrated into final wealth). These changes are defined with respect to a *reference point*, qualified as labile because it depends on decision makers' expectations and norms, as well as circumstances (framing). Usually, the reference point corresponds to the *status quo*.

- Second, decision makers exhibit a diminishing sensitivity to outcomes as they deviate from the reference point. In other words, agents are more sensitive to a wealth change close to the reference point than far away from it. Thus, the *value function* [3] for outcomes is usually concave above the reference point and often convex below it.

- Third, decision makers classify outcomes as either gains or losses relative to the reference point in an *editing phase*. This phase is preliminary to the *evaluation phase* in which the value of the prospect is computed. Their behavior is different in each of the two outcome domains, losses looming larger than gains because of *loss aversion*.

- Fourth, it is explicitly assumed that agents distort objective probabilities into subjective probabilities non-linearly, through a *probability weighting function*. Again, diminishing sensitivity applies and the strength of the distortion decreases as probabilities and outcomes go away from extreme values. [4] It was empirically shown that individuals tend to be more sensitive to a probability change close to the extreme values 0 and 1 than in the middle range. Thus, the weighting function commonly displays an 'inverse S-shape'.

Overall, in PT, risk behavior results from the interplay of these four phenomena, namely reference dependence, curvature of the value function, loss aversion and probability weighting. The resulting

[3]To emphasize the difference between EU and PT, Tversky and Kahneman (1992) used the term *value function* instead of *utility function*.

[4]The notion of extreme outcomes only exists in the *cumulative* version of PT (Tversky and Kahneman, 1992). As shown later, in cumulative PT, the weighting function applies to cumulative probabilities rather than single probabilities, the latter being the rule in Kahneman and Tversky's (1979) *separable* (or *original*) version of PT. Contrary to separable PT, cumulative PT satisfies stochastic dominance and can be applied to prospects with a large number of outcomes (Tversky and Kahneman, 1992). This is the version we consider throughout this paper.

empirical finding is risk aversion in the domain of (moderate and high) gains but risk seeking in the domain of (moderate and high) losses. By contrast, EU theory features only one preference parameter which fully describes risk behavior, utility curvature. Under this standard framework, individuals are found to be risk averse whatever the outcomes at stake.

Formally, under PT, any risky prospect defined by a set of monetary outcomes y_i with associated probabilities p_i can be written $(y_{-m}, p_{-m}; \ldots; y_i, p_i; \ldots; y_n, p_n)$, where gains are denoted by positive numbers ($0 < i < n$) and losses by negative numbers ($-m < i < 0$). The value of such a prospect is calculated as follows in the so-called *evaluation phase*:

$$PV(y_{-m}, p_{-m}; ...; y_n, p_n) = \sum_{i=-m}^{n} \pi_i . v(y_i) \tag{1}$$

where $v(.)$ is the decision maker's value function, satisfying $v(y_0) = 0$, $v''(y) < 0$ for $y > y_0$ (concavity above the reference point) and $v''(y) > 0$ for $y < y_0$ (convexity below the reference point), and π_i is a *decision weight* applied to each of the $n + m + 1$ potential outcomes. Compared to EU, in this expression, the shape of v is different for gains and for losses, and objective probabilities are replaced by decision weights. These weights result from the transformation of objective probabilities by a non-linear weighting function $\omega(.)$. If in $(y_{-m}, p_{-m}; \ldots; y_i, p_i; \ldots; y_n, p_n)$ outcomes are arranged in increasing order , then cumulative decision weights are defined by [5]:

$$\pi_i = \begin{cases} \omega^+(p_i + \ldots + p_n) - \omega^+(p_{i+1} + \ldots + p_n) & \text{if } 0 \leq i \leq n-1 \\ \omega^-(p_{-m} + \ldots + p_i) - \omega^-(p_{-m} + \ldots + p_{i-1}) & \text{if } 1-m \leq i < 0 \\ \omega^+(p_n) & \text{if } i = n \\ \omega^-(p_{-m}) & \text{if } i = -m \end{cases} \tag{2}$$

where $\omega^+(.)$ and $\omega^-(.)$ are strictly increasing functions from the unit interval into itself, satisfying $\omega^+(0) = \omega^-(0) = 0$, and $\omega^+(1) = \omega^-(1) = 1$.

[5] In cumulative PT, the probability weighting function operates on the *rank* of outcomes, defined as the probability of receiving an outcome that is higher (ranked better) (Wakker, 2010). Thus, good outcomes have small ranks and bad outcomes large ranks. With our notations, the rank of any y_i would be $p_{i+1} + \ldots + p_n$ if $0 \geq i \geq n-1$, and 0 if $i = n$.

3 Land allocation model and hypotheses

3.1 Portfolio setting

The adoption of a new perennial crop at farm level can be viewed as the solution of a portfolio problem [6] where land has to be allocated to competing divisible technologies (Feder and O'Mara, 1981; Just and Zilberman, 1988). For simplicity, we assume only two technologies are available to the farmer: a traditional one (denoted by an index j of 0), such as a cereal crop, and an innovative one (denoted by an index j of 1), a perennial crop. Each technology generates an annual stochastic payoff $r_j(t)$ (per unit area) which aggregates over the planning horizon T into a stochastic return, depending on the amount of land α_j allocated to the given technology. The allocation variables do not vary over time, meaning that the decision is irreversible. We assume that the aggregation follows the usual net present value rule with constant discounting. Payoffs from the cereal crop do not depend on the time period. Thus, the intertemporal stochastic return from the cereal crop is :

$$NPV_0 = \alpha_0 . \sum_t \delta^t . r_0 \qquad = \alpha_0 . x_0 \tag{3}$$

and that from the perennial crop is:

$$NPV_1 = \alpha_1 . \sum_t \delta^t . r_1(t) \qquad = \alpha_1 . x_1 \tag{4}$$

where δ is the farmer's discount factor, and x_i the annual stochastic return of crop i per unit area.

Perennial species have typically an irregular payoff pattern over time compared to annuals Bocquého and Jacquet (2010). Indeed, important plantation costs are incurred on the first year, while harvesting begins on the second or third year only. Meanwhile, some extra establishment costs are needed, for weed control for instance. It is well-known that discounting is unfavorable to such patterns, because benefits that are received in the future are strongly underweighted compared to costs that are concentrated in the first years. The higher the discount rate (the lower the discount factor), the larger the difference between the intertemporal value of cereal returns (Equation (3)) and perennial returns (Equation (4)), hence the less land allocated to the perennial crop. This analysis provides the first two hypotheses we want to test empirically:

[6] Originally designed by Markowitz (1952) to explain investment in financial securities, portfolio models are widely used in agricultural economics to model production choices at farm level.

Hypothesis 1 *Farmers' time preferences are expected to matter in the adoption of perennials, discounting having a negative effect.*

Hypothesis 2 *Factors reflecting constraints on cash availability are expected to be important barriers to the adoption of perennials.*

We further assume that the representative farmer behaves as a cumulative PT maximizer. Indeed, we showed experimentally that farmers in the sample exhibited PT rather than EU preferences when faced with risky choices (Bocquého et al., 2014). Following PT described in Section 2, farmer Θ cares about the following farm-level stochastic income:

$$y_\Theta = \sum_j \alpha_j . x_j - \ell_\Theta \tag{5}$$

which is defined relative to farmers' reference point ℓ_Θ. Thus, the farmer's problem is to select the land areas α_j so as to maximize the following prospective value :

$$PV = \sum_{y_\Theta} \pi_{y_\Theta} . v(y_\Theta) \tag{6}$$

where π_{y_Θ} is the decision weight applied to farm income y_Θ, and $v(.)$ is the farmers' value function. The maximization is constrained by the total amount of land L which is fixed, a reasonable assumption in the short term. Land is also assumed to be fully used. Hence, the land constraint can be written:

$$\sum_j \alpha_j = L, \qquad \alpha_j \geq 0 \qquad \forall j. \tag{7}$$

This leads to an additional hypothesis for the empirical analysis:

Hypothesis 3 *Factors reflecting land constraints are expected to be important determinants of the adoption of perennials.*

We build up a variant to this model by considering heterogeneous land resources. Land is either *regular* (also referred to as *non-marginal* or *high-profitability* in this paper) or *marginal*. Marginal land refers to land where traditional crops give significantly lower per hectare returns than the rest of the farm land. In this context, choice variables are doubled: the representative farmer decides how much of the regular land he or she wants to dedicate to the new technology, and also how much of the marginal land. Two options may be considered for the modeling of this extended portfolio problem. On the one hand, it could be hypothesized that farmers assess allocation options jointly. It means that they take into consideration the covariance between all payoffs, and assess the allocation options relative to a unique reference point. On the other hand, it is also relevant to suppose that farmers focus on the outcomes of allocation on regular land and on marginal land separately. [7] In this case, only the covariance between payoffs from the same type of land is accounted for, and the reference point may differ from one land type to the other. Indeed, as outlined by Wakker (2010), the reference point is labile, and varies with circumstances and individual expectations and norms. In this paper, we opt for the second option because it is highly probable that farmers do not have the same performance expectations for crops grown on regular land than for crops grown on marginal land. By doing so, one may argue that we underestimate the positive impact of uncorrelated risks on miscanthus adoption (see the positive effect of activity diversification described by Bocquého and Jacquet (2010)). However, in the PT framework, it is less problematic that under EU framework because diversification effects are clearly less prominent: decision makers often prefer to concentrate risks so as to keep low the potential for small losses, even if at the same time they keep high the potential for large losses. This is due to both their risk-seeking behavior in the loss domain and their aversion to losses compared to gains (Stracca, 2002; He and Zhou, 2011; Bernard and Ghossoub, 2010). As a consequence, the adoption model can be viewed as a double portfolio problem. The representative farmer selects land

[7] In the risk and psychological literature, this segregation of outcomes is known as *narrow framing*. Just like the coding of outcomes in gains or losses, it is a mental operation that can occur in the editing phase of PT. It is defined by Kahneman and Lovallo (1993) as the fact that '*people tend to consider decision problems one at a time, often isolating the current problem from other choices that may be pending, as well as from future opportunities to make similar decisions*'. More precisely, we refer here to *cross-sectional narrow framing*, as called by Thaler et al. (1997) for distinction with *intertemporal narrow framing* . A financial definition of *cross-sectional narrow framing* would be '*the tendency to treat individual gambles separately from other portions of wealth. In other words, when offered a gamble, people often evaluate it as if it is the only gamble they face in the world, rather than merging it with pre-existing bets to see if the new bet is a worthwhile addition*' (Barberis and Thaler, 2003). The consequence for portfolio problems is a concentration of risks because PT investors ignore the covariance between assets and the benefits of diversifying when it is low. The equity premium puzzle, i.e., the low level of diversification in stockholders' portfolio, is one famous empirical example of concentrated portfolios (see e.g. Shefrin and Statman, 2000). *Intertemporal narrow framing*, which is not accounted for in this paper, implies short evaluation periods, either because subjects evaluate assets frequently or because they have a short planning horizon. This is known as a *myopic* behavior. Because of the piece-wise form of the value function, myopic investors have a higher probability of observing a small gain, as well as a higher probability of observing a small loss than non-myopic investors. Thus, myopia increases the attractiveness of risky assets in the gain domain and decreases it in the loss domain. Yet, as investors are usually loss averse, they are likely to mostly focus on losses. As a consequence, subjects exhibiting a *myopic loss aversion* are expected to be less willing to take risks than the others (Benartzi and Thaler, 1995; Thaler et al., 1997).

areas α_j and β_j so as to maximize the following prospective values:

$$P \begin{cases} V_R = \sum_{y_\Theta} \pi_{y_\Theta}.v(y_\Theta) & \text{(8a)} \\ PV_M = \sum_{z_\hbar} \pi_{z_\hbar}.v(z_\hbar) & \text{(8b)} \end{cases}$$

with:

$$y_\Theta = \sum_j \alpha_j.x_j - \ell_\Theta, \qquad y_\hbar = \sum_j \beta_j.x'_j - \ell_\hbar,$$

subject to:

$$\sum_j \alpha_j = R, \qquad \sum_j \beta_j = M, \qquad \alpha_j, \beta_j \geq 0 \qquad \forall j,$$

where y_Θ and $z_\hbar$ are the stochastic returns from regular and marginal land respectively, defined in relation to farmer- and land-specific reference levels Θ and $\hbar$, α_j and β_j are the surface areas allocated to crop j on regular and marginal land respectively, and R and M are the total regular and marginal land areas ($R + M = L$).

The coding of outcomes as changes in wealth relative to a *reference point* occurs in the *editing phase*. Although not grounded in any theory, a widespread assumption states that the reference point corresponds to the *status quo*. But, as highlighted by Kahneman and Tversky (1979), '*there are situations in which gains and losses are coded relative to an expectation or aspiration level that differs from the status quo*'. In the context of the adoption of a new crop, it is reasonable to think that the reference level is either the mean return from the land use which is to be changed if the adoption occurs (status quo), or another amount most probably linked with the farm history (expectation level). In our problem, we consider these two options for regular land: the reference point can be the mean return from the cereal crop ($\ell_\Theta = \overline{x_0}$), or, due to specific circumstances, a much higher or lower value ($\ell_\Theta >> \overline{x_0}$ or $\ell_\Theta << \overline{x_0}$). For marginal land, we assume that the reference point is the mean return from the cereal crop on this type of land ($\ell_\Theta = \overline{z_0}$).

Developing the prospective value in Equation (6) (or in Equations (8a) and (8b)), we can explicitly distinguish positive outcomes from negative outcomes (relative to the given reference point). Because

$v'(y_\Theta) > 0$ for any y_Θ, $v(\ell_\Theta) = 0$, and $v(y_\Theta) < 0$ when $y_\Theta < 0$, we obtain:

$$PV = \sum_{y_\Theta > 0} \pi_{y_\Theta}.v(y_\Theta) - \sum_{y_\Theta < 0} \pi_{y_\Theta}.|v(y_\Theta)| \tag{9a}$$

$$= PV^+ - PV^- \tag{9b}$$

where PV^+ is the prospective value for gains and PV^- is the prospective value for losses. They can be interpreted as the *upside potential* and the *downside potential* of the crop mix. The optimal allocation decision is the one that maximizes the difference between the upside and the downside potential (Stracca, 2002; He and Zhou, 2011; Bernard and Ghossoub, 2010).

The upside and downside potentials are positive subjective values which depend, on the one hand, on farmers' tastes which are captured by the curvature of their value function and the strength of their loss aversion, and, on the other hand, on farmer's perceptions of income distributions, which are captured by the reference point and the strength of the probability distortion. Thus, we expect our empirical findings to confirm the following hypothesis:

Hypothesis 4 *Farmers' risk preferences matter in the adoption of perennials. Because the distribution of crop returns varies with the type of land, the impact of risk preferences is expected to vary if adoption occurs on regular land or on marginal land.*

3.2 Stochastic crop returns

In this section we complete the description of the adoption model by characterizing crop returns in terms of risk and reviewing in more detail the expected impact of PT preference parameters on the optimal perennial areas on regular and marginal land. [8].

[8] The optimal α_1 and β_1 cannot be derived analytically from the prospective value function in Equations (8a) and (8b) as the first and second order conditions cannot be solved in closed form. Indeed, in comparison to standard EU or mean-variance portfolio models, in PT models the value function is non-concave and non-smooth and the probability weighting function generates non-linearity with respect to probabilities. As a result, the prospective value function may have several local maxima, and PT models cannot be solved with common optimisation techniques which look for a global optimum (He and Zhou, 2011). Numerical analyses are thus valuable alternatives (e.g., Gomes, 2005; Berkelaar and Kouwenberg, 2004). Nevertheless, recently, some authors developed noteworthy analytical approaches to solve simple portfolio models under cumulative PT (see Bernard and Ghossoub (2010) and He and Zhou (2011) for a static, one-period setting, and Berkelaar and Kouwenberg (2004) and Jin and Zhou (2008) for a dynamic, continuous-time setting).

3.2.1 Probability distribution

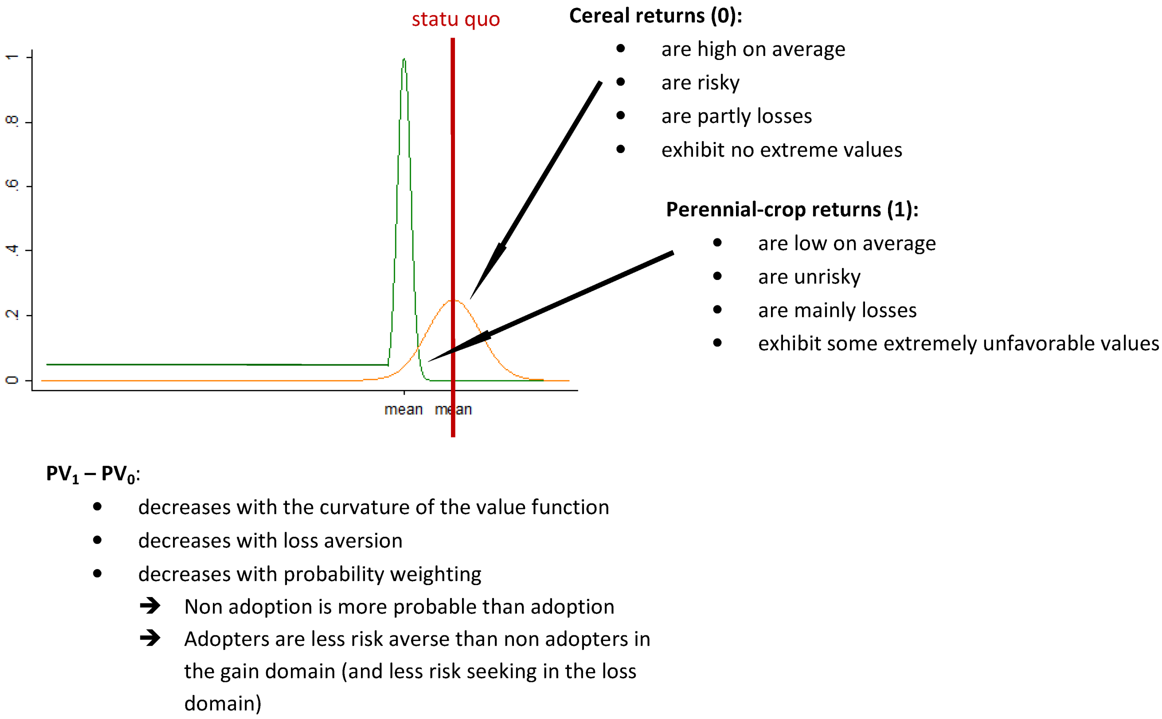
Like all crops, the probability distributions of cereals and perennials are dependent on the type of land where they are grown. However, because their biological cycles are fundamentally different, their needs in terms of field operations and their response to a change in pedo-climatic conditions are highly contrasted. Depending on the land type considered, their relative economic performances may even be inverted. Figure 1 depicts the return distributions of perennials and cereals as assumed in this paper, and detailed below.

Generally, average profit calculations tend to conclude that cereal crops are more profitable than perennial crops (see for instance Monti et al. (2007), Deverell et al. (2009), and Bocquého and Jacquet (2010) in the case of energy crops). However, most of them use yield and cost data corresponding to regular growing conditions. On the contrary, on marginal land, it is likely that perennials are, on average, the most profitable ones. If land is qualified as marginal because of an isolated location or a quirky plot shape, cereal costs increase much more than perennial costs because of the much higher number of field operations. If it is because of unfavorable pedo-climatic conditions, yield losses on cereals are much higher than yield losses on perennials, because of the resistance of the latter to poor soil conditions, drought and frost. As a result, in our problem, the mean return of the perennial crop is assumed to be lower than that of the cereal crop on regular land, but higher on marginal land ($\overline{x_1} < \overline{x_0}$ and $\overline{z_1} > \overline{z_0}$).[9] Crop-by-crop mean returns are all higher on regular land than on marginal land ($\overline{x_0} > \overline{z_0}$ and $\overline{x_1} > \overline{z_1}$). Thus, the empirical results should confirm one additional hypothesis:

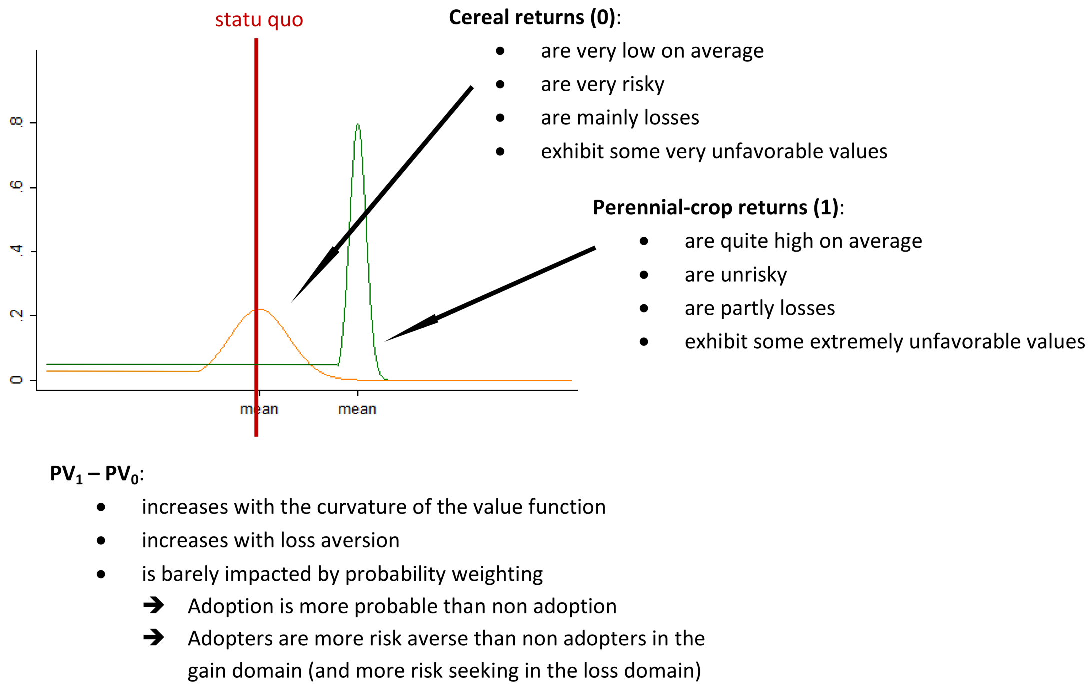
Hypothesis 5 *The availability of marginal land on the farm favors the adoption of perennials.*

Crop differences in resistance to drastic growing conditions also have implications on the distribution of returns around the mean: production risk on perennials is lower than on cereals, especially on marginal land (Bocquého, 2008). In addition, commercial perennials such as energy crops are most often grown under long-term supply contracts which guarantee to farmers a fixed price over the crop life-span and offer technical advice (Bocquého, 2008; Alexander et al., 2012). As a result, price risk and technical risk, which are critical for a crop sold on a new market and unknown by farmers are transferred to the processing industry. By contrast, food-crop prices are increasingly variable, due to more and more volatile international markets. It was shown in

[9]van der Hilst et al. (2010) validated this assumption in the Dutch context: they found that, on less suitable soils, perennial crops achieve better net present values than common rotations.



(a) Regular land



(b) Marginal land

Figure 1: Hypothesized distributions for returns from perennials and annuals according to land type

Bocquého (2008) that farmers do perceive production, price and technical risks to be lower on miscanthus than on wheat. A few other studies confirmed the fact that farmers view perennial crops as non risky. As a consequence, in our problem, perennials are modeled as risk-reducing innovations, especially if grown on marginal land. The variance of perennial returns is supposed to be much lower than that of cereal returns, whatever the type of land ($var(x_1) << var(x_0)$ and $var(z_1) << var(z_0)$), and the difference in variance is more marked on marginal land than on regular land ($var(z_0) - var(z_1) > var(x_0) - var(x_1)$).

We now wish to focus on a component of probability distributions which is often overlooked in risk assessment, the extreme events which are contained in the distribution tails. Because they are very unlikely and proportionally little impacted by the utility function, in the standard EU framework their role on risk behavior is low. By contrast, in cumulative PT, extreme outcomes are overweighted, and this psychological effect can have important consequences on risk behavior, especially when extreme outcomes are far from the reference point. In the case of annual crops, such extreme outcomes may be negative returns due to highly damaging climatic or sanitary events (frost, widespread pest attack..) causing an abnormally low production. The crop response and/or the frequency of the event, and thus the extent and the probability of the income loss, would be higher on marginal land than on regular land. Thus, we model cereal returns as a skewed-to-the-left distribution, skewness being higher on marginal land (fat left-tail) than on regular land (thin left-tail). As far as perennial crops are concerned, extreme events may be extremely negative returns because of the large up-front costs. An establishment failure is not uncommon for perennial crops, and, in the case of energy crops, the risk of a failure from the contract counterparty raises some concern among farmers (Alexander et al., 2012). The latter does not depend on land type. Hence, we assume that the distribution of perennial returns includes extremely negative values on both marginal and regular land.

3.2.2 Expected effect of risk preferences on adoption

We now turn to the analysis of the theoretical impact of PT preferences on the optimal crop mix, given the probability distributions of crop returns. We then infer more precise hypotheses on the direction of the effect of risk preferences on the adoption of perennials than Hypothesis 4.

The prospective value of a given crop mix depends on the ratio between the upside potential and the downside potential of the resulting return distribution (Equation (9b)), named hereafter *performance ratio*. On regular land, perennial returns are mostly in the loss domain, whereas cereal returns are mixed. On marginal land, perennial returns are mostly in the gain domain, whereas cereal returns are mixed. Thus, on regular land, if the farmer is neutral to risk, loss and probabilities, an increase of the share of perennials in the crop mix would lower the performance ratio. On the contrary, on marginal land, it would increase the performance ratio. Under PT, we need to consider the effect of each of the three PT parameters, namely the curvature of the value function, loss aversion and probability weighting. For each PT parameter, we first assume that the reference point is the mean cereal return, and second describe the changes that a modification of the reference point would imply.

Curvature of value function As mentioned in Section 2, PT value function is a piece-wise function, concave in the gain domain such as under EU, but convex in the loss domain. This last property implies a risk-seeking behavior over losses. In other words, when faced with all-loss prospects, subjects tend to prefer the riskier one because they get proportionally more pain from small losses than large losses.

On regular land, taking into account this non-linear value function does not change the negative direction of the impact of the share of perennials in the crop mix on the performance ratio. Indeed, risk reduction has a positive impact on the upside potential, but it is outweighed by a negative impact on the downside potential (perennial returns are mainly in the loss domain). As a result, the higher the curvature of the value function, the higher the diminution in the performance ratio, and the lower the optimal area of regular land planted with perennials.

On marginal land, symmetrically, perennial returns are mostly gains. Thus, an increase in the curvature of the value function has an opposite effect on the optimal perennial area, i.e., a positive effect.

In addition, by defining the domain of outcomes, the reference point has a major influence on the subsequent valuation of crop returns. For instance, a very high reference point on regular land moves cereal gains into the loss domain and shifts perennial returns away from the reference point in the loss domain. Thus, the adoption of perennials has no more risk-mitigation effect in the gain domain, and an increase of the curvature of the value function leads to a larger decrease of the performance ratio than when the reference point is equal to the mean cereal return. On marginal land, a very high reference point possibly makes the adoption of perennials have a negative effect on the performance ratio instead of a positive effect due to the all-loss distribution, and hence the curvature of the value function is negatively linked with adoption, like for regular land.

This leads to the following hypothesis :

Hypothesis 6 *When the reference point is the mean return of the traditional crop, the curvature of the value function is argued to have a negative effect on adoption on regular land and a positive effect on marginal land.*

Loss aversion PT also features loss aversion, which refers to the observed phenomenon that '*losses loom larger than gains*' (Kahneman and Tversky, 1984). [10] This asymmetry between gains and losses implies that the value of any asset with a distribution symmetrically distributed around the reference point is not null. Rather, it is negative because the downside potential is higher than the upside potential.

On regular land, accounting for loss aversion does not change the negative direction of the impact of perennial crops on the performance ratio either. This is because, overall, gains are replaced by losses (perennial returns are quasi all-loss while cereal returns are mixed). As a consequence, the higher the loss aversion, the higher the decrease in the performance ratio, and the lower the optimal share of perennials on regular land.

On the contrary, in the symmetric marginal-land context, loss aversion has a positive effect on the area of perennials.

If the reference point is so high that the two return distributions are all losses, on regular land the adoption of perennials still decreases the performance ratio under loss aversion (because the perennial mean return is lower than the cereal mean return, and thus losses get higher), but at a lower rate (because perennial losses replace cereal losses instead of ceereal gains). On the contrary, on marginal land, the adoption of perennials still increases the performance ratio (because the perennial mean return is higher that the cereal mean return), but at a lower rate (because cereal losses are replaced by perennial losses instead of perennial gains). As a result:

[10] Theoretically, loss aversion results from two properties: a higher curvature of the value function in the loss domain than in the gain domain and a linear coefficient applied to loss utilities. This 'global' loss aversion is sometimes called *behavioral loss aversion*. However, in most applications of PT, the parameter for curvature is the same in the gain and in the loss domain. Thus, behavioral loss aversion is only accounted for by the linear coefficient, and loss aversion refers indifferently to the behavior '*losses loom larger than gains*' or to the linear coefficient. '*The observed asymmetry between gains and losses is far too extreme to be explained by income effects or by decreasing risk aversion.*' (Kahneman and Tversky, 1984).

Hypothesis 7 *When the reference point is the mean return of the traditional crop, loss aversion is expected to have a similar effect on adoption than the curvature of the value function, i.e., a negative effect on regular land and a positive effect on marginal land.*

Probability weighting Under cumulative PT, the probability weighting function generally exhibits an inverse S-shape, implying the overweighting of extreme outcomes, especially if they are associated with small probabilities. It is as if the tails of probability distributions were fattened (and shortened), especially the very thin ones, to the detriment of the rest of the distribution.

Once again, on regular land, when accounting for probability distortion, the share of perennials still has a negative impact on the performance ratio. As explained before, on this type of land, extreme events mainly characterize perennial crops. Thus, the higher the probability weighting, the higher the decrease in the performance ratio, and the lower the optimal area of perennials on regular land.

On marginal land, crop income distributions relative to extreme events do not fundamentally change, but the probability of extremely unfavorable events on cereals increases frankly. Thus, the negative influence of a higher probability distortion on the adoption of perennials is not as strong as on regular land.

As we assumed in 2 that the probability weighting function is similar in the gain and loss domains, a change of the reference point is not expected to modify the effect of probability weighting on the optimal area of perennials.

Thus:

Hypothesis 8 *Probability weighting is expected to have a negative effect on adoption whatever the type of land. However, the effect should be stronger on regular land than on marginal land.*

Hypothesis 9 *A change in farmers' reference point is likely to modify the intensity of the effect of the curvature of the value function and of loss aversion on adoption. The reference point may vary with farm history.*

4 Data

4.1 Survey procedure

The study is based on a survey of miscanthus producers (or adopters) and non-producers (or non-adopters) mostly from the *Bourgogne* region, in the east of France, and more especially *Côte d'Or*, *Jura* and *Saône-et-Loire* departments (see Figure 2). In 2010, in *Côte d'Or*, 282 ha were planted with miscanthus or switchgrass and 351 ha in the whole *Bourgogne* region, which represented respectively 11% and 14% of the total French area (2,510 ha) at that time. Since 2009, most part of *Côte d'Or* and some part of the adjacent *Saône-et-Loire* and *Jura* have been eligible to diversification incentives from a national program for the reorganization of the sugar supply chain (*Programme de Restructuration National Sucre*), following the reform of the Common Market Organization for sugar, the EU sugar regime. Miscanthus and switchgrass production is one of the diversification activities which have benn supported. For farmers, the main benefits are subsequent plantation subsidies (40% of the incurred costs as a minimum, with a cap at 70,000 €, which corresponds roughly to 22 ha).

Being one of the most dynamic areas of miscanthus production in France, *Bourgogne* has the advantage for data collection of having a relatively high density of miscanthus producers. Main productions are cereals (soft wheat mainly) and oilseeds (rapeseed) on specialized farms, but livestock, market vegetables and wine are also important activities.

The population of interest consists of farmers living within the supply areas of two close processing plants located in *Aiserey* (south of *Côte d'Or*) and *Baigneux-les-Juifs* (north of *Côte d'Or*) (see Figure 3). These plants are dehydration plants originally dedicated to the processing of lucerne and sugar-beet pulp. Farmers from the *Aiserey* area are mainly located in the fertile plain of the *Saône* river, while most of the farmers from the *Baigneux-les-Juifs* area belong to the limestone plateau of *Bourgogne*. The climate is in both areas semi-continental, with long and harsh winters on the plateau. In the plain, cereals, oilseeds and proteincrops rotate with field vegetables (generally two vegetables per farm as a maximum).

For adopters, complete address lists were available from the two dehydratation plants. Non-adopters were sampled from the list of farmers having received subsidies from the European Common Agricultural Policy in 2008. To decrease potential information bias due to an incomplete dissemination of information about miscanthus, we restricted the pool of farmers to those living in

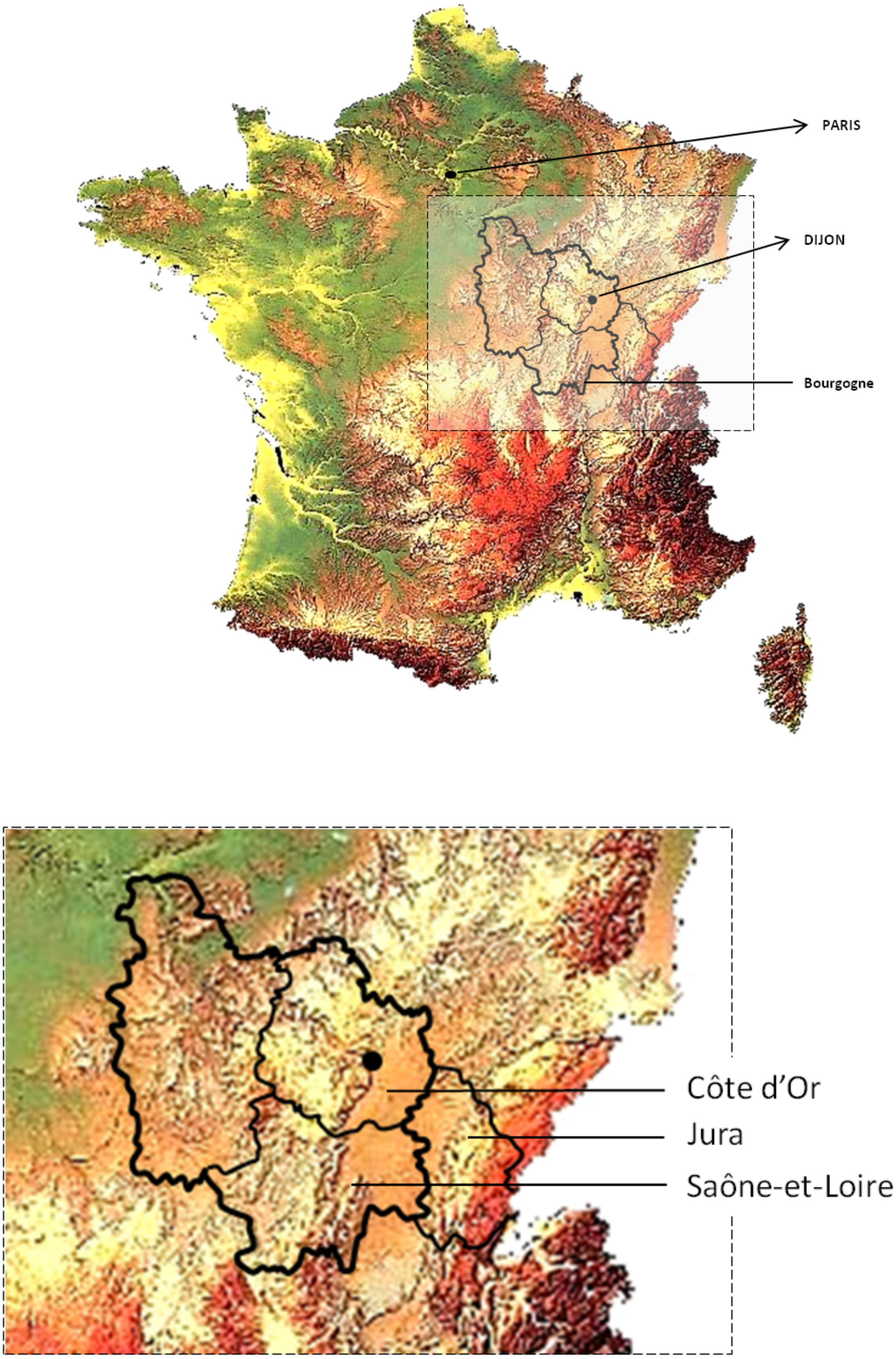


Figure 2: Location of the study area

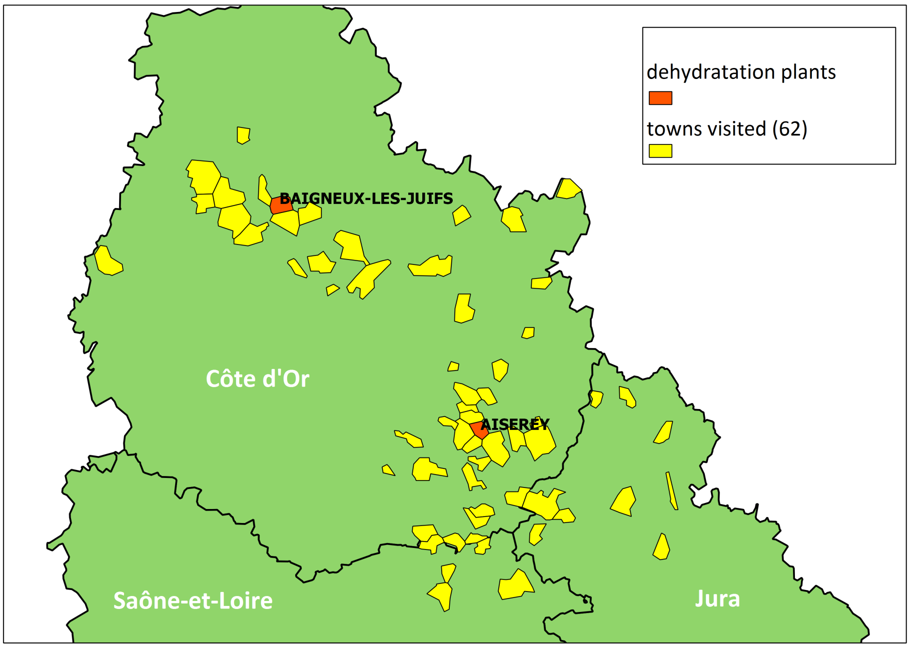


Figure 3: Location of towns visited

the towns featuring at least one miscanthus producer (592 farmers in 62 towns in total). Among them, 16% are miscanthus growers. Then, we built a stratified random sample from this initial pool of farmers, one strata encompassing all adopters, and the other stratum all non-adopters.

We randomly picked up 80 adopters and 152 non-adopters from the initial pool of farmers. We first contacted them by mail, followed up by a phone call a few days later to make an appointment. The survey was presented as being about innovation in agriculture. In the end, 111 farmers could be surveyed within the allotted time, and 102 questionnaires were fully filled, corresponding to a response rate of 44% on average (excluding farmers who were not reachable, lacked time or did not show up). [11] Finally, the sample consists of 57 adopters and 45 non-adopters, from 62 towns (see Figure 3).

We organized face-to-face interviews from February to June 2010. Each interview lasted around two hours. After the questionnaire was completed, farmers were invited to participate to a half-an-hour experiment aiming at measuring their preferences relative to risk, ambiguity and time. In this paper, we only use the results from the risk and time experiments.

[11] Compared to responses rates obtained in other adoption studies, it is rather high. For example, Jensen et al. (2007), Villamil et al. (2008) and Rämö et al. (2009), who investigated the interest in producing perennial energy crops among farmers or small private forest owners, reported response rates of respectively 24%, 21% and 41%. Mzoughi (2011) also highlights the difficulty of obtaining large response rates from French firms in his study about the role of moral and social concerns in farmers' adoption process: he obtained a response rate of 19% only.

The objectives of the questionnaire were twofold: identify the determinants of miscanthus adoption within the studied population and analyze miscanthus insertion in the actual production systems. In this paper, we report the results corresponding to the first objective only. The questionnaire was built after direct interviews with local extension services and staff of the processing plants, and using insights from a previous survey in central France (Bocquého, 2008). The questionnaire was also pre-tested on farmers from another area.

The design and procedure of the risk experiment is adapted from Tanaka et al. (2010) and described in detail in Bocquého et al. (2014). We recall here only the main information. The experimental design consists of three series of lottery choices, which are variants of Holt and Laury's (2002) multiple price lists. The 33 lottery choices submitted to each subject are provided in Appendix A. In each series, subjects are asked to pick the row in which they prefer lottery B (*risky*) to lottery A (*safe*). Subjects who are very risk-averse may never switch — and always choose lottery A — and subjects who are very risk-seeking may choose the risky lottery in the first row — and always choose lottery B. Risk neutral subjects would switch when lottery B overtakes lottery A in terms of expected value. Farmers were provided with an initial endowment of 15 € for their participation. After the subject had completed all three series, one row was randomly selected and the lottery initially chosen played for real money. Real money incentives are indeed recommended to ensure respondents' commitment to the experiment and avoid hypothetical bias.

The time experiment is also adapted from Tanaka et al. (2010), and described in Bocquého et al. (2013). It consists of 8 series of the multiple price list format. In each series, farmers are asked to make 10 choices between a small reward delivered today or in 1 year (option A), and a larger reward delivered later in the future, up to 3 years (option B) (see Appendix B). Like in the risk experiment, monotonic preferences are enforced by asking subjects to provide a unique switching point in each task, i.e., the reward for which their preference switches from option A to option B. A real payment mechanism was also implemented.

4.2 Descriptive statistics

In the literature, a wide range of factors has already been identified in the literature as strongly influencing farmers when they face the opportunity to grow a perennial energy crop. We tested a large number of variables and selected those giving the best trade-off between goodness-of-fit and parsimony in the estimated models. Table 1 describes the selected variables and Table 2 provides statistics for the entire sample and the two sub-samples of non-adopters and adopters.

Dependent variables Participation to miscanthus production whatever the land type, participation on regular land, and participation on marginal land are represented by binary variables *Adopter*, *RegularUsed*, and *MarginUsed* respectively. They take on the value 1 if the farmer had planted miscanthus at least once on the given land type at the time he or she was interviewed. On average, the probability of overall adoption is 18%, the probability of adoption on regular land 9%, and the probability of adoption on marginal land is 11%. These probabilities partly reflect the strong incentive that plantation subsidies represent when at the same time they reduce up-front costs and increase long-term profitability.

Adoption intensity (*MiscAcreage*) is measured as the cumulative acreage allocated to miscanthus in 2010.On average, adopters grow about 4.6 ha of miscanthus, representing 2.6% of the average farmland. Among adopters, 49% allocated only marginal land to miscanthus, 35% only regular land and 16% chose a mixed allocation. Thus, marginal land seems to be preferred to regular land to grow miscanthus.

Marginal land is land that farmers stated to match the following definition: '*Do you think some of your land is particularly difficult to farm relative to the rest of your land, due to high costs (included labor costs), low yields, or other constraints?*'. The question was asked at the very beginning of the questionnaire in order to avoid interferences with questions about miscanthus. In the end, land indicated as marginal mostly corresponds to poor soil conditions (64% of the total area declared as marginal): low fertility, hydromorphy or dryness, presence of stones.

Explanatory variables Explanatory variables can be divided into three groups: farmer characteristics (socio-demographics and economics), farm characteristics (resources, economic and geographical context), and farmers' preferences. On average, the interviewed farmers are 48 years old. Farming is the main income source for the households, but, on average, 26% comes from another professional activity than farming. The mean farm size is 169 ha, with 32% of the farm land being owned by the farmer. Farmers breeding livestock represent 24% of the sample, and those who were beet producers before the reform of the EU sugar regime 34%. On average, 80% of the sampled farmers have marginal land, and idle land represents 3% of the farm land.

Table 1: Variable description

Dependent variables	
Adopter	1=grows miscanthus; 0 otherwise
MiscAcreage	total acreage allocated to miscanthus (ha)
RegularUsed	1=grows miscanthus on regular land at least partly; 0=otherwise
MarginUsed	1=grows miscanthus on marginal land at least partly; 0=otherwise
Explanatory variables	
Farmer characteristics	
Age	age of the farmer (years)
ExtraInc	proportion of the household income coming from another professional activity than farming
Farm characteristics	
FarmSize	total arable area (100 ha)
LandOwned	proportion of land out of the arable area which is owned
Livestock	1=has livestock; 0 otherwise
ExBeet	1=former beet producer; 0 otherwise
Margin	1=has some marginal land on the farm; 0=otherwise
IdleLand	proportion of idle land out of the arable area in 2009
PlotSize	average plot size (ha)
Wood	1=owns woods; 0 otherwise
North	1=farm located in the northern part of the study area; 0 otherwise
WheatRisk[a]	importance of risk faced on soft wheat (1-5 score)
Individual preferences	
EnvironObjFirst[b]	1=reaching good environmental performances is the first objective; 0 otherwise
VConcavity	PT parameter for concavity of the value function in the gain domain
LossAversion	PT parameter for loss aversion
WeightExtreme	PT parameter for the weight given to extreme events
DiscountF	parameter for the exponential discount factor

[a] *WheatRisk* is the mean score of several Likert-type items measuring farmers' perception of wheat production exposure to several types of risks (1=not important at all, 5=very important): blight risk, pest risk, climate risk, weed risk, management risk, location risk, price risk, outlet risk, cost risk, environmental regulation risk. [b] *EnvironObjFirst* is set to 1 if farmers chose 'reaching good environmental performances' as their first objective in farming among a list of 18 potential objectives.

Table 2: Weighted descriptive statistics

	Full sample		Non-adopters		Adopters	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables						
Adopter	0.18	0.38	0.00	0.00	1.00	0.00
MiscAcreage	0.81	2.82	0.00	0.00	4.60	5.29
RegularUsed	0.09	0.29	0.00	0.00	0.51	0.50
MarginUsed	0.11	0.32	0.00	0.00	0.65	0.48
Explanatory variables						
Farmer characteristics						
Age	47.68	8.85	48.53	8.55	43.67	9.39
ExtraInc	0.26	0.25	0.25	0.26	0.31	0.23
Farm characteristics						
FarmSize	1.69	0.96	1.56	0.90	2.28	1.03
LandOwned	0.32	0.21	0.33	0.21	0.28	0.22
Livestock	0.24	0.43	0.24	0.43	0.23	0.42
ExBeet	0.34	0.48	0.31	0.47	0.49	0.50
Margin	0.80	0.40	0.78	0.42	0.93	0.26
IdleLand	0.03	0.03	0.03	0.03	0.04	0.04
PlotSize	6.67	3.73	6.41	3.36	7.86	5.03
Wood	0.35	0.48	0.36	0.48	0.32	0.47
North	0.24	0.43	0.24	0.43	0.25	0.43
WheatRisk	3.33	0.57	3.32	0.56	3.39	0.64
Individual preferences						
EnvironObjFirst	0.03	0.18	0.02	0.15	0.09	0.29
VConcavity	0.50	0.43	0.51	0.45	0.44	0.37
LossAversion	3.86	3.35	3.97	3.52	3.34	2.45
WeightExtreme	0.38	0.33	0.40	0.34	0.31	0.31
DiscountF	0.13	0.07	0.13	0.07	0.13	0.09
Nb. of observations	102		45		57	

The dummy variable *North* distinguishes farmers from *Baigneux-les-Juifs* area (*North*=1, 24% of the sample) from those from *Aiserey* area. As mentioned before, pedo-climatic conditions are less favorable in the north than in the south. Contract conditions are slightly less advantageous as well. However, the economic conditions surrounding miscanthus adoption are roughly homogeneous over both sub-areas. Indeed, the two dehydration plants are the only outlet for miscanthus, and they both offer incentive production contracts to farmers: all contracts guarantee a long-term outlet for the crop, at a minimum price, which is the main concern for farmers on an emerging market (Alexander et al., 2012; Bocquého and Jacquet, 2010). Policy conditions are also similar: nearly all adopters (50 out of 57) benefited from plantation subsidies from the regional diversification plan launched in 2009.

In this study, particular attention is paid to farmers' risk preferences. As already mentioned, they were elicited experimentally for each farmer in the sample assuming farmers were PT maximizers. The value function is assumed to exhibit a power form and is defined separately over gains and losses (Tversky and Kahneman, 1992):

$$u(y) = \begin{cases} y^{1-\sigma} & \text{if } y > 0 \\ 0 & \text{if } y = 0 \\ -\lambda(-y)^{1-\sigma} & \text{if } y < 0. \end{cases} \tag{10}$$

In this specification, σ is an index of concavity in the gain domain (and convexity in the loss domain) [12] and λ is the coefficient of loss aversion. The probability weighting function is (Prelec, 1998):

$$\omega(p) = \exp\left[-(-\ln p)^{(1-\gamma)}\right]. \tag{11}$$

Parameter γ controls the curvature of the weighting function and is an index of likelihood insensitivity. [13] If $\gamma > 0$, the weighting function has an 'inverse S-shape', whereas if $\gamma < 0$ the function takes the less conventional 'S-shape'.

The lotteries are such that any combination of choices in the three series determines a particular interval for the three parameter values. Parameter values are approximated by taking the midpoint of

[12] In Bocquého et al. (2014), σ is an index of *convexity*. In this article, for the ease of interpretation, we use an index of *concavity* by replacing σ by $1-\sigma$.

[13] Again, to facilitate interpretation, we replace the weighting parameter γ of Bocquého et al. (2014) by $1-\gamma$. Whereas in Bocquého et al. (2014) γ is an index of likelihood *sensitivity*, and $\gamma < 1$ characterizes an inverse S-shape, in this article, it is an index of likelihood *insensitivity*.

intervals. When there is no switch, the values at the boundary are used. Each parameter is then used as an explanatory variable for miscanthus adoption.

Variables *VConcavity* and *LossAversion* correspond to parameters σ and λ, and *WeightExtreme* to γ. On average, in the sample, *VConcavity* is positive (0.50) and *LossAversion* is higher than 1 (3.86), meaning that farmers exhibit the usual PT behavior, namely risk aversion in the gain domain, risk seeking in the loss domain and loss aversion. The higher *VConcavity*, the stronger the risk aversion in the gain domain (and the risk-seeking behavior in the loss domain). Similarly, the higher *LossAversion*, the stronger the aversion to loss relative to gains. On average, *WeightExtreme* is positive (0.38), meaning that farmers behave in accordance with the usual empirical finding: farmers tend to be more sensitive to changes in ranks close to the extreme values 0 and 1. The higher *WeightExtreme*, the more farmers focus on extreme outcomes.

In the experiment, we did not explicitly measure farmers' reference point, but assumed it was zero (*status quo*) Bocquého et al. (2014). Thus, we cannot explicitly control for the impact of farmers' reference point on adoption. However, *ExBeet* may be correlated to a high reference point because before the reform of the EU sugar regime, beet was a crop providing a quite high and stable income. As a consequence, former beet producers may have a higher reference point than other farmers.

Regarding time preferences, we assume standard stationary preferences of the exponential form and linear utility. By definition, the discount factor δ makes the present value of a monetary outcome available in t equal:

$$M_t = \delta^\tau M_{t+\tau} \qquad \delta \in]0;1] \tag{12}$$

where M_t and M_τ denote the monetary outcome for delivery at time t and τ respectively. For each respondent and each series, we derive from the given switching point an upper and a lower bound for the discount factor. The discount factor is then assumed to be equal to the mid-point of the interval. Variable *DiscountF* takes on the individual δ values and is 0.13 on average in the sample. The lower *DiscountF*, the stronger the farmer's discounting.

5 Econometric models

As it is often the case with data about the adoption of a divisible technology, the first variable of interest *MiscAcreage* yields many zero responses, and outside of the zero focal point, is is continuously distributed. The two other variables of interest *RegularUsed* and *MarginUsed* are dummies that also yield many zero responses.

Several econometric models are technically available to deal with such non-negative or binary variables and avoid biased estimates, but the choice of the suitable specification requires a careful examination of the way zero responses arise in the given problem. In our adoption problem, there are two main sources of zero responses. First, *MarginUsed* cannot be observed for farmers who do not have marginal land on their farm, leading to selected observations. However, we do not expect them to biase our estimates as the existence of marginal land is random with respect to the adoption decision. Second, in all three variables *MiscAcreage*, *RegularUsed* and*MarginUsed*, many zeros are corner solutions. Most often, in the literature on technology adoption, the corner solution issue is managed with the standard tobit model when the amount of land converted is available (e.g., Adesina and Baiduforson, 1995; Abadi Ghadim et al., 2005; Jensen et al., 2007; Roos et al., 2000). However, Tobit models are adequate for real censored data issues only, when observations are piled up at a limiting value for technical reasons related to the collection method for the data. In addition, applying the tobit procedure lays the assumption that the equation determining whether an observation is at the zero limit is the same as the equation explaining the positive values. This property conflicts with the fact that there may be two decisions at work in adoption models, first whether to adopt the technology or not, and second to what extent adopt it. Two-equation extensions of tobit models, like two-part models [14], do allow different mechanisms for the *participation* and *intensity* decisions. In these models, the first equation corresponds to a binary variable (participation equation) and the second equation to a positive variable *conditional* on having adopted in the first phase (intensity equation).

5.1 Adoption whatever the land type: tobit and two-part model

We analyze the determinants of miscanthus adoption whatever the land type by estimating first the usual tobit model, and second a linear two-part model which is more relavant for adoption problems. The intensity variable, i.e., the total amount of land allocated to miscanthus by farmer i, is denoted by y_i. It is a positive continuous variable with a mass point at 0 because for some agents the optimal

[14]Two-part models have been widely used in consumption studies and health economics (Jones, 1989, 2000; Ground and Koch, 2008), or finance (Moffatt, 2005). They have recently entered the field of agricultural and environmental economics (Martínez-Espiñeira, 2006; Bekele and Mekonnen, 2010; Mishra, 2009), including to explain technology adoption (Kassie et al., 2009; Teklewold et al., 2006; Smith et al., 2011).

decision is the corner solution $y_i = 0$. Let X_i be a vector of all observable explanatory variables (farmer and farm characteristics, farmers' individual preferences).

Standard tobit The tobit specification for the (unconditional) intensity variable is:

$$y_i^* = \beta X_i + \varepsilon_i, \qquad y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where β is the vector of parameters to be estimated, ε_i are independent and identically distributed (i.i.d.) stochastic error terms capturing unobserved heterogeneity in behavior (all unobservable factors having an effect on the variable of interest), and $\varepsilon_i | X_i \sim N(0, \sigma^2)$.

Parameters are estimated by maximum likelihood. If the sample observations are divided into those being zero and those being positive, the log-likelihood function is:

$$\ln L(y_i; \beta) = \sum_{i|y_i=0} \ln[1 - \Phi(\beta X_i/\sigma)] + \sum_{i|y_i>0} \ln\left[\frac{1}{\sigma}\phi\left(\frac{y_i - \beta X_i}{\sigma}\right)\right] \tag{14}$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

Two-part model In a two-part model, the participation decision and the (conditional) intensity decision are generated by distinct underlying processes (Cragg, 1971):

participation equation:

$$z_i^* = \gamma X_i + \nu_i, \tag{15}$$

intensity equation for non-zero responses:

$$y_i^* = \beta X_i + \varepsilon_i, \qquad y_i = \begin{cases} y_i^* & \text{if } z_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

where β and γ are vector of parameters to be estimated, ν_i and ε_i are random error terms, and $\nu_i|X_i \sim N(0, \delta^2)$. The distribution of $\varepsilon_i|X_i$ is truncated normal with lower truncation point $-\beta X_i$, based on a non-truncated normal distribution $N(0, \sigma^2)$ (Wooldridge, 2010). The truncation ensures that y_i^* is non-negative. The justification is that the value of the variable of interest y_i depends on the regime under which the variable is observed: it is a zero value if the participation condition is met and a positive value if not.

Following the usual Cragg's (1971) version of this model, we assume that ν_i and ε_i are independent conditional on the set of observed covariates. The log-likelihood of the independent two-part model is:

$$\ln L(y_i; \beta, \gamma) = \sum_{i|y_i=0} \ln\left[1 - \Phi(\gamma X_i)\right] + \sum_{i|y_i>0} \ln\left[\frac{1}{\sigma}\phi\left(\frac{y_i - \beta X_i}{\sigma}\right) \cdot \frac{\Phi(\gamma X_i)}{\Phi\frac{\beta X_i}{\sigma}}\right]. \quad (17)$$

The term $\frac{1}{\Phi\frac{\beta X_i}{\sigma}}$ ensures that the density integrates to unity over $y_i > 0$ (truncated distribution). [15]

From Equation (17), it is straightforward that the log-likelihood can be written as the sum of the log-likelihoods of a probit model and a truncated-at-zero regression model (Mc Dowell, 2003; Wooldridge, 2010). Hence, the parameter vectors γ and β are estimated separately, γ with Stata command *probit* applied to the full sample, and β_2 with command *truncreg* applied to the $y_i > 0$ observations. The two-part model reduces to the standard tobit model when $\gamma = \beta/\sigma$ (and explanatory variables are the same in the participation and the intensity equation).

5.2 Adoption according to land type: bivariate probit

The participation variable on regular land is denoted by y_i and the participation variable on marginal land is denoted by z_i. They are binary variables taking on the value 1 if farmer i grows miscanthus on the given land type and 0 otherwise. We assume that the two decisions are taken jointly, and thus that some unobserved factors may influence both decisions. As outlined above, zero responses from farmers having no marginal land are constrained observations, but they are not expected to generate

[15] The truncated distribution of y_i^* is the fundamental technical difference with Heckman selection models (also called tobit type II models). Thus, selection models are theoretically relevant to model selection issues only, where zeros are unobserved values, and not corner solutions issues. In these models, responses are not restricted to positive values, and thus are density consistent. Heckman selection models can also be viewed as a generalization of two-part models when the participation and intensity decisions are assumed to be correlated.

any bias.

We deal with this joint decision by estimating a *bivariate probit model*. Once again, let X_i be a vector of all observable explanatory variables (farmer and farm characteristics, farmers' individual preferences). The bivariate probit is written:

participation equation for regular land:

$$y_i^* = \beta X_i + \varepsilon_i, \qquad y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

participation equation for marginal land:

$$z_i^* = \gamma X_i + \nu_i, \qquad z_i = \begin{cases} 1 & \text{if } z_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

where β and γ are vector of parameters to be estimated and ν_i, ε_i are random error terms. The error terms are correlated and assumed to have a bivariate normal distribution such that $\begin{pmatrix} \nu_i \\ \varepsilon_i \end{pmatrix} \sim N(0, \Sigma)$, where $\Sigma = \begin{pmatrix} 1 & \sigma\rho \\ \sigma\rho & \sigma^2 \end{pmatrix}$ and ρ is the correlation coefficient. The dummies coding for the two participation variables are the expression of two latent variables y^* and z^* corresponding respectively to the amount of regular land and marginal land allocated to miscanthus. The correspondence is such that 0 codes for no allocation and 1 for any positive amount of land. We estimate the bivariate probit by maximum likelihood with Stata command *biprobit*. [16]

6 Results and discussion

For each of the models explaining miscanthus adoption, we estimate by maximum likelihood the average marginal effects of the explanatory variables. No major collinearity problem between the

[16]To account for the stratified survey design, we used for all estimations prefix *svy:* which computes corrected point estimates and standard errors based on weighted log-likelihoods. All estimations were performed with Stata 11.2 software.

Table 3: Marginal effects on miscanthus adoption

	Model T (tobit model)		Model A0 (two-part model)			
	E(MiscAcreage)		Pr(Adopter=1)		E(MiscAcreage|Adopter=1)	
Farmer characteristics						
Age	−0.038*	(0.019)	−0.006*	(0.003)	−0.011	(0.040)
ExtraInc	1.586*	(0.844)	0.203*	(0.120)	2.659	(1.964)
Farm characteristics						
FarmSize	0.562***	(0.175)	0.107***	(0.028)	−0.127	(0.444)
LandOwned	−1.177	(1.005)	−0.209	(0.175)	−0.398	(2.373)
1.Livestock	−0.437	(0.338)	−0.107*	(0.054)	1.300	(1.214)
1.ExBeet	0.714	(0.474)	0.135*	(0.077)	−0.736	(1.036)
1.Margin	0.568*	(0.329)	0.125**	(0.057)	−3.204	(3.421)
1.Wood	0.993*	(0.567)	0.112	(0.072)	1.386	(1.209)
1.North	−0.199	(0.368)	−0.005	(0.072)	−1.874	(1.171)
WheatRisk	0.128	(0.312)	0.026	(0.051)	0.112	(0.679)
Individual preferences						
1.EnvironObjFirst	0.782	(0.780)	0.281	(0.192)	−0.322	(1.108)
VConcavity	0.155	(0.386)	0.011	(0.065)	0.337	(0.833)
LossAversion	0.007	(0.054)	−0.000	(0.010)	0.128	(0.163)
WeightExtreme	−1.149*	(0.623)	−0.185**	(0.081)	−2.212	(2.063)
DiscountF	2.009	(2.265)	0.240	(0.380)	6.543	(4.851)
Nb. of observations	102		102		57	
Model p-value	0.01		0.03		0.83	
Proportion correctly predicted	0.84		0.86			
Proportion variance explained	0.10				0.33	

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design. In the case of the intensity equation of the two-part model, we report the marginal effects on the expected values for the outcome conditional on being positive.

explanatory variables was detected. [17] To assess the goodness-of-fit of the models, we mainly use their predictive power, i.e., the proportion of observations correctly predicted (for binary outcomes) and the proportion of variance explained (for continuous outcomes).

6.1 Adoption whatever the land type

In this section, we analyze the factors influencing adoption whatever the type of land, through a tobit model and several two-part models featuring different sets of explanatory variables.

6.1.1 Full set of explanatory variables

Estimates of the marginal effects in the base tobit and two-part models (models T and A0 respectively) are displayed in Table 3.

[17] To detect potential multicollinearity in the base set of explanatory variables, we computed the variance inflation factor (VIF) for each variable. This diagnostic statistic consists in computing $1/(1-R^2)$ for each coefficient in a simple regression, R^2 being the coefficient of determination. The VIF for a variable gives the increase in the variance of the coefficient that can be due to non-orthogonality with other variables (Greene, 2008, p.60). Results are given in Table 11 of Appendix C. As all coefficients are lower than 10, we argue than there is no major multicollinearity problem.

As it can be seen in the lower part of the table, models T and A0 predict the participation decision with the same accuracy (84% and 86% of the observations correctly predicted respectively). However, the two-part model A0 is much more reliable in explaining the variance in the intensity decision: 33% of the variance of the observations is explained against 10% for the tobit model. This means that it is worth disentangling the participation and intensity decisions to study miscanthus adoption. In the rest of the paper, we will focus on the results from the two-part specification which appears to be more accurate.

Participation decision Column 3 of Table 3 presents the marginal effects for the participation equation of the two-part model, i.e., farmers' decision about whether to allocate land to miscanthus.

Farmer and farm characteristics Significance Wald tests of variables show that extra-agricultural incomes (*ExtraInc*), farm size (*FarmSize*) and possession of marginal land (*Margin*) increase significantly the probability of miscanthus adoption (respectively at the 10, 1 and 5 per cent level). The positive effect of *ExtraInc* on adoption can be explained by a higher investment capacity in miscanthus plantation and a higher availability of funds to cover the lengthy establishment period. It can also reveal a more stable household income, and thus a higher capacity to cope with risk in farming. As far as *FarmSize* is concerned, on average, for a farmers' population like the one from which the sample was drawn, the probability of miscanthus adoption increases by 1.0 percentage point for every supplementary 10 ha farmed. Rämö et al. (2009), Roos et al. (2000), Villamil et al. (2008), and Breen et al. (2009) also found a positive effect of farm size on farmers' willingness to grow energy crops. Yet, in Jensen et al. (2007), the relationship between switchgrass adoption by U.S. Tennessee farmers and farm size was negative. Farm size can be viewed as a proxy for farmers' investment capacity: farmers having more land may have accumulated more savings, and hence be able to invest in miscanthus without needing a credit, which would entail extra costs. Another explanation may lie in the existence of fixed transaction costs such as costs of information acquisition: miscanthus requires an up-front investment in learning, despite the technical assistance offered by processors through production contracts. As for the binary variable *Margin*, farmers having marginal land are, on average, 12 points more likely to participate in miscanthus production than farmers having homogeneous land. This result confirms Hypothesis 3, that is, making marginal land more profitable is a major motivation for growing miscanthus.

Contrary to *FarmSize* and *Margin*, *Age* and *Livestock* have a significant negative effect on adoption (at the 10 per cent level). The effect of *Age* is quite strong: on average, the probability of adoption decreases by 6 points for every 10-year increase in farmers' age. Rämö et al. (2009) and Jensen et al. (2007) found a similar negative effect of age on the adoption of energy crops, respectively in Finland and Tennessee, U.S.A.. However, regarding short rotation willow, Roos et al.'s (2000) results are ambiguous. Farmers under 35 years and above 65 years were found to grow willow on a smaller surface area than the others, whereas farmers between 50 and 65 years were found to grow willow on a larger area. Possible explanations for the negative effect of age on technology adoption are twofold, either psychological or economic. First, as highlighted in the general literature about technology adoption, elder people tend to be more resistant to change because of the burden of habits. Second, elder farmers are closer to retirement than younger ones, thus their planning horizon is shorter and a long-term investment is less profitable for them. Similarly, farmers who have livestock are 11 points less likely to adopt miscanthus than field crop specialists. This is in line with Roos et al. (2000), Jensen et al. (2007) and Breen et al.'s (2009) results who showed that cattle breeding was negatively linked with energy-crop adoption. A possible explanation is cattle breeders have less land available for conversion to miscanthus. Indeed, marginal land may be used as pasture for cattle feeding, on the farm or outside the farm. If the feeding capacity of the farm greatly exceeds the cattle needs, farmers are able to sell hay to other farmers because they are equipped for cutting and conditioning hay. In other words, in cattle systems, marginal land is generally productive and likely to be either unavailable in the short term, or available but more profitable than planted with miscanthus.

Variable *ExBeet* also affects significantly participation (at the 10 per cent level), with a coefficient of 0.13. It means that former sugar-beet producers are more prone to adopt miscanthus than non ex-beet producers. They may be motivated by higher expected benefits because most of them are shareholders of the *Aiserey* dehydration plant. In addition, fixed transaction costs such as information gathering may be minimized because they are directly targeted by the regional diversification plan. Last, as explained in the next paragraph, former sugar-beet producers may use a high reference point when assessing crop outcomes.

Individual preferences Probability weighting (*WeightExtreme*) is the only preference variable with a significant effect on the participation decision (at the 5 per cent level). The marginal effect of *WeightExtreme* on the probability of miscanthus adoption is negative, meaning that the higher farmers overweight extreme events, the lower they tend to adopt miscanthus. This is consistent with the hypothesis made about the distribution of returns from miscanthus and Hypothesis 8. We showed in Section 3.2 that it was reasonable to think that, compared to a traditional crop such as wheat, miscanthus returns were quite unrisky but did involved extremely unfavorable events like an establishment failure or a contract counterparty failure. Thus, under this hypothesis, the fact that *WeightExtreme* decreases miscanthus attractiveness and the probability of its adoption makes sense. The effect is rather large, the probability of adoption increasing on average by a 1.8 percentage point when *WeightExtreme* increases by 0.1.

We are not able to report any significant effect of the preference variable *EnvironObjFirst*. It is a common finding for sustainability-related innovations, environmental benefits being generally of secondary importance in determining the attractiveness of such innovations to farmers (Pannell, 1999; Bathgate and Pannell, 2002).

Time preferences (*DiscountF*) are not found to have a significant effect on participation either. It may be due to the fact that, in *Bourgogne*, miscanthus establishment costs are heavily subsidized by the regional diversification plan .

Intensity decision Column 4 of Table 3 presents the marginal effects in the base two-part model for the intensity equation , i.e., the effects on the acreage farmers decided to allocate to miscanthus provided that they had decided to participate in this activity. We cannot find any significant effect on intensity, contrary to participation, which highlights the importance of considering the two decisions as separate ones.

The absence of effect from *FarmSize* tends to support the previous interpretation as farm size being a proxy for the costs of information acquisition (fixed) rather than for the investment capacity in plantation costs (variable). In the case of *Livestock* and *Margin*, the absence of effect on miscanthus acreage may seem surprising because both are linked with the extent of land appropriate for miscanthus production (i.e., more profitable than under the current use, and available in the short term). In fact, because miscanthus is in an early development phase, most farmers adopt miscanthus on small trial plots (Abadi Ghadim and Pannell, 1999). Hence, only part of the appropriate land is generally used, and the total extent of appropriate land is not a binding constraint in the intensity decision. The same explanation can also be invoked to justify the absence of effect from *FarmSize*: *FarmSize* is a proxy for farmers' investment capacity, but the effect is not visible because the liquidity constraint is not binding.

6.1.2 Alternative sets of explanatory variables

In this section, we test alternative specifications of the two-part model by varying the set of explanatory variables. Compared to base model A0, in model A1 individual preferences are omitted, and in model A2 *Margin* is replaced by *IdleLand* and *PlotSize*. The marginal effects estimated for these two alternative specifications are displayed in Table 4.

Participation decision The results obtained from model A0 are robust over the two alternative specifications: we observe similar significant effects of variables *Age*, *ExtraInc*, *FarmSize*, *Livestock*, *ExBeet*, *Margin* and *WeightExtreme*.

In model A2, we replaced *Margin* by *IdleLand* and *PlotSize* in order to use two objective and absolute description criteria for marginal land rather than a subjective and relative single criterion. We found that, on average, every increase of 1 point in the proportion of voluntary idle land increases significantly (at the 1 per cent level) miscanthus adoption by 2 percentage points. The rationale is probably the same that for *Margin*, that is farmers view miscanthus as a mean of making unproductive land profitable. However, *PlotSize* has no significant effect on participation, which suggests that marginal land includes other plots than those with unfavorable dimensions (or more generally an unfavorable geometry), like plots with poor growing conditions.

Intensity decision In model A2, some new effects appear as significant compared to model A0. First, *Livestock* has a (weakly) positive effect on the intensity decision, which contrasts with its negative effect on the participation decision. It suggests that, once livestock breeders have decided to participate in miscanthus production because they have appropriate land, they tend to allocate more land to the new crop than other farmers.

Second, *IdleLand* exhibits a significant positive effect on adoption intensity at the 1 per cent level. This means that the proportion of idle land is a binding constraint for miscanthus extension. This result supports the theoretical prediction that farmers allocate first idle land to miscanthus because it is where they can generate the largest profit increase. As the area of idle land per farm is very low, it is binding even with small trial plots. Similarly, *PlotSize* has a significant positive effect on adoption intensity, whereas it is not determinant in explaining participation. An explanation could be that,

Table 4: Marginal effects on miscanthus adoption for different sets of regressors

	Model A1 (omitting preferences)		Model A2 (replacing *Margin*)	
	Pr(Ado=1)	E(Misc|Ado=1)	Pr(Ado=1)	E(Misc|Ado=1)
Farmer characteristics				
Age	−0.007**	−0.014	−0.009***	0.011
	(0.003)	(0.027)	(0.003)	(0.041)
ExtraInc	0.193*	1.158	0.221*	2.877
	(0.099)	(1.283)	(0.116)	(1.957)
Farm characteristics				
FarmSize	0.097***	−0.325	0.097***	−0.362
	(0.027)	(0.421)	(0.027)	(0.431)
LandOwned	−0.183	−0.729	−0.089	−1.720
	(0.154)	(2.015)	(0.173)	(1.969)
1.Livestock	−0.101*	1.868	−0.084	2.836*
	(0.053)	(1.244)	(0.056)	(1.437)
1.ExBeet	0.160**	−0.798	0.140*	0.029
	(0.073)	(1.074)	(0.075)	(0.996)
1.Margin	0.096*	−3.057		
	(0.055)	(3.810)		
IdleLand			2.163***	37.029***
			(0.766)	(10.992)
PlotSize			0.013	0.194**
			(0.008)	(0.079)
1.Wood	0.107	0.980	0.129*	1.885
	(0.069)	(1.073)	(0.076)	(1.165)
1.North	0.042	−1.846	−0.089	−3.238***
	(0.070)	(1.116)	(0.069)	(1.126)
WheatRisk	0.020	−0.148	0.041	0.517
	(0.046)	(0.599)	(0.051)	(0.694)
Individual preferences				
1.EnvironObjFirst			0.375*	0.065
			(0.193)	(1.249)
VConcavity			0.029	0.366
			(0.061)	(0.877)
LossAversion			0.001	0.007
			(0.009)	(0.141)
WeightExtreme			−0.145*	−1.870
			(0.073)	(1.935)
DiscountF			0.249	7.648*
			(0.362)	(4.361)
Nb. of observations	105	57	102	57
Model p-value	0.01	0.54	0.04	0.41
Prop. correctly predicted	0.85		0.85	
Prop. variance explained		0.26		0.46

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design. In the case of the intensity equation, we report the marginal effects on the expected values for the outcome conditional on being positive (Ado: *Adopter*, Misc: *MiscAcreage*).

at farm level, allocating land to miscanthus is a plot-by-plot process. Indeed, in the overwhelming majority of cases, the allocation of plots to miscanthus follows an all-or-nothing rule. Thus, the higher the mean plot size, the higher the total miscanthus acreage on the farm, but there is no effect on the probability of adoption itself.

Third, *North* is significant at the 1 per cent level, and negatively correlated with miscanthus acreage. On average, farmers who deliver to the *Baigneux-les-Juifs* plant grow 3.2 ha less of miscanthus relative to farmers who supply the *Aiserey* plant. This is most likely due to the nature of the production contracts offered by the former. These contracts do not include any cash-advance system contrary to those offered by the latter. Such systems enhance farmers' capacity in investing in miscanthus establishment, an up-front cost which is proportional to the surface area. In addition, the pedo-climatic conditions on the plateau where *Baigneux-les-Juifs* is located are less favorable than in the south plain. Thus, farmers may be less confident relative to miscanthus adaptation to local growing conditions, and may prefer to trial it on very small plots to reduce the impact of a potential establishment failure on their income.

6.1.3 Interaction effects

Table 5 collates the estimates of the marginal effects in the two-part model when accounting for the interaction effects of *ExBeet* with *LossAversion* and *WeightExtreme* (model A3).

The effect of *LossAversion* on the probability of participation is -0.03 and significant if farmers are not former beet producers, whereas it is 0.04 (and unsignificant) if farmers are former beet producers. The first value tells us that, on average, the participation probability for non ex-beet producers decreases by around 3 points for every increase of 1 unit in the loss aversion parameter. This observation is consistent with Hypothesis 9 which states that farm history is likely to modify the effect of loss aversion on adoption through a change in the reference point. For non ex-beet producers, the reference point corresponds to the mean wheat return on regular land and the mean miscanthus return on marginal land. As loss aversion penalizes more all-loss distributions than mixed distributions, an increase in loss aversion has opposite effects on adoption depending on land type. It is a negative effect on regular land because miscanthus is more penalized than wheat, and a positive effect on marginal land because wheat is more penalized than miscanthus. The second result, namely the absence of effect of *LossAversion* on the probability of adoption, is consistent with former beet

Table 5: Marginal effects on miscanthus adoption when accounting for interaction effects

	Model A3			
	Pr(Adopter=1)		E(MiscAcreage|Adopter=1)	
Farmer characteristics				
Age	-0.005	(0.004)	-0.028	(0.042)
ExtraInc	0.198*	(0.116)	2.304	(1.849)
Farm characteristics				
FarmSize	0.119***	(0.024)	-0.125	(0.400)
LandOwned	-0.275*	(0.154)	-0.722	(2.214)
1.Livestock	-0.113**	(0.055)	1.355	(1.305)
1.ExBeet	0.176*	(0.092)	-0.789	(1.032)
1.Margin	0.130**	(0.052)	-3.776	(3.202)
1.Wood	0.165**	(0.076)	1.343	(1.158)
1.North	0.030	(0.077)	-1.990*	(1.109)
WheatRisk	0.038	(0.049)	0.137	(0.679)
Individual preferences				
1.EnvironObjFirst	0.220	(0.165)	-0.295	(1.227)
VConcavity	-0.012	(0.062)	0.672	(0.929)
LossAversion	-0.004	(0.011)	0.097	(0.168)
WeightExtreme	-0.204***	(0.073)	-2.318	(2.062)
DiscountF	0.256	(0.375)	6.546	(4.583)
Marginal effect of LossAversion *for each level of* ExBeet*:*				
LossAversion×0.ExBeet	-0.027**	(0.013)	-0.197	(0.336)
LossAversion×1.ExBeet	0.037	(0.025)	0.530	(0.396)
Marginal effect of WeightExtreme *for each level of* ExBeet*:*				
WeightExtreme×0.ExBeet	-0.228**	(0.108)	-3.536	(4.672)
WeightExtreme×1.ExBeet	-0.202	(0.157)	-3.780	(3.899)
Nb. of observations	102		57	
Model p-value	0.06		0.93	
Prop. correctly predicted	0.86			
Prop. variance explained			0.37	

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design. In the case of the intensity equation, we report the marginal effects on the expected value for the outcome conditional on being positive.

producers being concerned with replacing the high income from sugar beet and thus exhibiting a high reference point. It is likely that it only applies to land where beet can be grown, i.e., regular land. On this type of land, ex-beet producers may thus perceive all returns as losses, and an increase in loss aversion does not disfavor one crop more than the other.

Regarding the marginal interaction effect between *ExBeet* and *WeightExtreme*, similarly, it is significant only for non ex-beet producers (-0.23). It shows that, on regular land, high levels of probability distortion are a barrier to adoption mostly for non ex-beet producers. Indeed, it is likely that ex-beet producers have a more favorable representation of miscanthus incomes with respect to extreme events. As they are shareholders of the *Aiserey* dehydratation plant, they may be more informed about the plant commercial strategy, or more confident, and thus may not be worried about the counterparty risk.

6.2 Adoption according to land type

6.2.1 Full set of explanatory variables and alternative sets

Table 6 collates the estimates of the bivariate probit model (model L0) explaining farmers' decision (i) to adopt miscanthus on marginal land and (ii) to adopt miscanthus on regular land. The effects on the probability of adoption whatever the land type are in column 2, those on the probability of adoption on marginal land in column 4, and those on the probability of adoption on regular land in column 6. With this base specification of the bivariate probit model, the proportion of correctly predicted outcomes is 86% for adoption on any land, 88% for adoption on marginal land, and 88% for adoption on regular land. The first percentage is to be compared with the proportion of binary outcomes correctly predicted by model A0 (participation equation), i.e., 86%. It means that the predictive power of the bivariate probit and of the two-part model with respect to overall participation is similar.

Regarding explanatory variables, first note that model L0 gives results consistent with those from the participation equation of model A0. Indeed, we also find that *Age*, *ExtraInc*, *FarmSize*, *Livestock*, *ExBeet* and *WeightExtreme* have a significant effect on the probability of adoption whatever the type of land (column 2). The signs of the effects are as expected. Second, model L0 sheds light on the differences between adopting on marginal land and regular land. Several variables exhibit a significant effect on one type of land only: *Age*, *ExtraInc*, and *Livestock* on marginal land only, *ExBeet* and *WeightExtreme* on regular land only. This result is robust for nearly all of them when alternative sets

Table 6: Marginal effects on miscanthus adoption according to type of land

	Model L0 (bivariate probit)					
	Pr(MarginUsed=1,RegularUsed=1)		Pr(MarginUsed=1)		Pr(RegularUsed=1)	
Constant						
Farmer characteristics						
Age	-0.007**	(0.003)	-0.007**	(0.003)	-0.003	(0.002)
ExtraInc	0.215*	(0.110)	0.178*	(0.094)	0.089	(0.085)
Farm characteristics						
FarmSize	0.101***	(0.025)	0.061***	(0.021)	0.067***	(0.018)
LandOwned	-0.138	(0.163)	-0.025	(0.127)	-0.153	(0.121)
1.Livestock	-0.094*	(0.053)	-0.089**	(0.039)	-0.028	(0.046)
1.ExBeet	0.144*	(0.076)	0.067	(0.058)	0.119**	(0.059)
1.Margin	0.016	(0.035)			0.021	(0.047)
1.Wood	0.120*	(0.066)	0.081	(0.059)	0.074	(0.052)
1.North	0.016	(0.068)	0.001	(0.056)	0.019	(0.055)
WheatRisk	0.025	(0.042)	-0.003	(0.038)	0.037	(0.037)
Individual preferences						
1.EnvironObjFirst	0.123	(0.104)	0.108	(0.135)	0.050	(0.132)
VConcavity	0.019	(0.062)	0.042	(0.053)	-0.021	(0.039)
LossAversion	0.003	(0.009)	0.003	(0.007)	0.001	(0.006)
WeightExtreme	-0.134*	(0.071)	-0.070	(0.061)	-0.101*	(0.055)
DiscountF	0.379	(0.337)	0.304	(0.298)	0.169	(0.232)
ρ						
Nb. of observations	102		102		102	
Model p-value	0.00		0.00		0.00	
P. c. p. (any land)	0.86					
P. c. p. (marginal land)			0.88			
P. c. p. (regular land)					0.88	

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design.

of variables are used, as shown in columns 2 and 4 of Table 7 (model L1 [18] and L2).

The reason why *Age* and *ExtraInc* have an effect on adoption on marginal land, but not on regular land is unclear. The case of *Livestock* is easier to explain. On marginal land, livestock keepers are 9 points less likely to adopt miscanthus than farmers who have only crop activities. This effect, significant at the 5 per cent level, confirms that many livestock keepers may not view miscanthus production as an attractive activity because their marginal land is already used for fodder. Marginal plots are productive and needed in the short term. [19] By contrast, on regular land, *Livestock* has no significant effect on adoption, meaning having livestock not only decreases the overall probability of adoption, but also increases the share of regular land allocated to miscanthus. [20]

As respects *ExBeet*, our results suggest that being a former beet producer modifies adoption on regular land mostly. This is in line with the assumption made above that the high income expectations are not valid for marginal land where farmers never grew sugar beet. The wish to obtain high yields is another possible interpretation. Indeed, as former beet producers are more involved in the development of miscanthus production, they may want to set an example for other farmers or replicate rhizomes.

As far as *WeightExtreme* is concerned, it is likely that it does not have any impact on adoption on marginal land because both miscanthus and wheat exhibit extreme events. Thus, the overweighting of extreme events is not as unfavorable to miscanthus as on regular land.

6.2.2 Interaction effects

Table 8 collates the estimates of the bivariate probit model when accounting for the interaction effects between *ExBeet* and *LossAversion* or *WeightExtreme* (model L3). On regular land, the effect of the interaction between *ExBeet* and *LossAversion* is similar to that obtained with the participation equation of model A3: the effect of *LossAversion* on the probability of adoption on regular land is estimated to be -0.02 for non ex-beet producers and is significant at the 10 per cent level. Such an effect is not observed on marginal land because, as explained before, reconversion from beet can be associated with high income expectations on regular land only.

Regarding the marginal interaction effect between *ExBeet* and *WeightExtreme*, it is again

[18]In model L1, *Margin* is omitted in the equation explaining adoption on marginal land because all farmers allocating marginal land to miscanthus obviously do have some.

[19]In the longer term, some farmers may decide to reduce their herd and allocate the land made available to miscanthus.

[20]This last result is to be confirmed because the marginal effect of *Livestock* on the probability of adoption on regular land is negative although not significant.

Table 7: Marginal effects on miscanthus adoption according to type of land for different sets of regressors

	Model L1 (omitting preferences)		Model L2 (replacing *Margin*)	
	Pr(MUsed=1)	Pr(RUsed=1)	Pr(MUsed=1)	Pr(RUsed=1)
Farmer characteristics				
Age	−0.007***	−0.003	−0.007**	−0.003
	(0.003)	(0.002)	(0.003)	(0.002)
ExtraInc	0.146*	0.077	0.176*	0.079
	(0.078)	(0.070)	(0.094)	(0.082)
Farm characteristics				
FarmSize	0.056***	0.059***	0.061***	0.062***
	(0.020)	(0.016)	(0.021)	(0.016)
LandOwned	−0.035	−0.149	−0.024	−0.125
	(0.112)	(0.111)	(0.128)	(0.118)
1.Livestock	−0.085**	−0.027	−0.090**	−0.007
	(0.037)	(0.044)	(0.039)	(0.048)
1.ExBeet	0.073	0.137**	0.066	0.127**
	(0.055)	(0.058)	(0.058)	(0.056)
1.Margin	.	−0.007		
		(0.047)		
IdleLand			.	1.016**
				(0.505)
PlotSize			.	0.007
				(0.005)
1.Wood	0.072	0.083*	0.082	0.076
	(0.054)	(0.048)	(0.059)	(0.053)
1.North	0.020	0.050	0.001	−0.027
	(0.055)	(0.057)	(0.056)	(0.052)
WheatRisk	−0.003	0.029	−0.004	0.046
	(0.035)	(0.030)	(0.039)	(0.039)
Individual preferences				
1.EnvironObjFirst			0.107	0.053
			(0.140)	(0.139)
VConcavity			0.041	−0.025
			(0.052)	(0.037)
LossAversion			0.003	0.001
			(0.007)	(0.006)
WeightExtreme			−0.070	−0.073
			(0.061)	(0.052)
DiscountF			0.302	0.178
			(0.300)	(0.227)
ρ				
Nb. of observations	105	105	102	102
Model p-value	0.00	.	0.00	.
P. c. p. (any land)	0.85		0.86	
P. c. p. (marginal land)	0.89		0.88	
P. c. p. (regular land)		0.89		0.89

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design. MUsed: *MarginUsed*, RUsed: *RegularUsed*.

Table 8: Marginal effects on miscanthus adoption according to type of land when accounting for interaction effects

	Model L3					
	Pr(MarginUsed=1,RegularUsed=1)		Pr(MarginUsed=1)		Pr(RegularUsed=1)	
Farmer characteristics						
Age	−0.006**	(0.003)	−0.006**	(0.003)	−0.002	(0.002)
ExtraInc	0.200*	(0.110)	0.188*	(0.097)	0.059	(0.081)
Farm characteristics						
FarmSize	0.114***	(0.021)	0.065***	(0.020)	0.079***	(0.020)
LandOwned	−0.195	(0.147)	−0.042	(0.123)	−0.210**	(0.105)
1.Livestock	−0.105**	(0.052)	−0.084**	(0.040)	−0.048	(0.051)
1.ExBeet	0.180**	(0.089)	0.088	(0.068)	0.153**	(0.076)
1.Margin	0.024	(0.030)			0.031	(0.040)
1.Wood	0.171**	(0.066)	0.103	(0.064)	0.125**	(0.060)
1.North	0.035	(0.069)	0.018	(0.058)	0.026	(0.062)
WheatRisk	0.034	(0.044)	0.004	(0.039)	0.040	(0.041)
Individual preferences						
1.EnvironObjFirst	0.076	(0.092)	0.071	(0.123)	0.024	(0.106)
VConcavity	0.007	(0.062)	0.034	(0.052)	−0.027	(0.044)
LossAversion	−0.000	(0.009)	0.003	(0.008)	−0.003	(0.007)
WeightExtreme	−0.152**	(0.069)	−0.081	(0.061)	−0.112**	(0.054)
DiscountF	0.395	(0.333)	0.343	(0.304)	0.146	(0.234)
Marginal effect of LossAversion *for each level of* ExBeet*:*						
LossAversion×0.ExBeet	−0.021*	(0.011)	−0.007	(0.008)	−0.020*	(0.010)
LossAversion×1.ExBeet	0.036*	(0.019)	0.024	(0.018)	0.027	(0.016)
Marginal effect of WeightExtreme *for each level of* ExBeet*:*						
WeightExtreme×0.ExBeet	−0.187*	(0.106)	−0.059	(0.076)	−0.174*	(0.093)
WeightExtreme×1.ExBeet	−0.133	(0.130)	−0.139	(0.137)	−0.054	(0.116)
ρ						
Nb. of observations	102		102		102	
Model p-value	0.00		0.00		0.00	
P. c. p. (any land)	0.87					
P. c. p. (marginal land)			0.86			
P. c. p. (regular land)					0.87	

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design.

significant on regular land only and for non ex-beet producers (-0.17). We do not observe such an interaction effect on marginal land because, as mentioned before, competing land uses like wheat production also exhibit extremely unfavorable events on marginal land.

To check the robustness of models A0 and L0 to sampling and outliers, we ran the same estimations (i) on a random sub-sample representing 80% of the full sample (models A4 and L4), and (ii) after deleting the three farmers growing more than 20 ha of miscanthus (models A5 and L5). Results are reported in Table 12 for models A4 and A5, and Table 13 for models L4 and L5 (Appendix C). Results are not fundamentally different from those obtained with the base specifications A0 and L0, apart for those relative to the intensity equation of A5. Indeed, the marginal effects of *FarmSize* and *WheatRisk* become significant at the 5 per cent level when the three outliers are discarded. It could mean that early adopters who allocate a large amount of land to miscanthus have specific adoption determinants. In particular, they may not be affected at first by land availability and risk borne at farm level.

7 Conclusion

We mixed survey and experimental data to investigate the impact of individual risk an time preferences on the adoption of perennial energy crops by farmers in *Bourgogne*, France. Risk preferences were elicited from a behavioural model, namely prospect theory, whereas standard exponential time discounting underlies time preferences.

Our results demonstrate that farmers faced with the decision of whether to adopt perennial energy crops display a different behaviour depending on their degree of loss aversion and probability distortion. The more loss averse the farmer, and the more he or she weights extreme events are given, the less likely is miscanthus adoption. However, the effect of loss aversion is highly dependent on farmers' reference level, which may be related to farm history. We show that the negative effect of loss aversion on adoption does not hold if farmers have high income expectations. Furthermore, our results highlight the importance of taking information on land type into consideration when assessing the impact of PT risk preferences on adoption. Indeed, because perennials are generally less profitable than annuals on regular land, but more profitable on marginal land, we find that loss aversion has a negative effect on adoption on regular land only. In addition, because extremely unfavorable outcomes are likely for both perennials and annuals on marginal land, we found that probability weighting has a negative effect on adoption on regular land only as well. We are not able to show empirically any robust effect of time preferences on adoption, possibly because in the area under study farmers are offered large plantation subsidies as well as cash-advance systems through production contracts. Furthermore, the results show that farm characteristics are also relevant when investigating the adoption of a new crop. The proportion of low-profitability land has a strong positive effect on adoption. On the contrary, livestock keepers are less prone to adopt perennial energy crops than other farmers.

Our findings have important implications for the design of policies aiming at enhancing the production of energy crops in a sustainable way. First, we recommend policymakers and processors to target areas where farmland is heterogeneous, adoption being more probable on marginal land than on regular land. Second, unfavorable extreme events such as an establishment or a counterparty failure deserve a special attention. Actions ensuring either a reduction of the objective probability of such events or a diminution of their consequence on farmers' income may be an effective way of increasing the the total area of perennial energy crops. For instance, regarding the risk of an establishment failure, we recommend that public or private extension services encourage farmers to grow the crops where pedo-climatic conditions have been proved to be acceptable. Promoting these crops in areas where growing conditions are too drastic or untested may be useless because farmers would be paralyzed by the fear of loosing the whole plantation. As already offered in some contracts, processors may also want to include a special clause to share plantation costs with farmers in case of a crop failure. As regard the risk of a default from the contract counterparty, we encourage contractors to secure commercial outlets for farmers' biomass. Processors may also enhance farmers' trust by presenting a credible long-term strategy relative to their activities using local biomass. They could also sign up a partnership with other buyers, each partner committing to buy each other's feedstock in the event of one partner's failure. Third, risk-reduction measures relative to perennial energy crops may have opposite effects in terms of supply and sustainability. If reducing the impact of extreme events can foster adoption overall, it is also likely to go against sustainability objectives by increasing the share of regular land allocated to perennials to the detriment of marginal land. As a consequence, risk-reduction measures should be assessed based on a trade-off analysis between supply security and bioenergy sustainability.

Our use of a behavioural risk model to examine the adoption of perennial energy crops by farmers in France reveals results that standard decision models cannot provide. PT holds promise for deepening our understanding of the process leading to the adoption of perennial plant systems in general, and other innovations yielding similar characteristics. Rank-dependent models can be successfully applied to innovations yielding unlikely extreme outcomes, an establishment failure for instance, and sign-dependent models can shed new light on the adoption process of innovations with land-specific performances, due to resilience for instance.Understanding drivers of and barriers to perennial crop adoption would be highly relevant for food and ecosystem security (Glover et al., 2010; Pannell, 2001a; Bathgate and Pannell, 2002). In addition, our study contributes to the debate about the external validity of experimental measures (Roe and Just, 2009). By finding a significative relationship between farmers' real behavior and farmers' risk preferences as measured in a within-sample experiment, we support the use of experimental field measures to inform decision-making.

Some limitations of this study suggest directions for further research. To begin with, the number of observations in the sample is limited. Increasing the sample size may have led to more clear-cut conclusions and may have revealed some other significant relationships. In particular, we would have been able to control for more farm and land types. A small sample is a common drawback of quantitative studies when the data come from face-to-face surveys, due to the high cost of collecting information, especially in developed countries. However, in our view, the availability of experimental preference measures definitely outweighs the disadvantages of a small sample size.

In addition, one may argue that our control of farmers' reference point is weak because we use a proxy subject to different interpretations, namely whether farmers are former beet producers. An option to obtain a clean measure of farmers' income expectations would be to directly ask farmers what their income targets are, but self-reported data are known to suffer from serious biases when mental contents are concerned. Further research is needed on methodologies that could deliver accurate measures of reference points and, improve the construct validity of empirical studies testing reference-dependent preferences.

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Appendices

A Design of the risk experiment

Table 9: Lottery choices in the risk experiment

	Option A		Option B		Expected payoff difference (A-B)
Series1					
Row	Prob 30%	Prob 70%	Prob 10%	Prob 90%	
1	400	100	680	50	77
2	400	100	750	50	70
3	400	100	830	50	60
4	400	100	930	50	52
5	400	100	1060	50	39
6	400	100	1250	50	20
7	400	100	1500	50	-5
8	400	100	1850	50	-40
9	400	100	2200	50	-75
10	400	100	3000	50	-155
11	400	100	4000	50	-255
12	400	100	6000	50	-455
Series2					
Row	Prob 90%	Prob 10%	Prob 70%	Prob 30%	
1	400	300	540	50	-3
2	400	300	560	50	-17
3	400	300	580	50	-31
4	400	300	600	50	-45
5	400	300	620	50	-59
6	400	300	650	50	-80
7	400	300	680	50	-101
8	400	300	720	50	-129
9	400	300	770	50	-164
10	400	300	830	50	-206
11	400	300	900	50	-255
12	400	300	1000	50	-325
13	400	300	1100	50	-395
14	400	300	1300	50	-535
Series3					
Row	Prob 50%	Prob 50%	Prob 50%	Prob 50%	
1	250	-40	300	-210	60
2	40	-40	300	-210	-45
3	10	-40	300	-210	-60
4	10	-40	300	-160	-85
5	10	-80	300	-160	-105
6	10	-80	300	-140	-115
7	10	-80	300	-110	-130

Design adapted from Tanaka et al. (2010). Lottery payoffs are in euros.

B Design of the time experiment

Table 10: Lottery choices in the time experiment

Series	Option A Reward (in euros)	Option A Delay (in years)	Option B Reward (in euros)	Option B Delay (in years)
1	400	1	400, 408, 416, 424, 432 440, 456, 472, 488, 504	2
2	400, 392, 384, 376, 368 360, 344, 328, 312, 296	0	400	1
3	400	1	400, 416, 433, 449, 467 484, 520, 557, 595, 635	3
4	400, 384, 368, 352, 336 320, 288, 256, 224, 192	0	400	2
5	200	1	200, 204, 208, 212, 216 220, 228, 236, 244, 252	2
6	200, 196, 192, 188, 184 180, 172, 164, 156, 148	0	200	1
7	800	1	800, 832, 865, 899, 933 968, 1040, 1114, 1191, 1270	3
8	800, 768, 736, 704, 672 640, 576, 512, 448, 384	0	800	1

C Misspecification checks

Table 11: Variance inflation factor of base explanatory variables

	VIF
Farmer characteristics	
Age	1.781
ExtraInc	1.520
Farm characteristics	
FarmSize	1.377
LandOwned	1.753
Livestock	1.440
ExBeet	1.440
Margin	1.261
Wood	1.520
North	1.425
WheatRisk	1.474
Individual preferences	
EnvironObjFirst	1.561
VConcavity	1.346
LossAversion	1.526
WeightExtreme	1.267
DiscountF	1.303

VIF are computed manually in order to account for our survey design.

Table 12: Marginal effects on miscanthus adoption for different sub-samples

	Model A4 (random selection)		Model A5 (discarding outliers)	
	Pr(Adopter=1)	E(MiscAcreage|Adopter=1)	Pr(Adopter=1)	E(MiscAcreage|Adopter=1)
Farmer characteristics				
Age	−0.007***	−0.047	−0.006*	−0.039
	(0.003)	(0.043)	(0.003)	(0.029)
ExtraInc	0.111	2.024	0.146	−0.519
	(0.084)	(1.644)	(0.119)	(1.189)
Farm characteristics				
FarmSize	0.113***	−0.422	0.107***	−0.649**
	(0.021)	(0.436)	(0.028)	(0.274)
LandOwned	−0.268**	−1.457	−0.219	−0.291
	(0.113)	(1.874)	(0.174)	(1.658)
1.Livestock	−0.142***	−0.541	−0.127**	0.505
	(0.029)	(0.898)	(0.048)	(0.522)
1.ExBeet	0.123***	0.948	0.139*	0.248
	(0.047)	(0.970)	(0.075)	(0.752)
1.Margin	0.188***	0.958	0.142***	0.353
	(0.030)	(2.167)	(0.052)	(1.039)
1.Wood	0.081*	0.959	0.089	−0.025
	(0.049)	(0.960)	(0.071)	(0.748)
1.North	−0.012	0.727	0.002	0.295
	(0.051)	(1.296)	(0.072)	(0.837)
WheatRisk	0.024	−0.847	0.009	−1.245**
	(0.037)	(0.637)	(0.049)	(0.578)
Individual preferences				
1.EnvironObjFirst	0.176	−0.751	0.241	0.136
	(0.195)	(1.230)	(0.188)	(0.961)
VConcavity	−0.023	0.645	0.005	0.699
	(0.048)	(0.952)	(0.064)	(0.832)
LossAversion	−0.005	0.190	−0.003	−0.003
	(0.007)	(0.170)	(0.010)	(0.109)
WeightExtreme	−0.190***	−1.094	−0.159*	1.143
	(0.064)	(1.259)	(0.080)	(1.153)
DiscountF	0.246	1.192	0.088	0.045
	(0.264)	(4.285)	(0.381)	(3.290)
Nb. of observations	307	49	99	54
Model p-value	0.00	0.70	0.05	0.71
Prop. correctly predicted	0.89		0.86	
Prop. variance explained		0.22		0.23

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design. In the case of the intensity equation, we report the marginal effects on the expected values for the outcome conditional on being positive.
Model A4 is estimated on a random subsample where 20% of the observations are discarded.
Model A5 is estimated on a subsample where farmers growing 20 ha or more of miscanthus are discarded.

Table 13: Marginal effects on miscanthus adoption according to type of land for different sub-samples

	Model L4 (random selection)		Model L5 (discarding outliers)	
	Pr(MarginUsed=1)	Pr(RegularUsed=1)	Pr(MarginUsed=1)	Pr(RegularUsed=1)
Farmer characteristics				
Age	−0.006***	−0.003	−0.007**	−0.003
	(0.002)	(0.002)	(0.003)	(0.002)
ExtraInc	0.164**	0.105	0.174*	0.020
	(0.074)	(0.067)	(0.095)	(0.078)
Farm characteristics				
FarmSize	0.050***	0.061***	0.058***	0.063***
	(0.016)	(0.016)	(0.021)	(0.017)
LandOwned	−0.061	−0.165*	−0.021	−0.151
	(0.087)	(0.089)	(0.129)	(0.117)
1.Livestock	−0.089***	−0.064**	−0.092**	−0.046
	(0.030)	(0.032)	(0.038)	(0.040)
1.ExBeet	0.036	0.097**	0.071	0.121**
	(0.039)	(0.045)	(0.058)	(0.058)
1.Margin	.	0.003	.	0.036
		(0.043)		(0.042)
1.Wood	0.076	0.105**	0.074	0.053
	(0.050)	(0.050)	(0.059)	(0.049)
1.North	−0.027	−0.015	0.003	0.038
	(0.039)	(0.043)	(0.057)	(0.056)
WheatRisk	−0.011	0.015	−0.002	0.021
	(0.031)	(0.029)	(0.039)	(0.032)
Individual preferences				
1.EnvironObjFirst	0.129	0.055	0.118	0.043
	(0.136)	(0.099)	(0.143)	(0.117)
VConcavity	0.042	0.013	0.045	−0.021
	(0.044)	(0.041)	(0.052)	(0.038)
LossAversion	0.001	−0.001	0.004	−0.002
	(0.006)	(0.006)	(0.007)	(0.006)
WeightExtreme	−0.060	−0.088*	−0.088	−0.066
	(0.050)	(0.050)	(0.063)	(0.049)
DiscountF	0.142	0.025	0.255	0.023
	(0.228)	(0.224)	(0.304)	(0.216)
ρ				
Nb. of observations	307	307	99	99
Model p-value	0.01	.	0.00	.
P. c. p. (any land)	0.98		0.85	
P. c. p. (marginal land)	0.98		0.88	
P. c. p. (regular land)		0.97		0.88

*, ** and *** stand for significance at the 10, 5 and 1% level, respectively. The marginal effects are evaluated at the observed values in the dataset and then averaged (average marginal effects). For binary variables, they are computed as the effect of a discrete change from 0 to 1. The standard errors (in parentheses) are adjusted for our survey design.
Model L4 is estimated on a random subsample where 20% of the observations are discarded.
Model L5 is estimated on a subsample where farmers growing 20 ha or more of miscanthus are discarded.