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# Redesigning oilseed tree biofuel systems in India

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ABSTRACT

Liquid biofuel production has been widely promoted as a rural development strategy in the South. Yet, the development of biofuel value chains faces many context-specific challenges. In this empirical study we use a labelled choice experiment to assess smallholder farmer preferences for alternative production systems, value chain organisations and market developments for a biofuel program using oilseed trees (neem (*Azadirachta indica*), pongamia (*Millettia pinnata*), mahua (*Madhuca longifolia*)) in Karnataka state, India. Our results demonstrate that biofuel programs can benefit from ex ante analyses to improve their design. We find that most farmers (71%) are likely to adopt biofuel trees in most scenarios, especially species with relatively high yields, low labour requirements and high oilseed prices. Nevertheless, value chain reorganization through contracting and labour provision proves to be the key lever to stimulate adoption. This calls for further research on effective contract design and implementation, and for developing alternative business models. Our results imply that next to high opportunity costs of land, also high opportunity costs of labour can be a barrier to biofuel tree adoption. If biofuel programs are to succeed, they have to move beyond the idea of smallholder biofuel production on marginal lands with surplus labour.

## 1. Introduction

In the past two decades, production of liquid biofuels has been widely promoted in developing countries as a clean energy source fostering rural development (Sorda et al., 2010). Liquid biofuels are argued to increase energy security, in particular in countries heavily depending on imported fuel (Sorda et al., 2010), and mitigate climate change (Fargione et al., 2008; Tilman et al., 2009). Furthermore, feedstock production, processing and marketing could serve as a source of income, employment, trade and technology spillovers for local communities (Ewing and Msangi, 2009; Riera and Swinnen, 2016). However, many concerns have been raised about the interference of biofuels with food production and markets (Koh and Ghazoul, 2008; Zhang et al., 2013), as well as about the inclusiveness and efficiency of biofuel value chains, and land grabbing (Arndt et al., 2011; Cotula et al., 2008; Lee et al., 2011). Production of non-food crops – predominantly jatropha (*Jatropha curcas*) – on wasteland plantations has been hyped as a solution to the food versus fuel debate. Yet, it is being contested whether such 'unproductive' and 'underutilized' lands effectively do not have any community functions and opportunity costs (Baka, 2014; Borras et al., 2011). Economic viability of such systems critically depends on seed yields, which proved to be lower than expected and highly variable (Achten et al., 2014; Ariza-Montobbio and Lele, 2010; Muys et al., 2014). In addition, there is no consensus on which value chain organisation and degree of (de)centralization lead to most welfare benefits (Altenburg, 2011; Negash and Swinnen, 2013; van Eijck et al., 2014b). In reality, many context-specific technical, ecological, socio-economic and institutional opportunities and constraints exist for a successful implementation of liquid biofuel programs, and these are often insufficiently understood (Florin et al., 2014; Muys et al., 2014; van Eijck et al., 2014a). Many biofuel projects have failed to gain momentum, and some large investment projects have not paid off (Sanderson, 2009; Singh et al., 2014; van Eijck et al., 2014a).

As jatropha wasteland plantations have not lived up to the expectations, alternative production systems have been explored (Altenburg et al., 2009; Faße et al., 2014; Sharma et al., 2016). Small-

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scale integration of multipurpose oilseed trees within the existing farming system, i.e., as agroforestry systems, might hold significant pro-poor potential (Achten et al., 2010; Muys et al., 2014; Sharma et al., 2016). In this low input – high diversity – high resilience system (Tilman et al., 2006), low production inputs are coupled to multiple products, uses and co-benefits,[2] thereby limiting investment risks for smallholder farmers. Nevertheless, also in these systems feedstock production entails land, labour and capital opportunity costs for farmers, while benefits and risks depend on the production system, value chain organisation and market conditions (Altenburg, 2011; Florin et al., 2014; van Eijck et al., 2014b). Understanding how these context-specific factors play a role in smallholders' decisions whether to cultivate feedstock or not, is crucial to the design and implementation of biofuel projects and the development of biofuel value chains (Achten et al., 2014; Florin et al., 2014). There is an emerging empirical literature on biofuel adoption by smallholders in developing countries, but studies mainly focus on jatropha and mostly investigate adoption through an ex-post evaluation of a single biofuel program (e.g., Axelsson et al., 2012; Goswami and Choudhury, 2015; Kuntashula et al., 2014; Montefrio et al., 2015; Mponela et al., 2011; Negash and Swinnen, 2013; Soto et al., 2015).

In this paper we take a different view to address both shortcomings. Starting from an existing biofuel program, we use an ex-ante approach to predict (the variability in) smallholder preferences for alternative production systems, value chain organisations and market developments. This allows us to assess the potential of hypothetical changes in these characteristics and the likelihood that alternative biofuel programs are adopted. We do this by conducting a discrete choice experiment (CE) with 396 farmers in Hassan district, Karnataka state, India. In this region, a small-scale decentralized model of biofuel development, where oilseed trees (including pongamia (*Millettia pinnata*), neem (*Azadirachta indica*) and mahua (*Madhuca longifolia*)) are cultivated in agroforestry systems, is being promoted since 2007 by the government through training and planting programs, marketing support, cooperative establishments and distribution of processing equipment. Oilseed trees have received little if any attention in the literature on biofuels (Achten et al., 2014). Yet, trees are inherently a long-term investment – because of their maturation period and long lifetime – requiring long-term commitments of land, and involving upfront investments as well as yield and price risks (Khanna et al., 2017). The latter holds in particular for biofuels, given substantial policy and market uncertainties (Chen and Önal, 2014; Kumar et al., 2012; Locke and Henley, 2013). This makes adoption studies, and ex-ante approaches in particular, all the more relevant. There is a large interest for biofuel production on marginal lands and for tree-based biofuel programs in India (Gunatilake et al., 2014), which makes this study directly relevant from a policy perspective.

While other papers have used CEs for ex-ante assessments of smallholders' technology adoption (e.g., Kikulwe et al., 2011; Lambrecht et al., 2015; Scarpa et al., 2003) or marketing and contracting preferences (e.g., Abebe et al., 2013; Schipmann and Qaim, 2011; Van den Broeck et al., 2017), this paper is to the best of our knowledge the first to address smallholders' adoption of alternative biofuel trees through a CE.

## 2. Methodology and data

### 2.1. Research area

Since the beginning of this century, the Indian government has expressed large interest in liquid biofuels (Gunatilake et al., 2014). This has been mainly driven by energy security concerns – currently 70% of the domestic oil demand is covered by imports; this share is estimated to increase to over 90% by 2040 (IEA, 2015) – as well as by the potential of biofuel production and consumption for rural development (Altenburg et al., 2009; Gunatilake et al., 2014). The government implemented various policies,[3] eventually setting an ambitious 20% blending target for bioethanol and biodiesel in gasoline and diesel, respectively, by 2017, supported by subsidized prices and fiscal incentives (Sorda et al., 2010). These policies require biofuels to be exclusively produced from feedstocks that limit competition with food production, such as molasses for bioethanol, and non-edible tree borne oilseeds produced on wasteland plantations of jatropha (and pongamia) for biodiesel (Biswas and Pohit, 2013). However, a variety of ecological (e.g., low yields on marginal soils, susceptibility to pests), socio-economic (e.g., lack of land, ownership and usufruct rights, economic unviability) and institutional (e.g., lack of research and extension, competing fuel subsidy schemes) constraints has resulted in slow progress towards the specified targets (Altenburg, 2011; Biswas and Pohit, 2013; Kumar et al., 2012). The 2013 level of blending was still below 1% (IEA, 2015).

Alternatives to large-scale wasteland plantations have been explored in India as well (Altenburg et al., 2009). Since 2007, such an approach is brought into practice in Hassan district, Karnataka state, India, through a government – university partnership.[4] The biofuel program in Hassan aims to integrate various oilseed trees (including pongamia, neem and mahua) in smallholder farms on field edges, in homegardens and on fallow land. They do so by (1) conducting awareness and training programs on oilseed tree cultivation and biofuels, (2) distributing high-yielding oilseed tree seedlings to farmers free of charge, (3) offering minimum support prices for oilseeds, (4) establishing biodiesel cooperatives within villages for streamlining biodiesel activities, and (5) distributing small-scale oil-expelling equipment for local processing. Pongamia, neem and mahua are native species whose wood, leaves, fruits and seeds have long been used for various purposes. Seed oil is traditionally used for pesticidal, medicinal, cosmetic and/or industrial purposes, while seed cake is used as an organic fertilizer, pesticide and/or fodder. Accordingly, oilseed collection from trees on community and private land is known as a traditional marginal activity, and oilseed value chains, involving middlemen and local oil mills, do exist, especially for neem and pongamia (Altenburg et al., 2009). In addition, seed oil can serve as a lamp fuel, as a small blend in (modified) diesel engines, and can be processed to biodiesel.

Hassan district has a population of about 1.8 million inhabitants, 79% of them living in rural areas, and comprises some 2600 villages, which are clustered into 38 administrative units termed *hoblis* (DCO, 2014). It is a geophysically diverse region containing three agro-ecological zones (dry, transition, hill) characterized by a distinct rainfall regime (Fig. 1). Correspondingly, a wide variety of crops are being cultivated, including several plantation crops such as coconut in the dry and transition zone, and coffee, pepper and cardamom in the hill zone (DES, 2016). The average farm size (2.02 ha) in the hill zone is considerably larger than the district's average (1.06 ha) (DAC&FW, 2017). Agricultural production is mostly done by smallholders, with landholding sizes below 1 ha for 65% of the farmers and below 2 ha for 89% of the farmers (DAC&FW, 2017). About 27% of the cultivated land is irrigated (DES, 2015).

[2] Co-benefits in agroforestry systems can include for example improved soil fertility, biodiversity and soil conservation, pest control, carbon sequestration, labour and income diversification, and increased farm resilience (Sileshi et al., 2007).

[3] This includes the Ethanol Blended Petrol program (2003), the National Mission on Biodiesel (2003) and the National Policy on Biofuels (2008) (Sorda et al., 2010).

[4] The Karnataka State Bio Energy Development Board and the University of Agricultural Sciences Bangalore.

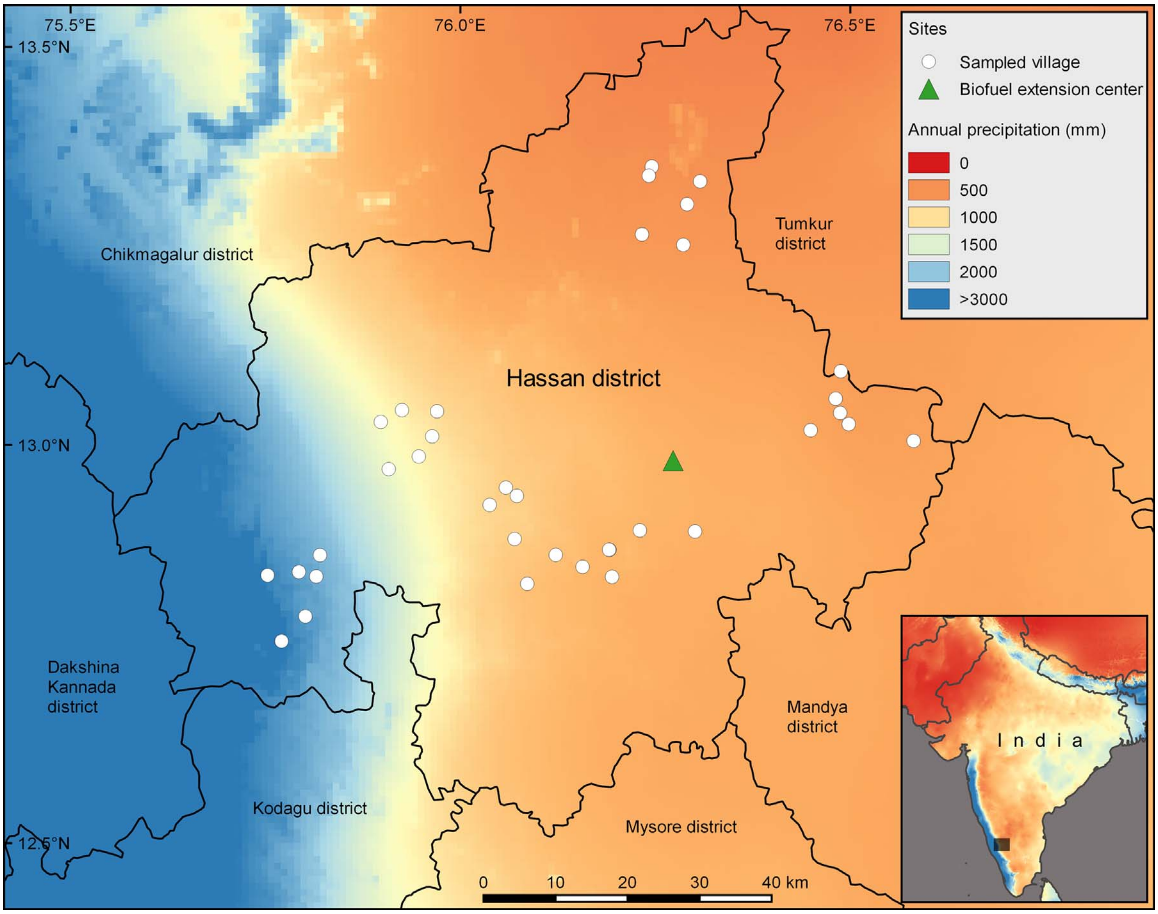


**Fig. 1.** Map of Hassan district, Karnataka state, India. The map locates the biofuel extension centre, sampled villages and a climatological gradient (WorldClim data (Hijmans et al., 2005)).

### *2.2. Choice experiment*

#### *2.2.1. Concept*

This study aims to assess the potential of various alternative designs of biofuel programs towards smallholder adoption. A choice experiment (CE) is used, which is a stated preference method introduced by Louviere and Hensher (1982). In the CE, respondents are presented a series of *choice cards* (one at a time), with each choice card including a hypothetical situation in which they get three biofuel tree seedling offers by a company.[5] A given offer (= *alternative*) is characterized by the tree species (= *label*), as well as by a set of cultivation, value chain and market conditions (= *attributes*). Within a given choice card, the three alternatives are mutually differentiated by the values (= *levels*) of the label and attributes. For each choice card, respondents are asked to either choose the alternative they prefer most, or none of them (= *opt-out*). The choice behaviour allows us to indirectly infer a utility function based on the label and attributes.

#### *2.2.2. Label, attributes and levels, opt-out*

A labelled choice experiment is used, with the three tree species as labels. This means that each choice card contains one offer of pongamia tree seedlings, one offer of neem tree seedlings and one offer of mahua tree seedlings. Studies on technology adoption rarely assign labels to the alternatives, which are consequently considered generic – such as generic crop varieties (Kikulwe et al., 2011; Lambrecht et al., 2015) or animal breeds (Scarpa et al., 2003). Because biofuel trees cannot be generically presented, since each tree species has distinct intrinsic characteristics (e.g., harvest period, seed properties, uses and co-benefits) for which farmers might have certain preferences, a labelled CE is used. In addition, the labelled CE allows farmers' preferences for the attributes to differ across species.

Relevant attributes and levels are identified and refined based on focus group discussions with farmers, and on interviews with biofuel program collaborators and local experts. Four attributes are selected: 1) oilseed yield, 2) maturation period, 3) contractual agreement, and 4) oilseed price (Table 1). Many other attributes, such as seedling prices, input support, logistic arrangements, and oil and seedcake prices, as well as other labels, including other species and species combinations, were considered at the design stage. However, to limit the conceptual and cognitive complexity (and thereby reduce the risk of attribute non-attendance by the respondents), only four attributes are retained. Together, the four attributes constitute two principal determinants for adoption: economic profitability and investment risk.

The first two attributes (*oilseed yield* and *maturation period*) relate to cultivation features. Low oilseed yields have often been the principal reason for limited potential and adoption of biofuel projects (Sanderson, 2009; van Eijck et al., 2014a). In the specific case of trees the maturation period (= time until first fruiting) and associated lag for return on investments, might imply additional investment risk and uncertainty for the farmer (Alexander et al., 2012). There is still a large need for more knowledge on actual yields of these essentially undomesticated plants, and for the development of fast-maturing, high-yielding and agro-ecologically adapted cultivars, through genetic (e.g.,

[5] A generic company is presented to the farmer. In terms of interpretation, this company could be identified as the current biofuel program partnership, but all the same as an alternative actor (e.g., private investor, public-private partnership) after transformation of the current value chain.

**Table 1**
Attributes and attribute levels of the choice experiment.

| Attribute | Attribute level |
|---|---|
| Oilseed yield[a] | Status quo: yield of local accessions of used species[b]<br>+ 50%<br>−50% |
| Maturation period | Status quo: tree age at first fruiting of local accessions of used species[c]<br>+ 2 years<br>−2 years |
| Contractual agreement | Status quo: no contract<br>Contract 1: supply commitment (SC)<br>Contract 2: supply commitment & collection labour provision (SC & LP) |
| Oilseed price[d] | 10, 17, 25, 32, 45, 65 INR/kg |

[a] Oilseed yield increases with tree age and is assumed to stabilize at 20 years after maturation.
[b] Annual oilseed yield at stabilization for status quo: 60 kg/tree for pongamia, 30 kg/tree for neem, 100 kg/tree for mahua.
[c] Maturation period for status quo: 5 years for pongamia and neem, 9 years for mahua.
[d] INR = Indian National Rupee. 1 EUR = 74.2 INR in August 2015 (= status quo levels).

breeding, genetic modification) and technical (e.g., grafting) means (Altenburg, 2011; Sharma et al., 2016). Given this potential wide range of yield and maturation figures, farmers' preferences for these cultivation features are investigated by including oilseed yield as the absolute amount of oilseeds produced (in kg/tree), and maturation period as the age at which the tree starts yielding (in years) thereby influencing the temporal occurrence of absolute yield levels. Together, they compose the temporal *oilseed yield pattern* (in kg/tree at different ages, defined and displayed up to age thirty). Each is defined by three levels: a species-specific reference level reflecting these features for currently used superior local accessions, while oilseed yield can be increased or decreased by 50%, and maturation can be advanced or delayed by two years.[6] The full set of oilseed yield patterns is included in Table A.1.

The third attribute (*contractual agreement*) relates to how farmers can be engaged in biofuel value chains. While the current public program focuses on independent farm production, there are numerous examples of contract-farming models for biofuels, in India and elsewhere (Altenburg et al., 2009; German et al., 2011; Negash and Swinnen, 2013; Padula et al., 2012; Shepherd, 2013; van Eijck et al., 2014b), albeit rarely involving trees. For both the company and the farmers, a contractual agreement could share and largely reduce risks, uncertainties and transaction costs, especially given the novelty of the biofuel tree value chain with its associated policy and market uncertainties, and its long-term investment nature involving revenue lags (Alexander et al., 2012; Bijman et al., 2010; Eaton and Shepherd, 2001; Khanna et al., 2017). We define three contractual agreements under which seedlings are provided free of charge. In the reference state – which reflects the current biofuel program – there is no contract: farmers produce independently and can choose whether to collect oilseeds or not, and how these are processed or marketed. Nevertheless, the company still offers to buy the seeds at the farm gate at the indicated *oilseed price* (= the fourth attribute). In case of the contract levels, there is an obligation to collect and supply the seeds to the company, which guarantees to buy these at the farm gate at the indicated oilseed price.[7] In contract 1 seed collection is the responsibility of the farmer (through either household or hired labour), while in contract 2 the company provides labourers for seed collection (in this case, the farmer solely provides the land and basic cultivation practices, which comes closer to a land leasing set-up than an outgrower set-up).[8]

The fourth attribute is the *oilseed selling price*. At the time of CE implementation, oilseed prices for pongamia, neem and mahua fluctuated around 22, 15 and 25 INR/kg, respectively. Similar to oilseed yield, low prices have often been the principal reason for marginal profitability and failure of adoption in biofuel projects (van Eijck et al., 2014a). Since oilseed prices heavily depend on a variety of factors, including fossil fuel prices, government policies and mandates (e.g., blending targets, fuel subsidies), efficiency at the various value chain stages, private investments etc., many future price scenarios may be deemed possible. Therefore a wide price range (10–65 INR/kg) is allowed for each species. It is essential to understand at which price levels (dis)adoption thresholds are surpassed.

Apart from the three alternatives, each choice card contains an *opt-out*, allowing the respondents to choose none of the alternatives (the opt-out is considered the fourth alternative/label in each choice card). This reflects their disinterest in cultivating biofuel trees, at least under the conditions of that choice card. This also reflects the reality in which the adoption of biofuel trees is a voluntary choice of the farmer. Not including an opt-out option would lead to forcing respondents to choose a tree alternative and likely to an overestimation of the willingness to adopt (Hensher, 2010).

### *2.2.3. Design and implementation*

The CE was implemented in August - September 2015 in Hassan district. A three-stage stratified random sample was drawn. In the first stage, 1, 2 and 3 hoblis[9] were purposefully[10] selected in the hill, dry and transition zone, respectively[11] (Table A.2). In the second stage, the villages within each hobli were stratified according to the degree of implementation of the biofuel program. Subsequently, villages were randomly drawn within the strata such that in each of the six hoblis six villages were selected (Fig. 1; Table A.2). In the third stage, a systematic sample of 11 farm-households was drawn in each of the 36 villages, resulting in a sample of 396 households. In addition to the CE, household survey data were collected using a quantitative structured questionnaire, which included general modules on household demographics, land and non-land assets, farm production and marketing, employment and income, and social network; and a specific module questioning involvement in the biofuel program. For the analysis in this paper, 10 households are dropped due to incomplete and/or erroneous data, reducing the final sample to 386 households.

Ngene software was used to create a D-efficient design (D-error = 0.0708), resulting in a total of 64 choice cards, equally distributed over eight choice series. Priors of the parameters were derived from focus group discussions and interviews with experts. Each respondent was randomly assigned to one choice series, in which the eight choice cards were graphically represented to facilitate respondents' understanding (Fig. 2). Implementation of the CE involved a comprehensive explanation of the experiment's purpose, hypothetical nature and choice tasks, as well as the use of two dominant cards and one test card, prior to the actual choice series. An information chart summarizing the principal features of each of the three species (Fig. A1), as well as three corresponding oilseed samples, were presented along with the choice cards.

[6] It is important to also model the impact of decreases/delays in yield/maturation relative to the status quo, to account for (1) the uncertainty on figures for existing accessions, and (2) possible trade-offs between yield and maturation period.

[7] Oilseed supply amounts would be determined by the company through a monitoring system.

[8] Both contracts were specified to apply up to 10 years after maturation.

[9] A hobli is an administrative unit in Hassan district, see Section 2.1.

[10] Implementation of the biofuel program varies greatly throughout the district. The hoblis were purposefully selected to maximize the variation in implementation at village level (= stratification variable at second sampling stage).

[11] For each zone, the number of selected hoblis reflects the share of its population in the total district population.

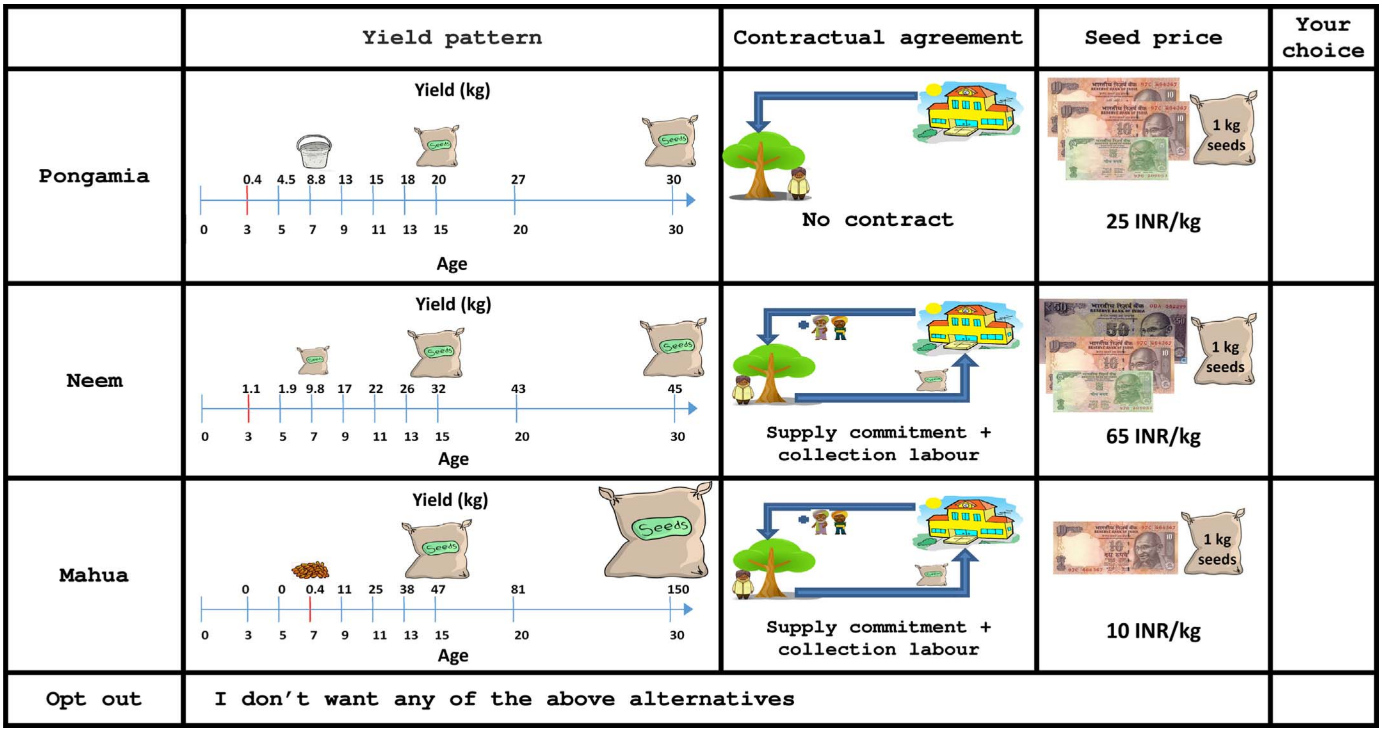


**Fig. 2.** Example of a choice card. Oilseed yield and maturation period are graphically presented as one, i.e., the oilseed yield pattern. The choice cards were translated to the local language (Kannada) for the experiment.

### 2.3. Econometric analysis

#### 2.3.1. Basic model

Discrete choice theory is based on Lancaster's (1966) assumption that respondents derive utility from the properties of each alternative and select the alternative that maximizes their utility, thereby revealing their preferences. Individual choice behaviour is assumed to be probabilistic. In this random utility maximization framework (McFadden, 1973), the utility of an alternative consists of a deterministic component depending on the label and attributes, and an unobservable stochastic component:

$$U_{in} = ASC_i + \sum_{k=1}^{4} \beta_{ik} X_{ik} + \varepsilon_{in} \tag{1}$$

where respondent $n$ derives utility $U_{in}$ from alternative $i$. In this study, this conditional logit model encompasses a set of four utility equations corresponding to the three tree species and the opt-out. In each equation the label contributes to the utility as an alternative-specific constant $ASC_i$. Neem serves as the reference label, i.e., its $ASC$ is set to zero. In the tree species equations[12] each attribute $k$ contributes to the utility through its level $X_{ik}$, which is weighed by an alternative-specific coefficient $\beta_{ik}$. The status quo levels serve as reference for the three categorical attributes,[13] i.e., the $\beta_{ik}$ are set to zero for the status quo $X_{ik}$. While the attribute coefficients $\beta_{ik}$ are easiest interpreted when using dummy coding, in a dummy-coded model the alternative-specific constants $ASC_i$ confound the label effects with the attribute reference level effects (Bech and Gyrd-Hansen, 2005). Only when using effects coding, the $ASC_i$ can be effectively interpreted as the effect of the tree species (Bech and Gyrd-Hansen, 2005). Therefore, both a dummy-coded and an effects-coded model are estimated; $\beta_{ik}$ are reported from the former, and $ASC_i$ from the latter. The stochastic component $\varepsilon_{in}$ is assumed to be independent and identically distributed (IID) extreme value type I (Gumbel) (Ben-Akiva and Lerman, 1985).

#### 2.3.2. Preference and scale heterogeneity

In model (1), the utility contributions of the labels ($ASC_i$) and attributes ($\beta_{ik}$) are assumed not to vary across respondents, i.e., preferences are assumed to be identical within the population. To allow for *preference heterogeneity* across respondents, the utility equations can be estimated with a latent class model (LC) (Boxall and Adamowicz, 2002). This finite mixing approach distributes the respondents over a discrete set of latent classes, with preferences assumed homogeneous within and heterogeneous across classes:

$$U_{in|p} = ASC_{i|p} + \sum_{k=1}^{4} \beta_{ik|p} X_{ik} + \varepsilon_{in|p} \tag{2}$$

where utilities $U_{in|p}$, alternative-specific constants $ASC_{i|p}$, alternative-specific coefficients $\beta_{ik|p}$ and stochastic components $\varepsilon_{in|p}$, are estimated with a conditional logit model for each latent class $p$.

While preference heterogeneity has been widely acknowledged and accounted for, *scale heterogeneity* and the differentiation between both sources of heterogeneity has been largely neglected in empirical work (Louviere et al., 2002; Louviere and Eagle, 2006; Swait, 2006; Swait and Louviere, 1993). In models (1) and (2), the stochastic component $\varepsilon_{in}$ is assumed to be identically distributed, and thus its variance $\sigma$ is assumed constant across respondents. This error variance can be thought of as a measure of choice determinism (or choice consistency). In reality, it likely differs across respondents because of differences in capability to understand and process the choice task, or because of differences in commitment to the experiment (Hess and Stathopoulos, 2013; Swait and Adamowicz, 2001). Error variance heterogeneity across respondents is expressed in the utility equation through a scale parameter $\lambda_n$. This scale parameter $\lambda_n$ is inversely proportional to the error variance $\sigma_n$, i.e., the larger the error variance, the smaller the scale (Ben-Akiva and Lerman, 1985):

[12] For the utility equation of the opt-out there are logically no attributes defined. In this case, the $\sum_{k=1}^{4} \beta_{ik} X_{ik}$ term drops from the equation.

[13] "Oilseed yield", "maturation period" and "contractual agreement". The former two can also be considered as continuous variables. However, considering them as categorical variables improves model fit.

$$U_{in|p} = \lambda_n ASC_{i|p} + \sum_{k=1}^{4} \lambda_n \beta_{ik|p} X_{ik} + \varepsilon_{in|p} \tag{3}$$

The commonly used LC model (model (2)) implicitly assumes the error variance and thus the scale to be constant, so that all $\lambda_n$ can be arbitrarily set to one and dropped from the equation. Eq. (3) however reveals that if the error variance (or scale) is heterogeneous across respondents,[14] then the scaled preference parameters $\lambda_n$ $ASC_{i|p}$ and $\lambda_n$ $\beta_{ik|p}$ instead of the actual preference parameters $ASC_{i|p}$ and $\beta_{ik|p}$ are being estimated, and thus preference heterogeneity is confounded with scale heterogeneity (Ben-Akiva and Lerman, 1985). In other words, although latent class differentiation in the LC model is usually interpreted as preference heterogeneity, it may actually reflect scale heterogeneity, or a combination of both.

To separate and account for both preference and scale heterogeneity, a scale-adjusted latent class model (SALC) is estimated (Magidson and Vermunt, 2007). In addition to allocating respondents to *preference classes* in the same way as the LC model, the SALC model analogously distributes respondents over a discrete set of latent *scale classes*, with the scale parameter assumed constant[15] within but varying across classes:

$$U_{in|sp} = \lambda_s ASC_{i|p} + \sum_{k=1}^{4} \lambda_s \beta_{ik|p} X_{ik} + \varepsilon_{in|sp} \tag{4}$$

where $U_{in|sp}$, $\varepsilon_{in|sp}$ and $\lambda_s$ are the utilities, stochastic components and scale parameter in scale class *s*, respectively ($\lambda$ is set to one for a reference scale class to allow identification) and all other parameters defined in (2). In the SALC model specified in (4), preference and scale classes are independent from each other.[16] This implies that when moving from the reference scale class to scale class *s*, the preference parameters $ASC_{i|p}$ and $\beta_{ik|p}$ need to be multiplied for all preference classes by $\lambda_s$.

Membership probabilities for each preference and scale class (= size of the classes) are estimated through a multinomial logit model ('membership function') (Boxall and Adamowicz, 2002; Thiene et al., 2015):

$$P(s, p) = \frac{\exp(\theta_p + \eta_s)}{\sum_s \sum_p \exp(\theta_p + \eta_s)} \tag{5}$$

where for each preference class *p* a constant $\theta_p$ and for each scale class *s* a constant $\eta_s$ is estimated ($\theta_p$ and $\eta_s$ were set to one for a reference preference/scale class to allow identification). Notice that this unconditional membership function does not contain respondent-specific predictor variables. Rather, respondent class membership probabilities are estimated a posteriori based on their sequence of choices, and respondents are assigned to the preference/scale class with the highest probability (modal a posteriori estimation) (Skrondal and Rabe-Hesketh, 2004). The sources of preference and scale heterogeneity are described by comparing respondent characteristics across classes.

Multiple SALC models are estimated with varying numbers of preference and scale classes. The fit and parsimony of these models is compared using various information criteria: Bayesian information criterion (BIC), Akaike information criterion (AIC), Akaike information criterion 3 (AIC3) and consistent Akaike's information criterion (CAIC) (Andrews and Currim, 2003).

#### 2.3.3. Adoption probabilities

To effectively assess the potential of alternative designs of the biofuel program towards smallholder adoption, the SALC model is used to simulate adoption outcomes for different program set-ups. More specifically, both the current program and various alternatives are defined in terms of attribute values, and thereby constitute hypothetical choice sets. For these choice sets, the choice probabilities for each alternative within each preference-scale class are predicted as:

$$\pi_{i|sp} = \frac{\exp(\lambda_s ASC_{i|p} + \sum_{k=1}^{4} \lambda_s \beta_{ik|p} X_{ik})}{\sum_{j=1}^{4} \exp(\lambda_s ASC_{j|p} + \sum_{k=1}^{4} \lambda_s \beta_{jk|p} X_{jk})} \tag{6}$$

where $\pi_{i|sp}$ is the probability that alternative *i* is chosen out of all four alternatives in the choice set, in preference class *p* and scale class *s*, and all other parameters defined in (4) (Boxall and Adamowicz, 2002; Magidson and Vermunt, 2007).[17]

## 3. Results

### 3.1. Model selection

The fit and parsimony of different SALC models are compared in Table A.3. While BIC and CAIC advise to use a 5-preference-2-scale class model, AIC and AIC3 penalize relatively less for an increase in complexity. However, when estimating five or more preference classes, standard errors of the estimates for the small classes become very large, and the classification error increases strongly. Therefore, results will be analysed for the 4-preference-2-scale class model.

### 3.2. SALC model results

The model results imply that both scale and preference heterogeneity exist. The SALC model reveals clear differences in preferences through the identification of four distinct preference classes (PC), with class probabilities of 38.0%, 32.8%, 19.1% and 10.1%. The model reveals a distinct relative difference in choice determinism through the identification of two scale factors $\lambda_1 = 1$ (large scale and determinism) and $\lambda_2 = 0.095$ (small scale and determinism), with class probabilities of 88.0% and 12.0%, respectively. While the preference parameters for both scale classes are identical considering multiplication with the scale factor, Davis et al. (2016) advise to report and interpret them for each scale class explicitly, since standard errors are not necessarily proportionally rescaled, and significance levels may therefore differ.

#### 3.2.1. Large scale and high determinism

The scaled preference parameters for the large scale class ($\lambda_1 = 1$; P ($\lambda_1$) = 0.88) are reported in Table 2. With regard to the alternative *labels*, there is a clear distinction between preference classes 1 and 2 (PC1, PC2), who on average do not opt out, and preference classes 3 and 4 (PC3, PC4), who on average do opt out. While the $ASC_{\text{opt-out}}$ is only significant for PC3,[18] assigning respondents to a preference class reveals that PC1 and PC2 consist exclusively of respondents who never selected the opt-out alternative and PC4 of respondents who always selected the opt-out alternative.[19] This distinct behaviour explains the large $ASC_{\text{opt-out}}$ standard errors (and lack of significance) for these classes and implies that the estimated preference parameters for PC4 cannot be interpreted. Furthermore, the positive and significant ASC for pongamia and mahua (relative to neem) for both PC1 and PC2

[14] Error variance (or scale) could also be heterogeneous across alternatives and/or across choice tasks. This is not considered in the empirical analysis.

[15] This implies that SALC models only partially differentiate between preference and scale, since the scale distribution is discretized and scale is therefore still considered constant within a given scale class. Models with continuous preference and scale distributions, such as the G-MNL model (Fiebig et al., 2010), could serve as an alternative, but their ability to effectively disentangle preference and scale heterogeneity is still debated (Hess and Rose, 2012).

[16] This assumption can easily be relaxed. However, for this empirical case study, the correlation did not prove to be significant.

[17] Models and probabilities are estimated through likelihood maximization with Latent Gold Choice 5.1 Advanced. Preference and scale class characterization is performed in Stata 14.2.

[18] $ASC_{\text{opt-out}}$ in PC3 is also significant for both pongamia (p = 0.059) and mahua (p = 0.002) as reference level instead of neem.

[19] We checked whether this was related to assigning specific choice series, but PC4 respondents are roughly equally distributed over the choice series.

**Table 2**
Estimated scaled utility equation parameters of the 4-preference-2-scale class model, for the large scale class ($\lambda_1$ = 1).

| | Preference class 1<br>Probability: 33.3 % | Preference class 2<br>Probability: 28.9 % | Preference class 3<br>Probability: 16.8 % | Preference class 4<br>Probability: 8.9 % |
|---|---|---|---|---|
| **Neem** | | | | |
| Oilseed yield: + 50% | 1.216 (0.521)** | -0.513 (0.290)* | -0.825 (0.510) | 1.442 (4.924) |
| Oilseed yield: - 50% | -2.598 (1.166)** | -0.980 (0.276)*** | -0.488 (0.481) | -15.873 (17.261) |
| Mat. period: - 2 years | -0.508 (0.512) | -0.643 (0.290)** | -1.192 (0.494)** | 0.131 (3.768) |
| Mat. period: +2 years | -1.857 (0.689)*** | -0.358 (0.306) | -0.668(0.478) | -2.616 (12.324) |
| Contract 1: SC[a] | -0.565 (0.780) | -0.148 (0.261) | 0.403 (0.750) | 1.159 (3.620) |
| Contract 2: SC & LP[b] | 2.097 (0.514)*** | -0.521 (0.336) | 5.513 (0.657)*** | -42.073 (41.490) |
| Price | 0.078 (0.014)*** | 0.066 (0.007)*** | 0.024 (0.011)** | 0.102 (0.141) |
| **Pongamia** | | | | |
| ASC | 1.740 (0.680)** | 0.972 (0.328)*** | 0.792 (0.655) | 22.641 (17.003) |
| Oilseed yield: + 50% | 1.638 (0.373)*** | 0.407 (0.278) | -0.313 (0.430) | 0.929 (2.472) |
| Oilseed yield: - 50% | -2.227 (0.420)*** | -0.868 (0.259)*** | -0.682 (0.478) | -0.907 (3.178) |
| Mat. period: - 2 years | -0.004 (0.310) | 0.001 (0.254) | -1.452 (0.450)*** | 0.689 (2.938) |
| Mat. period: +2 years | 0.325 (0.378) | 0.137 (0.264) | -0.657 (0.429) | 1.840 (2.737) |
| Contract 1: SC[a] | 0.938 (0.434)** | 0.010 (0.246) | 3.234 (0.806)*** | -1.226 (2.279) |
| Contract 2: SC & LP[b] | 2.891 (0.564)*** | -0.288 (0.308) | 7.669 (0.891)*** | -5.987 (8.238) |
| Price | 0.108 (0.014)*** | 0.066 (0.009)*** | 0.032 (0.012)*** | 0.021 (0.058) |
| **Mahua** | | | | |
| ASC | 3.123 (0.723)*** | 0.894 (0.342)*** | -0.072 (0.731) | 5.305 (19.494) |
| Oilseed yield: + 50% | 0.280 (0.363) | 1.025 (0.296)*** | 0.394 (0.448) | -3.842 (6.140) |
| Oilseed yield: - 50% | -2.875 (0.510)*** | 0.335 (0.316) | -0.288 (0.471) | -4.991 (7.155) |
| Mat. period: - 2 years | 0.222 (0.344) | 0.157 (0.265) | 1.087 (0.436)** | 4.603 (7.440) |
| Mat. period: +2 years | -0.083 (0.306) | 0.063 (0.289) | -0.059 (0.487) | -2.878 (12.472) |
| Contract 1: SC[a] | 0.585 (0.310)* | -0.160 (0.302) | 2.075 (0.830)** | -31.973 (27.663) |
| Contract 2: SC & LP[b] | 2.493 (0.447)*** | 0.015 (0.274) | 6.595 (0.847)*** | -34.418 (28.531) |
| Price | 0.128 (0.022)*** | 0.060 (0.010)*** | 0.030 (0.011)*** | -0.234 (0.345) |
| **Opt-out** | | | | |
| ASC | -42.786 (29.393) | -37.734 (29.526) | 1.639 (0.480)*** | 30.741 (17.683)* |

*Notes*: reported ASCs were estimated in an effects-coded model, reported attribute coefficients in a dummy-coded model. Sample consists of 386 respondents, resulting in 3087 observations. Standard errors are reported between parentheses. Significant effects are indicated as follows:
[a] SC = supply commitment.
[b] SC & LP = supply commitment & collection labour provision.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

respondents imply that these respondents have a clear preference for pongamia and mahua over neem; PC1 respondents also have a preference for mahua over pongamia (as revealed by the larger ASC of mahua ($p < 0.001$)). For PC3 the ASC for pongamia and mahua are both not significant, implying that these respondents do not have a clear preference for a particular species.

With regard to the cultivation features, *oilseed yield* is a relevant attribute for PC1 and PC2 but not for PC3. Among PC1 and PC2 respondents there is a significant negative preference for lower yields and/or a significant positive preference for higher yields (except for neem in PC2) while the yield attribute is never significant for PC3 respondents. For the *maturation period*, an opposite pattern is observed. Whereas PC1 and PC2 respondents are in general indifferent to this attribute (except for neem), maturation period is a more important attribute for PC3. More specifically, PC3 respondents dislike a shorter maturation of three instead of five years for neem and pongamia, while they prefer a shorter maturation of seven instead of nine years for mahua.

While PC1 and PC2 respondents are quite similar with respect to preferences for cultivation features, their preferences for *contractual agreements* differ. PC2 respondents are entirely indifferent to any type of contract. PC1 and PC3 respondents have similar preferences for contractual agreements: positive preferences for both types of contracts but higher preferences for a contract foreseeing labour for seed collection – for neem only the latter contract is significant. For PC3 respondents the contractual agreement is distinctly the dominant attribute.[20] Finally, as expected there is a positive preference for higher *oilseed prices* for all species and throughout the different preference classes.

### 3.2.2. Small scale and low determinism

The scaled preference parameters for the small scale class ($\lambda_2$ = 0.095; P($\lambda_2$) = 0.12) are reported in Table 3. Davis et al.'s (2016) recommendation to report these explicitly and not merely provide the scale factor $\lambda_2$ as is common in past studies, is indeed illustrated: while the preference patterns are identical, only the most significant parameters for the large scale class are significant for the small scale class as well, although mostly only at a significance level of 10%. The $ASC_{opt\text{-}out}$ parameters form the only exception to this, since they are now significant for all preference classes. PC1 and PC2 again consist exclusively of respondents who never selected the opt-out alternative, but the nine respondents in PC4 are not systematic opt-outers.[21] Along with the 31 systematic opt-outers of the large scale class they determine the preference pattern in PC4, which is due to the specific choice behaviour of the former very erratic.

## 3.3. Latent class characterization

Table 4 reports the mean differences in characteristics across the preference and scale classes. When considering only the large scale class $\lambda_1$, some systematic differences underlie the identified preference heterogeneity. First, PC4 respondents are distinguished by some key demographic indicators, including lower school attainment, a larger share of female-headed households and a larger share of adult women. Second, wealth and income sources differ among the PCs. PC3 respondents have on average more assets, higher living standards and

[20] The relative importance of attributes within alternatives, between alternatives and between classes, can be quantified by calculating marginal rates of substitution (e.g., willingness to pay) (not shown here).

[21] These respondents opted out for between 1 and 5 out of the 8 choice cards.

**Table 3**
Estimated scaled utility equation parameters of the 4-preference-2-scale class model, for the small scale class ($\lambda_2$ = 0.095).

| | Preference class 1<br>Probability: 4.6 % | Preference class 2<br>Probability: 4.0 % | Preference class 3<br>Probability: 2.3 % | Preference class 4<br>Probability: 1.2 % |
|---|---|---|---|---|
| **Neem** | | | | |
| Oilseed yield: + 50% | 0.116 (0.073) | -0.049 (0.036) | -0.079 (0.061) | 0.137 (0.463) |
| Oilseed yield: - 50% | -0.247 (0.167) | -0.093 (0.052)* | -0.047 (0.051) | -1.510 (1.552) |
| Mat. period: - 2 years | -0.048 (0.054) | -0.061 (0.040) | -0.113 (0.072) | 0.013 (0.358) |
| Mat. period: +2 years | -0.177 (0.108) | -0.034 (0.033) | -0.064 (0.056) | -0.249 (1.167) |
| Contract 1: SC[a] | -0.054 (0.079) | -0.014 (0.026) | 0.038 (0.074) | 0.110 (0.343) |
| Contract 2: SC & LP[b] | 0.200 (0.107)* | -0.050 (0.043) | 0.525 (0.258)** | -4.003 (3.627) |
| Price | 0.007 (0.004)* | 0.006 (0.003)** | 0.002 (0.002) | 0.010 (0.013) |
| **Pongamia** | | | | |
| ASC | 0.169 (0.107) | 0.094 (0.054)* | 0.077 (0.074) | 2.197 (1.426) |
| Oilseed yield: + 50% | 0.156 (0.082)* | 0.039 (0.035) | -0.030 (0.043) | 0.088 (0.239) |
| Oilseed yield: - 50% | -0.212 (0.108)** | -0.083 (0.046)* | -0.065 (0.054) | -0.086 (0.301) |
| Mat. period: - 2 years | 0.000 (0.030) | 0.000 (0.024) | -0.138 (0.078)* | 0.066 (0.280) |
| Mat. period: +2 years | 0.031 (0.039) | 0.013 (0.027) | -0.063 (0.051) | 0.175 (0.267) |
| Contract 1: SC[a] | 0.089 (0.061) | 0.001 (0.023) | 0.308 (0.170)* | -0.117 (0.222) |
| Contract 2: SC & LP[b] | 0.275 (0.144)* | -0.027 (0.034) | 0.730 (0.362)** | -0.570 (0.723) |
| Price | 0.010 (0.005)** | 0.006 (0.003)* | 0.003 (0.002)* | 0.002 (0.006) |
| **Mahua** | | | | |
| ASC | 0.303 (0.165)* | 0.087 (0.050)* | -0.007 (0.071) | 0.515 (1.873) |
| Oilseed yield: + 50% | 0.027 (0.036) | 0.098 (0.058)* | 0.038 (0.045) | -0.366 (0.563) |
| Oilseed yield: - 50% | -0.274 (0.140)* | 0.032 (0.036) | -0.027 (0.048) | -0.475 (0.665) |
| Mat. period: - 2 years | 0.021 (0.034) | 0.015 (0.027) | 0.104 (0.065) | 0.438 (0.687) |
| Mat. period: +2 years | -0.008 (0.029) | 0.006 (0.028) | -0.006 (0.047) | -0.274 (1.174) |
| Contract 1: SC[a] | 0.056 (0.039) | -0.015 (0.030) | 0.197 (0.122) | -3.042 (2.447) |
| Contract 2: SC & LP[b] | 0.237 (0.121)** | 0.001 (0.026) | 0.627 (0.311)** | -3.275 (2.474) |
| Price | 0.012 (0.006)** | 0.006 (0.003)* | 0.003 (0.002)* | -0.022 (0.031) |
| **Opt-out** | | | | |
| ASC | -4.152 (2.341)* | -3.662 (1.924)* | 0.159 (0.090)* | 2.983 (1.431)** |

*** $p < 0.01$.
*Notes*: reported ASCs were estimated in an effects-coded model, reported attribute coefficients in a dummy-coded model. Sample consists of 386 respondents, resulting in 3087 observations. Standard errors are reported between parentheses. Significant effects are indicated as follows:
[a] SC = supply commitment.
[b] SC & LP = supply commitment & collection labour provision.
** $p < 0.05$.
* $p < 0.1$.

larger houses, whereas the opposite is true for PC2 and PC4 respondents. PC2 respondents are also more involved in off-farm work, and PC4 respondents rely less on farming as an income source. Third, PC4 respondents are less involved in extension events. Both PC3 and PC4 respondents live on average somewhat closer to a city, while they are also more frequently located in areas with higher rainfall. Fourth, the distinct difference in opt-out behaviour between PC1 and PC2 on the one hand, and PC3 and PC4 on the other, is reflected in the current presence of biofuel trees. PC4 respondents also have fewer tree species on their farms. However, household participation in biofuel program activities is not related to preference heterogeneity.

When comparing both scale classes to each other, few significant differences are observed between the two classes. Small scale class respondents (who answer less consistently) are more likely to engage in off-farm work, to live less remote and to participate in the biofuel program.

### 3.4. Likelihood of adoption

Adoption outcomes for both the current biofuel program and alternative program designs are simulated in Table 5. Preference heterogeneity results in distinct adoption outcomes across preference classes. This is in particular the case for scale class $\lambda_1$. First, PC1 respondents adopt trees in all scenarios and have a clear preference for mahua with adoption probabilities ranging from 83% to 97% in the different scenarios. Different program designs do not have any substantial impact on the likelihood of adoption. Second, PC2 respondents also adopt trees in all scenarios, but adoption probabilities are more equally distributed across the species and more sensitive to changes in cultivation features and prices. Pongamia has the highest adoption probability in all but one scenario, ranging from 43% to 54%. With low yields, PC2 respondents are most likely to adopt mahua (whose yield is relatively higher, see Table A.1). The adoption probability of neem (whose current price is the lowest) increases substantially with equal oilseed prices for all species. Contract specification does not have a major impact on the relative species preferences. Third, PC3 respondents have a low probability of adoption, 16% under the current program conditions. Higher oilseed yields and a shorter maturation period do not stimulate adoption at all. Yet, with increasing prices, the adoption probability increases to 35% (with a price of 40 INR/kg) and 40% (with a price of 65 INR/kg). Contract farming also induces a higher adoption probability and results in opting out not to be the dominant alternative anymore. A contract with only supply commitment (= contract 1) increases the likelihood of adoption to 66%, and even up to 77% if combined with a price increase to 40 INR/kg. A contract involving labour provision (= contract 2) increases adoption to 99%, even when combined with a low price level of 10 INR/kg. In contract-farming arrangements, pongamia is distinctly the most preferred species. Fourth, PC4 respondents do not adopt any of the tree species in any of the scenarios.

With regard to the scale class differentiation, the relatively smaller degree of choice determinism in scale class $\lambda_2$ results in less distinct choice probabilities. While the order of the alternatives in terms of choice probability is the same as in scale class $\lambda_1$ – since preference parameters are identical apart from the scale factor – probability differences for scale class $\lambda_2$ are much smaller throughout, and choice sets with an extremely dominant alternative do not occur.

Finally, note the clear positive correlation between the predicted adoption probabilities for the current biofuel program (SQ scenario in Table 5), and the current biofuel tree presence (Table 4). This indicates

**Table 4**
Latent class characterization by assigning respondents to a preference/scale class through modal a posteriori estimation.

| Characteristic | Scale $\lambda_1 = 1$ | | | | | | | | | | Scale $\lambda_2 = 0.095$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | PC1<br>N = 133 | | PC2<br>N = 110 | | PC3<br>N = 71 | | PC4<br>N = 31 | | Total<br>N = 345 | | Total<br>N = 41 | |
| | Mean | St. Err. | Mean | St. Err. | Mean | St. Err. | Mean | St. Err. | Mean | St. Err. | Mean | St. Err. |
| **Demographic characteristics** | | | | | | | | | | | | |
| Number of household (HH) members | 4.38 | (0.14) | 4.35 | (0.14) | 4.21 | (0.20) | 4.45 | (0.37) | 4.34 | (0.08) | 4.46 | (0.30) |
| Gender of HH head (1 = female) | 0.11 | (0.03) | 0.05 | (0.02) | 0.13 | (0.04) | 0.23 | (0.08)* | 0.10 | (0.02) | 0.15 | (0.06) |
| Age of HH head (years) | 55.11 | (1.12) | 51.36 | (1.16)** | 53.49 | (1.42) | 54.58 | (2.36) | 53.54 | (0.67) | 53.76 | (1.98) |
| Share of women among HH adults | 0.49 | (0.01) | 0.47 | (0.02) | 0.52 | (0.02)* | 0.60 | (0.03)*** | 0.50 | (0.01) | 0.49 | (0.02) |
| School attainment (1 = at least 1 HH member completed at least 6 years of schooling) | 0.94 | (0.02) | 0.95 | (0.02) | 0.92 | (0.03) | 0.77 | (0.08)** | 0.92 | (0.01) | 0.98 | (0.02) |
| **Assets & Income** | | | | | | | | | | | | |
| Exploited land (ha) | 1.47 | (0.15) | 1.40 | (0.15) | 1.63 | (0.21) | 1.50 | (0.33) | 1.48 | (0.09) | 1.33 | (0.17) |
| Amount of tropical livestock units | 1.55 | (0.14) | 1.54 | (0.18) | 1.87 | (0.33) | 1.28 | (0.22) | 1.59 | (0.11) | 1.63 | (0.26) |
| Assets and living standards index[a] | 0.20 | (0.20) | -0.42 | (0.25)*** | 0.79 | (0.33)* | -0.49 | (0.26) | 0.06 | (0.13) | -0.38 | (0.26) |
| Off-farm work by at least 1 HH member (1 = yes) | 0.41 | (0.04) | 0.55 | (0.05)** | 0.44 | (0.06) | 0.55 | (0.09) | 0.48 | (0.03) | 0.63 | (0.08)* |
| Share of farm income in total income | 0.68 | (0.03) | 0.62 | (0.04) | 0.61 | (0.05) | 0.49 | (0.07)*** | 0.63 | (0.02) | 0.55 | (0.06) |
| Surface of the house per adult-equivalent HH member ($m^2$) | 48.24 | (2.43) | 45.67 | (5.24)* | 63.70 | (4.63)*** | 36.78 | (3.86)** | 49.58 | (2.19) | 41.21 | (3.40) |
| Total annual income per adult-equivalent HH member ($^*10^4$ INR[b]) | 9.52 | (1.18) | 8.44 | (0.85) | 10.23 | (1.11) | 9.18 | (1.32) | 9.29 | (0.59) | 7.91 | (0.97) |
| **Location & Institutions** | | | | | | | | | | | | |
| Distance to nearest administrative headquarter (km) | 16.50 | (0.66) | 15.13 | (0.64) | 14.28 | (0.93)** | 12.20 | (1.06)*** | 15.22 | (0.40) | 12.97 | (0.99)* |
| Rainfall (1 = annual rainfall at hobli level > 1250 mm) | 0.27 | (0.04) | 0.35 | (0.05) | 0.41 | (0.06)* | 0.48 | (0.09)** | 0.34 | (0.03) | 0.24 | (0.07) |
| Extension (1 = at least 1 HH member attended agricultural extension event[c] in past 5 years) | 0.31 | (0.04) | 0.27 | (0.04) | 0.37 | (0.06) | 0.06 | (0.04)*** | 0.29 | (0.02) | 0.27 | (0.07) |
| **Biofuel experience** | | | | | | | | | | | | |
| BP[d] in village (1 = yes) | 0.65 | (0.04) | 0.77 | (0.04)** | 0.63 | (0.06) | 0.77 | (0.08) | 0.70 | (0.02) | 0.90 | (0.05)*** |
| Household involved in BP (1 = yes) | 0.20 | (0.03) | 0.16 | (0.04) | 0.21 | (0.05) | 0.13 | (0.06) | 0.19 | (0.02) | 0.39 | (0.08)*** |
| Number of different tree species on farm | 3.61 | (0.20) | 2.90 | (0.15)** | 3.18 | (0.25) | 2.19 | (0.28)*** | 3.17 | (0.11) | 3.15 | (0.31) |
| Biofuel tree species on farm (1 = yes) | 0.64 | (0.04) | 0.59 | (0.05) | 0.51 | (0.06)* | 0.29 | (0.08)*** | 0.57 | (0.03) | 0.61 | (0.08) |

*Note*: Fisher's exact test (for dichotomous variables) and Wilcoxon-Mann-Whitney test (for ordinal and interval variables) are used to test differences in means. For PC2, PC3 and PC4, differences in means with PC1 are tested. For scale class $\lambda_2$, differences in means with scale class $\lambda_1$ are tested. Significant effects are indicated as follows:

[a] Index calculated through principal component analysis. An increase indicates more assets / higher living standards.

[b] INR = Indian National Rupee. 1 EUR = 74.2 INR in August 2015.

[c] Extension events includes agricultural exhibitions, field demonstrations and agricultural trainings.

[d] BP = biofuel program activities, which includes awareness & training programs and/or planting program and/or cooperative establishment and/or provision of oil-expelling equipment.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

that stated preferences correspond to revealed preferences, although the former are more clear-cut along the preference classes than the latter.

## 4. Discussion

### 4.1. Interpretation of results

The choice experiment demonstrates distinct preferences among farmers towards the biofuel program and possible alternative value chain organisations, market conditions and cultivation features. We find that 38% of the sampled farmers (PC1) adopt mahua in any scenario ('mahua adopters'); 33% (PC2) adopt biofuel trees in any scenario but have less clear-cut species preferences ('flexible adopters'); 19% (PC3) are only willing to adopt (mainly pongamia) under contractual agreements, especially contracts with provisioning of collection labour ('potential adopters'); and 10% (PC4) do not adopt biofuel trees under any scenario ('non-adopters'). This implies that the adoption potential of agroforestry-based biofuel systems in Hassan, India is high, and that there is potential to improve the design of biofuel programs to increase adoption rates and better satisfy the needs and preferences of smallholder farmers.

First, results show that farmers are not indifferent towards which biofuel tree species they adopt. Lower preferences for neem likely relate to some intrinsic unfavourable oilseed characteristics: substantially lower yields in comparison with pongamia and mahua (Table A.1), labour-intensive seed collection due to a small seed size, seed collection during the peak-labour monsoon season, and higher chances of spoilage in this season. The consistent high preferences for mahua among the 'mahua adopters' likely relate to its large seeds and the use of its leaves as fodder. Pongamia is also a preferred species, which likely relates to larger seeds being collected in the dry, lean season.

Second, the results support the emphasis on the economic profitability of biofuel programs in the literature (Ariza-Montobbio and Lele, 2010; Borman et al., 2013; van Eijck et al., 2014a). Economic profitability of biofuel programs hinges on oilseed yields, oilseed prices and opportunity costs of land and labour. The main incentives for farmers in Hassan district to adopt biofuel trees are increased yields, increased prices and labour provision through contract farming. The literature also puts emphasis on the revenue lag and associated investment risk of smallholder perennial-based systems, in particular for the poorest smallholders (Alexander et al., 2012; Kumar et al., 2012; Sharma et al., 2016). Khanna et al. (2017) in particular use a CE to show the importance of discount rates and upfront investments, and to a lesser extent riskiness of returns, for adoption of perennial energy crops in the U.S. Our results only partially support these observations. We find that

**Table 5**
Simulated adoption outcomes for the current biofuel program and hypothetical alterations to it.

| Scenario[a] | Alternative | Predicted choice probabilities | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Scale $\lambda_1 = 1$ | | | | Scale $\lambda_2 = 0.95$ | | | |
| | | PC1 | PC2 | PC3 | PC4 | PC1 | PC2 | PC3 | PC4 |
| SQ | Pongamia | 0.04 | **0.49** | 0.05 | 0.00 | 0.31 | **0.34** | 0.24 | 0.23 |
| | Neem | 0.01 | 0.27 | 0.09 | 0.00 | 0.28 | 0.33 | 0.25 | 0.15 |
| | Mahua | **0.95** | 0.24 | 0.01 | 0.00 | **0.41** | 0.32 | 0.21 | 0.20 |
| | Opt-out | 0.00 | 0.00 | **0.84** | **1.00** | 0.00 | 0.01 | **0.31** | **0.41** |
| SQ + 50% yield | Pongamia | 0.14 | **0.47** | 0.04 | 0.01 | 0.33 | **0.35** | 0.23 | 0.26 |
| | Neem | 0.03 | 0.10 | 0.04 | 0.00 | 0.28 | 0.30 | 0.24 | 0.18 |
| | Mahua | **0.83** | 0.43 | 0.02 | 0.00 | **0.39** | 0.34 | 0.22 | 0.14 |
| | Opt-out | 0.00 | 0.00 | **0.89** | **0.99** | 0.00 | 0.01 | **0.31** | **0.42** |
| SQ - 50% yield | Pongamia | 0.07 | 0.32 | 0.03 | 0.00 | 0.32 | 0.33 | 0.23 | 0.27 |
| | Neem | 0.02 | 0.16 | 0.06 | 0.00 | 0.28 | 0.31 | 0.25 | 0.04 |
| | Mahua | **0.91** | **0.52** | 0.01 | 0.00 | **0.40** | **0.35** | 0.21 | 0.16 |
| | Opt-out | 0.00 | 0.00 | **0.90** | **1.00** | 0.00 | 0.01 | **0.32** | **0.53** |
| SQ - 2 years mat. period | Pongamia | 0.03 | **0.54** | 0.01 | 0.00 | 0.31 | **0.35** | 0.21 | 0.22 |
| | Neem | 0.01 | 0.16 | 0.03 | 0.00 | 0.27 | 0.31 | 0.23 | 0.14 |
| | Mahua | **0.96** | 0.31 | 0.04 | 0.06 | **0.42** | 0.33 | 0.24 | 0.28 |
| | Opt-out | 0.00 | 0.00 | **0.92** | **0.94** | 0.00 | 0.01 | **0.32** | **0.37** |
| SQ 10 INR/kg | Pongamia | 0.07 | **0.43** | 0.04 | 0.00 | 0.31 | **0.34** | 0.23 | 0.21 |
| | Neem | 0.06 | 0.38 | 0.09 | 0.00 | 0.30 | 0.34 | 0.25 | 0.14 |
| | Mahua | **0.87** | 0.19 | 0.01 | 0.02 | **0.39** | 0.32 | 0.20 | 0.27 |
| | Opt-out | 0.00 | 0.00 | **0.87** | **0.98** | 0.00 | 0.01 | **0.31** | **0.39** |
| SQ 40 INR/kg | Pongamia | 0.04 | **0.45** | 0.08 | 0.00 | 0.31 | **0.34** | 0.24 | 0.24 |
| | Neem | 0.01 | 0.39 | 0.15 | 0.00 | 0.28 | 0.34 | 0.26 | 0.19 |
| | Mahua | **0.94** | 0.16 | 0.02 | 0.00 | **0.41** | 0.31 | 0.21 | 0.15 |
| | Opt-out | 0.00 | 0.00 | **0.75** | **1.00** | 0.00 | 0.01 | **0.30** | **0.42** |
| SQ 65 INR/kg | Pongamia | 0.03 | **0.46** | 0.15 | 0.01 | 0.31 | **0.35** | 0.25 | 0.25 |
| | Neem | 0.00 | 0.40 | 0.23 | 0.00 | 0.26 | 0.34 | 0.26 | 0.25 |
| | Mahua | **0.97** | 0.14 | 0.03 | 0.00 | **0.43** | 0.31 | 0.21 | 0.08 |
| | Opt-out | 0.00 | 0.00 | **0.60** | **0.99** | 0.00 | 0.01 | **0.28** | **0.42** |
| SQ Contract 1 | Pongamia | 0.06 | **0.53** | **0.56** | 0.00 | 0.32 | **0.35** | **0.28** | 0.26 |
| | Neem | 0.00 | 0.25 | 0.06 | 0.00 | 0.25 | 0.32 | 0.23 | 0.21 |
| | Mahua | **0.94** | 0.22 | 0.04 | 0.00 | **0.42** | 0.32 | 0.22 | 0.01 |
| | Opt-out | 0.00 | 0.00 | 0.34 | **1.00** | 0.00 | 0.01 | 0.27 | **0.52** |
| SQContract 1 40 INR/kg | Pongamia | 0.06 | **0.49** | **0.66** | 0.00 | 0.32 | **0.35** | **0.29** | 0.25 |
| | Neem | 0.00 | 0.36 | 0.07 | 0.00 | 0.25 | 0.34 | 0.23 | 0.25 |
| | Mahua | **0.94** | 0.15 | 0.04 | 0.00 | **0.42** | 0.31 | 0.22 | 0.01 |
| | Opt-out | 0.00 | 0.00 | 0.23 | **1.00** | 0.00 | 0.01 | 0.26 | **0.49** |
| SQ Contract 2 | Pongamia | 0.06 | **0.47** | **0.78** | 0.00 | 0.32 | **0.34** | **0.31** | 0.23 |
| | Neem | 0.01 | 0.21 | 0.16 | 0.00 | 0.27 | 0.32 | 0.26 | 0.01 |
| | Mahua | **0.93** | 0.32 | 0.06 | 0.00 | **0.41** | 0.33 | 0.24 | 0.01 |
| | Opt-out | 0.00 | 0.00 | 0.01 | **1.00** | 0.00 | 0.01 | 0.19 | **0.75** |
| SQ Contract 2 10 INR/kg | Pongamia | 0.10 | **0.43** | **0.74** | 0.00 | 0.32 | **0.34** | **0.30** | 0.23 |
| | Neem | 0.04 | 0.31 | 0.20 | 0.00 | 0.29 | 0.33 | 0.27 | 0.00 |
| | Mahua | **0.86** | 0.26 | 0.05 | 0.00 | **0.39** | 0.32 | 0.24 | 0.02 |
| | Opt-out | 0.00 | 0.00 | 0.01 | **1.00** | 0.00 | 0.01 | 0.20 | **0.75** |

[a] SQ refers to the status quo levels for all attributes (Table 1), which correspond to the current biofuel program. Alterations to the current biofuel program are explicitly specified as attribute level changes.

supply contracts (which decrease marketing risk and policy uncertainties) provide an additional incentive to adopt mahua and pongamia only for more endowed respondents ('potential adopters' and 'mahua adopters'). The lower contract preferences for neem might be due to its more widespread commercialization and/or because respondents are more reluctant to supply obligations for this least preferred species. With regard to revenue lags, we find respondents to be mostly indifferent towards the temporal dimension of the oilseed yield, as expressed by the maturation period. Trees only provide substantial yields in the long run (Table A.1), and minimal cultivation practices other than seed collection are involved. This might explain the limited interest in short-term gains through advancing maturation, as compared to maximizing long-term gains, for instance through increasing oilseed yields.

Third, we find particularly distinct preferences for contracts involving labour provision. 'Mahua adopters' and especially 'potential adopters' likely have higher opportunity costs of labour as they are more endowed, and the latter more frequently located in high rainfall areas. This can explain their large preferences for labour provision, which in case of the 'potential adopters' dominates all other attributes. 'Flexible adopters' on the other hand likely have lower opportunity costs of labour as they are less endowed and more involved in low-return off-farm work (mainly agricultural and industrial wage work), and are therefore willing to adopt without labour provision. 'Non-adopters' likely lack the knowledge to adopt (tree-based) innovations under various conditions because of lower schooling, less extension involvement, lower farm dependency, and less experience with (biofuel) trees. Their systematic selection of the opt-out alternative might result from lexicographical preferences, protest behaviour or simplifying heuristics to cope with complex choices (Meyerhoff and Liebe, 2009; von Haefen et al., 2005).

Fourth, although heterogeneity in choice determinism (scale) is demonstrated, it could not be clearly characterized. A possible explanation might be adverse experiences with the biofuel program, resulting in less time and commitment to the CE. The lack of significant differences between the scale classes suggests that ability for and commitment to the choice tasks are difficult to measure, which is in line with the verdict that scale heterogeneity cannot be characterized easily (Hess and Stathopoulos, 2013).

Finally, we found a strong positive but no perfect correlation between predicted and current tree adoption. This discrepancy might result to a certain extent from hypothetical bias (Hensher, 2010). Yet we believe bias to be limited because native tree species have traditional uses and a commercial history, such that respondents understand the opportunities and constraints. In addition, because biofuel trees grow spontaneously on many farms they might be present among many 'potential adopters' and 'non-adopters'. On the other hand, various obstacles to adoption were mentioned by 'mahua adopters' and 'flexible adopters', including a lack of knowledge, a lack of access to planting material and effective outreach of the biofuel program, and agro-ecological constraints (see also Altenburg et al., 2009; Bijman et al., 2010; Mabiso, 2012). Furthermore, the status quo attribute levels (Table 1) might not correspond to the actual situation farmers currently face, due to uncertainty on the cultivation features, a poorly established value chain and/or market failures.

### 4.2. Methodological reflections

The recent choice modelling literature has pointed to several sources of bias in CEs, including hypothetical bias (Hensher, 2010), attribute non-attendance (Collins et al., 2013), choice indeterminism (Louviere and Eagle, 2006) and taste differences (Boxall and Adamowicz, 2002). We consider the likelihood of hypothetical bias to be limited because of the research set-up. While controlling for attribute non-attendance is becoming common in the literature, various authors have contested the importance of attribute non-attendance bias as well as its proper identification in current models (Campbell et al., 2012; Hess et al., 2013; Ortega and Ward, 2016). Therefore, and because our CE displays only three attributes, we refrain from including attribute non-attendance correction models. We consider choice indeterminism and preference/taste heterogeneity as the main sources of bias in this experiment, which is accounted for in the applied analytic approach.

Further, we want to highlight two particular strengths of the choice experiment method, which at the same time imply limitations for the study scope. First, a CE allows creating an experimental setting, but works best if the study scope and research question are meticulously defined in advance. This should translate in a design where only the most relevant attributes are maintained while other conditions are strictly framed, as conceptual, cognitive and mathematical complexity tend to expand easily. One should be aware that this limits the lessons that can be learned from a CE: no conclusions can be made on the effect of other framings and attributes (in our case, e.g., price volatility, input support, community land cultivation, other value chain actors). In addition, although it makes a CE a straightforward and fast method, with limited and targeted data collection, it does not provide any additional data to answer new questions arising from the CE results, which strongly calls for follow-up research (this is illustrated in particular in Section 5, the part on contract specifications). Second, a CE leads to a flexible tool to predict the potential of any hypothetical technical, ecological, socio-economic and institutional changes, as long as they can be defined in terms of attribute levels. However, it does not assess which of these changes are most likely and/or advisable; this should be derived from other studies and policies (this is illustrated in particular in Section 5, the part on alternative business models).

## 5. Conclusions and policy implications

In this empirical study we have used a choice experiment to assess smallholder preferences for oilseed tree-based biofuel programs. Our findings point to a large potential for biofuel tree adoption, as well as to opportunities to tailor the biofuel program and its targeting, in Hassan district. First, value chain reorganization through contracting and labour provision is the key lever to effectively increase the amount of adopters. The importance of this to assure effective seed collection is apparent from current collection figures: while 35.6% of all respondents have mature pongamia, neem and/or mahua trees, only 12.7% of all respondents have collected seeds from any of these species in the past 12 months. This emphasizes the bottleneck of labour provision and calls for the development of alternative business models, where (landless) labourers willing to collect oilseeds are matched to labour-constrained farmers providing the land for feedstock cultivation. This obviously raises many social, contractual and logistic issues for farmers, private companies and the government, especially when feedstock areas are small (Altenburg et al., 2009; Mabiso, 2012). Additional insights are required to decide who should be the main actor in such set-ups (smallholders, private companies or the government) and how the value chain should be structurally and spatially organized, while supply chain dynamics and actor-specific profitability, under various conditions, should also be further explored (Altenburg et al., 2009; Chen and Önal, 2014; Van Eijck et al., 2012). Also further exploration of contract specifications (e.g., duration, input support, enforcement and renegotiation, trustworthiness, quality standards) for an effective design is needed, especially given the long-term commitments (Alexander et al., 2012; Eaton and Shepherd, 2001; Khanna et al., 2017; Montefrio et al., 2015; Shepherd, 2013). Khanna et al. (2017) provide an excellent example on how contract specification preferences can be assessed through a CE, and find for instance a robust positive effect of input support on adoption of perennial energy crops in the U.S., while the effect of contract duration is more ambiguous. Second, program developments should primarily focus on increasing economic profitability. Results imply that increasing yields is more important than advancing maturation for increased profitability, which implies breeding programs should primarily focus on yields. Third, despite its agronomical and technical potential as a biofuel feedstock, there is only limited scope to further promote neem, except in particular settings or when aiming explicitly at well-balanced species mixtures, for instance as a risk-reducing strategy.

This case study provides some lessons for biofuel programs in general. First, our study supports the rationale for agroforestry-based biofuel innovations and demonstrates that biofuel programs can benefit from ex ante analyses. These analyses can support the design of systems and extension efforts (e.g., species choice, value chain organisation, R&D priorities) for increased adoption and improved impact (see also Franzel and Scherr, 2002; Mercer and Snook, 2005). Second, the study points to contract farming as a feasible strategy to increase adoption and feedstock supply, under the erratic (bio)fuel markets and policies. The latter might complicate contract enforcement and compromise economic viability for producers and companies. Yet, the multipurpose nature of the native oilseed trees might play a role in decreasing the hazard of contract breach, as the actors can turn to alternative uses when market conditions and/or policies are less conducive, while biofuel feedstock continues to build up. Third, biofuel rationales and policies have mainly focused on opportunity costs of land, and programs have mainly focused on (multipurpose) feedstock grown on underutilized lands. Our study illustrates that also opportunity costs of labour are crucial to address, e.g. through alternative business models or mechanisation of harvesting (see also van Eijck et al., 2014a, 2014b). If biofuel programs are to succeed, they have to move beyond the idea of smallholder biofuel production on marginal lands with surplus labour.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.enpol.2018.01.030.

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