# Three Essays on Consumer and Producer Decision-Making

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# Dedication

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# Abstract

This dissertation aims to address a few recent theoretical and methodological developments to better understand individual decision-making. Consumer purchases of community supported agriculture are decision-making under risk. In this case, essay one incorporates prospect theory in behavioral economics to a discrete choice experimental design, and simultaneously estimate consumer preferences for product attributes and risk parameters including loss aversion, diminishing sensitivity, and probability weighting. Not only consumer purchasing decisions involve risk and uncertainty, producers' production decision-making is also affected by individual risk preferences. Thus, in the second essay, we explore the preference differences between conventional crop producers and specialty crop producers using behavioral economics models, and the results shed lights on risk mitigation and policies related production contract design. Given the recent developments in estimation methods, the third essay assesses US households' organic produce purchases using the method of machine learning. This study compares the predictive accuracy of organic budget share between econometric models and machine learning methods, which provides some initial insights into the effectiveness of using machine learning methods to estimate household demand.

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# Chapter 1

# General Introduction

This dissertation explores recent developments in both stated and revealed decision-making analysis. From a theoretical aspect, we apply Cumulative Prospect Theory (CPT), the cornerstone of behavioral economics, to understand consumers' and producers' decision-making under risk and uncertainty. From methodological aspect, we conduct field experiments in a survey format to collect stated decisions and apply machine learning methods to estimate big data. From a practical aspect, we seek for marketing implications of a popular alternative farming system, Community Supported Agriculture (CSA), and explore the risk mitigation methods for specialty crop production. Specifically, each chapter in this dissertation is explained as follows.

In Chapter 2, "Investigating Consumer Purchasing Decision for Community Supported Agriculture," We use the framework of CPT to investigates consumers' CSA purchasing decisions under risk and uncertainty. We analyze discrete choice experiment data by employing a CPT framework that allows for flexible reference points and individual preference heterogeneity. For product attributes, the estimation results identify significant

CSA intrinsic purchasing utility, followed by price, product variety, and distance. The parameter estimates of loss aversion, risk curvature, and probability weighting vary significantly across the loss model, the gain model, and the full model with both gain and loss. Further comparison between different model specifications suggests that CPT model with the control of all risk parameters generates better goodness of fit than the Expected Utility model. Results from market sensitivity analysis indicate that while CSA operator transfers production risk partially to its members, this transferred risk becomes the determinant of CSA market share in return. In addition, the results shed light on consumer behavior when purchasing products with risky prospect and provide marketing implications for CSA.

In addition to consumers, producers' decisions such as crop insurance, contract agreement, and technology adoption, also involve considerable risk and uncertainty. Particularly, specialty crop production is more vulnerable to risk and requires more intensive management than commodity crop production, while risk mitigation tools are comparatively limited. In Chapter 3, "Risk Preference Comparison between Commodity Crop Producers and Specialty Crop Producers," we use lottery experiment to apply CPT framework to analyze risk preferences of US producers, and further compare the preference differences between commodity crop and specialty crop producers. Reference-dependent, diminishing sensitivity, loss aversion and probability weighting, as well as certain farm characteristics and producer demographics, are found to have a significant impact on grower risk attitudes. Additionally, we do not observe significant differences in the base CPT estimates between commodity crop and specialty crop producers. However, after adding the explanatory variables, the relationships between risk behavior and individual

characteristics vary between the two types of producers. Meanwhile, the predicted distributions of risk preferences also indicate a higher level of loss aversion perceived by specialty crop producers. Those results shed lights on agricultural policies and designs of contract and insurance.

While chapter 2 and 3 collect and analyze stated decision data, it is almost inevitable to fully avoid hypothetical bias under experimental setting. However, revealed decisions, such as purchasing record, are the true reflection of consumer behavior in daily life. Combing the recent public interest in big data, chapter 4 assesses machine learning (ML) methods in demand estimation of organic fresh produce. ML is becoming one of the most anticipated methods in demand estimation. However, it is still uncertain how ML methods perform relative to traditional econometric methods under different scales of data. This study estimates and compares the out-of-sample predictive accuracy of household budget share for organic fresh produce using two parametric models and five ML methods. Results show that ML method, particularly support vector machine and random forest, performs better than econometric models under regular sample size. Contrarily, when dealing with big data, econometric models reach to same accuracy level to forward stepwise, forward stagewise, and Lasso, while support vector machine and random forest present possible overfitting problem. This study illustrates the competence of ML methods in demand estimation, but choosing the optimal method need to consider the product specifics, sample size, and observable features

# Chapter 2

# Investigating Consumer Purchasing Decision for Community Supported Agriculture: An Application of Cumulative Prospect Theory

## 2.1 Introduction

Understanding decision making under risk and uncertainty has been the focal point of consumer study for the past decades, especially after the underlying axiom of expected utility theory (EUT) was challenged (e.g., Allais paradox, Kahneman and Tversky 1979; Equity premium puzzle, Benartzy and Thaler 1995). Numerous studies have provided compelling evidence showing decision makers violate EUT systematically, including the linear evaluation of probabilities (Abdellaoui, Bleichrodt, and l'Haridon 2008), lack of loss aversion measurements (Booij, Van Praag, and van de Kuilen 2010), limited control on risk estimation other than utility curvature (Rabin 2000), and deviated utility assessment without a reference point (Kőszegi and Rabin 2006).

To overcome the shortcomings of EUT in analyzing consumer decision under risk (uncertainty), CPT by Tversky and Kahneman (1992) is the most recognized non-EUT framework to adequately describe individual decision-making under risk. Compared to the utility measured by absolute wealth in EUT, the utility in CPT is derived from gain and loss, which is relative to a reference point (often the status quo). In addition, decision-makers are assumed to become less sensitive to changes in outcomes further away from the reference point (diminishing sensitivity), and much more sensitive to loss than to gain of the same magnitude (loss aversion). Lastly, CPT proposes that individuals tend to overvalue low probabilities and undervalue intermediate and high probabilities, so the utility outcome is evaluated by weighted probabilities instead of objective probabilities.

To connect individual utility theories to consumer decision-making in real life, discrete choice experiments (DCE) has been widely used. In DCE, a product is decomposed into and described by the most important product attributes; then individuals are asked to make choices in hypothetical or real alternative scenarios, goods or services. DCE is typically estimated with the assumption of EUT, and has been applied to a wide range of consumer preference topics such as the acceptance of neoteric products (Yue et al. 2015), Willingness to Pay (WTP) for food attribute improvements (Lusk and Schroeder 2004), health-related decision analysis (de Bekker-Grob, Ryan, and Gerard 2012), and public perceptions of environmental policies (Hanley, Wright, and Adamowicz 1998).

Not only DCE is typically designed and estimated under EUT, consumer preferences for product attributes are generally studied in isolation from risk parameter elicitation, even when product attributes contain risky prospects. For example, Hayes at al. (1995) utilized EUT framework to estimate WTP for risks of food-borne diseases using an experimental

auction, and Krupnike et al. (2002) elicited consumer preferences for mortality risk reduction assuming consumers maximize their expected utility. In contrast, most of the empirical studies analyzing risk preferences using CPT framework are implemented in a single domain such as money (e.g., Booij, Van Praag, and van de Kuilen 2010), Health (e.g., Bleichrodt and Pinto 2000), and time (e.g., Abdellaoui and Kemel 2014). In fact, when conducting consumer preference analysis for products with risks or uncertainties, significant relationships are often found between the preferences for product attributes and preferences for risks (Mitchell 1999). Hence, estimating product attribute preferences without controlling risk preferences or failing to include preferences for product attributes when eliciting risk preferences could both lead to estimation biases. Furthermore, for the applications of DCE, Wilcox (2008) stated that any account of the structure of DCE under risks without considering stochastic choices and consumer heterogeneity is unacceptable.

To our knowledge, the only empirical work that analyzes DCE with the incorporation of CPT risk preferences was conducted by Jindal (2015) in which the author tested risk preferences for extended warranties for washing machine. Building on Jindal's work, we further improved the estimation in four aspects. First, while Jindal (2015) only focused on the uncertainty of loss, we extended the model of consumer risk preferences by including both possible loss and gain. Next, to measure the decreased/increased utility when loss/gain occurs, we introduce a parameter to capture real utility changes in addition to monetary variation. Third, in Jindal (2015), the estimated coefficient of probability weighting parameter is greater than 1, which generates an S-shaped probability weighting function. This is contrary to most of the prior studies where an inverse S-shaped probability weighting function is the norm (e.g., Tversky and Kahneman 1992; Gonzalez and Wu

1999; Prelec 1998; Bocquého, Jacquet, and Reynaud 2014). Comparatively, our study identifies an inverse S-shaped function for gains, and we explore why the weighting parameter tends to be S-shaped for the possible loss model. Finally, the extended warranty is an add-on service for washing machines, and paying the additional price for the warranty may challenge the identification of reference point for the product itself. Thus, in order to clearly control the reference point and modify the method to be commonly applicable for general consumer products, we apply the DCE model under the framework of CPT to analyze consumer purchasing decision for Community Supported Agriculture (CSA).

As an affordable and convenient channel to increase the consumption of vegetable and fruits, CSA has grown rapidly over the past thirty years. According to the US Department of Agriculture (USDA), the very first CSA operation started in 1986, and there were CSA 60 farms in 1990. Over time, CSA gradually receives its popularity and expanded to 1,000 farms in the early 2000s (USDA, 2004), and this number had further increased to 12,617 in 2012 (USDA, 2014), and it is expected that CSA will continue to grow in the forthcoming years (Vasquez et al. 2017). In CSA, consumers pledge support and partner to a local farm operation to share the risks of loss and possibility of gains in food production (Ernst and Woods 2013). By paying an up-front subscription payment in advance, CSA members receive fresh, local produce throughout the growing season, along with enhanced community connection, strengthened sustainability support, and other added benefits[1].

[1] Other added benefits may include but are not limited to: generating a community friendly farm for people to participate in food production and pick up their own food; serving as outdoor classroom for children and students to learn about agriculture, encouraging the awareness of environmental protection around local communities, supporting local farmers and so on.

Purchasing CSA directly associates with both risk of loss and benefit of bonus gain. For example, Woods et al. (2009) surveyed 205 CSA producers and nearly one in three (29%) CSAs did not produce all the anticipated products in their shares, while 26% produced excess products to their customers. Among the consumer studies pertaining to CSA, Bernard, Bonein, and Bougherara (2016) is the only work that considered both preferences for risks and product attributes. They interviewed 162 CSA members in France in which they elicit participants' risk attitudes using binary lottery choices and their preferences for product attributes using a state choice survey. However, their elicitation of risk preferences and product attribute preferences were estimated separately, and a recent study has criticized the lottery experiment as it may violate the monotonicity property of preference (Apesteguia and Ballester 2018).

Given the characteristics of CSA, CPT is undoubtedly a more suitable theory in explaining the consumer purchasing behaviors compared to EUT. For example, contrary to the EUT that assumes consumer preference depends on absolute levels of wealth, CPT argues that the perceived outcome depends on the changes in wealth, as gain and loss, relative to a reference point. Once the reference point is defined, loss aversion is further assumed so that the steepness of loss function relative to the steepness of gain function is greater than 1. For CSA purchases, consumers are likely to weigh the value of the final product by comparing it to the subscription price, and this price can be straightforwardly defined by the up-front payment, so loss occurs when the final product is worth less than the upfront payment, and gain takes place when the final product is worth more than the upfront payment. Under the same magnitude of loss and gain, loss hurts CSA consumers more than gain pleases them (Bernard, Bonein, and Bougherara 2016).

Overall, this study's contributions to the literature are multifold. First, we structurally incorporate CPT parameters, namely reference dependent, diminishing sensitivity, loss aversion, and probability weighting, into DCE design and compare the results with those of EUT models. Second, compared to previous risk preference elicitation methods where only monetary characteristic (e.g., lottery) are used (e.g., Abdellaoui, Bleichrodt, and l'Haridon 2008; Tanaka, Camerer, and Nguyen 2010, Bocquého, Jacquet, and Reynaud 2014), our framework is applicable for analyzing the risk preferences for multi-attribute consumer products. Third, most previous studies elicit risk reference parameters and product attribute preference parameters separately, which might lead to estimation biases when treating these two sets of parameters being interdependent and estimating the parameters separately (Mitchell 1999). Our framework simultaneously estimate both product attribute preference parameters and risk parameters and thus avoids possible biases. Fourth, our model allows for preference heterogeneity for target variables and flexible reference points that are individual- and choice- specific. Lastly and empirically, this study is the first attempt to evaluate attribute preferences and risk preferences for CSA, which provides important marketing implications to the suppliers of CSA.

The remainder of the paper is organized as follows. Section 2 introduces the experimental design of our online survey; section 3 describes the discrete choice model; section 4 summarizes the data; section 5 presents the results of reduced form model and the full model; and section 6 concludes the paper with discussions, implications, and limitations.

## 2.2 Experimental Design

### *2.2.1 Product Attributes and Attribute Levels*

Recent studies of CSA characteristics show that product variety and pick-up distance are the major attributes for consumers. For the variety of produce, Adam (2006) emphasized that it is the key attribute in overall satisfaction for CSA shareholders. Using online survey data, Vassalos, Gao, and Zhang (2016) indicated the limited variety and the cost of CSA were among the top three factors that discourage people from making a purchase. In addition to consumer preference, Paul (2015) also highlighted the importance of crop variety in minimizing farm risks. For distance, Connolly and Klaiber (2014) identified significant premium were associated with CSA's off-site delivery and convenient pick-up locations, and additional miles of the pick-up location from the metro area leads to the decrease in CSA share price. Similarly, Burnett, Kuethe, and Price (2011) reported a positive correlation between shorter distance and higher price premium of CSA. Based on the previous literature and our interview with a small of group of consumers, the product attributes we included in our choice experiment are up-front payment, number of product varieties, and distance to pick-up location. The attributes for risks include chance of loss due to poor harvest/chance of getting bonus produce due to good harvest, value of loss due to poor harvest/value of bonus produce due to good harvest.

Each attribute includes multiple levels (Table 2-1). The price levels ($400, $500, $600) are determined based on the findings of the previous literature. Connelly and Klaiber (2014) reported an average price for 20-week subscription of 453 CSAs is approximate $520 with the standard deviation of $136. Khanal (2016) analyzed share prices of 466 CSAs and found an average weekly price of $26.9. Chase (2007) used $560 and $350 as

the base prices for organic and regular subscriptions for 20 weeks. The loss and gain probabilities range from 5% to 80%, and higher percentages are included to estimate the probability weighting parameters with the full interval between 0 and 1. Additionally, we included four scenarios with 0% or 100% of loss/gain to account for the situation of making purchasing decisions without any risks.

### *2.2.2 Choice Experiment Design*

Two groups of discrete choice questions were designed to collect data for risk preference analysis, a group for possible losses and another for possible gains. There are 24 choice scenarios in each group, each scenario contains three options, including 2 CSA options and an opt-out option. The combinations of the attributes in each option are determined by a fractional factorial design that aims to minimize scenario number, maximize profile variation and achieve the highest efficiency. Besides, we informed the respondents that 1) if the potential loss or gain does not occur, then the actual value received from a CSA farm equal to the up-front payment value, and 2) besides the variations in the major attributes, all other characteristics are identical across CSA options (e.g., farmers' background, production practice, product freshness, size of share, etc.).

Figure 2-1 shows an example of choice scenarios under possible loss, appendix figure A-1 shows a similar example for the possible gain scenarios. Before the discrete choice questions are presented to respondents, we first ask about their familiarity with CSA. Then a brief introduction is shown to provide respondents with information about CSA and associated risks and benefits (appendix figure A-2). To ensure the respondents fully understand the mechanism of CSA, a multiple-choice question is asked to test their knowledge about CSA. Only those who answer the question correctly could proceed to the

discrete choice question sections. Each respondent answered two blocks of 12 discrete choice questions. All questions are presented in randomized order to avoid order effect. Additionally, to ensure the quality of survey response, we added one screening discrete choice question (appendix figure A-3) in each block and time screenings for all questions. If a respondent answers the screening discrete choice question incorrectly, he/she is not allowed to complete the experiment. In addition, time screening excluded participants who did not spend enough time to comprehend and answer the questions. At the end of the survey, we ask the respondents about their basic socio-demographics including age, gender, education and income level, marital status, race, occupation, etc.

## 2.3 Methodology

### *2.3.1 Model Framework*

From previous CPT studies, it is widely assumed that reference point is equivalent to one's status quo or current assets (e.g., Kahneman and Tversky 1992; Tanaka, Camerer, and Nguyen 2010; Bocquého, Jacquet, and Reynaud 2014). In our experiment of CSA purchase, if a consumer chooses a CSA option, the current asset should be equal to the up-front payment associated with the chosen option, then s/he will compare the final asset (received value of chosen CSA) with the current asset (up-front payment of chosen CSA) to assess the payoff of the product.

Therefore, the CPT utility $PU$ can be measured by

$$PU = \begin{cases} v^g(y-r) + v(y) + \epsilon^g; & if\ y \geq r \\ v^l(y-r) + v(y) + \epsilon^l; & if\ y < r \end{cases}$$

where $r$ is the reference point, $y$ is the risk-neutral utility index consumer $i$ gets from choosing CSA option $j$, $\epsilon^g$ and $\epsilon^l$ are the random utility errors that are unobserved in the

study, $v(y)$ is the consistent value function[2] for buying product $j$, and $v^g(\cdot)$ and $v^l(\cdot)$ are the increased/decreased value functions in the gain and loss domain, respectively.

Assuming the random utility errors are type I extreme value distributed, for any domain $\{g, l\}$, consumer chooses option $j$ if and only if

$$PU_j \geq PU_{j'}$$

where $j, j' \in J$, and $j \neq j'$. We define $d_j = 1$ if option $j$ is chosen. Thus, utilizing multinomial logit model analysis, the conditional choice probability (CCP) that the consumer chooses option $j$ is characterized as

$$\Pr\{d_j = 1\} = \frac{\exp\left(v(y_j - r_j) + v(y_j)\right)}{1 + \sum_{j' \in J} \exp\left(v(y_{j'} - r_{j'}) + v(y_{j'})\right)}$$

indicating consumer compare each option under CPT and chooses the option with the highest utility outcome. Given the CPT framework, we can integrate and elicit both product attributes (CSA purchasing utility, up-front payment, number of product varieties, and distance to pick-up location) and risk parameters (risk curvature, loss aversion, and probability weighting) simultaneously. The specific model is outlined in the following sections.

### *2.3.2 Utility Index*

With the experimental design of our discrete choice question, consumers choose between $J = 3$ options including 2 CSA options and 1 opt-out option for $S = 24$ scenarios, 12 for possible loss and 12 for possible gain. Each option is characterized by 3 product

[2] 'Value function' was first used by Kahneman and Tversky (1979) to show the existence of gain and loss separated by reference point, and to differentiate value function in prospect theory with the utility function in expected utility theory, where the outcome state is entirely defined by functional form.

attributes (upfront payment price $p_{js}$, product variety $n_{js}$, distance to pick-up location $d_{js}$) and 2 risk attributes (percentage of poor or good harvest ($\pi_{js}^{-}$ $or$ $\pi_{js}^{+}$), and value of loss or gain ($p_{js}^{-}$ $or$ $p_{js}^{+}$)). We define a vector space $\boldsymbol{x}_{js} = (p_{js}, n_{js}, d_{js})$ representing product attributes. Given consumer heterogeneous preference which is measured by the parameter vector $\boldsymbol{\theta}_i$, if consumer $i$ chooses CSA option $j$ in scenario $s$, the deterministic utility index $y_{ijs}^{\pm} = y(\boldsymbol{x}_{js}|\boldsymbol{\theta}_i)$ can be defined as

$$y_{ijs}^{\pm} = c_{ijs} + n_{js}\beta_i + d_{js}\gamma_i - p_{js}\delta_i$$

where $c_{ijs}$ is the intrinsic consumption utility subject $i$ obtained from buying CSA option $j$ in scenario $s$. Utility $c_{ijs}$ measures the additional benefits from purchasing CSA that are not covered by the product attributes included in the choice experiments. It might include local and quality-assured food, increased involvement in local community, and satisfaction from supporting local sustainability. $\beta_i$ and $\gamma_i$ are coefficients for variety and distance, respectively, and $\delta_i$ is the coefficient for price.

For loss, there is a certain possibility that a monetary loss will occur from the final product, which means the consumer will possibly receive his/her CSA subscription box with a value lower than paid upfront payment. In this case, if CSA option *j* chosen by consumer $i$ in scenario $s$ results in a loss of $p_{js}^{-}$, then the utility index of loss $y_{ijs}^{-}$ is defined as[3]

$$y_{ijs}^{-} = \eta_{ijs}^{-} + p_{js}^{-}\delta_i$$

[3] The utility change occurs in a later period when weekly CSA subscription is delivered. Thus, there is a time difference between consumers invest their current asset and realize a possible loss or gain in the final asset. It is arguable that there is time discounting (hyperbolic discounting) effect (Laibso 1997) for a future change of utility outcome. However, we believe this time discounting effect is minimized under our survey design, because respondents are making simultaneous choice for both current product and final product condition. Additionally, we have tried to include an extra parameter for time discounting and found the parameter to be statistically insignificant.

where $\delta_i$ is the same price coefficient as in equation (4), $\eta_{ijs}^{-}$ measure utility change other than monetary loss. For example, when loss occurs, the consumer will not be refunded for the monetary loss. Additionally, she/he would need to spend money on produce elsewhere to fulfill their weekly need, which leads to extra cost (utility deduction) in time, transportation, and grocery consumption.

Similarly, for gains, when consumer receives extra produce with additional monetary value of $p_{js}^{+}$, then the utility index of gain $y_{ijs}^{+}$ consumer $i$ gets from purchasing CSA option $j$ in scenario $s$ is

$$y_{ijs}^{+} = \eta_{ijs}^{+} + p_{js}^{+}\delta_i$$

where $\eta_{ijs}^{+}$ captures additional utility increase other than monetary benefits, such as utility obtained from consuming extra produce.

### *2.3.3 Value Function*

Following Tversky and Kahneman (1992) and other empirical studies (Tanaka, Camerer, and Nguyen 2010; Jindal 2015), the value function is constructed by a two-part power functional form given by

$$v\left(y_{ijs}^{k}\right) = \begin{cases} \left(y_{ijs}^{k}\right)^{\alpha_i}; & y_{ijs}^{k} \geq 0 \\ -\lambda_i\left(-y_{ijs}^{k}\right)^{\alpha_i}; & y_{ijs}^{k} < 0 \end{cases}$$

In this functional form, $k$ is the utility index $k \in \{\pm, -, +\}$, $\alpha_i > 0$ represents the concavity of utility curvature[4] for gains, and $\lambda_i > 0$ measures the degree of loss aversion. If the subject is more sensitive to loss than to gain then $\lambda_i > 1$. Otherwise $0 < \lambda_i < 1$.

[4] In EU theory, under the same functional form, $\alpha_i$ controls the level of risk preference, $\alpha_i < 1$ stand for risk averse, $\alpha_i = 1$ is risk neutral, and $\alpha_i > 1$ indicates risk seeking. However, under CPT specification, $\alpha_i$ only reflects the curvature of the value function, because risk preference is determined by a joint effect of risk curvature, loss aversion, and probability weighting.

The power parameters for loss and gain are assumed to be identical ($\alpha_i$), meaning the curvature for gain and loss are symmetric around the reference point. This is in line with the most empirical studies using CPT (e.g., Abdellaoui, Bleichrodt, and l'Haridon 2008; Tanaka, Camerer, and Nguyen 2010), and Wakker (2010) further proved that to accurately estimate loss aversion for power utility function form, the power for gain and loss must be the same.

### *2.3.4 Cumulative Prospect Theory Utility*

To estimate CPT utility, we first define the probability weighting function. In EUT, the utility of an uncertain prospect is the sum of outcome utility weighted by probability (Tversky and Kahneman 1992), but in CPT, the utility of each outcome should be multiplied by a decision weight instead of the actual probability. Previous studies (e.g., Tversky and Kahneman 1992; Wu and Gonzalez 1996; Prelec 1998; Gonzalez and Wu 1999; Abdellaoui, Bleichrodt, and l'Haridon 2008) have shown the probability weighting function $\omega(\cdot)$ should exhibit inverse S-shaped curvature (from concave to convex), small probabilities are overweighted ($\omega(p_{small}) > p_{small}$) and moderate and high probabilities are underweighted ($\omega(p_{moderate/high}) > p_{moderate/high}$). Additionally, the probability weighting function must be strictly increasing, and $\omega(0) = 0$ and $\omega(1) = 1$. With the S-shaped value function $v(\cdot)$ and inverse S-shaped probability weighting function $\omega(\cdot)$, the combined utility function could satisfy the fourfold pattern risk preference in CPT: risk aversion for loss of small probabilities and gain of large probabilities and risk seeking for loss of large probabilities and gain of small probabilities.

Following Tversky and Kahneman (1992), Camerer and Ho (1994), and Wu and Gonzalez (1996), we adopt a single parameter form for the probability weighting function as[5]

$$w_i(\pi_{js}) = \frac{\pi_{js}^{\mu_i}}{\left(\pi_{js}^{\mu_i} + (1-\pi_{js})^{\mu_i}\right)^{\frac{1}{\mu_i}}}$$

where $\pi_{js}$ is the probability of loss/gain for option $j$ in scenario $s$, and $\mu_i$ is the individual-specific weighting parameter to be estimated.

Jointly using the specifications of utility index $y_{ijs}^{c}$, value function $v(\cdot)$, and probability weighting function $\omega(\cdot)$, we can define the CPT utility. In the case of possible loss, we set the value of certain loss to be $v(y_{ijs}|loss) = v(y_{ijs}^{\pm}) - v(y_{ijs}^{-})$, indicating the final value equals to the deterministic consumption utility minus utility deduction due to loss. Thus, the CPT utility that consumer $i$ gets from purchasing CSA option $j$ in scenario $s$ under possible loss is

$$\begin{aligned}
PU_{ijs}^{-} &= w_i^{-}(\pi_{js})v(y_{ijs}|loss) + [1 - w_i^{-}(\pi_{js})]v(y_{ijs}^{\pm}) + \epsilon_{ijs}^{-} \\
&= w_i^{-}(\pi_{js})[v(y_{ijs}^{\pm}) - v(y_{ijs}^{-})] + [1 - w_i^{-}(\pi_{js})]v(y_{ijs}^{\pm}) + \epsilon_{ijs}^{-} \\
&= w_i^{-}(\pi_{js})v(y_{ijs}^{\pm}) - w_i^{-}(\pi_{js})v(y_{ijs}^{-}) + v(y_{ijs}^{\pm}) - w_i^{-}(\pi_{js})v(y_{ijs}^{\pm}) + \epsilon_{ijs}^{-} \\
&= v(y_{ijs}^{\pm}) - w_i^{-}(\pi_{js})v(y_{ijs}^{-}) + \epsilon_{ijs}^{-} \\
&= v_{i,-}^{*}(\boldsymbol{x}_{js}, p_{js}^{-}, \pi_{js}) + \epsilon_{ijs}^{-}
\end{aligned}$$

[5] Another probability weighting function that is widely adopted is proposed by Prelec (1998) is $w_i(\pi_{js}) = \exp[-(-\ln\pi_{js})^{\mu_i}]$. However, studies have shown no significant difference of risk parameter estimates using both forms of weighting function (Gonzalez and Wu 1999; Jindal 2015). Similar results have also been found in our study.

Similarly, define $v(y_{ijs}|gain) = v(y_{ijs}^{\pm}) + v(y_{ijs}^{+})$, then in the circumstance of possible gain, the CPT utility $PU_{ijs}^{+}$ can be derived as

$$\begin{aligned} PU_{ijs}^{+} &= w_i^{+}(\pi_{js})v(y_{ijs}|gain) + [1 - w_i^{+}(\pi_{js})]v(y_{ijs}^{\pm}) + \epsilon_{ijs}^{+} \\ &= v(y_{ijs}^{\pm}) + w_i^{+}(\pi_{js})v(y_{ijs}^{+}) + \epsilon_{ijs}^{+} \\ &= v_{i,+}^{*}(\boldsymbol{x}_{js}, p_{js}^{+}, \pi_{js}) + \epsilon_{ijs}^{+} \end{aligned}$$

where $w_i(\pi_{js})$ is the weighted probability consumer $i$ gets from purchasing CSA option $j$ in scenario $s$, and $\epsilon_{ijs}$ is the random utility error. If the respondent chooses to opt-out, then his or her CPT utility $PU_{ijs}^{0}$ equals $\epsilon_{ijs}^{0}$. With this model specification we can easily test the model's goodness of fit by estimating loss aversion-only (set risk curvature equals to 1), risk only (set loss aversion equals to 1) and probability weighting-free models and compare them to the full CPT model and EUT model.

### *2.3.5 Estimation*

Recall the model framework outlined in section 5.1, assume the random utility error $\epsilon_{ijs}$ to be type I extreme value distributed, consumer $i$ chooses CSA option $j$ in scenario $s$ if and only if

$$v_{i,+/-}^{*}(\boldsymbol{x}_{js}, p_{js}^{+/-}, \pi_{js}) + \epsilon_{ijs}^{+/-} \geq v_{i,+/-}^{*}\left(\boldsymbol{x}_{j's}, p_{j's}^{+/-}, \pi_{j's}\right) + \epsilon_{ij's}^{+/-}$$

where $j, j' \in J$, and $j \neq j'$. Implementing multinomial logit model, the CCP that consumer $i$ chooses option $j$ in scenario $s$ is characterized as

$$\Pr\left\{D_{ijs}^{+/-} = 1\right\} = \frac{\exp\left(v_{i,+/-}^{*}(\boldsymbol{x}_{js}, p_{js}^{+/-}, \pi_{js})\right)}{1 + \sum_{j' \in J} \exp\left(v_{i,+/-}^{*}\left(\boldsymbol{x}_{j's}, p_{j's}^{+/-}, \pi_{j's}\right)\right)}$$

and $D_{ijs}^{+/-} = 1$ when option $j$ in scenario $s$ is chosen by consumer $i$.

During identification, risk curvature and probability weighting parameter are exponentially transformed ($\alpha_i = \exp(\sigma_i)$ and $\mu_i = \exp(\rho_i)$) to ensure monotonically increasing. To estimate individual preference parameters $\boldsymbol{\theta}_i = (d_{ijs}, \beta_i, \gamma_i, \delta_i, \sigma_i, \rho_i, \rho_i)$, we implement a hybrid Markov Chain Monte Carlo (MCMC) algorithm with normal heterogeneity distribution $\theta_i \sim N(\Delta' z_i, V_\theta)$, where the mean of the random effects distribution is dependent on the values of the demographic variables, $z_i$, and the estimated matrix of coefficients, $\Delta$. Set the priors distribution as

$$\text{vec}(\Delta | V_\theta) \sim N(\text{vec}(\bar{\Delta}), A^{-1} \otimes V_\theta)$$

The prior on the covariance matrix is

$$V_\theta \sim \text{IW}(v, V_0)$$

where the second-stage priors are set to be diffuse, and the Wishart is set to have expectation I with very small degrees of freedom such that $v = \dim(\theta_i) + 3$. Thus, estimates of $\boldsymbol{\theta}_i$ can be obtained by MCMC approach with a Random Walk Metropolis-Hastings step[6]. Further details of specification can be found in Rossi, Allenby, and McCulloch (2005), and we modified *bayesm* package (Rossi 2015) in R (R Core Team, 2016) to conduct our analysis.

## 2.4 Data

The nation-wide online survey was distributed through Qualtrics™, [7] in January 2017. Qualtrics™ is a professional survey company that has been widely used by researchers. For example, Yue et al. (2015) investigated heterogeneous consumer preference for

[6] For further Bayesian estimation details, please refer to Chapter 5 in Rossi, Allenby, and McCulloch (2005)

[7] The data for this paper was collected using Qualtrics. Copyright© [2017] Qualtrics. Qualtrics and all other Qualtrics product or service names are registered trademarks or trademarks of Qualtrics, Provo, UT, USA. http://www.qualtrics.com

nanofood and genetically-modified food using the Qualtrics™ panel of 1,117 respondents. Saunders et al. (2013) surveyed 3,748 respondents using Qualtrics™ to evaluate consumer preference for food origins. For our study, data from a total number of 470 respondents were collected from 48 different states, generating 11,280 choice responses.

## 2.5 Results

The summary statistics of respondents' socio-demographic characteristics are reported in Table 2-2. The average age of respondents was 52 years old; the average level of the highest education was some college or associate's degree, and average household income ranged from $35,001 to $50,000. Additionally, most of the respondents were married (77%), Caucasian (90%), and female (69%). About 11% of them had kids under 12 years old, and 18% were unemployed. Regarding CSA, 44% of respondents stated that they were familiar with CSA, and 5% had experience of or were subscribing CSA.

### *2.5.1 Initial Analysis using Mixed Logit Model*

Mixed logit model was first adopted to provide a baseline understanding of preferences. Four models were estimated, and the estimation results are summarized in Table 2-3. Each model varies in the combination of dependent variables, model 1 tests CSA attributes and potentially received value (up-front payment plus gain or up-front payment minus loss), model 2 includes CSA attributes, up-front payment and the product of probability and loss/gain, model 3 is similar to model 2 but changes the up-front payment to potential received value, and model 4 modifies model 2 by including the $2^{nd}$ and $3^{rd}$ orders of probabilities. For the ease of comparison, we rescaled the range of possible loss/gain from -150 to 150 to the range of -1 to 1 throughout the analysis, so the price level is also rescaled to the range of 0 to 4 accordingly.

The estimated coefficients of the variables in all four models are statistically significant at 0.1% level. Especially, the intrinsic utility of CSA is the highest among all product attributes, meaning most of the respondents chose one of the CSA options rather than opt-out. Additionally, having a good variety of produce (11-15 varieties compared to 6-10 varieties) and low distance to pick-up place (5 miles compared to 10 miles) are also substantially valued. For up-front payment and possible-received value, significant negative effects are found, meaning consumers are significantly sensitive to the price increase. The estimated coefficients of the interactive terms of probability and gain/loss in model 2 and 3 indicate that consumers strongly prefer a possible increase in the final value of CSA product to the extent that is significantly higher than the decrease in upfront price. This substantial sensitivity to possible loss may indicate a strong loss aversion. Lastly, the coefficients of the higher orders of the probability in model 4 indicate the probability's impact on consumer choice is non-linear, and probability weighting in CPT may remedy such probability distortion.

### *2.5.2 Bayesian Estimation Results for CPT Discrete Choice Model*

The full model contains 33,840 choice observations, with 16,920 for the possible loss model and 16,920 for the possible gain model. One hundred thousand MCMC simulations were performed, and every $20^{th}$ draw was retained for analysis. Appendix figure A-4 and A-5 show the convergence of posterior log-likelihood evaluated at the posterior draws, and the rejection rate indicating the proportion of draws that are rejected by the algorithm, respectively. Those computations are performed for each iteration for each respondent in the Markov chain. It is essential to note that in the Bayesian analysis, the draws converge in distribution to the posterior distribution of the model parameters, in contrast to other

forms of estimations (e.g., maximum likelihood) where convergence is to a point (Rossi, Allenby, and McCulloch 2005). In this case, both convergences of log-likelihood and rejection rate indicate a satisfactory goodness-of-fit for the model. Figure 2-2 shows the density of posterior distribution for taste parameters of the full model. By allowing heterogeneity, each respondent has his/her individual-specific estimates. We provide an example of the posterior distribution for one respondent in appendix figure A-6. According to the figures, the posterior distributions are concentrated with convergent tail bounds.

#### *2.5.2.1 Comparison of Different Models*

Table 2-4 reports the model estimates for the full model with both loss and gain, the loss model, and the gain model, respectively. The reported indexes include the posterior population mean, standard deviation, 5% and 95% credible interval (C.I.).

In the full model estimation results, a significant CSA intrinsic utility is found, meaning that apart from price, variety, and distance, consumers are still generally in favor of purchasing CSA rather than opt-out, and the intrinsic utility is usually obtained from supporting local community, having fresh and healthy food, knowing the source and production practice of the produce, and environmental protection, etc. Comparing product attributes, we found price (unit decrease of $150) to be the most important factor affecting respondents' decisions, followed by a good variety of produce (11-14 varieties compared to 6-10 varieties), and a low distance to the pick-up location (5 miles compared to 10 miles). Similar patterns are also shown in the gain models. For the loss model, the magnitude of the coefficients for CSA intrinsic utility, variety and distance are higher compared to those in the other two models, which is reasonable because product attributes need to generate more value to offset the utility deduction of possible loss due to poor harvest.

For the risk parameters, the population means of risk curvature is estimated to be 0.79, 0.51 and 0.98 for the full model, the loss model, and the gain model, respectively. Those estimates for risk curvature are consistent with the prior empirical estimates of 0.5 – 1.0 (e.g., Tversky and Kahneman 1992; Wu and Gonzalez 1996; Abdellaoui 2000; Donkers et al. 2001, Harrison and Rutström 2008). Further comparing the distribution of population mean for risk curvatures between the three models in Figure 2-3, it is obvious that the average utility curvature for the gain model is closer to linearity ($\alpha = 1$), which is because risk is minimized under the circumstance that only gain would occur. Meanwhile, substantial heterogeneity within risk curvature estimate is observed for the gain model. On the other hand, utility curvature under the loss circumstance is extremely concave around 0.5, and the full model neutralizes both curvature levels. The difference of risk curvatures between loss and gain models demonstrates that people behave more diminishing sensitivity towards possible loss than possible gain.

Figure 2-4 demonstrates the distribution of population mean for loss aversion parameter ($\lambda$) and the 90% credible interval among the three models. Reasonably, loss aversion has its most effect in the loss model (2.31), which is consistent with findings by Tversky and Kahneman (1992) and Bocquého, Jacquet, and Reynaud (2014) where $\lambda$ was reported to be around 2.29. Other studies also identified a wide range of 1.07 to 3.2 for loss aversion (e.g., Andersen et al. 2006; Abdellaoui, Bleichrodt, and Paraschiv 2007; Tu 2005). Such variation is understandable based on the significant heterogeneity for the loss model shown in Figure 2-4. Next, the loss aversion estimate in the gain model indicates a mild loss seeking behavior (0.84). The full model's loss aversion parameter is 1.71, indicating a mild loss aversion when possible loss and gain could both occur.

The probability weighting parameter in the gain model is 0.67, showing inversed S-shaped probability distortion in the circumstance of possible gain. For the full model and the loss model, probability weighting is estimated to be greater than 1, indicating S-shaped weighting functions. While these estimates are in line with Jindal (2015), such functional shape opposes to most of the prior prospect theory studies where the parameter ranges between 0.5 to 1 with inverse S-shaped weighting functions (e.g., Tversky and Kahneman 1992; Booij and van de Kuilen 2009; Tanaka, Camerer, and Nguyen 2010). There are two possible explanations. First, our design of possible gain choice scenarios is identical to the lottery decisions where respondents are comparing and choosing between possible monetary gains. However, when individuals are facing the reserved scenarios of possible loss, instead of overweighing small probabilities, people also reverse probability distortion to underweight small probabilities and overweight medium to large probabilities of loss. Especially in the case of purchasing CSA, consumers may neglect very small probabilities of risk in loss while extremely reluctant to purchase if there is medium or large probability of loss. The second explanation of S-shaped probability weighting in loss model is attributed to the limited flexibility of functional form. Because the adopted functional form has invariant fixed point and inflection point at around 0.4, meaning that the probability weighting function is estimated to be concave up to $\pi \approx 0.40$ and convex beyond this point (Wu and Gonzalez 1996; Prelec 1998). Therefore, as the inflection point for CSA purchase is very likely to be much lower than 40%, we adopted a modified probability weighting function with elevation parameter and identified S-shaped probability weighting in a rescaled loss model (see appendix).

Lastly, the risk intercepts for possible loss and gain are significant with similar magnitude (7.31 and 7.39), meaning that non-monetary utility change upon the occurrence of loss or gain is substantial. The loss intrinsic utility decrease represents the extra cost in time, transportation and grocery consumption to offset loss in CSA subscription, and the gain intrinsic utility increase reflects the value and potential use of bonus produce. For the full model's non-monetary risk intercept, the intercepts of loss and gain models offset each other and result in a slightly negative value (-0.31).

#### *2.5.2.2 Comparison between Different Model Specifications*

We further compare the models' goodness of fit with varied model specifications. Specifically, we compare the full model with loss-free model ($\lambda = 1$), curvature-free model ($\alpha = 1$), weighting-free model ($\mu = 1$), and EUT model ($\lambda = \mu = 1$). The estimation results are reported in Table 2-5, where we use log marginal density[8] and trimmed log marginal density (removing lower and upper 2% outliers) to measure the comparative goodness of fit for each model specification. Both indexes suggest that the full model has the best goodness of fit among all model specifications, and EUT model has the lowest goodness of fit index. The results support that CPT model taking full account of probability weighting, risk curvature, and loss aversion captures consumer purchasing decision under risk and uncertainty in our data is better than EUT model.

For risk parameters, weighting-free model has the lowest goodness of fit, followed by curvature-free model, and loss-free model leads to the smallest decrease in log marginal density. Therefore, comparing the three risk parameters, probability weighting is most

[8] The log marginal density is computed using the Newton-Raftery approximation, please refer to Newton and Raftery (1994) for more details.

influential. Missing probability weighting function causes an increase in risk parameter and a decrease in loss aversion to re-adjust the shape of curvature. Meanwhile, using a linear (curvature-free) value function also discount the estimate of loss aversion, because the degree of risk-averse is controlled by both risk curvature and loss aversion in CPT. However, risk curvature has a greater impact since loss-free model only decrease the goodness of fit by a small amount compared to the full model. Lastly, similar to the mixed logit model analysis, changing the model specification do not affect the relative importance of product attributes.

Although the three risk parameters vary in their impacts on the models' goodness of fit, missing any single risk parameter leads to reduced effects of the other two parameters. Therefore, we conclude that the risk parameters are interrelated and people's risk preferences are jointly determined by probability weighting, risk curvature and loss aversion in CPT.

### *2.5.3 Consumer Socio-demographics' Impact on Risk Preferences*

Socio-demographic variables were mean-centered, so the mean of random effects distribution can be interpreted as the average respondent's part-worths (Rossi, Allenby, and McCulloch 2005). The posterior means and standard deviations of demographic variable effects are summarized in Table 2-6.

Regarding familiarity and experience with CSA, those who indicated being not familiar with CSA generally value CSA, and its product attributes more, they are also more risk averse with steeper risk curvature and stronger loss aversion compared to respondents who had some knowledge about CSA. Compared to participants who had less experience with CSA, those who had the experience of subscribing CSA perceive less intrinsic value while

put higher values on variety and distance, indicating these two attributes are more important for existing CSA purchasers. Meanwhile, they care less about price and possible loss than people who have not purchased CSA.

The consumer group with a stronger preference for purchasing CSAs tend to be older and more educated, white male with higher income and larger household, which is consistent with findings by Lang (2005) and Vassalos, Gao, and Zhang (2016). Meanwhile, increases in age, education and household size also lead to higher sensitivity to price. Interestingly, being married, retired and having kids negatively affect their utilities on purchasing CSA but they are also less price sensitive, possibly because of their unwillingness to change from their status quos and reluctant to accept CSA as a new way of grocery shopping. With respect to people's risk preferences, we find that being retired, white, and male and having children all contribute to decreased loss aversion, while participants are more loss averse if they are older, female, married or having a larger family. Lastly, CSA non-monetary utility would decrease if the final perceived value becomes lower than the up-front payment value, unless the respondent had subscribed CSA before or had higher income level.

### *2.5.4 Market Sensitivity Analysis*

Given the results from both CPT and EUT estimations, we conduct a market sensitivity analysis with the variation of both CSA price and possible gain/loss. Assuming a representative 20-week CSA operation that offers a good level of product variety and 5 miles distance to pick-up location, along with a fixed percentage of 20% for the occurrence of possible loss/gain, we calculate the market share as the percentage of the sample population who are willing to purchase CSA under certain combination levels of price and

gain/loss value. Figure 2-5 shows the three-dimensional surface plots of market share sensitivity comparison between CPT and EUT frameworks, the price of CSA subscription service ranges from $300 to $750, and gain/loss value is set to be in a reasonable range of -$150 and $150.

There are four graphs showing different angles of the market share three-dimensional surface in Figure 2-5. Graph 1 and 2 present the incremental angle and decremental angle of price and gain/loss, respectively. Starting from the combination of low price ($300) and large possible loss (-$150), the market share under EUT framework is estimated to be around 75%, significantly higher than the market share of 41% under CPT framework. It is majorly due to the disutility of possible loss generated from people's loss aversion and probability weighting. The discrepancy of market share between EUT and CPT gradually diminishes with the increase in both CSA price and possible value change in received product, and becomes indifferent at the surface area where price reaches higher than $700 and no possible loss could occur, then the market shares under CPT shifts higher than those under EUT framework. This reduced market share discrepancy can be majorly explained by the stronger price effect and lower possible gain/loss effect for EUT model compared to the full model. Specifically, from the price angle in Graph 3, it is obvious that conditional on a fixed gain/loss value, market share under EUT significantly and increasingly reduced by about 25% when the CSA price increases from $300 to $750, while the change of market share was around 4% for CPT model. Galt (2013) explained consumers' insensitivity towards CSA price from the perspective of the original CSA concept, as consumers prioritize the added value of CSA (e.g., well-being of farmers) over their own economic interest, and price is not the consumers' sole consideration. From the perspective of

possible gain/loss exhibited in Graph 4, market share under CPT becomes more sensitive. For example, from a $150 loss to a $150 bonus produce in the final received product, EUT model slightly increased the market share from 47% to 52% under a fixed price of $750, but CPT model predicts a significant increase in market share from 37% to 58%, where it surpasses the level of EUT market share at around $5 in loss. Meanwhile, with the loss aversion effect, we also observe that the marginal rate of increase in market share is relatively higher in the loss domain than that in the gain domain.

## 2.6 Discussion and Conclusions

Under the framework of CPT, we investigate consumers' CSA purchasing decisions under risk and uncertainty using DCE method with flexible reference points. We found that when making decisions toward CSA purchase, consumers tend to be risk seeking for low probability of bonus produce and high probability of loss in produce, risk averse for low probability of loss and high probability of gain. Additionally, under the same size of loss and gain, consumers are more sensitive to loss than gain. Therefore, we conclude that risk preferences in CPT, namely reference dependent, loss aversion, diminishing sensitivity and probability weighting significantly affect consumers' decision making-process of CSA purchase.

In response to the reference-dependent preference, CSA suppliers need to be careful when deciding the subscription price. Because consumers would refer the up-front price as a reference of initial wealth output, and weight the final value of products with respect to the reference value to determine if they receive a gain or loss. In the case of good harvest with extra produce, diminishing sensitivity implies that farmers should present the bonus produce to purchasers as much as 30% of the up-front value to achieve the maximized

utility increase[9]. However, if the extra produce is truly substantial, presenting too much bonus to CSA consumers will lead to a diminished utility increase once maximized utility change in gain is reached, so farmers should also consider marketing the extra produce through farmers' markets, food bank or other market outlets. Similarly, in loss situation due to poor harvest (unexpected weather, pest or resource shortage, etc.), farmers should try to make up the small loss for consumers, particularly under the significant loss aversion. But if the loss is substantial, a small offset would not comfort consumers significantly due to diminished sensitivity in loss.

Our results also shed light on the implications on marketing CSA to potential customers. Since this risk information cannot be withheld in CSA marketing, and the risk of loss is a major drawback for CSA participation, operators could counter the negative effect of possible loss by emphasizing if the farm has a good production history with bonus produce, even if there is only a small possibility of getting limited production surplus. Because consumers tend to overweight small probabilities in the gain domain and are mostly risk-averse for bonus produce. Meanwhile, attributes of CSA should be fully explained as consumers strongly prefer an increased variety of fresh produce with a willingness to pay of $6.28/week to improve CSA variety from fair (6-10) to good (11-15)[10], and they are also willing to pay $3.16/week to have a pick-up location in 5 miles instead of 10 miles. Lastly, giving the significant intrinsic preference for CSA, farmers should highlight the associated CSA benefits apart from the weekly fresh produce, those

[9] Using the estimated coefficient of Risk Curvature ($\alpha$), 0.79, utility increase in gain compared to linear utility ($x^{0.79} - x$) achieves to the maximum level at 33% over the reference point.

[10] Willingness to pay value is calculated from the commonly used approach of dividing attribute coefficient by price coefficient, similar application can be sourced from Yue et al. (2015) and Lockshin et al. (2006).

extra benefits include but not limited to supporting local farmers, involving in local communities, and contributing to sustainability and environmental protection, etc. In line with Lang (2008) and Pole and Kumar (2015), our study reaffirmed the socio-demographic background of targeted CSA consumers tend to be older-aged, Caucasian, affluent, and educated.

Further sensitivity analysis suggests that the market share responds differently to the CPT and EUT frameworks. Using the estimation results from EUT model, CSA market share is dominated by the changes in subscription price while relatively insensitive to changes in possible gain/loss. However, controlling all risk parameters under the CPT framework, market share becomes primarily controlled by possible gain/loss instead of CSA price. As CPT better captures consumer risk preference in decision-making than EUT, the sensitivity results of market share reemphasize the importance of risk mitigation for CSA operations. As a result, we conclude that while CSA, as an alternative farming system, transfers production risk partially to its members, but this transferred part of risk, in return, becomes the determinant of CSA market share,  Given the lack of single-crop insurance policy for many vegetables and fruits (Robinson, Marlow, and Madeley 2013), and the large impact of spatial shocks on small and geographically dispersed farms such as CSA (Ligon 2011), operators should carry out essential practices to avoid risk and address uncertainty during the growing season. For example, the high tunnel system could be one of the most effective practices for CSA production as it helps operators to improve plant health and quality, reduce energy use, and extend growing period. USDA has recently acknowledged the benefits of high tunnel practice and promoted the High Tunnel System Initiative to provide producers with financial and technical support (USDA NRCS, 2015).

Additionally, to protect CSA farms with insurance product, the Federal Crop Insurance Act has implemented the Whole Farm Revenue Protection (WFRP) plan in the 2015 crop year, which provides a risk management safety net for all crop on the farm regardless of the crop varieties (USDA 2015). Overall, CSA operators should take advantage of the available risk reduction tools to ensure a loss-free production for risk-sensitive consumers.

The full CPT model fits our data significantly better than the EU model, and we further identify the relative importance of each risk parameter. As one of the first attempts to study consumer preference for non-monetary products under risk and uncertainty, we believe the CPT incorporated DCE method can be applied to a wider range of preference elicitations such as insurance, subscription service, vacation destination and environmental policy.

Table 2-1. Designed Characteristic Levels in Choice Experiment

| Characteristics | Explanation | Levels |
|---|---|---|
| Up-front Payment | Total price for a 20-week representative CSA subscription | 1. $400<br>2. $500<br>3. $600 |
| Number of Product Varieties | Number of average product varieties received in each subscription | 1. Fair, 6-10 varieties<br>2. Good, 11-15 Varieties |
| Distance to Pick-up Location | Distance to the nearest CSA pick-up location from your work place or home | 1. 5 miles<br>2. 10 miles |
| V1: Chance of Loss due to Poor Harvest | Probability (in percentage) that you will receive produce at a value less than what you have paid for due to uncontrolled factors | 0% to 80% with 5% interval |
| V2: Chance of Getting Bonus Produce due to Good Harvest | Probability (in percentage) that you will get bonus produce at the value that is higher than what you have paid for due to good harvest | 0% to 80% with 5% interval |
| V1: Value of Loss due to Poor Harvest | If poor harvest occurs, how much monetary value will be lost from the total up-front payment | 1. -$50<br>2. -$100<br>3. -$150 |
| V2: Value of Bonus Produce due to Good Harvest | In case of good harvest, how much monetary value will be gained additional to the up-front payment | 1. $50<br>2. $100<br>3. $150 |

V1, V2 indicate version 1 and version 2 of the surveys. Version 1 tests the circumstance of possible loss, and version 2 tests the circumstance of possible loss

Table 2-2. Statistical Summary of Socio-Demographics (N=470)

| Demographic Characteristic | Explanation | Mean (SD) or Percentage (%) |
|---|---|---|
| Age | Age of Respondents<br>1. Younger than 30<br>2. 31 to 40 years old<br>3. 41 to 50 years old<br>4. 51 to 60 years old<br>5. 61 to 70 years old<br>6. Older than 70 | 4.19 (1.42) |
| Education | Highest level of education completed:<br>1. Some high school or less<br>2. High school diploma/GED<br>3. Some college<br>4. Associate's degree<br>5. College diploma<br>6. Some graduate school<br>7. Graduate/professionals degree | 3.74 (1.64) |
| Income | Total family income earned in previous year:<br>1. $15,000 or under<br>2. $15,001 - $25,000<br>3. $25,001 - $35,000<br>4. $35,001 - $50,000<br>5. $50,001 - $65,000<br>6. $65,001 - $80,000<br>7. $80,001 - $100,000<br>8. $100,001 - $150,000<br>9. Over $150,000 | 4.04 (2.18) |
| Household Size | Number of people live in household | 2.26 (1.19) |
| Male | Percentage of male respondents | 31% |
| Married | Percentage of married respondent | 77% |
| Kid | Percentage of having kid under 12 years old | 11% |
| White | Percentage of race identified as white | 90% |
| Unemployed | Percentage of unemployed respondents | 18% |
| CSA Member | Percentage of respondents who subscripted to CSA previously | 5% |
| Not Familiar | Percentage of respondent who indicated themselves to be not familiar with CSA | 56% |
| Total Duration | Average time to complete the survey (in seconds) | 987 (778) |

Table 2-3. Estimation Results from Mixed Logit Analysis

| Variables | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| CSA | 1.38*** | 2.50*** | 3.36*** | 2.89*** |
| | (0.07) | (0.11) | (0.09) | (0.11) |
| Good Variety | 0.41*** | 0.60*** | 0.77*** | 0.65*** |
| | (0.05) | (0.05) | (0.05) | (0.05) |
| Low Distance | 0.11*** | 0.28*** | 0.45*** | 0.38*** |
| | (0.04) | (0.04) | (0.04) | (0.05) |
| Price | | -0.58*** | | -0.71*** |
| | | (0.03) | | (0.04) |
| Price + Gain or Price - Loss | -0.25*** | | -0.88*** | |
| | (0.02) | | (0.03) | |
| $\pi * p^{+/-}$ | | 3.31*** | 5.23*** | -6.70*** |
| | | (0.15) | (0.17) | (0.43) |
| $\pi^2 * p^{+/-}$ | | | | 28.72*** |
| | | | | (1.57) |
| $\pi^3 * p^{+/-}$ | | | | -16.26*** |
| | | | | (0.32) |
| Log Likelihood | -11490 | -10935 | -10599 | -10335 |
| $\chi^2$-test | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 33840 | 33840 | 33840 | 33840 |

Note: A single asterisk (*), double asterisks (**), and triple asterisks (***) denote significance at 5%, 1%, and 0.1% levels, respectively.

Table 2-4. Model Estimates for Full Model, Loss Model and Gain Model

| **Variable** | **Pop. Mean** | **Pop. SD** | **5% C.I.** | **95% C.I.** |
|---|---|---|---|---|
| | | *Full Model* | | |
| CSA Intrinsic ($c$) | 8.69 | 0.48 | 7.98 | 9.56 |
| Price ($\delta$) | 1.85 | 0.10 | 1.70 | 2.02 |
| Variety ($\beta$) | 1.55 | 0.09 | 1.41 | 1.70 |
| Distance ($\gamma$) | 0.78 | 0.08 | 0.65 | 0.89 |
| Probability Weight ($\mu$) | 1.22 | 0.05 | 1.13 | 1.31 |
| Risk Curvature ($\alpha$) | 0.79 | 0.03 | 0.74 | 0.84 |
| Loss Aversion ($\lambda$) | 1.71 | 0.14 | 1.52 | 1.94 |
| Risk Intercept ($\eta$) | -0.31 | 0.24 | -0.69 | 0.07 |
| Observations | 33,840 | | | |
| Log Marginal Density | -6749.00 | | | |
| Trimmed Log M.D. | -6705.56 | | | |
| | | *Possible Loss Model* | | |
| CSA Intrinsic ($c$) | 12.89 | 0.50 | 12.17 | 13.80 |
| Price ($\delta$) | 1.98 | 0.16 | 1.68 | 2.22 |
| Variety ($\beta$) | 2.81 | 0.30 | 2.29 | 3.30 |
| Distance ($\gamma$) | 1.34 | 0.20 | 1.03 | 1.73 |
| Probability Weight ($\mu$) | 1.34 | 0.09 | 1.19 | 1.49 |
| Risk Curvature ($\alpha$) | 0.51 | 0.03 | 0.47 | 0.56 |
| Loss Aversion ($\lambda$) | 2.29 | 0.10 | 2.15 | 2.48 |
| Risk Intercept ($\eta$) | 7.31 | 0.29 | 6.80 | 7.79 |
| Observations | 16,920 | | | |
| Log Marginal Density | -3637.13 | | | |
| Trimmed Log M.D. | -3587.67 | | | |
| | | *Possible Gain Model* | | |
| CSA Intrinsic ($c$) | 6.56 | 0.56 | 5.73 | 7.62 |
| Price ($\delta$) | 2.06 | 0.16 | 1.82 | 2.34 |
| Variety ($\beta$) | 1.45 | 0.09 | 1.31 | 1.62 |
| Distance ($\gamma$) | 0.50 | 0.10 | 0.35 | 0.66 |
| Probability Weight ($\mu$) | 0.67 | 0.06 | 0.59 | 0.78 |
| Risk Curvature ($\alpha$) | 0.98 | 0.06 | 0.88 | 1.07 |
| Loss Aversion ($\lambda$) | 0.84 | 0.14 | 0.63 | 1.12 |
| Risk Intercept ($\eta$) | 7.39 | 0.67 | 6.18 | 8.57 |
| Observations | 16,920 | | | |
| Log Marginal Density | -3323.16 | | | |
| Trimmed Log M.D. | -3270.26 | | | |

Note: This table reports the heterogeneous estimation results for product attributes and risk parameters under different circumstances. The reported statistics including population mean, population standard deviation, and the 95% credibility interval, log marginal density, and trimmed log marginal density.

Table 2-5. Comparison of Model Estimates for Full Model, Loss-free Model, Curvature-free Model, Weighting-free model, and Expected Utility Model (N=33,840)

| **Variable** | **Pop. Mean** | **Pop. SD** | **5% C.R.** | **95% C.R.** |
|---|---|---|---|---|
| | | *Full Model* | | |
| CSA Intrinsic ($c$) | 8.69 | 0.48 | 7.98 | 9.56 |
| Price ($\delta$) | 1.85 | 0.10 | 1.70 | 2.02 |
| Variety ($\beta$) | 1.55 | 0.09 | 1.41 | 1.70 |
| Distance ($\gamma$) | 0.78 | 0.08 | 0.65 | 0.89 |
| Probability Weight ($\mu$) | 1.22 | 0.05 | 1.13 | 1.31 |
| Risk Curvature ($\alpha$) | 0.79 | 0.03 | 0.74 | 0.84 |
| Loss Aversion ($\lambda$) | 1.71 | 0.14 | 1.52 | 1.94 |
| Risk Intercept ($\eta$) | -0.31 | 0.24 | -0.69 | 0.07 |
| Log Marginal Density | -6749.00 | | | |
| Trimmed Log M.D. | -6705.56 | | | |
| | | *Loss-free Model* | | |
| CSA Intrinsic ($c$) | 6.50 | 0.46 | 5.84 | 7.40 |
| Price ($\delta$) | 1.34 | 0.11 | 1.19 | 1.56 |
| Variety ($\beta$) | 1.17 | 0.09 | 1.04 | 1.33 |
| Distance ($\gamma$) | 0.56 | 0.07 | 0.44 | 0.68 |
| Probability Weight ($\mu$) | 1.09 | 0.05 | 1.01 | 1.18 |
| Risk Curvature ($\alpha$) | 0.89 | 0.04 | 0.83 | 0.95 |
| Risk Intercept ($\eta$) | -1.59 | 0.28 | -2.06 | -1.17 |
| Log Marginal Density | -6841.33 | | | |
| Trimmed Log M.D. | -6757.64 | | | |
| | | *Curvature-free Model* | | |
| CSA Intrinsic ($c$) | 5.82 | 0.29 | 5.37 | 6.24 |
| Price ($\delta$) | 1.34 | 0.10 | 1.20 | 1.53 |
| Variety ($\beta$) | 1.15 | 0.07 | 1.04 | 1.29 |
| Distance ($\gamma$) | 0.58 | 0.07 | 0.48 | 0.69 |
| Probability Weight ($\mu$) | 1.19 | 0.07 | 1.08 | 1.31 |
| Loss Aversion ($\lambda$) | 1.11 | 0.07 | 1.01 | 1.23 |
| Risk Intercept ($\eta$) | -0.92 | 0.25 | -1.36 | -0.54 |
| Log Marginal Density | -7034.89 | | | |
| Trimmed Log M.D. | -6951.65 | | | |
| | | *Weighting-free Model* | | |
| CSA Intrinsic ($c$) | 5.86 | 0.25 | 5.47 | 6.31 |
| Price ($\delta$) | 1.27 | 0.09 | 1.13 | 1.44 |
| Variety ($\beta$) | 1.10 | 0.06 | 1.01 | 1.21 |
| Distance ($\gamma$) | 0.56 | 0.07 | 0.45 | 0.68 |
| Risk Curvature ($\alpha$) | 0.93 | 0.29 | 0.42 | 1.41 |

| | | | | |
|---|---|---|---|---|
| Loss Aversion ($\lambda$) | 1.10 | 0.07 | 0.98 | 1.22 |
| Risk Intercept ($\eta$) | -1.61 | 0.61 | -2.82 | -0.79 |
| Log Marginal Density | -7130.05 | | | |
| Trimmed Log M.D. | -7023.12 | | | |
| | *Expected Utility Model* | | | |
| CSA Intrinsic ($c$) | 5.50 | 0.17 | 5.22 | 5.77 |
| Price ($\delta$) | 1.10 | 0.05 | 1.01 | 1.18 |
| Variety ($\beta$) | 0.96 | 0.04 | 0.89 | 1.02 |
| Distance ($\gamma$) | 0.46 | 0.04 | 0.39 | 0.53 |
| Risk Curvature ($\alpha$) | 0.62 | 0.26 | 0.27 | 1.22 |
| Risk Intercept ($\eta$) | -1.48 | 0.11 | -1.67 | -1.30 |
| Log Marginal Density | -7181.40 | | | |
| Trimmed Log M.D. | -7130.53 | | | |

*Note*: This table reports the heterogeneous estimation results for product attributes and risk parameters under different model specification. The reported statistics including population mean, population standard deviation, and the 95% credibility interval. In-sample goodness of fit is measured by the log marginal density calculated using the sampling method of Newton and Raftery.

Table 2-6. Posterior Mean and Standard Deviation of Socio-demographic Effect

| Demographics | $c$ | $\delta$ | $\beta$ | $\gamma$ | $\ln(\mu)$ | $\ln(\alpha)$ | $\lambda$ | $\eta$ |
|---|---|---|---|---|---|---|---|---|
| Intercept | 8.68 | 1.85 | 1.55 | 0.78 | 0.20 | -0.24 | 1.71 | -0.31 |
| | (0.49) | (0.11) | (0.09) | (0.08) | (0.05) | (0.04) | (0.14) | (0.31) |
| Not Familiar | 1.04 | 0.25 | 0.34 | 0.14 | -0.13 | -0.06 | 0.11 | -0.21 |
| | (0.67) | (0.19) | (0.16) | (0.18) | (0.08) | (0.06) | (0.14) | (0.53) |
| Subscribed | -0.79 | -0.61 | 0.45 | 0.20 | 0.02 | 0.09 | -0.36 | 0.10 |
| | (1.75) | (0.41) | (0.39) | (0.31) | (0.23) | (0.14) | (0.40) | (1.34) |
| Age | 0.89 | 0.22 | 0.15 | 0.10 | 0.06 | 0.01 | 0.09 | -0.13 |
| | (0.34) | (0.09) | (0.08) | (0.08) | (0.04) | (0.03) | (0.08) | (0.26) |
| Male | 0.38 | -0.01 | -0.02 | 0.02 | 0.07 | -0.08 | -0.15 | -0.77 |
| | (0.70) | (0.20) | (0.17) | (0.15) | (0.09) | (0.07) | (0.22) | (0.63) |
| Education | 0.10 | 0.07 | 0.07 | 0.07 | 0.03 | -0.02 | 0.01 | -0.12 |
| | (0.21) | (0.05) | (0.05) | (0.04) | (0.03) | (0.02) | (0.07) | (0.20) |
| Married | -1.32 | -0.38 | -0.23 | -0.14 | 0.13 | 0.00 | 0.13 | -0.35 |
| | (0.99) | (0.25) | (0.22) | (0.19) | (0.10) | (0.08) | (0.26) | (0.73) |
| Kid | -1.55 | -0.51 | -0.02 | -0.18 | -0.46 | 0.17 | -0.32 | -0.27 |
| | (1.46) | (0.35) | (0.36) | (0.27) | (0.18) | (0.13) | (0.43) | (1.21) |
| Household Size | 0.46 | 0.05 | 0.09 | 0.03 | 0.06 | 0.00 | 0.03 | -0.28 |
| | (0.42) | (0.10) | (0.09) | (0.08) | (0.05) | (0.03) | (0.10) | (0.29) |
| White | 0.42 | 0.47 | 0.18 | 0.25 | 0.00 | 0.16 | -0.81 | -1.46 |
| | (1.34) | (0.34) | (0.29) | (0.28) | (0.14) | (0.11) | (0.38) | (0.91) |
| Income | 0.10 | -0.02 | 0.00 | -0.01 | -0.04 | 0.00 | 0.04 | 0.15 |
| | (0.21) | (0.05) | (0.05) | (0.04) | (0.02) | (0.02) | (0.04) | (0.13) |
| Retired | -1.06 | -0.18 | 0.07 | -0.13 | 0.04 | 0.03 | -0.31 | -0.02 |
| | (0.84) | (0.23) | (0.23) | (0.16) | (0.10) | (0.08) | (0.22) | (0.64) |

Note: This table summarizes the posterior means and standard deviations of demographic variable effect, socio-demographic variables were mean-centered before the analysis, so the mean of random effects distribution can be interpreted as the average respondent's part-worths.

**CSA Loss Scenario**

**Scenario Questions are the major part of the research. This survey only consists a total of 24 choice scenarios and a few background questions. So please compare the options carefully and answer the question to the best of your ability.**

| Attribute | Option A | Option B | Option C |
|---|---|---|---|
| Up-front Payment | $500 | $600 | Neither option A nor B |
| Number of Product Varieties | Good (11-15 varieties) | Fair (6-10 varieties) | |
| Distance to Pick-up Location | 10 miles | 5 miles | |
| Chance of Loss due to Poor Harvest | 25% | 10% | |
| Value of Loss due to Poor Harvest | $50 | $100 | |

**If these were the only options available to you, which option would you choose?**

| I would choose option A | I would choose option B | I would choose option C |
|---|---|---|
| ○ | ○ | ○ |

Figure 2-1. Screenshot of discrete choice scenario example in possible loss circumstance

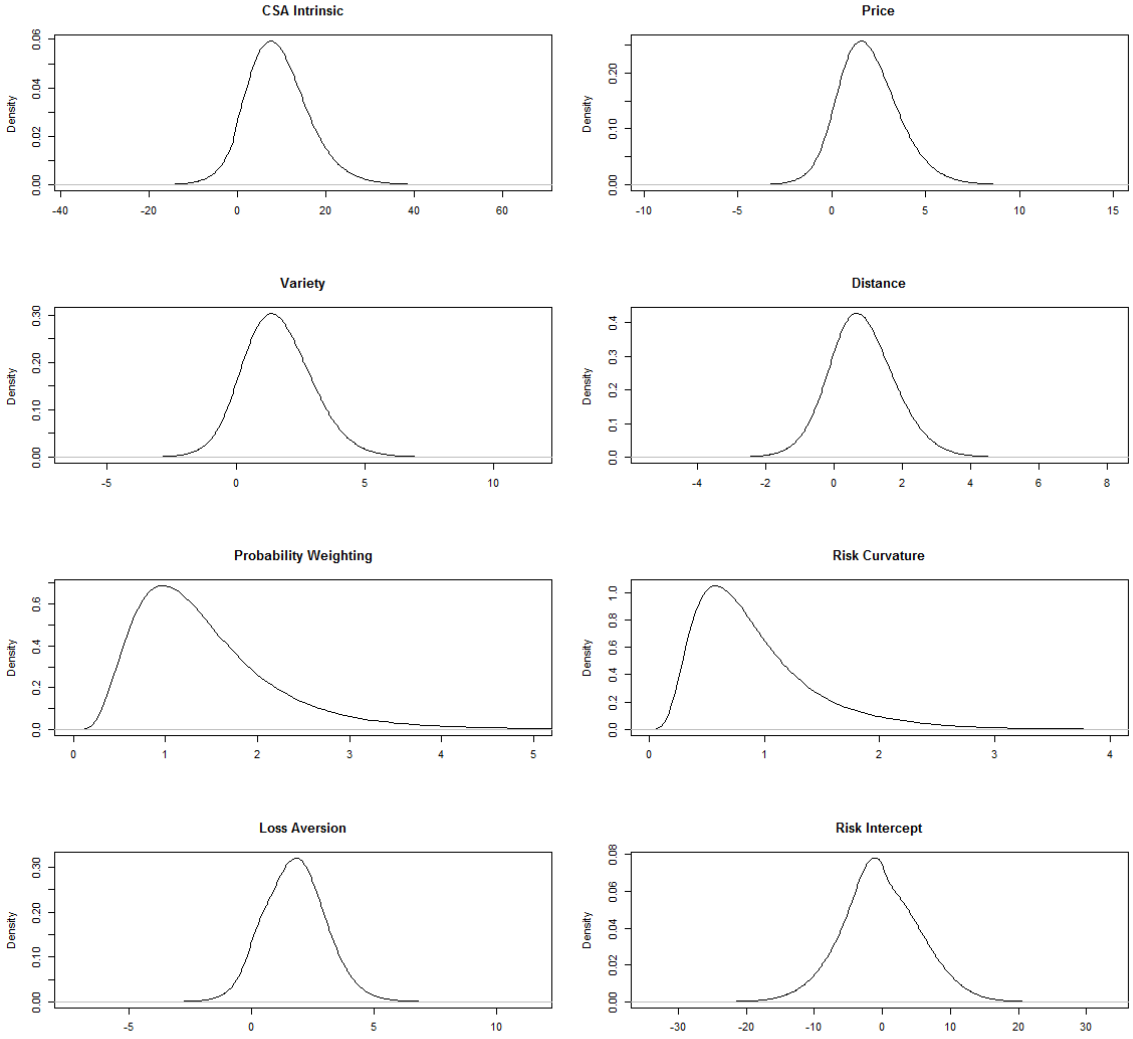


Figure 2-2. Posterior distribution of heterogeneity for full model

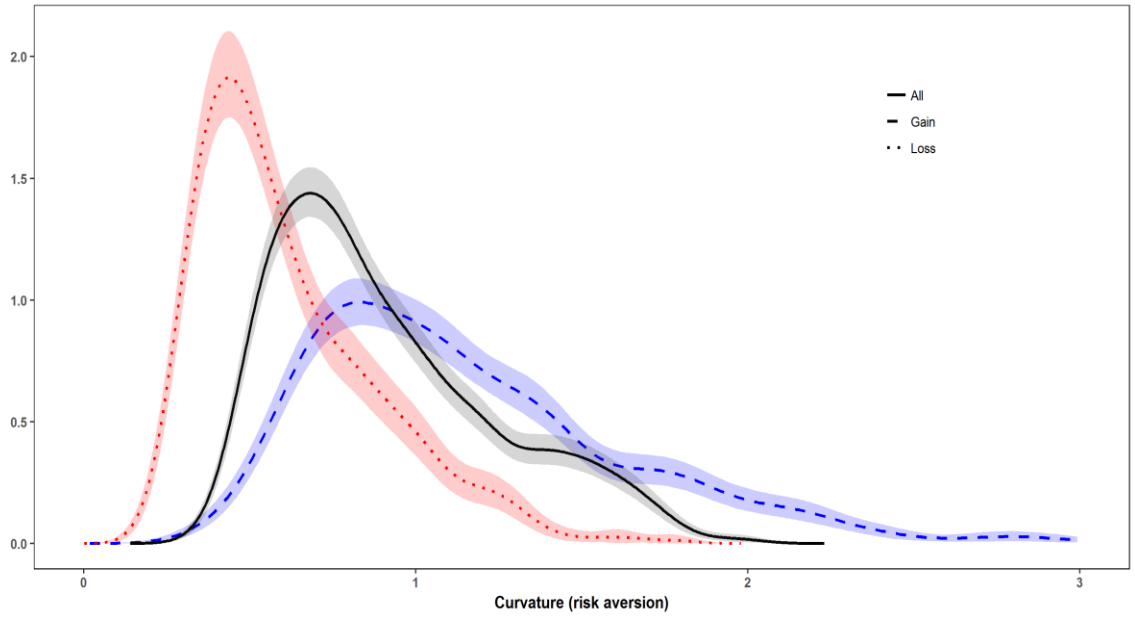


Figure 2-3. Compare heterogeneous population mean and 90% credibility region of risk curvature ($\alpha$) for full model, loss model and gain model

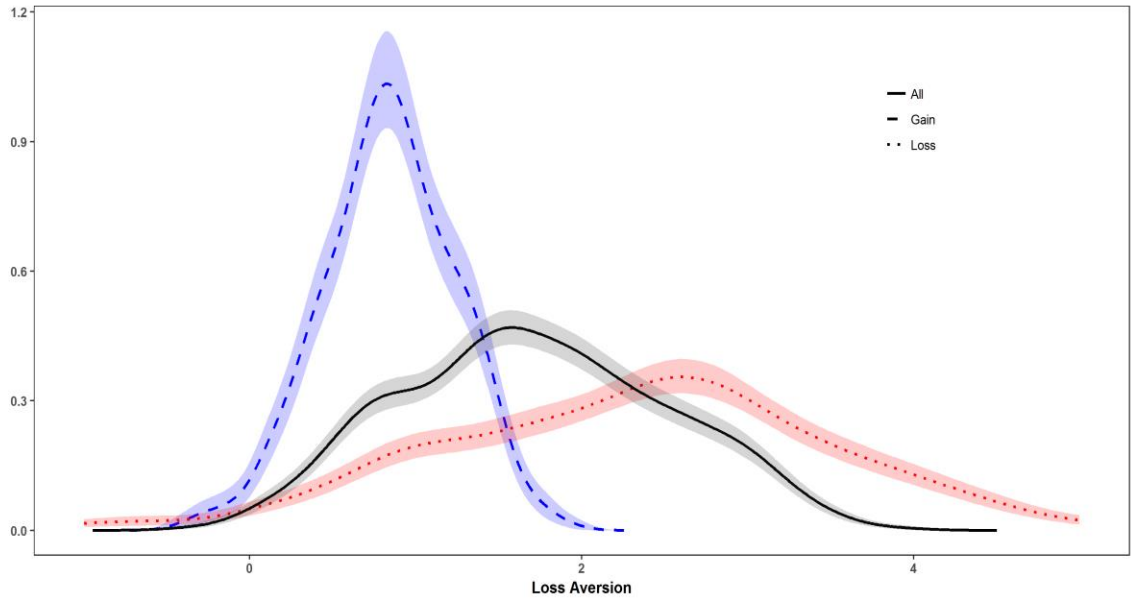


Figure 2-4. Compare heterogeneous population mean and 90% credibility region of loss aversion ($\lambda$) for full model, loss model and gain model

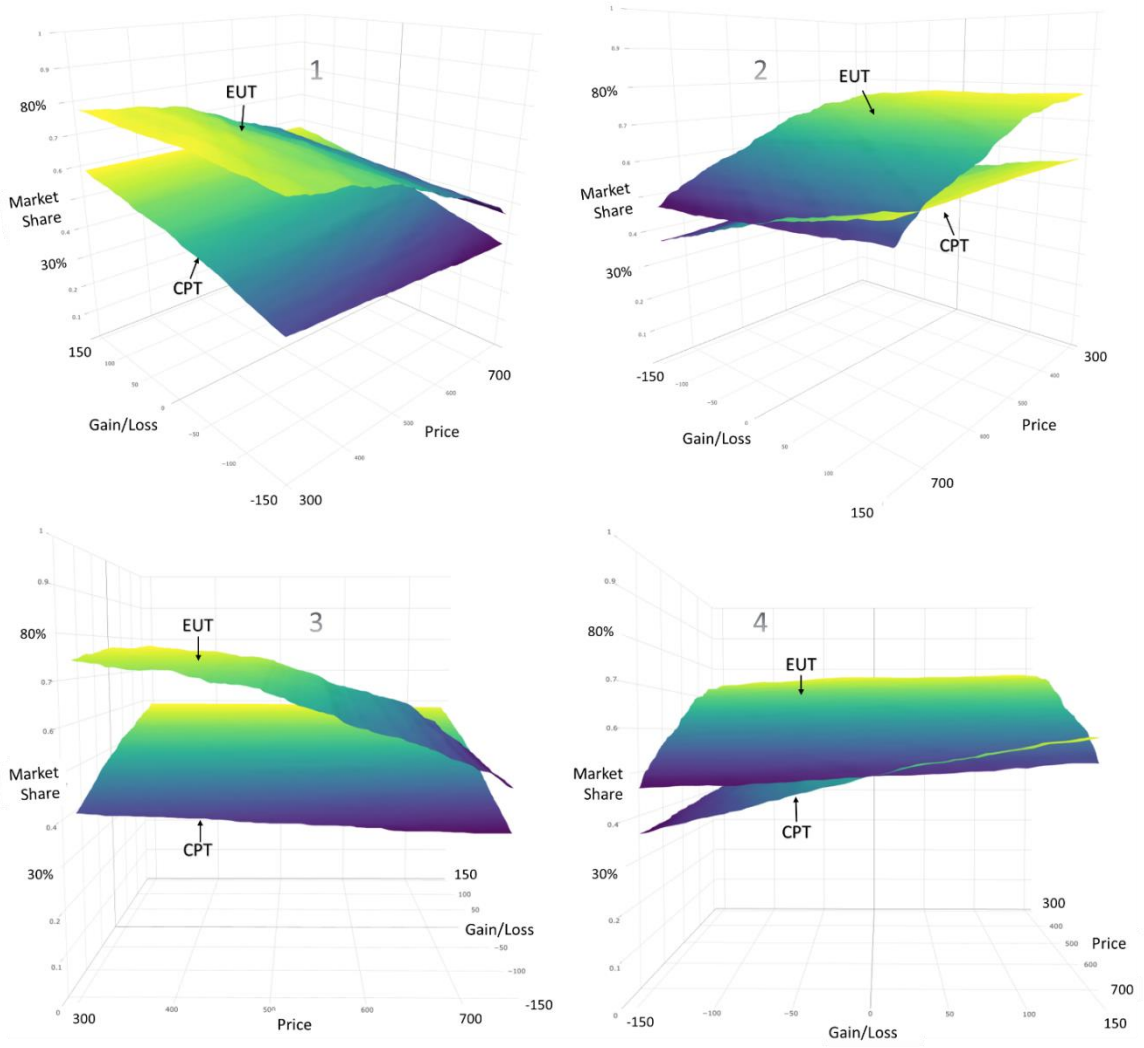


Figure 2-5. Market share sensitivity comparison between EUT model and CPT model in response to changes in CSA price and possible gain/loss. Graph 1 and 2 show the incremental angle and decremental angle of price and gain/loss, respectively, graph 3 indicates the pricing sensitivity effect and graph 4 indicates gain/loss sensitivity effect.

# Chapter 3

# Risk Preference Comparison between Commodity Crop Producers and Specialty Crop Producers

## 3.1 Introduction

Risk and uncertainty influence almost every decision pertaining to agriculture production, such as technology adoption, crop variety, production practice, and insurance choice. Prior agricultural risk elicitations have been mainly studied using the expected utility theory (EUT)[11] (e.g., Lin et al., 1974; Moschini and Hennessy, 2001). However, numerous empirical studies have questioned EUT's accuracy in explaining decisions under risks (e.g., Allais, 1953; Kahneman and Tversky, 1979). To overcome the documented violations of EUT, cumulative prospect theory (CPT) accurately captures the experimental evidence on risk-taking (Barberis, 2013; Tversky and Kahneman, 1992). CPT is modified from the original prospect theory (PT) by Kahneman and Tversky (1979) through adding

[11] EUT was initially developed by Von Heumann and Morgenstern (1947), assumes the decision maker chooses between risky or uncertain prospects by calculating and comparing their expected utility values.

cumulative decision weights. Compared to EUT where utility is measured based on absolute wealth, CPT derives utility relative to a reference point and classifies outcomes as gains and losses, which is known as reference dependence (Tversky and Kahneman, 1992). To evaluate risk preference, CPT also introduces diminishing sensitivity, loss aversion, and probability weighting.

CPT can be a useful alternative theory in explaining some of the producers' agriculture production decisions. First, producers are often not willing to pay a small premium to purchase crop insurance but rather bear the risk of possible large loss. Historically, it has been proved that voluntary crop insurance participation in the United States were low with only 25% of eligible area under coverage before the 1990s, even after 30% subsidy was offered in the Federal Crop Insurance Act of 1980 (Walker et al., 1986; Glauber et al., 2002; Glauber, 2013). The participation of crop insurance did not improve until the Congress started to make insurance compulsory along with significantly increased subsidy level in 1994 (Glauber, 2013). This contradicts the assumptions of EUT, where producers are expected to voluntarily purchase crop insurance without subsidy as long as the premium is smaller than the predicted value of possible large losses. However, such risk behavior can be better explained by CPT, as it assumes decision makers are mostly risk averse for gains but risk seeking for losses. Second, under the influence of loss aversion, producers often demand much more to give up an object (technology, policy, contract) than they would be willing to pay to gain it, which is known as the endowment effect (Thaler, 1980; Kahneman et al., 1991). For example, studies show the endowment effect caused producers' reluctance to employ agri-environmental schemes (Dupraz et al., 2003; Espinosa-Goded et al., 2010; Christensen et al., 2011), sustainable agricultural policy

(Schulz et al., 2014), and payment-for-environmental-services programs (Ma et al., 2012). Meanwhile, Bocquého et al. (2014) found that producers are more sensitive to penalties than to rewards when dealing with production contracts. Lastly, producers use decision weights instead of objective probabilities in making their decisions, which can be influential in coverage-level decisions for crop insurance. While Du et al. (2014) found no empirical support of EUT for risk-averse producers toward actuarially-fair premiums, Babcock (2015) employed CPT to justify producers' insurance decisions, and found that producers tend to overweight low probability outcomes.

Given the theoretical suitability of applying CPT to producer decisions under risk and uncertainty, a few recent studies have used CPT to empirically explore risk preferences among producers. Nguyen and Leung (2009) investigated the risk preferences of fishermen in Vietnam using CPT, they found that fishermen are less risk averse and less sensitive to probability weighting changes compared to individuals of other occupations. Tanaka et al. (2010) interviewed 181 Vietnam farmers, identified statistically significant CPT parameters, found that loss averse and risk averse are negatively affected by wealth. Liu and Huang (2013) adopted a CPT model to explore the effect of risk preferences on pesticide use by cotton producers in China; their results indicate farmers who are more risk averse and less loss sensitive prefer to use greater amount of pesticides. In Europe, Bocquého et al. (2014) assessed risk preferences of 111 French producers using both EUT and CPT, confirmed the concave utility curvature that captured from EUT, and further found significant parameter estimates for loss aversion and probability weighting. More recently, Piet and Bougherara (2016) revisited the unanticipated participation of crop insurance among farmers in France and proved CPT is better suited for explaining their

risk preferences than EUT. Besides producers, many studies have implemented CPT to test people's risk preferences towards money (e.g., Booij and Van de Kuilen, 2009), time (e.g., Abdellaoui and Kemel, 2014), and health (e.g., Bleichrodt and Pinto, 2000). A list of previous CPT studies with risk parameter estimates is summarized in Table 3-1.

Risks faced by producers differ significantly in what kinds of crops they grow. Generally, two major crop types can be classified, commodity crops and specialty crops. Commodity crops are the plants that normally traded at the commodity market instead of direct sales, such as wheat, corn, and soybean. They are often grown in large quantities and are relatively nonperishable and undifferentiated. On the contrary, specialty crops are fruits and vegetables, tree nuts, dried fruits and horticulture and nursery crops, including floriculture (USDA, 2014). Most specialty crops are grown on small to medium-sized farms and are usually consumed or purchased in the direct market. According to USDA NASS (2014), there are approximately 14 million acres of specialty crops in the United States, including 1.4 million acres of nursery, trees, and woody crops.

Specialty crops producers face different risks from commodity crop producers. From production aspects, growing specialty crops requires more intensive management with labor and capital than producing commodity crops (Weisensel and Schoney, 1989), and most specialty crops are susceptible to weather risks such as extreme fluctuations in temperature and precipitation (Fleege et al., 2004; Collier et al., 2008). Since many specialty crops are produced by relatively smaller farms, spatial shocks have a larger impact on both individual producers and aggregated supply than those of commodity crops where the production is geographically dispersed (Ligon, 2011). On the demand side, the perishability of specialty crops leads to less market power for producers, which often

compels producers to accept market prices during the harvest period (Vassalos et al., 2013). Significant yield variation also leads to price volatility, generating financial instability to producers. From policy prospective, until recently, producers who grow primarily specialty crops do not receive substantial benefits from farm safety net programs like commodity crop producers (Mercier, 2016). The lack of single-crop policy leaves many specialty crop farms with little or no insurance coverage (Robinson et al., 2013). In 2014, the crop insurance premium of specialty crops only accounted for just over 8% of total premiums (Paggi, 2016), which reflects lower coverage levels, particularly for floricultural crops. Therefore, specialty crop producers face increased uncertainty compared to commodity crop producers, but the channels for them to mitigate risk are limited. As a result, new insurance products for specialty crops are in great demand, and the Federal Crop Insurance Act has already been working on new risk management tools. For example, in 2015, the Adjusted Gross Revenue (AGR) program was converted to the Whole Farm Revenue Protection (WFRP) plan of insurance to incorporate several improvements for specialty crop farms including higher liability limits and coverage levels, allowances for expanding operations, increased premium subsidy, and the availability of replant payments (USDA, 2015). In 2015 growing season, WFRP had a higher premium subsidy rate and lower loss ratio than all other federal crop insurance programs (Olen and Wu, 2017). In order to develop effective tools, it is imperative to understand the risk preferences of U.S. specialty crop producers and explore how their preferences differ from commodity crop producers. However, to our knowledge, no producer risk preference elicitation study has been conducted in the United States, and none of the previous relevant studies has investigated

the risk preference difference between commodity crop producers and specialty crop producers. In this paper, we aim to fill these knowledge gaps.

## 3.2 Survey Design

We used the experimental design employed by Holt and Laury (2002), Tanaka et al. (2010) and Bocquého et al. (2014) to elicit producers' risk preferences. The questions include three series of lottery choices, each consisting of a succession of binary choices. Series 1 and series 2 contain choices between a safe choice (option A) and an incremental risky choice (option B) with positive payoffs. Series 3 has choices with mixed payoffs (both positive and negative) with equal probabilities for each option. The expected value of option A in series 1 and 2 is consistent and initially greater than the expected value of option B, then the value of option B steadily increases and surpasses the expected value of option A until it is significantly greater than option A in the last choice scenario. In series 3, the expected value of mixed payoffs in option A is also greater than option B at the beginning, then it decreases, while the expected value of option B increases and eventually outweigh that of option A. Therefore, we expect a risk averse individual would choose option A in more scenarios of each series than a risk seeking individual, and risk neutral individuals would probably switch their choice from option A to option B at the choice where the expected values of option A and B become equivalent. All three series of risk elicitation questions are shown in Figure 3-1. To help the respondents fully understand the risk election questions, a lottery choice example is provided in the question instructions, and written explanation regarding the example is also presented.

According to the Figure 3-1, the values of payoffs vary significantly from -$210 to $6000 with the mean expected value of $286.5. We include extremely high payoffs to

ensure the occurrence of the switch from safe choice to risky choice, so that the utility function curvature can be better captured. Additionally, the decisions made by producers are usually associated with a significant variation of monetary outcomes, such as the crop insurance decisions under unpredicted harvest.

Besides the risk elicitation question, we also ask respondents about their production practices, field crops, crop insurance coverage, preferences for insurance, indemnity history, basic farm operation information and their socio-demographics. For data quality purpose, we suggest that the survey should be completed by the farm owner, lessee, or manager with the responsibility of farm-level decisions.

## 3.3 Empirical Method

For lottery choices, the reference point can be straightforwardly defined as the monetary neutral point ($0). Given the choices made from risk elicitation questions and associated payoffs ($y$) of the chosen option, we assume the value function $u(x)$ as a two-part power functional form:

$$u(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -\lambda(-x)^{\alpha} & if\ x < 0 \end{cases}$$

where $\alpha$ measures utility curvature and is often between 0 and 1. Smaller $\alpha$ indicates higher degree of concavity in gains, convexity in losses, and increased diminishing sensitivity. $\lambda$ ($\lambda > 0$) measures the level of loss aversion and captures the asymmetric curvature relative to the reference point. $\lambda > 1$ implies loss aversion and $\lambda < 1$ indicates loss seeking. In most cases, loss averse behaviors are observed (Abdellaoui et al., 2007; Booij and Van de Kuilen, 2009).

Following Tversky and Kahneman (1992), Wu and Gonzalez (1996), Gonzalez and Wu (1999), and Babcock (2015), we specify the probability weighting function $w(p)$ as[12]

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{\frac{1}{\gamma}}}$$

where $p$ is the cumulative probability, and $\gamma$ ($\gamma > 0$) is the probability weighting parameter to be estimated. When $\gamma$ is between 0 and 1, the probability weighting function is inverse S-shaped, $\gamma = 1$ means the nonexistence of probability distortion ($w(p) = p$). Most prior empirical studies have shown individuals tend to overweight small probabilities and underweight large probabilities (e.g. Abdellaoui et al., 2005; Harrison and Rutström, 2008; Camerer and Ho, 1994).

In the risk elicitation experiment, subjects make consecutive choices between lottery options. For choice question $j$, let $(x_1, p;\ x_2)$ denote the binary prospect with outcome $x_1$ of probability $p$ and outcome $x_2$ of probability $1-p$. Integrating the value function and probability weights, the CPT value of each lottery choice $PU(x_1, p;\ x_2)$ can be shown as follows:

$$\mathrm{PU}(x_1, p;\ x_2) = \begin{cases} w(p)\cdot u(x_1) + [1-w(p)]\cdot u(x_2) & \text{if } x_1 \geq x_2 \geq 0\ (Gain\ domain) \\ & \text{or } x_1 \leq x_2 \leq 0\ (Loss\ domain), \\ w(p)\cdot u(x_1) + w(1-p)\cdot u(x_2) & \text{if } x_1 \geq 0 \geq x_2\ (Mixed\ domain) \end{cases}$$

Therefore, assuming utility maximization, the observed choices made by individual $i$ can be explained by $\Delta_i^{\mathrm{PU}}$, the difference between the CPT utility of lottery A and B

$$\Delta_i^{\mathrm{PU}} = \mathrm{PU}_i^{\mathrm{A}} - \mathrm{PU}_i^{\mathrm{B}}$$

[12] The original specifications of both weighting function and value function in Tversky and Kahneman (1992) has separate parameters assigned for loss and gain domain. However, most empirical studies using CPT (e.g. Abdellaoui et al., 2008; Tanaka et al., 2010) have used one-parameter weighting function, and Wakker (2010) further explained that the power estimator for gains and losses must be identical to capture an accurate loss aversion.

Following Bocquého et al. (2014), we set up the choice model based on the random utility theory (Manski and Lerman, 1977). The utility difference is attributed to deterministic preference and unobserved heterogeneous random error. Given individual characteristic(s) $\mathrm{X}_i$, choices $\mathrm{C}_i^*$ can be further specified as

$$\mathrm{C}_i^* = \Delta_i^{\mathrm{PU}}(\mathrm{X}_i) + \varepsilon_i = \theta_0 + \theta \mathrm{X}_i + \varepsilon_i \quad \text{and} \quad \mathrm{C}_i = \begin{cases} \mathrm{A} & \text{if } \mathrm{C}_i^* > 0 \\ \mathrm{B} & \text{otherwise} \end{cases}$$

where $\theta_0$ is constant coefficient and $\theta$ is preference coefficient(s) corresponding to $\mathrm{X}_i$. $\varepsilon_i$ is the random utility error term that assumed to be type I extreme value distributed. As such, given individual specific characteristics, the probability that individual $i$ chooses option A is

$$\Pr(\mathrm{A}|\mathrm{X}_i) = \Pr\left(\Delta_i^{\mathrm{PU}} + \varepsilon_i > 0 | \mathrm{X}_i\right) = 1 - \Pr\left(\varepsilon_i \le -\Delta_i^{\mathrm{PU}} | \mathrm{X}_i\right) = 1 - \Phi\left(-\Delta_i^{\mathrm{PU}}(\mathrm{X}_i)\right)$$

$$= \Phi\left(\Delta_i^{\mathrm{PU}}(\mathrm{X}_i)\right)$$

where $\Phi(\cdot)$ is the function for normal distribution. Using maximum likelihood method, we estimate preference parameters and the risk parameters with the following likelihood model

$$\ln L^{\mathrm{PT}}(\mathrm{C}, \mathrm{X}|\theta_0, \theta, \alpha, \lambda, \gamma)$$

$$= \sum_k \left[\ln \Phi\left(\Delta_k^{\mathrm{PU}}\right) \times I(\mathrm{C}_k = A) + \ln[1 - \Phi\left(\Delta_k^{\mathrm{PU}}\right)] \times I(\mathrm{C}_k = B)\right]$$

where $k$ denotes the chosen choices $j$ integrated over individual $i$, $I$ is the indicator function, and $\mathrm{C}_k$ indicate the choice of lottery options A or B. Then we can get

$$\left(\hat{\theta}_0, \hat{\theta}, \hat{\alpha}, \hat{\lambda}, \hat{\gamma}\right) = \arg\max \ln L^{\mathrm{PT}}(\mathrm{C}, \mathrm{X}|\alpha, \lambda, \gamma)$$

Note that when $\lambda = 1$ and $\gamma = 1$, the CPT model specification can be simplified to EUT model with power utility function

$$u(x) = \begin{cases} x^{\alpha} & if\ x \ge 0 \\ -(-x)^{\alpha} & if\ x < 0 \end{cases}$$

Unlike CPT model where the risk preference is jointly controlled by risk curvature, loss aversion, and probability weighting, the degree of risk aversion in the EUT model is solely determined by $\alpha$ $(\alpha > 0)$. Traditional EUT (Von Neumann and Morgenstern, 1947) describes utility to be universally concave or convex, but recent experimental studies showed EUT utility can be efficiently elicited under gain or loss domains (Tanaka et al., 2010; Bocquého et al.,2014). Therefore, $\alpha < 1$ indicates risk aversion with concave utility in gains while risk seeking in losses, $\alpha > 1$ leads to convex utility curvature in gains (risk seeking) while risk averse in losses, $\alpha = 1$ is risk neutral under linear utility function. Additionally, with $\gamma = 1$, the expected utility of each lottery option is simply

$$\mathrm{EU}(x_1, p;\ x_2) = p \cdot u(x_1) + (1-p) \cdot u(x_2)$$

Similarly, we can estimate EUT preference parameters using maximum likelihood method

$$\ln L^{\mathrm{EU}}(\mathrm{C}, \mathrm{X}|\theta_0, \theta) = \sum_k \left[\ln \Phi\left(\Delta_k^{\mathrm{EU}}\right) \times I(\mathrm{C}_k = A) + \ln\left[1 - \Phi\left(\Delta_k^{\mathrm{EU}}\right)\right] \times I(\mathrm{C}_k = B)\right] \quad \text{and}$$

$$\left(\hat{\theta}_0, \hat{\theta}\right) = \arg\max \ln L^{\mathrm{ET}}(\mathrm{C}, \mathrm{X}|\theta_0, \theta)$$

The maximum likelihood estimation is conducted using Stata with modified implementation strategy adapted from Harrison and Rutstrőm (2008), and we allow the standard errors to be individually correlated. Additionally, we perform several model estimations to compare the estimated results and goodness of fit across different model setups with different explanatory variables.

## 3.4 Result and Discussion

Our surveys were distributed to 750 producers located in Minnesota, the United States in January 2017. In total, 114 surveys were returned, 13 of which were discarded due to

incomplete responses. The farm characteristics and producers' demographics are summarized in Table 3-2. About 31% of the 101 respondents produce specialty crops on their farms, including vegetables, mushrooms, fruits, nuts, and floriculture crops[13]. The rest of respondents grow commodity crops such as corn, soybean, wheat, barley, beans, peas, oilseed crops, etc., including four respondents producing both specialty and commodity crops. Additionally, 25% of farms also raised livestock for profit. Twenty-one percent of farms were fully owned by producer respondents, and the average reported acreages of farms were 72 and 1507 acres for specialty crop and commodity crop, respectively. Regarding the crop insurance information, 70% of farms were reported to be covered, and 21% had claimed for indemnity in the 2016 growing season.

For producer respondents' socio-demographic background, the average age was 58, with 91% of them being male, and 55% had received a 4-year college degree. The mean income of their 2016 production season was around $85,000. For their attitudes toward crop insurance[14], 27% of producers considered actual revenue plus potential indemnity need to be greater than expected revenue plus farmer-paid premium for insurance, and 30% believed the actual revenue plus potential indemnity need to be greater than expected revenue. For lottery experiment, the distributions of switching points for overall respondents are reported in Figure 3-2.

We first present estimation results of CPT parameters without including any explanatory variables and compare the coefficient differences between commodity crop producer and specialty crop producer. Then we analyze specialty crop producer and commodity crop

[13] A list of specialty crops can be found at: https://www.ams.usda.gov/services/grants/scbgp/specialty-crop.
[14] Three types of crop insurance beliefs are adopted from Babcock (2015).

producer models under different specifications of explanatory variables, including farm characteristic model, demographic model, and a model combining specialty crop producers and commodity crop producers. Next, using the combined model, we compare the heterogenous risk preferences between commodity crop producers and specialty crop producers.

### *3.4.1 Risk Preference*

Table 3-3 shows the comparison of base CPT model estimates for all producers, commodity crop producers, and specialty crop producers. All the estimated CPT parameters, including risk curvature ($\alpha$), loss aversion ($\lambda$ ), and probability weighting ($\gamma$), are statistically significant at 0.01 level.

For the model with all producer responses, the risk curvature is estimated to be 0.33, showing significant concavity for gains and convexity for losses in utility. It is in line with Bocquého et al. (2014) where they identified a risk curvature of 0.28 from 107 producers in France. Similar empirical results, 0.49 and 0.22, have also been found by Gonzalez and Wu (1999), and Camerer and Ho (1994), respectively. The results also show producer respondents have strong loss aversion at with $\lambda$ =1.60. Our loss aversion coefficient is close to the findings of previous studies. For example, Pennings and Smidts (2003) identified a value of 1.81 for hog farmers, and Schmidt and Traub (2002) estimated the loss aversion parameter to be 1.43 for college students. For probability weighting, an inverse S-shaped function is observed with $\gamma$ to be 0.70. Hence, producer respondent tends to overweight small probabilities for gains and large probabilities for losses, while underweight small probabilities for losses and large probabilities for gains. This is also consistent with findings from most of empirical studies including Tversky and Kahneman (1992), Wu and

Gonzalez (1996), Bleichrodt and Pinto (2000), and Andersen et al. (2006). T-test results indicates no significant differences between these estimated parameters for commodity crop producers and specialty crop producers without adding explanatory variables of farm characteristics and socio-demographics.

After incorporating explanatory variables, for each CPT estimated parameter, the predicted distributions are compared between specialty crop producers and commodity producers (Figure 3-3). Individual parameters ($\hat{\alpha}, \hat{\lambda}, \hat{\gamma}$) are calculated using the combined model with farm and individual characteristics. For risk curvature parameter, the heterogeneous coefficients for both commodity crop producers and specialty crop producers are normally distributed and concentrated between 0.3 and 0.4, which is consistent with the base model estimates when excluding explanatory variables. We also observe the distribution pattern of risk curvature for specialty crop producers is left-skewed with a relative kurtosis around 0.25, indicating a small sample of specialty crop producers poses a higher diminishing sensitivity over risk than most commodity crop producers. For loss aversion, while most of the estimated coefficients lie between 1 and 2 for commodity crop producers, there are considerable loss aversion estimates that are greater than 2 for specialty crop producers. It is reasonable as specialty crops are relatively vulnerable to extreme weathers (Ho et al., 2018), require intensive management (Weisensel and Schoney, 1989), and lack of risk protection measures (Robinson et al., 2013). For probability weighting, similar to estimates in Table 3-3 ($\gamma$=0.69 for commodity crop and $\gamma$=0.72 for specialty crop producers), both types of producers have similar distributions of probability weighting parameters, and all of the predicted individual probability weighting parameters are smaller than 1, showing inverse-S shaped probability distortion. While the

probability weighting parameters are similar for the two types of producers, the underlying sources of probability weighting could be different. Commodity crop producers are sensitive to the change of risk probability possibly because they are operating larger farm sizes and crop quantities, so a slight change of risk probability could affect significant crop yield (MacDonald et al., 2013). Comparatively, the weighted risk probabilities for specialty crop producers could mostly attributed to serious risk exposure due to limited yield and revenue protection (Ligon, 2011).

### *3.4.2 Farm Characteristics and Producer Demographics*

Table 3-4 reports the how farm characteristics (model 1), producer demographics (model 2), or both farm and producer characteristics (model 3) affect each risk parameter. The model goodness of fit becomes increasingly significant as more explanatory variables are included. In model 1, none of the farm characteristics has a significant impact on loss aversion and probability weighting, leading the constant coefficients to be close to the base parameter estimates without explanatory variables. Meanwhile, raising livestock for profit and claiming indemnity in the previous growing season are negatively associated with risk curvature parameter, leading to an increased level of diminishing sensitivity. In addition to farm characteristics, model 2 has a few significant socio-demographic variables. Variables *Male*, *Belief1*, and *Belief2* are estimated to be significant negative toward the risk curvature parameter estimate, while *Belief2* indicates increased level of probability distortion and higher income relates to decreased loss aversion.

In the combined model with all the explanatory variables, we found that *Belief2* still have significant positive correlation on both levels of diminishing sensitivity and probability weighting. We conclude that compared to the producers who consider

'potential indemnity need to be greater than self-paid premium (*Belief3*),' producers who think 'actual revenue plus potential indemnity need to be greater than expected revenue (*Belief2*)' are more sensitive to risks and associated risk probabilities. This result is reasonable because when purchasing crop insurance, decision makers who frame broadly usually take account of more risky factors than those who frame narrowly by only considering factors such as the exchange of premium and indemnity. Similarly, for risk curvature parameter, we observe that younger and being male can be more tolerant to risks than older and being female, which is consistent with the findings by Roe (2015). We also find if the respondent had reported indemnity in the last growing season, the risk aversion increases. It is straightforward as producers who suffered production loss would be more worried about the risks. For probability weighting estimation, our results indicate producers who had completed college are less sensitive to changes in risk probability than producers without a college degree, meaning higher education equips individual to become more rational to be aligned with expected utility assumptions. Producers who planned to cover their crops with insurance are also less distorted on risk probabilities compared to those who do not purchase crop insurance, possibly because the covered producers need to worry less about the probability changes in risky situations. Finally, for the degree of loss aversion, the only significant explanatory variables for all producers is income. The higher the income level, the more financial security can be achieved, making producers less averse to losses. Bocquého et al. (2014) reported the similar results for French wheat farmers.

Separate estimation results for commodity crop producers and specialty crop producers are reported in Table 3-5 and Table 3-6, respectively. Regarding the effects of farm characteristics and producer demographics on the risk parameter estimates, a few notable

differences between commodity crop producers and specialty crop producers are observed. First, owning farmland has an incremental effect on loss aversion for commodity crop producers, but has a decreased effect for specialty crop producers. One explanation is that commodity crops are usually grown under larger farm operations than specialty crops, so potential risks such as severe weather would be more harmful to the commodity crop producers particularly if they are the landowners, which lead to an increased loss aversion. Another possible explanation is that due to the lack of established price guarantee for specialty crops, many producers market their produce via vertical contracts with intermediaries (Belasco et al., 2013). Thus, compared to land renters whose risks are solely controlled by the production yields under fixed price, landowners could utilize their land to produce a portfolio of crops or rent to other growers to partially offset the impact of the potential loss. Second, while beliefs in the crop insurance decision have a major impact on risk curvature and probability weighting for commodity crop producers, it does not significantly affect specialty crop producers' risk preferences. This may simply because existing insurance options are not satisfying specialty crop producers' needs or they are not familiar with the available options (Robinson et al., 2013; Paggi, 2016). Third, for specialty crop, older producers are estimated to be more averse to loss and less weighted toward probability change in risks, whereas age has no strong effect on commodity crop producers. Lastly, specialty crop producers who planned to cover their crops in the coming growing season or managed larger farm operations are significantly more objective toward risk probabilities (shifting $\gamma$ closer to 1), while commodity crop producers' risk preferences are not significantly determined by insurance decision and farm size. This is possibly because

there are fewer variations in farms size and insurance options for commodity crop producers.

### *3.4.3 EUT estimates*

Table 3-7 reports EUT estimates using the same power functional form as the CPT model. As discussed in the method section, risk aversion is entirely defined by the power estimator $\alpha$. Similar to CPT estimation results, we also observe a significant risk aversion at 0.52 in the base model, indicating a concave utility curvature in gains and convex in losses. Column 2 and 3 in Table 3-7 provide separate model estimates with the inclusion of farm characteristics and producer demographics, and most of the identified explanatory variables are also statistically significant in the combined model as shown in column 4. *Belief2* and *age* contribute to higher degrees of both risk aversion in EUT model and risk curvature in CPT model. Additionally, in line with the EUT results in Roe (2015), producers with higher education level are more likely to be less risk tolerant than those who did not completed a college degree. Interestingly, producers who managed more acreage of farmland are found to have higher risk tolerance. This is not as expected because larger farm size usually indicates higher loss when potential risks occur. This relationship further diminishes in the CPT model, where we find the effect of *acreage* only affects the distortion of risk probability not the risk curvature.

## 3.5 Conclusion

In this study, CPT has been empirically employed to examine producers' risk preferences and compare the differences of risk perceptions between commodity crop producers and specialty crop producers. Our results confirmed that producers' sensitivity to gain/loss change diminishes further away from the reference point. Additionally,

producers' aversion to loss is 1.6 times of the favor to gains with the same magnitude, and they overweight small probability changes while underweight large probability changes. Our results are consistent with previous findings from Tversky and Kahneman (1992), Tanaka et al., (2010), and Bocquého et al. (2014). Further comparing to the EUT model estimates, CPT model generates better goodness of fit and is more suitable to explain producers' decision-making under risk.

From the CPT estimation results, we found that producers who treat crop insurance decision as an isolated tradeoff between potential indemnity and producer-paid premium are more risk tolerant than those who broadly frame their decision by incorporating the risks of future revenue. This may provide insights into the identification of reference point when designing crop insurance. Babcock (2015) also explained that narrow framing of crop insurance decision might explain actual choices better than broad framing. In addition, older female producers who claimed indemnity tend to have a higher diminishing sensitivity to outcome change, wealthier producer are less loss averse, and higher educated producers who plan to cover their crops are less likely to distort objective probabilities.

In light of risk preferences for commodity crop producers, we reemphasize the importance of federal subsidy for voluntary participation in crop insurance. This is because producers tend to avoid a certain small input and take the risk of a potentially large loss, as they are risk averse for gains and risk seeking for losses. This provides a possible explanation for the unanticipated popularity of commodity crop insurance before the 1990s. Furthermore, loss aversion implies that commodity crop producers are resistant to changes in technology, production practice, and policy, etc. It costs more to demand them to give up an object than they would be willing to pay to gain it, even if the object leads to

favorable outcomes. Therefore, under the circumstance of adopting new crop variety and production technology, it is essential to carry out educational programs to ensure producers' understanding of associated benefits, especially for those who own their farmland.

For specialty crop producers, our CPT estimates indicate they are also significantly risk sensitive, loss averse, and probability distorted. Moreover, as specialty crops are more vulnerable to weather risks, and require more intensive management than commodity crops, the predicted preference distribution from the combined model indicate that specialty crop producers perceive a higher level of loss aversion than commodity crop producers. Those findings shed lights on the future design of specialty crop contract and insurance. Due to a higher level of price volatility and financial instability, many specialty crop producers choose to manage their risks by marketing their produce via vertical contracts. The design of such contracts should consider specialty crop producers' reference point and loss aversion. Reference point determines the range of acceptable base price and loss aversion signifies producers' higher disutility over contracted penalties than rewards, which implies the optimal contract design may incorporate lower base price plus reward incentive rather than higher based price with penalty scheme. Furthermore, in response to limited risk mitigation assistance for specialty crops, federal crop insurance assistance has been undergoing developments of new risk management tools, including WFRP that tailored to protect diversified farms under one policy against revenue losses due to multi-peril hazards (USDA, 2015). Given the results of significant and heterogeneous probability weighting effects for specialty crop producers, it might also be attractive to offer them single-peril insurance policy aiming at specialty crop specific risks such as targeted insects.

Such policy could provide protection over strong probability weighted perils, while offered at lower prices than traditional multi-peril insurance.

Identifying producer risk preference is the first step in understanding their production decision under uncertainty and risk. The results of our study may carry biases due to limited sample size, so further studies could be carried out to further verify our results with sufficient national representative respondents. Besides, based on the estimations of CPT framework, studies can be conducted to analyze or simulate producers' optimal choices of insurance coverage, variety, technology adoption, and risk management practice (e.g., high tunnels). Meanwhile, it is worthwhile to consider CPT framework in designing contract and crop insurance under the differentiation of crop type, farm characteristics, and producer demographics.

Table 3-1. Summary of Empirical Estimates of Risk Parameters from Previous CPT Studies

| *Risk Curvature (gain/loss domain)* | *Loss Aversion* | *Probability Weighting (gain/loss domain)* | *Obs.* | *Subject* | *Domain* | *Country* | *Source* |
|---|---|---|---|---|---|---|---|
| 0.88 | 2.25 | 0.61 / 0.69 | 25 | Student | Money | U.S. | Tversky and Kahneman (1992) |
| 0.50 | . | 0.71 | 420 | Student | Money | U.S. | Wu and Gonzalez (1996) |
| . | . | 0.69 | 92 | Student | Health | Netherlands | Bleichrodt et al. (1999) |
| 0.39 / 0.84 | . | . | 64 | Student | Money | Netherlands | Fennema and Van Assen (1999) |
| 0.49 | . | 0.44 | 10 | Student | Money | U.S. | Gonzalez and Wu (1999) |
| 0.89 / 0.92 | . | 0.60 / 0.70 | 64 | Student | Money | France | Abdellaoui (2000) |
| . | . | 0.67 | 51 | Student | Health | Spain | Bleichrodt and Pinto (2000) |
| 0.62 | . | 0.44 | 2593 | Public | Money | Netherlands | Donkers et al. (2001) |
| 1.14 / 1.06 | . | 0.52 / 0.52 | 181 | Student | Money | Switzerland | Fehr-Duda et al. (2006) |
| 0.86 / 0.80 | 2.04 | . | 48 | Student | Money | France | Abdellaoui et al. (2007) |
| 0.86 / 1.06 | 2.61 | 0.46 / 0.45 | 48 | Student | Money | France | Abdellaoui et al. (2008) |
| 0.86 / 0.83 | 1.58 | 0.62 / 0.60 | 2000 | Public | Money | Netherlands | Booij et al. (2010) |
| 0.90 / 1.25 | . | 0.31 / 0.34 | 448 | Student | Money | CH, CN | Bruhin et al. (2010) |
| 0.46 | . | 1.38 | 531 | Farmer | Money | IN, UG, ET | Harrison et al. (2010) |
| 0.61 | 2.63 | 0.74 | 181 | Farmer | Money | Vietnam | Tanaka et al. (2010) |
| 0.72 / 0.73 | 1.31 | . | 46 | Finance | Money | France | Abdellaoui et al. (2013) |
| . | 1.18 | 0.46 / 0.49 | 80 | Student | Money | Netherlands | Attema et al. (2013) |
| 0.48 | 3.47 | 0.69 | 320 | Farmer | Money | China | Liu and Huang (2013) |
| 0.79 / 1.15 | 5.70 | 0.59 / 0.62 | 70 | Student | Money | France | Abdellaoui and Kemel (2014) |
| 0.94 / 1.06 | 2.54 | 0.29 / 0.39 | 70 | Student | Time | France | Abdellaoui and Kemel (2014) |
| 0.28 | 2.28 | 0.66 | 111 | Farmer | Money | France | Bocquého et al. (2014) |
| 0.62 | 1.39 | 0.82 | 186 | Farmer | Money | France | Piet and Bougherara (2016) |

Table 3-2. Summary Statistics of Farm Characteristics and Producer Demographics (n=101)

| *Characteristic* | *Explanation* | *Mean (SD)/ Percentage (%)* |
|---|---|---|
| *Farm Characters* | | |
| Specialty Crop | 1 if the major crop in this farm contains specialty crop; 0 otherwise | 30.7% |
| Livestock | 1 if the farm also raise livestock for profit; 0 otherwise | 24.8% |
| Own Land | 1 if the operated farmland is 100% owned by respondent; 0 otherwise | 28.7% |
| Claim | 1 if the respondent claimed indemnity in last growing season; 0 otherwise | 20.8% |
| Cover | 1 if the respondent is adopting crop insurance; 0 otherwise | 70.3% |
| Acreage | Total acres of farms under operation | 1062.0 (1959.2) |
| *Producer Demographics* | | |
| Age | Age of respondent producer | 58.1 (12.7) |
| Male | 1 if the respondent if male; 0 otherwise | 91.1% |
| College | 1 if the respondent received 4-year college degree; 0 otherwise | 55.4% |
| Income | 2016 growing season gross income from farm operations:<br>1. Less than $25,000<br>2. $25,000 – $49,999<br>3. $50,000 – $74,999<br>4. $75,000 – $99,999<br>5. $100,000 – $249,999<br>6. $250,000 – $499,999<br>7. $500,000 –$999,999<br>8. More than $1,000,000 | 4.7 (2.5) |
| Belief1[a] | 1 if the respondent believes actual revenue plus potential indemnity need to be greater than expected revenue plus producer-paid premium for insurance when considering crop insurance; 0 otherwise | 26.7% |
| Belief2 | 1 if the respondent believes actual revenue plus potential indemnity need to be greater than expected revenue when considering crop insurance; 0 otherwise | 29.7% |
| Belief3 | 1 if the respondent believes potential indemnity need to be greater than producer-paid premium for insurance when considering crop insurance; 0 otherwise | 30.7% |

[a.] Beliefs in crop insurance are adopted from Babcock (2015).

Table 3-3. Estimation Results of CPT Models without Explanatory Variables

| CPT Variable | All Producer | Commodity Crop Producer | Specialty Crop Producer |
|---|---|---|---|
| Risk Curvature ($\alpha$) | 0.327*** | 0.324*** | 0.331*** |
| | (0.010) | (0.013) | (0.012) |
| Loss Aversion ($\lambda$) | 1.596*** | 1.558*** | 1.693*** |
| | (0.123) | (0.144) | (0.230) |
| Probability Weighting ($\gamma$) | 0.697*** | 0.690*** | 0.723*** |
| | (0.019) | (0.025) | (0.028) |
| Observation | 3,333 | 2,442 | 1,023 |
| No. of Respondents | 101 | 74 | 31 |

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 3-4. Estimation Results for All Producer Respondents

| | 1: Farm Characteristic Model | | | 2: Demographic Model | | | 3: Combined Model | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ |
| Constant | 0.333*** | 1.744*** | 0.667*** | 0.377*** | 2.067** | 0.644*** | 0.414*** | 1.635 | 0.522** |
| | (0.021) | (0.303) | (0.035) | (0.072) | (1.013) | (0.191) | (0.089) | (1.016) | (0.211) |
| Belief1 | | | | -0.046* | 0.141 | -0.021 | -0.044 | 0.179 | -0.043 |
| | | | | (0.026) | (0.274) | (0.053) | (0.035) | (0.293) | (0.058) |
| Belief2 | | | | -0.054** | 0.100 | -0.119** | -0.046** | 0.018 | -0.119** |
| | | | | (0.025) | (0.328) | (0.054) | (0.020) | (0.311) | (0.052) |
| Income | | | | 0.002 | -0.125** | 0.011 | 0.000 | -0.117* | 0.007 |
| | | | | (0.004) | (0.054) | (0.011) | (0.005) | (0.063) | (0.017) |
| Male | | | | 0.070* | -0.489 | -0.020 | 0.071* | -0.443 | 0.026 |
| | | | | (0.038) | (0.766) | (0.113) | (0.041) | (0.625) | (0.111) |
| Age | | | | -0.001 | 0.007 | 0.001 | -0.002* | 0.013 | 0.001 |
| | | | | (0.001) | (0.011) | (0.002) | (0.001) | (0.011) | (0.001) |
| College | | | | -0.021 | 0.293 | 0.039 | -0.027 | 0.385 | 0.085* |
| | | | | (0.023) | (0.242) | (0.047) | (0.022) | (0.252) | (0.043) |
| Livestock | -0.045* | 0.503 | 0.030 | | | | -0.043 | 0.464 | 0.042 |
| | (0.027) | (0.382) | (0.052) | | | | (0.027) | (0.360) | (0.051) |
| OwnLand | -0.002 | 0.315 | 0.009 | | | | 0.019 | -0.087 | 0.011 |
| | (0.023) | (0.320) | (0.043) | | | | (0.029) | (0.300) | (0.065) |
| Claim | -0.084* | -0.135 | -0.028 | | | | -0.079* | -0.259 | -0.040 |
| | (0.047) | (0.396) | (0.095) | | | | (0.047) | (0.381) | (0.090) |
| Cover | 0.020 | -0.434 | 0.042 | | | | 0.019 | -0.135 | 0.105** |
| | (0.019) | (0.299) | (0.038) | | | | (0.021) | (0.304) | (0.053) |
| Acreage | 0.000 | -0.000 | -0.000 | | | | 0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | | | | (0.000) | (0.000) | (0.000) |
| Model *p*-value | | 0.079 | | | 0.026 | | | 0.001 | |
| Obs./No. of R. | | 3,300/100 | | | 3,333/101 | | | 3,300/100 | |
| Test the significance of PT variables (*p*-value) | | | | | | | | | |
| $\lambda$: constant = 1 | | 0.000 | | | | | | | |
| $\theta$: constant = 1 | | 0.000 | | | | | | | |

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 3-5. Estimations Results for Commodity Crop Producers

| | 1: Farm Characteristic Model | | | 2: Demographic Model | | | 3: Combined Model | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ |
| Constant | 0.336*** | 1.770*** | 0.690*** | 0.451*** | 4.484*** | 0.578*** | 0.532*** | 3.691** | 0.492*** |
| | (0.031) | (0.351) | (0.053) | (0.079) | (1.371) | (0.148) | (0.122) | (1.556) | (0.184) |
| Belief1 | | | | -0.036 | 0.150 | -0.089 | -0.020 | 0.259 | -0.106* |
| | | | | (0.030) | (0.305) | (0.068) | (0.032) | (0.321) | (0.060) |
| Belief2 | | | | -0.057** | 0.091 | -0.185** | -0.058** | -0.044 | -0.168** |
| | | | | (0.028) | (0.359) | (0.082) | (0.026) | (0.419) | (0.077) |
| Income | | | | 0.003 | -0.143* | 0.021 | 0.013 | -0.035 | 0.020 |
| | | | | (0.007) | (0.075) | (0.015) | (0.020) | (0.117) | (0.031) |
| Male | | | | -0.006 | -2.324** | 0.001 | 0.041 | -2.005 | 0.039 |
| | | | | (0.037) | (1.172) | (0.106) | (0.039) | (1.563) | (0.112) |
| Age | | | | -0.002 | -0.001 | 0.001 | -0.003** | -0.002 | 0.001 |
| | | | | (0.001) | (0.013) | (0.002) | (0.001) | (0.013) | (0.002) |
| College | | | | -0.009 | 0.272 | 0.025 | -0.031 | 0.377 | 0.080 |
| | | | | (0.027) | (0.273) | (0.054) | (0.026) | (0.313) | (0.054) |
| Livestock | -0.032 | 0.697 | 0.026 | | | | -0.056 | 0.619 | 0.018 |
| | (0.036) | (0.426) | (0.060) | | | | (0.041) | (0.419) | (0.060) |
| OwnLand | 0.013 | 1.293** | -0.005 | | | | 0.057 | 0.930* | 0.022 |
| | (0.033) | (0.534) | (0.061) | | | | (0.062) | (0.532) | (0.126) |
| Claim | -0.089* | -0.018 | -0.010 | | | | -0.102** | -0.126 | -0.039 |
| | (0.053) | (0.423) | (0.101) | | | | (0.052) | (0.431) | (0.098) |
| Cover | 0.004 | -0.711* | 0.004 | | | | -0.012 | -0.457 | 0.108 |
| | (0.031) | (0.381) | (0.054) | | | | (0.034) | (0.373) | (0.069) |
| Acreage | 0.000 | 0.000 | -0.000 | | | | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | | | | (0.000) | (0.000) | (0.000) |
| Model *p*-value | | 0.316 | | | 0.126 | | | 0.012 | |
| Obs./No. of R. | | 2,409/73 | | | 2,442/74 | | | 2,409/73 | |
| Test the significance of PT variables (*p*-value) | | | | | | | | | |
| $\lambda$: constant = 1 | | 0.000 | | | | | | | |
| $\theta$: constant = 1 | | 0.000 | | | | | | | |

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 3-6. Estimation Results for Specialty Crop Producers

| | 1: Farm Characteristic Model | | | 2: Demographic Model | | | 3: Combined Model | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ | $\alpha$ | $\lambda$ | $\gamma$ |
| Constant | 0.347*** | 2.204*** | 0.680*** | 0.486*** | -2.465 | 0.530* | 0.271 | -4.680** | 0.657*** |
| | (0.019) | (0.469) | (0.039) | (0.132) | (1.499) | (0.292) | (0.177) | (2.108) | (0.213) |
| Belief1 | | | | -0.040* | 0.450 | 0.255** | -0.086 | 2.155 | 0.063 |
| | | | | (0.022) | (0.567) | (0.116) | (0.053) | (1.414) | (0.097) |
| Belief2 | | | | -0.023 | -0.313 | 0.067 | 0.038 | 1.555 | -0.260 |
| | | | | (0.043) | (0.794) | (0.091) | (0.070) | (1.069) | (0.184) |
| Income | | | | -0.001 | -0.057 | -0.013 | 0.016 | 0.029 | -0.096*** |
| | | | | (0.007) | (0.098) | (0.029) | (0.010) | (0.157) | (0.027) |
| Male | | | | 0.051 | 1.554 | -0.021 | 0.122* | 1.306 | -0.238 |
| | | | | (0.059) | (1.017) | (0.126) | (0.070) | (1.250) | (0.161) |
| Age | | | | -0.002*** | 0.036** | 0.003 | -0.002 | 0.083** | 0.005** |
| | | | | (0.001) | (0.017) | (0.003) | (0.001) | (0.032) | (0.002) |
| College | | | | -0.046 | 1.004* | 0.037 | 0.071 | 1.703 | 0.073 |
| | | | | (0.038) | (0.544) | (0.100) | (0.064) | (1.147) | (0.081) |
| OwnLand | -0.031 | -0.569 | -0.009 | | | | -0.037 | -1.911* | 0.187 |
| | (0.025) | (0.452) | (0.053) | | | | (0.043) | (0.991) | (0.123) |
| Cover | 0.028 | -0.415 | 0.111** | | | | -0.027 | -1.055 | 0.281*** |
| | (0.029) | (0.498) | (0.055) | | | | (0.045) | (0.709) | (0.109) |
| Acreage | -0.000 | 0.000 | 0.000 | | | | -0.000 | -0.002 | 0.004*** |
| | (0.000) | (0.002) | (0.000) | | | | (0.000) | (0.005) | (0.001) |
| Model *p*-value | | 0.119 | | | 0.011 | | | 0.009 | |
| Obs./No. of R. | | 1,023/31 | | | 1,023/31 | | | 1,023/31 | |
| Test the significance of PT variables (*p*-value) | | | | | | | | | |
| $\lambda$: constant = 1 | | 0.003 | | | | | | | |
| $\theta$: constant = 1 | | 0.000 | | | | | | | |

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

No respondents of specialty crop producers reported raising livestock for profit or claimed indemnity in previous growing season, so those two variables were omitted in the model estimation

Table 3-7. EUT model Estimation Results

| | 1: Base model | 2: Farm Character Model | 3: Demographic Model | 4: Combined Model |
|---|---|---|---|---|
| $\alpha$ | 0.523*** | 0.544*** | 0.801*** | 0.833*** |
| | (0.072) | (0.074) | (0.133) | (0.164) |
| Belief1 | | | -0.023 | 0.005 |
| | | | (0.030) | (0.034) |
| Belief2 | | | -0.090*** | -0.084** |
| | | | (0.030) | (0.033) |
| Income | | | 0.008 | 0.003 |
| | | | (0.005) | (0.006) |
| Male | | | 0.038 | 0.067 |
| | | | (0.070) | (0.099) |
| Age | | | -0.003*** | -0.003*** |
| | | | (0.001) | (0.001) |
| College | | | -0.096*** | -0.102** |
| | | | (0.030) | (0.043) |
| Livestock | | -0.047 | | -0.033 |
| | | (0.033) | | (0.030) |
| Own | | -0.026 | | 0.017 |
| | | (0.032) | | (0.033) |
| Claim | | -0.084* | | -0.051 |
| | | (0.047) | | (0.043) |
| Cover | | 0.041 | | -0.016 |
| | | (0.031) | | (0.050) |
| Acreage | | 0.000*** | | 0.000*** |
| | | (0.000) | | (0.000) |
| Stochastic Error | 7.858* | 9.776** | 15.286* | 18.136* |
| | (4.195) | (4.744) | (8.297) | (10.929) |
| Model *p*-value | | 0.000 | 0.000 | 0.000 |
| Observations | 3,333 | 3,300 | 3,333 | 3,300 |

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

***Lottery Series 1*** *(all value indicating gains)*

| Row Number | Option A | | Option B | |
|---|---|---|---|---|
| | **30%** Probability | **70%** Probability | **10%** Probability | **90%** Probability |
| 1 | $400 | $100 | $680 | $50 |
| 2 | $400 | $100 | $750 | $50 |
| 3 | $400 | $100 | $830 | $50 |
| 4 | $400 | $100 | $930 | $50 |
| 5 | $400 | $100 | $1,060 | $50 |
| 6 | $400 | $100 | $1,250 | $50 |
| 7 | $400 | $100 | $1,500 | $50 |
| 8 | $400 | $100 | $1,850 | $50 |
| 9 | $400 | $100 | $2,200 | $50 |
| 10 | $400 | $100 | $3,000 | $50 |
| 11 | $400 | $100 | $4,000 | $50 |
| 12 | $400 | $100 | $6,000 | $50 |

***Lottery Series 2*** *(all value indicating gains)*

| Row Number | Option A | | Option B | |
|---|---|---|---|---|
| | **90%** Probability | **10%** Probability | **70%** Probability | **30%** Probability |
| 1 | $400 | $300 | $540 | $50 |
| 2 | $400 | $300 | $560 | $50 |
| 3 | $400 | $300 | $580 | $50 |
| 4 | $400 | $300 | $600 | $50 |
| 5 | $400 | $300 | $620 | $50 |
| 6 | $400 | $300 | $650 | $50 |
| 7 | $400 | $300 | $680 | $50 |
| 8 | $400 | $300 | $720 | $50 |
| 9 | $400 | $300 | $770 | $50 |
| 10 | $400 | $300 | $830 | $50 |
| 11 | $400 | $300 | $900 | $50 |
| 12 | $400 | $300 | $1,000 | $50 |
| 13 | $400 | $300 | $1,100 | $50 |
| 14 | $400 | $300 | $1,300 | $50 |

***Lottery Series 3*** *(note there is probability of losses in this series)*

| Row Number | Option A | | Option B | |
|---|---|---|---|---|
| | **50%** Probability | **50%** Probability | **50%** Probability | **50%** Probability |
| 1 | $250 | –$40 | $300 | –$210 |
| 2 | $40 | –$40 | $300 | –$210 |
| 3 | $10 | –$40 | $300 | –$210 |
| 4 | $10 | –$40 | $300 | –$160 |
| 5 | $10 | –$80 | $300 | –$160 |
| 6 | $10 | –$80 | $300 | –$140 |
| 7 | $10 | –$80 | $300 | –$110 |

Figure 3-1. Screenshot of the lottery question used to elicit producer risk preference

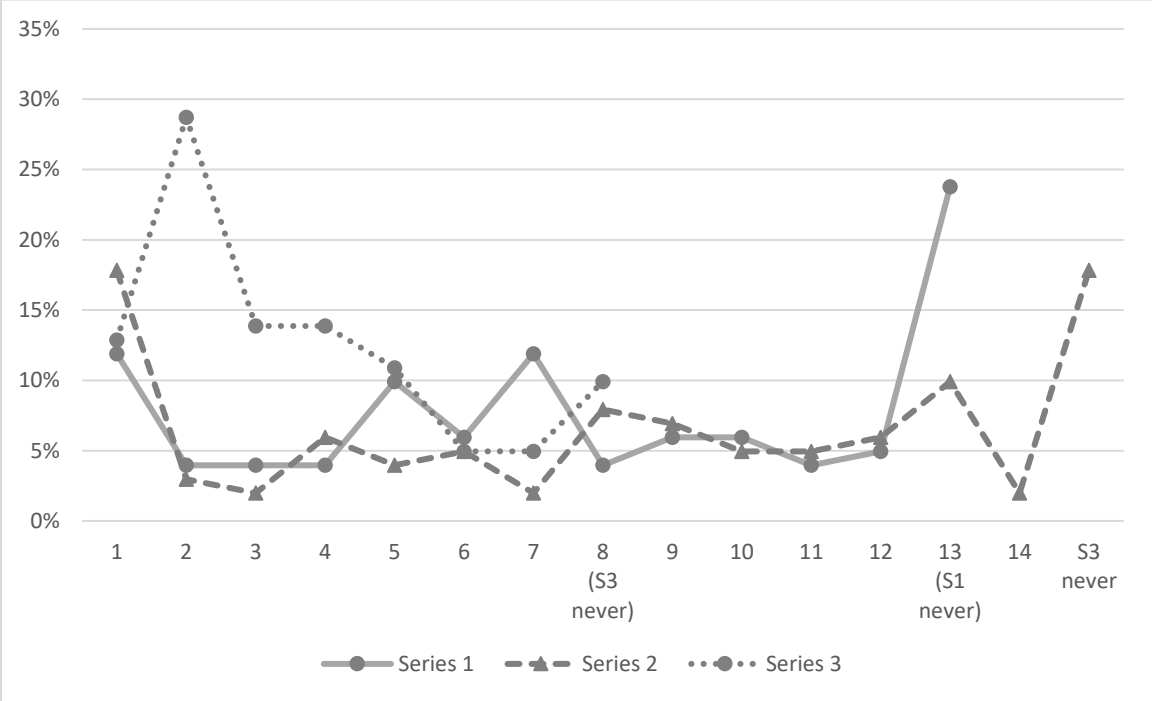


Figure 3-2. Percentage change of switching points made by producer respondents

Conclusions

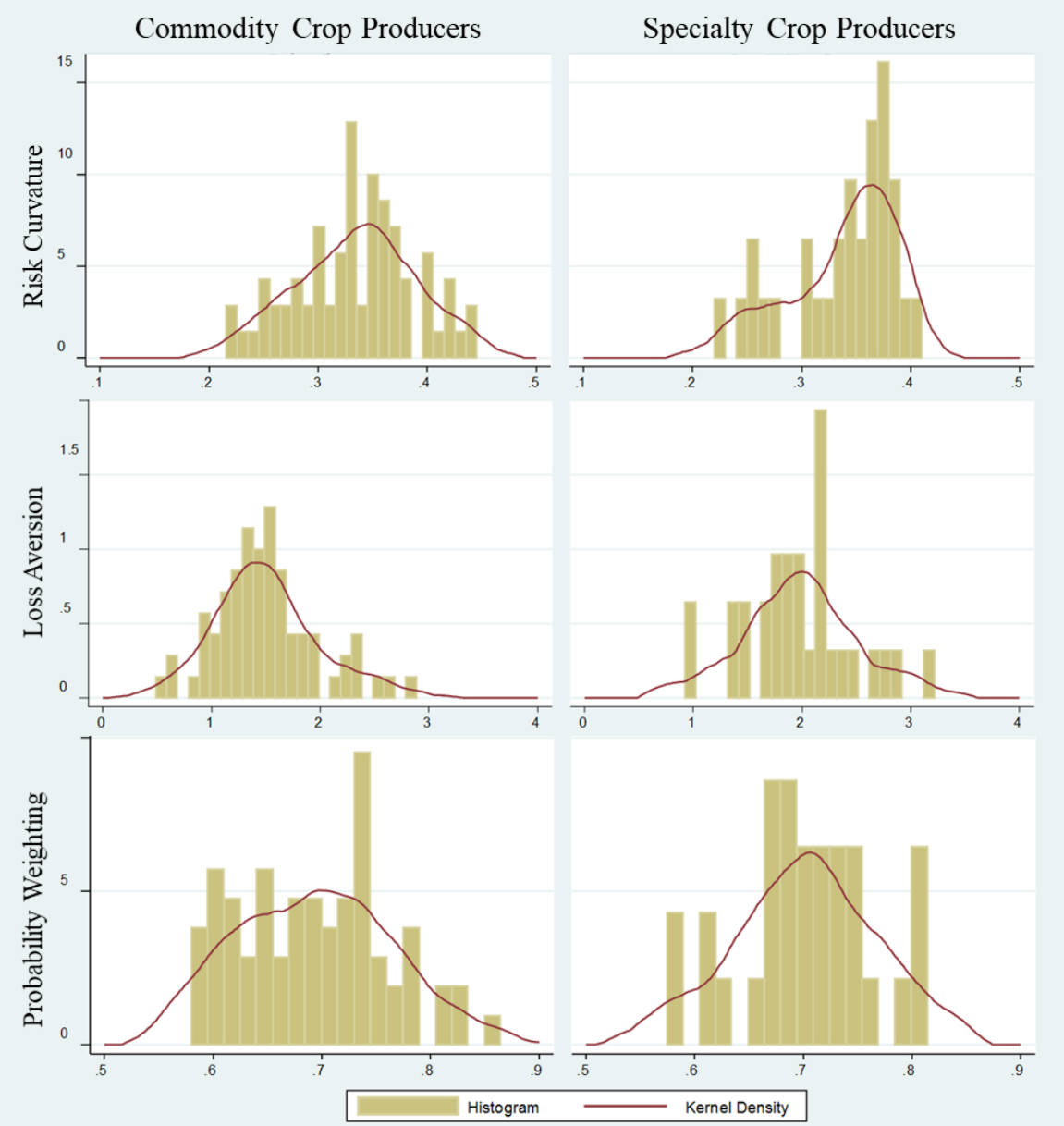


Figure 3-3. Comparison of predicted CPT parameter distributions between commodity crop and specialty crop producers

# Chapter 4

# Estimating Demand for Organic Fresh Produce Using Machine Learning Methods

## 4.1 Introduction

In the age of information explosion, applied economists have been exploring new tools to provide novel insights in using big data, among which Machine learning (ML) is one of the most promising methods that have been increasingly applied in social science. The early use of ML is mostly in the field of computer science and statistics, but its algorithms have been proven to be effective in classification and prediction of large datasets. Particularly, ML methods can also be used in solving empirical economic problems in regression or clustering analysis. Most applications of ML in applied economics belong to the category called supervised machine learning[15], it is a data-driven selective approach instead of parametric estimation, and it typically involves using a set of covariates to

[15] Another category of machine learning is called unsupervised learning, where there is no outcome measure, and the basic target is to classify or describe the associations among input data.

predict an outcome, and using the presence of the outcome variable to guide the learning process (Hastie, Tibshirani, and Friedman 2001). For example, dividing observed covariates and outcomes data into training and test data sets, supervised ML could construct estimators from the training data with certain learning algorithms, and then use those estimators to predict outcomes in the test data based on the corresponding values of covariates. As noted by Athey (2017), estimating unbiased estimator is not the primary goal of ML, rather, the goal is to achieve the optimal goodness-of-fit in an independent test set by minimizing predicted outcomes' deviations from actual outcomes.

Some of the most commonly used supervised ML methods are LASSO, ridge, random forest, support vector machines, and regression trees and Varian (2014) provided an overview of those popular ML methods. For empirical applications, Athey (2017) summarized representative uses of ML in economic literature from solving causal inference problems to predicting policy effects. Blumenstock (2018) showed that combining phone data and ML can estimate the wealth of individuals in different economic environments. Senia et al. (2018) applied ML algorithms to USDA FoodAPS household data and identified causal relationships between socio-demographic factors and food acquisition decisions, such that obesity is caused by poor health and diet status, and Lusk (2017) compared conventional modeling (logit model) and ML (classification tree) to predict binary outcome of vegetarian, and the in-sample and out-of-sample percentages of correct predictions were statistically similar for the two methods. While ML is receiving increasing attention in its application in economics, several studies have questioned the effectiveness and stability of ML tools. For example, Carbonneau et al. (2008) assessed ML for forecasting distorted demand signals in the extended supply chain, and suggested that while

neural networks and support vector machines have the best performance, the accuracy of prediction were not statistically better than that of the regression models such as linear regression and logit model. Mullainathan and Obermeyer (2017) found that using ML in health care analysis, particularly under unnormalized health data, could cause magnified selection errors.

Given the increased richness and availability of consumer data (Scanner, Panel, Survey), economists have started to explore using ML methods in predicting consumer choice and demand. Still, compared to the wide application of ML method in development, environment, and health economics, its application in consumer demand is relatively limited. As a representative demand estimation study using ML, Bajari et al. (2015) applied ML methods to predict the quantity demand of 3,149 salty snack products using the IRI scanner data, and compared the results of demand estimation with that of parametric models. The comparative results indicate that ML methods, particularly random forest and support vector machine, produce superior predictive accuracy than linear regression or logit model. Building upon the empirical evidence of market demand estimation from Bajari et al. (2015), we aim to adopt the similar methods to explore the predictive power in household demand estimation. Two factors could potentially affect the effectiveness of ML relative to parametric approaches in the case of household demand estimation. First, given the complexity of scanner data in Bajari et al. (2015), predicting the market demand of grocery could involve many thousands of explanatory variables including product-specific and store-specific fixed effects, but household demand predictions are mainly based on consumer socio-demographic background, which generates smaller covariate matrix and avoids multi-collinearity problems. In such case, parametric models could

potentially become more efficient. Thus, we are interested in the performance of ML when predicting consumer demand under limited covariates. Second, while previous studies have proven the effectiveness of ML in dealing with large data, it is uncertain how ML would out/under-perform parametric models when the sample size is small. Traditional sources of consumer demand data are collected by surveys and polls, where the completed sample is usually between 1,000 and 1,500 respondents (Lusk, 2017). Therefore, another objective of this study is to investigate the capacity of ML in predicting household demand with small data size. We apply both ML methods and parametric models to estimate households' organic budget share of fresh produce using Nielsen consumer panel data.

Organic food consumption has been robustly increasing over the past 30 years, achieving $43 billion in 2016, which accounts for 5.3% of total food sales in the United States. (OTA, 2017). Among all organic food category, fresh vegetable and fruits accounted for 40% of total U.S. organic food sales, and has been the top-selling organic food category during the past 30 years[16] (USDA, 2017). Additionally, while consumers are increasingly health-conscious, the growth of organic fresh produce consumption in 2016 (8.4%) almost tripled the growth rate of total fresh produce sales (3.3%). In return to producers, it is also estimated that organic farms are 35% more profitable than the average farm (OTA, 2018). From a consumer economics perspective, as organic consumption gradually becomes a mainstream of fresh produce, researchers have been trying to examine the attitudes and behaviors of the organic purchaser. While there is no pinpoint to identify organic purchasers, studies show that a typical household that consumes organic fresh

[16] Followed by dairy, packaged/prepared foods, beverages, bread/grains, snack food, meat/fish/poultry, and condiments (USDA, 2017).

produce tend to be fluent (Lin et al. 2009), more educated (Smed 2012), with children in household(Smith et al. 2009), and those who hold positive beliefs and attitudes toward organics and cooking (Li et al. 2007). Therefore, given the fast growth of organic fresh produce consumption, finding an effective approach to predict the household level budget share of organic purchase would benefit all stakeholders in the organic food supply chain in adopting and implementing marketing strategies.

Therefore, focusing on the household-level organic budget share of fresh produce, this study explores the predictive power of popular ML methods (stepwise regression, forward stagewise regression, LASSO, random forests, support vector machine) and econometric models (OLS and Logit) for both regular-sized sample (1000) and big data sample.

The remainder of the paper is structured as follows. Method section describes each of the analytical approaches used in the study and the strategy for model comparison, results section shows the goodness-of-fit indexes and comparative statistics, discussion and conclusion section summarizes the study and provides the implications and limitations of the study.

## 4.2 Method

Following Bajari et al. (2015), we test and compare different models by using the cross-validation approach with out-of-sample prediction and combined weighting. The basic steps are 1) randomly split data into three segments including 60% as training set, 25% as testing set, and 15% as validation set. 2) Fit training set data into all models to produce in-sample prediction. 3) Use trained models from the training set to make out-of-sample predictions on the validation set, and compare the actual outcome and predicted outcome variable by calculating the root-mean-square error (RMSE). 4) In validation set, regress

predicted outcomes on the actual outcome in a linear model, estimate the percentage weight for each model by constraining coefficient sum to be 1. 5) Use trained model to predict the testing set, meanwhile, incorporate percentage weights from step 4 to produce a prediction in the testing set using combined model. Additionally, in order to assess the predictive accuracy in case of regular-sized sample, we randomly extract 1,000 sample size before the above steps, and repeat the loop for 1,000 times to calculate average RMSE, percentage weight and associated confidence interval for each model. Therefore, it is straightforward to compare the predictive accuracies of ML methods and parametric models under both cases of regular-sized sample and big sample.

Two parametric regressions including linear and logit model, and five ML methods including stepwise and incremental stagewise regression, support vector machines, LASSO, and random forest are adopted in this study. Each model uses the same variables: setting organic budget share of fresh produce to be the outcome variable, the covariates are socio-demographic variables including household size, age, income, type of residence, age and presence of children, employment status, education, marital status, race, and geographic region.

### *4.2.1 Linear Regression and Logit Model*

Given the organic budget share of fresh produce for household $i$, the basic model specification under linear regression would be

$$s_i = c + \boldsymbol{\beta} \boldsymbol{X}_i + \epsilon$$

where $s_i$ is the organic budget share for household, $\boldsymbol{X}_i$ is a vector of variables associated with parameters $\boldsymbol{\beta}$, and $\epsilon_i$ is the idiosyncratic error term. In ordinary least squares,

parameter $\beta$ is estimated by a closed-form formula $(\boldsymbol{X}'\boldsymbol{X})^{-1}(\boldsymbol{X}'\boldsymbol{Y})$, where $X$ is the matrix of observed variables and $Y$ is a vector of outcome variable.

Logit models have frequently been used in consumer demand estimations (e.g., Hanemann 1984; Berry 1995; Nevo 2000). Following the model specification of organic budget share, and assuming the error term to be Type I Extremely Distributed, the market share can be estimated by:

$$s_i = \frac{\exp(\boldsymbol{\beta X}_i)}{\sum_{j \in I} \exp(\boldsymbol{\beta X}_j)}$$

where $j$ represents the rest of households other than $i$. Compared to the OLS, logit model captures unobserved household-level heterogeneity.

### *4.2.2 Forward Stepwise, Forward Stagewise, and Lasso*

The least squares estimate often have low bias but large variance, which causes limitations in prediction accuracy (Friedman et al. 2001). Forward stepwise selection starts with the intercept, and then sequentially search over a set of covariates until the highest correlation with the residual is found, and add the predictor that improves the model fit the most into the next model. This algorithm produces a series of nested models and runs until no covariate with significant correlation with the error term exists.

Comparatively, forward stagewise regression is an iterative technique that builds up the regression function in successive small steps (Efron et al. 2004). It starts with a similar algorithm to the forward stepwise regression. In each stage, it looks for the variables that are most correlated with the residual, then it computes linear regression coefficient of the residual on the chosen variable, and add it to the current model. The key is in each iteration, the chosen variable is only multiplied by a small number instead of the correlation of the

variable with the residual. Again, this process continues until none of the variables is correlated with the residual.

The Lasso is also a constrained version of the OLS regression, and the algorithm can be shown as:

$$\min_{\beta} \frac{1}{2}\sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda(t - \sum_{j=1}^{p}|\beta_j|)$$

where $t$ is the tuning parameter that shrinks the OLS coefficients toward 0 while improving prediction accuracy.

### *4.2.3 Support Vector Machine*

While forward stepwise, forward stagewise, and Lasso creates optimal separating hyperplanes to linearly separate two classes, support vector machine covers the nonlinear and nonseparable cases when the classes overlap. According to Bajari et al. (2015), support vector machine uses the following form to maximize the margin between adjunctive support vectors:

$$\min_{\beta} \sum_{i=1}^{n} V(y_i - x_i\beta) + \frac{\lambda}{2}\|\beta\|$$

and the penalty function is:

$$V_\epsilon(r) = \begin{cases} 0 & \text{if } |r| < \epsilon \\ |r| - \epsilon & \text{otherwise} \end{cases}$$

where $\epsilon$ is the tuning parameter and it decides the error term that to be included in the regression.

### *4.2.4 Random Forest*

Random forest (Breiman, 2001) uses regression tree to minimize the variance of an estimated prediction function, which is a concept of bootstrap aggregation. The algorithm

starts with bootstrapping the training data, then grows a random-forest tree to the bootstrapped data, and recursively builds de-correlated trees at each terminal node until the minimum node size is reached. The regression predictor at a new point $x$ is then:

$$\hat{f}_{rf}^{B} = \frac{1}{B}\sum_{b=1}^{B} T_b(x)$$

where $B$ is the number of trees, $T_b$ indicates one random-forest tree with bootstrapped data.

## 4.3 Result

This study uses 2016 Nielsen Consumer Panel Dataset from the Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The data were collected from 55,666 households with detailed purchasing information such as what products household purchased over the year along with socio-demographic information such as household size, income, age, etc. The household sample of the dataset are geographically dispersed and are projectable to the total U.S. population.

In the data set, each observation represents a transaction record of purchase, which is consisted of the product UPC code, quantity, price, coupon, as well as associated labeling information including an organic claim variable showing whether the purchased item is organic or not. After summing up the total expenditure of organic fresh produce throughout the year for each household, and divided by the expenditure of total fresh produce purchase, the average organic budget share for fresh produce among the sample household is 9.76% with the standard deviation of 16% and minimum/maximum to be 0 and 1.

To compare the out-of-sample predictive accuracy, RMSE is a frequently used that measures forecasting errors between predicted values from training and observed values. We also calculate the standard error of RMSEs to measure the predictive stability. Last, following Bajari et al. (2015), percentage weight is calculated by combining all models linearly with nonnegative weights, so a combined model prediction can be calculated based on each individual model predictions and associated percentage weights. To be comparable across models, both outcome variable and covariates matrix are the same for all econometric and ML models.

Starting from the case of regular-sized sample, randomly draw 1,000 households out of the total 55,666 households, Table 4-1 shows the comparison statistics of average RMSE and standard error for 1,000 repeated draws. After training each model with the training set, the predictors from ML methods generally perform better than the econometric models in terms of minimizing out-of-sample prediction error. The predictive accuracy rankings are identical in validation set and test set, and the standard error in testing set is smaller than validation set because of the larger data size. For the validation set, predictions from the combined model are also being compared with the actual outcome, it is calculated by regressing observed outcome on a constrained set of predictions from all seven models, and then adding up the predictions with assigned percentage weight for each model. As expected, the combined model generates the best prediction accuracy for the validation set with RMSE to be 0.158, and it also minimizes the most out-of-sample predictive error for testing set with an RMSE of 0.160. For percent weight, two ML methods, support vector machine and random forest, have the largest weights of 33.76% and 36.88%, respectively, followed by forward stagewise, logit model, and Lasso. Linear model and forward stepwise

only receive less than 2% of predictive percent weight. Interestingly, the most weighted models do not equal to the smallest RMSE, which is consistent with Bajari et al. (2015), possibly because covariances of models tend to fit actual outcome better than certain sub-set of covariances.

Table 4-2 provides the predictive accuracy statistics using the full sample of 55,666 households, with 8,244 validation households and 14,103 testing households. While the ranking of predictive accuracy is the identical for both validation set and testing set, the performance of econometric models reaches to the same level as ML methods including forward stepwise, forward stagewise, and Lasso. Meanwhile, support vector machine and random forest have the lowest RMSEs of 0.163 and 0.162, respectively, and the combined model has the best predicative accuracy. The percent weights indicate that logit model predictions not only have the lowest predictive error, but also contribute to major percent weight of 63%. In the second place, Lasso explains 27% of the combined model, each of support vector machine and random forest share around 5% of weight, and the rest models do not receive weight in the combined model. Lastly, Given the large sample size, bootstrapped standard error is statistically small, indicating good predictive stability on RMSE.

## 4.4 Discussion

Increasing the sample size from a regular demand survey sample size (1000) to big data (55,666), the predictive accuracies of econometric models improve significantly. Especially, the RMSE of logit model increases from the second highest to the lowest, generating the best predictive accuracy in the big data. Among ML methods, the predictions from forward stepwise, forward stagewise, and Lasso also received major

improvements with similar magnitude after the increase of sample size, but support vector machine and random forest only corrected limited predictive errors with the increase in data size. From percent weight perspective, according to Figure 4-1, support vector machine and random forest dominated the combined predictive accuracy in the regular-sized sample. However, when sample size increases to 50,000 level, logit model, and Lasso have the best predication accuracy.

With regular-sized survey sample, machine learning methods, especially support vector machine and random forest, could be used to estimate and predict household organic budget share with socio-demographic variables. support vector machine construct separate hyperplanes, which is more flexible than stepwise, stagewise, and Lasso methods, while random forest averages multiple decision trees to achieve better accuracy with small variance with small sample size. However, when the data size becomes extremely large, both support vector machine and random forest become relatively less powerful than other ML methods and econometric models. This is possibly due to overfitting, where in-sample training become too accurate that dampens the flexibility of out-of-sample prediction. On the other hand, logit model and linear regression become increasingly accurate for out-of-sample predictions as the perceived information from training set become abundant enough. A possible explanation is that econometric model prediction suffers extreme variations under a set of large covariates but a small number of observations. Once the number of observations are large enough for training parametric models, then large covariates with precise parameter estimates could benefit the out-of-sample predictions made by econometric models.

Unlike the results from Bajari et al. (2015) where random forest and support vector machine perform the best in predicting the number of snacks sold in market level, the prediction of household-level organic budget share behaves most accurately with the logit model for large data size. Furthermore, in this study, random forest and support vector machine receives major predictive power when the training data size is around 600. This does not indicate that two studies contradict with each other, on the contrary, it brings new insights into demand estimation using ML methods: the accuracy of out-of-sample prediction using any methods could vary significantly based on two factors, the choice of covariates/parameters and the number of training examples (sample size). This study tests variations in both factors as oppose to Bajari et al. (2015), which altered the relative performance of ML methods in demand estimation.

## 4.5 Conclusion

This study assesses the use of machine learning methods in estimating and predicting household budget share for organic fresh produce, and compare them to the traditional econometric models. Distinctive results are identified between the cases of regular-sized sample and big data. In 1,000 sample, ML methods generally outperform parametric models in out-of-sample predictions, with support vector machine and random forest being the top 2 reliable methods. However, when the sample size increases to 50,000 level, linear and logit model become as good as ML methods including forward stepwise, forward stagewise, and Lasso. Comparatively, support vector machine and random forest turn into the lowest performed fitting models in the case of using big data.

It has to be noted that the results of this study only apply to the organic produce budget share estimation with household socio-demographic variables. Therefore, given the raising

interest in applying ML method in demand estimation (Lusk 2017; Senia et al. 2018), further exploration can be conducted to identify suitable tuning algorithms that correponding to the specifics of observable parameters and sample size. It is also worth-noting that the training process of ML methods normally operates in a "black box," which leads to limited traceability for further modification of the covariates. Based on the results of this study as well as Bajari et al. (2015), ML method is competent in demand estimation and prediction as it is easy to use and relatively free of assumptions. However, researchers should be careful when only one method has to be decided as both the results from Carbonneau et al. (2008) and our study indicate that parametric model could outperform ML methods when using big data. Overall, every demand estimation varies in both parameter choices and data volumes, so the optimal method should be weighted based on specific demand attributes and data availability.

Table 4-1. Prediction Error Comparison between Models under Regular Size Data Size

| | Validation set | | Testing set | | Percent Weight |
|---|---|---|---|---|---|
| | Average RMSE | Std. Err | Average RMSE | Std. Err | |
| Linear | 0.16533 | 0.02105 | 0.16518 | 0.01578 | 1.36% |
| Logit | 0.16797 | 0.02136 | 0.16770 | 0.01618 | 9.33% |
| Forward stepwise | 0.16529 | 0.02103 | 0.16513 | 0.01578 | 1.78% |
| Forward stagewise | 0.16349 | 0.02111 | 0.16327 | 0.01582 | 9.51% |
| Lasso | 0.16348 | 0.02109 | 0.16328 | 0.01583 | 7.37% |
| Support vector machine | 0.16432 | 0.02398 | 0.16403 | 0.01786 | 33.76% |
| Random forest | 0.16343 | 0.02104 | 0.16326 | 0.01566 | 36.88% |
| Combined | 0.15785 | | 0.16029 | | |
| Num. of obs. | 150 | | 250 | | |

Table 4-2. Prediction Error Comparison between Models for Full Data

| | Validation set | | Testing set | | Percent Weight |
|---|---|---|---|---|---|
| | RMSE | Std. Err | RMSE | Std. Err | |
| Linear | 0.15382 | 0.00040 | 0.15380 | 0.00031 | 0.00% |
| Logit | 0.15374 | 0.00044 | 0.15361 | 0.00035 | 63.05% |
| Forward stepwise | 0.15381 | 0.00039 | 0.15380 | 0.00032 | 0.00% |
| Forward stagewise | 0.15380 | 0.00041 | 0.15378 | 0.00031 | 0.00% |
| Lasso | 0.15380 | 0.00041 | 0.15378 | 0.00028 | 27.42% |
| Support vector machine | 0.16333 | 0.00024 | 0.16289 | 0.00023 | 4.36% |
| Random forest | 0.16190 | 0.00099 | 0.16248 | 0.00071 | 5.16% |
| Combined | 0.15368 | | 0.15357 | | |
| Num. of obs. | 8244 | | 14103 | | |

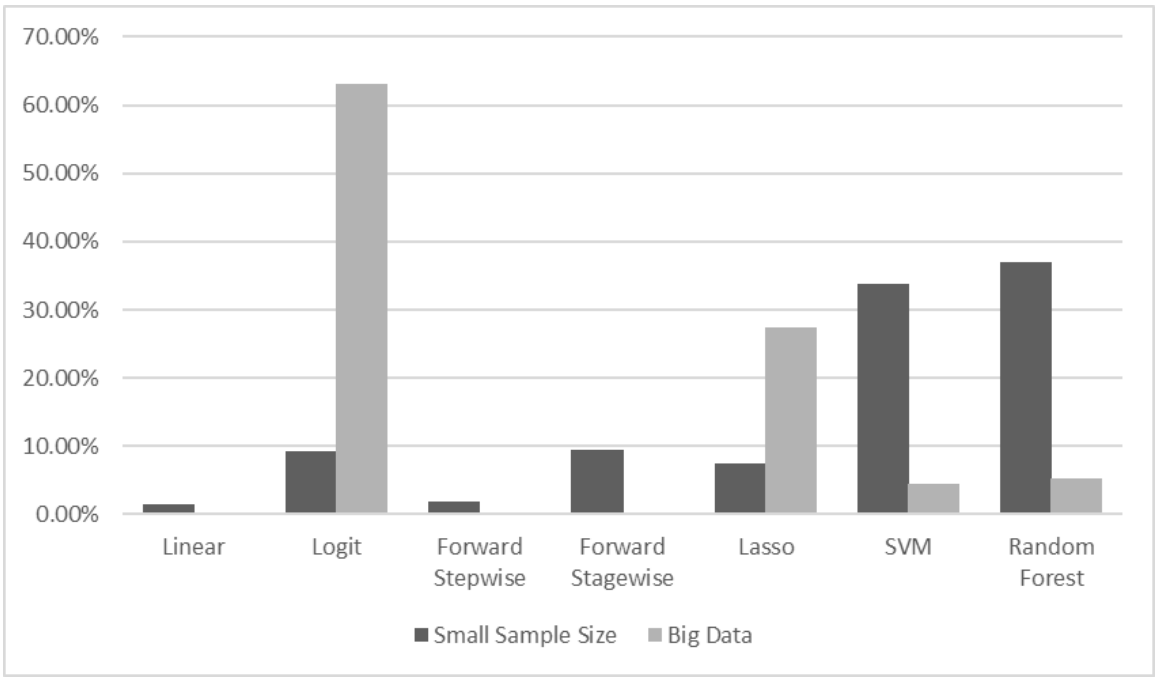


Figure 4-1. Percentage weight of explanatory accuracy comparison

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# Appendix A

## Further Estimation of Probability Weighting Parameter

In the result part, though we find an inverse S-shaped probability weighting function in the gain model, the full model produces an S-shaped weighting function, which is resulted from the incorporation of data from the loss model. Having a weighting parameter greater than 1 is at odds with the predominant shape of previous prospect theory studies, so we conduct further analysis to investigate the causes for the S-shaped probability weighting function for the loss model.

We propose two major causes that contribute to the misestimate of weighting parameter. First, both existing empirical regularities about the probability weighting functions, π^μ/(π^μ+(1-π)^μ )^(1/μ) (Tversky and Kahneman, 1992) and exp(- 〖(-lnπ)〗 ^μ (Prelec, 1998), are proposed based on the experiments of lottery decisions. The basis of lottery decisions is monetary gain, which is equivalent to our CSA case of the gain model with bonus produce, and might not be applicable to the loss model. Second, existing functional forms share a common invariant fixed point and inflection point at around 0.4, meaning that the probability weighting function is estimated to be concave up to π≈0.40

and convex beyond this point (Wu and Gonzalez, 1996; Prelec, 1998). Given the risk attitudes under CPT follow a fourfold pattern, this inflection point implies that consumers are risk averse for possible bonus produce with probabilities lower than 40% and risk seeking for gains with probabilities higher than 40%. However, this inflection point is not practical for the possible loss circumstance in our CSA study. Because 40% of chance to suffer a loss can be perceived as unacceptable for consumers to purchase CSAs, and the inflection point for CSA loss is much closer to 0, causing the diminished concave region under low probability becomes too narrow for the existing functional forms to capture. As a result, in the loss model, the probability weighting function neglects the concave region under very small probabilities and recognizes the probability weighting as a largely convex and S-shaped model.

To address the two reasons above, we modified the probability weighting function by adding one more parameter to the functional form, $\zeta\pi^{\mu}/(\zeta\pi^{\mu}+(1-\pi)^{\mu})^{(1/\mu)}$, where $\zeta$ primarily controls elevation and $\mu$ controls curvature (Lattimore et al., 1992). An adjustable elevation parameter allows inflection point to move downward. Furthermore, we dropped the choice scenarios that contains probability higher than 60% and rescaled the remaining probability from 0 – 0.6 to 0 – 1. As such, the concave region of low probability of possible losses can be enlarged and better captured by the weighting function. The estimate comparison between regular loss model and rescaled loss model with modified probability weighting function is presented in table A-1. As expected, the weighting curvature ($\mu$) becomes 0.80 with elevation ($\zeta$) of 0.57, showing an inverse S-shaped weighting function for the rescaled loss model. Meanwhile, dropping high percentage choice questions causes an underestimation on price and risk intercept, and an upward bias of loss aversion.

Therefore, using one-parameter probability weighting function might not produce an inverse S-shaped curvature for loss model, but it can still capture the most weighting functional region under convexity and improve the overall goodness of fit. Along with a satisfactory estimation for the gain model, we believe it is still the best practice to use the original functional form without dropping and rescaling the data set for the loss model.

Table A - 1. Compare Model Estimates between Regular Loss Model and Rescaled Loss Model

| **Variable** | **Pop. Mean** | **Pop. SD** | **5% C.R.** | **95% C.R.** |
|---|---|---|---|---|
| | *Regular Loss Model* | | | |
| CSA Intrinsic ($c$) | 12.89 | 0.50 | 12.17 | 13.80 |
| Price ($\delta$) | 1.98 | 0.16 | 1.68 | 2.22 |
| Variety ($\beta$) | 2.81 | 0.30 | 2.29 | 3.30 |
| Distance ($\gamma$) | 1.34 | 0.20 | 1.03 | 1.73 |
| Probability Weight ($\mu$) | 1.34 | 0.09 | 1.19 | 1.49 |
| Risk Curvature ($\alpha$) | 0.51 | 0.03 | 0.47 | 0.56 |
| Loss Aversion ($\lambda$) | 2.29 | 0.10 | 2.15 | 2.48 |
| Risk Intercept ($\eta$) | 7.31 | 0.29 | 6.80 | 7.79 |
| Observations | 16,920 | | | |
| Log Marginal Density | -3637.13 | | | |
| Trimmed Log M.D. | -3587.67 | | | |
| | *Rescaled Loss Model* | | | |
| CSA Intrinsic ($c$) | 10.27 | 0.54 | 9.59 | 11.59 |
| Price ($\delta$) | 0.86 | 0.22 | 0.46 | 1.17 |
| Variety ($\beta$) | 2.39 | 0.38 | 1.85 | 3.14 |
| Distance ($\gamma$) | 1.33 | 0.33 | 0.76 | 1.85 |
| Weighting Elevation ($\zeta$) | 0.57 | 0.19 | 0.33 | 0.98 |
| Probability Weight ($\mu$) | 0.80 | 0.19 | 0.51 | 1.13 |
| Risk Curvature ($\alpha$) | 0.36 | 0.03 | 0.31 | 0.41 |
| Loss Aversion ($\lambda$) | 3.20 | 0.63 | 2.27 | 4.20 |
| Risk Intercept ($\eta$) | 0.89 | 0.35 | 0.36 | 1.44 |
| Observations | 9,870 | | | |
| Log Marginal Density | -2638.32 | | | |
| Trimmed Log M.D. | -2609.12 | | | |

Note: This table reports the heterogeneous estimation results for regular loss model and rescaled loss model. For rescaled model, we dropped choice questions that contains loss probability higher than 60%, then rescaled the rest percentage data to 0-1. A two-parameter weighting function is used to estimate rescaled loss model with one additional parameter measuring weighting elevation.

**CSA Gain Scenario**

**Scenario Questions are the major part of the research. This survey only consists a total of 24 choice scenarios and a few background questions. So please compare the options carefully and answer the questions to the best of your ability.**

| Attribute | Option A | Option B | Option C |
|---|---|---|---|
| Up-front Payment | $500 | $600 | Neither option A nor B |
| Number of Product Varieties | Good (11-15 varieties) | Good (11-15 varieties) | |
| Distance to Pick-up Location | 10 miles | 5 miles | |
| Chance of Getting Bonus Produce due to Good Harvest | 50% | 25% | |
| Value of Bonus Produce due to Good Harvest | $50 | $100 | |

**If these were the only options available to you, which option would you choose?**

| I would choose option A | I would choose option B | I would choose option C |
|---|---|---|
| ○ | ○ | ○ |

Figure A - 1. Screenshot of discrete choice scenario example in possible gain circumstance

## Introduction

**What is Community Supported Agriculture?**

Community Supported Agriculture consists of a community of individuals who pledge support to a farm operation so that the farmland becomes, either legally or spiritually, the community's farm, with growers and consumers providing mutual support and sharing the risks and benefits of food production.

Here is how CSA works: a farmer offers a certain number of "shares" to the public. Typically, the share consists of a box of vegetables. Interested consumers purchase a share ("membership" or a "subscription") and in return receive a box (bag, basket) of seasonal produce each week throughout the farming season, as well as satisfaction gained from reconnecting to community and land, and participating directly in own food production.

**Risks**

While membership in a CSA farm means sharing in the bounty of the season, it also means sharing in the risks of farming, such as poor harvests due to unfavorable weather or pests. By paying for food prior to planting, CSA members essentially assume the possibility of risks and understand that a refund will not be issued if less crops are harvested.

**Benefits**

Besides an increased involvement in local community, CSA members have the access to local, healthy and fresh produce at a competitive price, and in a convenient way. Additionally, at times when CSA farms have a good harvest, members may receive their subscription with extra produce as bonus, which values more than their up-front price.

Figure A - 2. Screenshot of the introduction page presented to respondents prior to discrete choice questions

**CSA Loss Scenario**

**Scenario Questions are the major part of the research. This survey only consists a total of 24 choice scenarios and a few background questions. So please compare the options carefully and answer the question to the best of your ability.**

| Attribute | Option A | Option B | Option C |
|---|---|---|---|
| Up-front Payment | $500 | $400 | Neither option A nor B |
| Number of Product Varieties | Fair (11-15 varieties) | Fair (6-10 varieties) | |
| Distance to Pick-up Location | 10 miles | 5 miles | |
| Chance of Loss due to Poor Harvest | 25% | 10% | |
| Value of Loss due to Poor Harvest | $150 | $50 | |

**This is a screening question, please choose Option B?**

| I would choose option A | I would choose option B | I would choose option C |
|---|---|---|
| ○ | ○ | ○ |

Figure A - 3. Screen shot of the screening choice question example

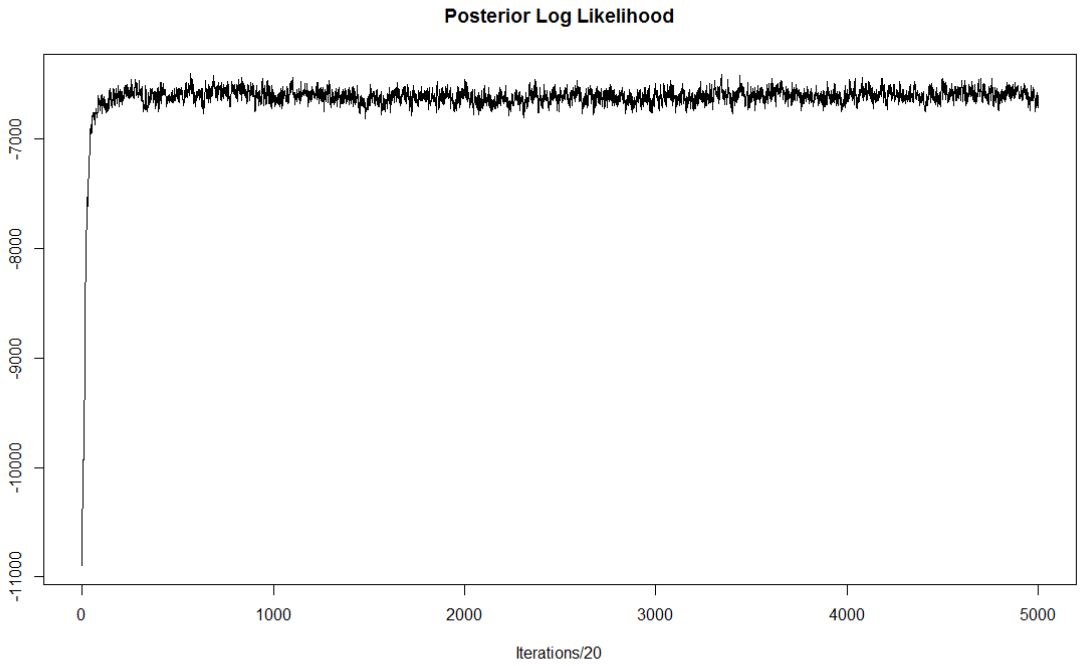


Figure A - 4. Values of the log-likelihood of the data evaluated at posterior draws of individual-level taste estimates: every 20th draw retained for analysis

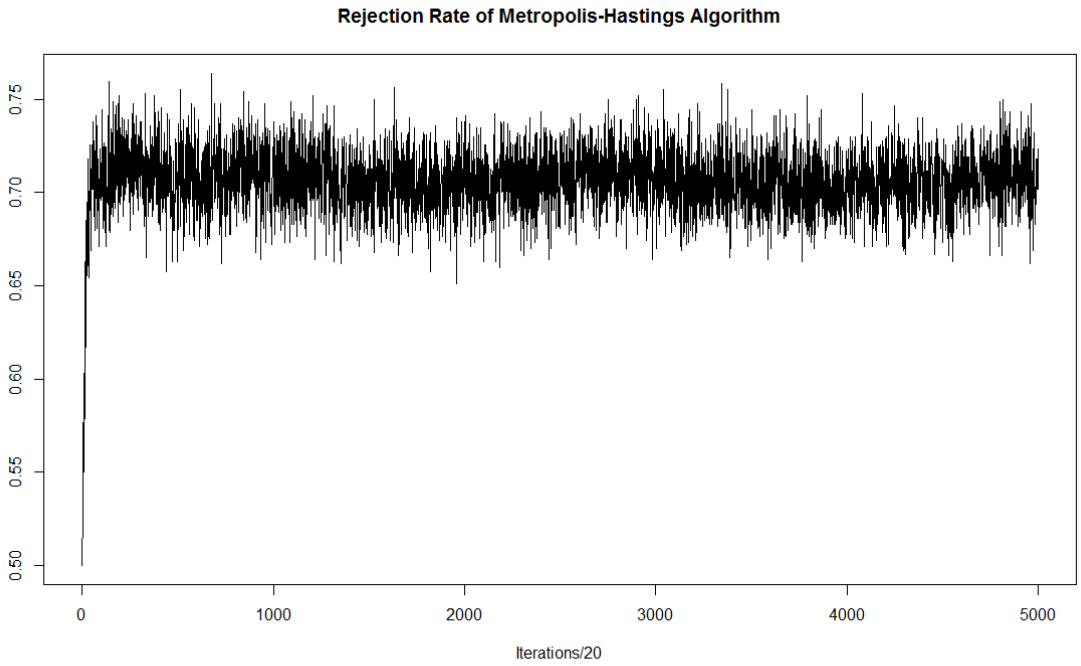


Figure A - 5. Rejection rate of Metropolis-Hastings algorithm: every 20th draw retained for analysis

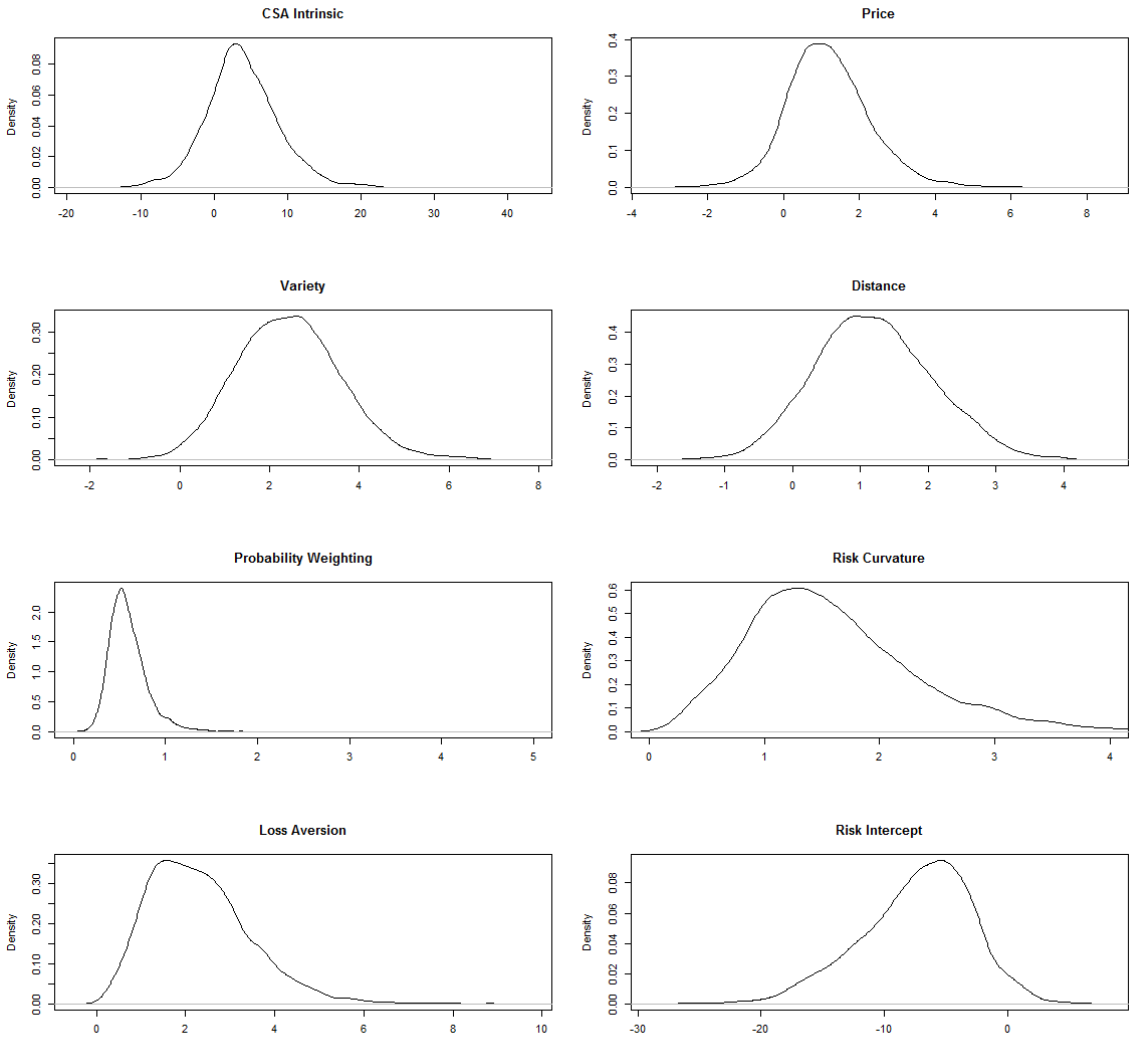


Figure A - 6. Posterior distribution of taste parameters for respondent no. 100