MINIMUM-DATA ANALYSIS OF ECOSYSTEM SERVICE SUPPLY WITH RISK AVERSE DECISION MAKERS

by

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This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citation, bibliographic style, and consistency, and is ready for submission to the Division of Graduate Education.

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STATEMENT OF PERMISSION TO USE

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ABSTRACT

There is a need for models that produce results that are both timely and sufficiently accurate to be useful to policy makers. The minimum-data approach of Antle and Valdivia (2006) responds to this need by supplying a spatially explicit first order approximation that models ecosystem supply by producers. However, producers in developing nations often are observed to deviate from simple expected profit maximization. Risk is one possible explanation for this divergence. This study builds upon the minimum-data approach by allowing for risk averse producer preferences. The study presents a framework for translating relative risk aversion measurements into the parameters needed for the mean-standard deviation utility function. This study utilizes experimental and econometric measurements of risk aversion by other researchers to parameterize the model. Historic weather data are used with crop yield models to simulate temporal variation in crop yields.

The model is used to simulate the supply of carbon sequestration in Machakos, Kenya. At low levels of risk, producers behave in a manner consistent with risk neutrality. However as risks and risk aversion levels increase, there is an increasing divergence from the behavior implied by expected profit maximization. The effects of varying the structure of risk preferences were also examined. This study finds that, consistent with the results in a number of other studies, the level of risk aversion is generally a more important factor in simulated behavior than the structure of risk preferences. This study also examines the effects of increasing the spatial variation of returns. As the spatial variation of returns increases, the predicted producer behavior converges on a fifty percent rate of adoption of the carbon sequestering system, regardless of other parameters. Overall, this study finds that - at levels of risk aversion measured in similar populations in developing nations - the inclusion of risk aversion in the model provides an explanation for why the observed behavior of producers appears to diverge from expected profit maximization.

CHAPTER 1

INTRODUCTION

There is a need for models that allow researchers to find results that are both timely and sufficiently accurate to be useful to policy makers. The minimum-data approach (MD) of Antle and Valdivia (2006) responds to this need by supplying a spatially-explicit approach that provides the means of modeling ecosystem supply by producers. Producers in developing nations often appear to deviate from the goal of simple profit maximization. Risk is one possible explanation for that divergence. This study builds upon the MD approach by allowing for risk averse producers. The original MD approach assumed producers were risk neutral. The assumption of risk neutrality is consistent with the "minimum-data" goal of providing a useful first-order approximation that is sufficiently accurate for policy analysis. However, there is abundant evidence showing that decision makers may be risk averse in their decision making (Binswanger, 1981; Kachelmeier and Shehata, 1992; Holt and Laury, 2002). Therefore, there is reason to believe that incorporating risk into models dealing with the developmental world would be fruitful.

The minimum data risk aversion (MDR) approach presented in the study is a generalization of the original MD approach by allowing for producers to be risk averse. This study also presents a framework for translating the unit-free relative risk aversion measure (R) into the risk aversion parameters needed for the mean-standard deviation (MSU) utility function. This study uses a range of values for R taken from previous studies that represent an appropriate range of risk aversion relevant to this study.

The study presents a sensitivity analysis using MDR in the Machakos region of Kenya by modeling the potential supply of carbon (C) sequestration by producers at different levels of risk aversion. Machakos, Kenya is a region that is representative of the poorest farmers in many developing nations. According to the United Nations Human Development Report's (2008) human development index, Kenya is ranked at 148th out of 177 countries. The U.N. human development index is composed of a number of indices including life expectancy, educational attainment, and income. Within Kenya, per capita gross domestic product is about four U.S. dollars per day. The Machakos region is even poorer, with the majority of the population living at or beneath the international poverty line of about a dollar a day. According to Ravallion et al. (2008), in 2004, approximately one in five people in developing world lived at that same level of about a dollar a day. Kenya also has experienced rapid soil degradation, with as much as a sixty to eighty percent decline in soil-organic carbon within the last thirty years (Lal, 2006). In addition to a loss of soil-organic carbon being associated with decreased yields in several experiments (Larney et al., 2000; Bauer and Black, 1994), a decrease in soil-organic carbon is a contributing factor in the increase in greenhouse gas emissions (Lal, 2006).

Curbing the decline of soil-organic carbon levels in developing nations is a potential mechanism for sequestering carbon as well as potentially mitigating the poverty faced by many poor farmers (Antle and Stoorvogel, 2008). Several studies have estimated the economic potential for the supply of carbon in developing nations (Niles et al., 2002; Antle et al., 2003). However, none of these empirical studies has incorporated risk and risk preferences into the analysis. This study uses risk aversion values econometrically and experimentally estimated by other researchers to calibrate the study. Temporal variation estimates are generated with crop models using historic weather information.

The sensitivity analysis shows that the degree and structure of risk aversion preferences are potentially important predictive elements in modeling carbon contract participation. At low levels of risk aversion, incorporating risk does not substantially change the expected behavior of producers relative to that of risk neutrality. At high levels of *temporal* variance and high risk aversion levels, incorporating risk substantially changes the expected behavior of risk averse producers relative to risk neutral producers. The structure of risk preferences is important when producers are very risk averse and face high risk levels. *Spatial* variation is also shown to be an important predictive element in contract participation rates. As spatial variation become large enough, contract participation rates converge to fifty percent regardless of other parameters. This result occurs because the expected returns of the contract scenario are either so profitable or so unprofitable that no plausible level of contract payment could substantially influence producer behavior. Overall, this study finds that at levels of risk aversion measured in similar populations in developing nations, the inclusion of risk aversion in the model provides an explanation for why the observed behavior of producers appears to diverge from expected profit maximization.

CHAPTER 2

LITERATURE REVIEW

The minimum data (MD) approach of Antle and Valdivia (2006) provides a first order approximation of the supply of ecosystem services by producers. This approximation implicitly assumes that producers are risk neutral. However many studies have found that risk aversion is common among decision makers (Binswanger, 1981; Holt and Laury, 2002). This study includes risk preferences within the minimum data approach by using a mean-standard deviation utility function (MSU). This study also presents a framework for translating the common measure for relative risk aversion (R) into the MSU framework. It uses estimates of R taken from other researchers to calibrate a sensitivity analysis. This sensitivity analysis is implemented using data from the Machakos region of Kenya, where the population faces similar conditions to many of the poorest producers in developing nations.

This chapter introduces production under output uncertainty. It presents a framework for predicting producer behavior under uncertainty as a function of producer preferences. The decisions that producers make have the ability to increase ecosystem services and, in particular, carbon sequestration. Producers who have no direct incentive to provide ecosystem services make private decisions that result in a lower supply of carbon than is socially optimal. To rectify the situation, it may be possible to create a publicly or privately structured incentive program to reward producers for supplying carbon sequestration. A structured incentive program could reward farmers on the basis of annual expected carbon sequestered.

Production Economics

Let p be a vector of prices with subsets p_o the output price and p_c a row vector of input prices. With y defined as stochastic temporal output, x as an input vector, short run profits (W) equals:

$$\mathrm{W} \equiv p_o y(x) - p_c x.$$

Under this framework, a simple profit maximizer would choose a level of inputs that maximizes expected profits $\left(E(\mathrm{W})\right)$. Assuming that there exists a local maximum, let x^* be the inputs that maximize the profit equation. A profit maximizer's profit function is $W(p) \equiv W\left(x^*(p)\right)$.

Let $u(W)$ be the utility derived from agricultural production returns. There are utility function forms that are potentially a better fit in modeling producer preferences. However, in response to data limitations and the goal of providing a model that is sufficiently accurate and timely for policy analysis, this study assumes that utility derived from agricultural production returns is evaluated separately from expected utility derived from alternative income sources.

Only looking at the utility that is a function of W yields $u(\mathrm{W}) = u(p_o y - p_c x)$. For logical ordering of utility it is required that $\frac{\partial u}{\partial \mathrm{W}} > 0$. Risk averse (RA) and neutral

(RN) producers have utility functions defined by $\frac{\partial^2 u}{\partial W^2} < 0$ and $\frac{\partial^2 u}{\partial W^2} = 0$ respectively. The following figures illustrate two production options which share the same expected return of W_0. Option 1 assumes returns are risk free (no uncertainty) return of W_0. Let δ be a potential gain or loss. Option 2 has risk in the form of a 50-50 potential return of either $W_0 + \delta$ or $W_0 - \delta$.

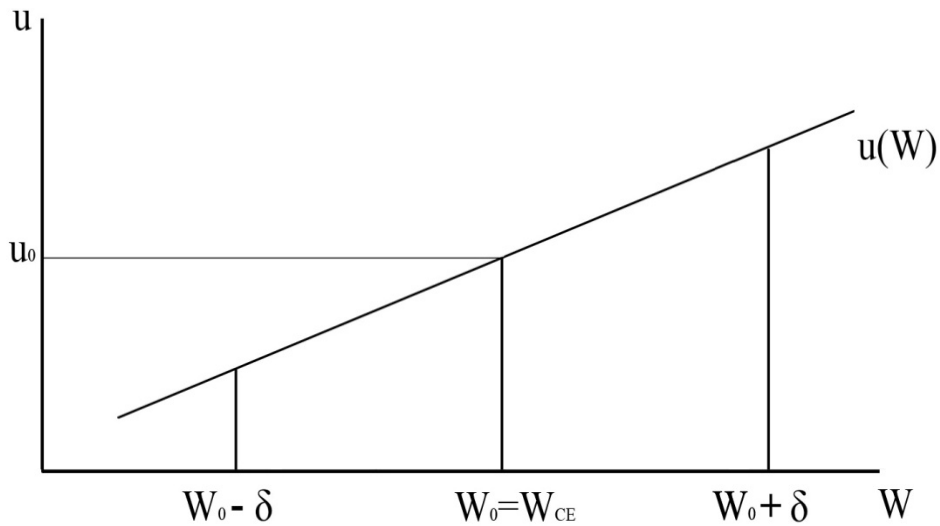

Figure 1: A utility curve u for a RN producer as a function of wealth (W).

The risk neutral producer illustrated in figure 1 is indifferent between the two production options. He makes his production choice based upon only the expected return of the production options. For the risk neutral producer, both production options have the same return value, therefore both have the same expected utility. The risk neutral producer is indifferent between the two options.

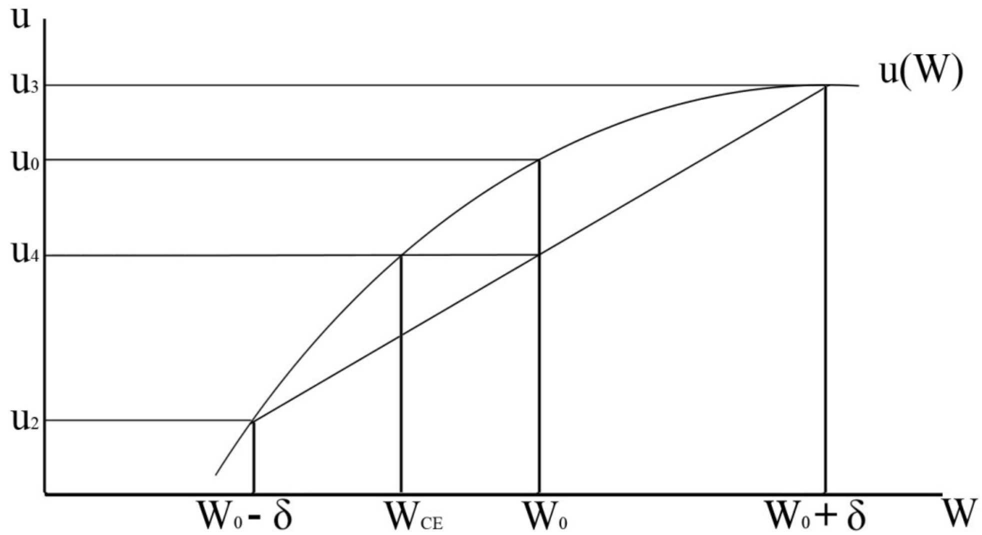

Figure 2: A utility curve u for a RA producer as a function of wealth (W).

The risk averse producer prefers production option 1 because it has the same expected return (W_0) as the other option, but has no risk. The expected utility of option 1 is u_0. The expected utility of option 2 is found where W_0 intersects the line drawn between $W_0 + \delta$ and $W_0 - \delta$[1]. Option 2 is shown to be inferior to option 1 because the expected utility of option 2 is the point u_4 and is less than the expected utility of option 1 (u_0). The lower expected utility of option 2 can also be expressed in terms of certainty equivalents. The certainty equivalent is the income the producer would be willing to receive in order to attain the same level of expected utility. The certainty equivalent for option 2 (W_{CE}) is less than the reward for option 1(W_0), which also indicates that the RA producer would prefer option 1.

[1] This is the weighted average of potential returns in terms of utility.

Risk Preferences

Risk averse behavior is frequently observed in experimental studies. In a recent study with 175 student participants in four universities in the United States, using a series of lotteries, Holt and Laury (2002) found that even when the maximum real payoff for all prizes was extremely small, less than 4 U.S. dollars, two-thirds of participants behaved with risk aversion. When the payoffs were scaled up to the highest potential outcome of 346 U.S. dollars, the average respondent demonstrated "high" levels of risk aversion. As many as 1/3 of respondents avoided any possibility of the low potential outcome of 9 U.S. dollars when at all possible, even when the risky option had an average expected return 166 U.S. dollars above the risk free award of 180 U.S. dollars.

Risk preferences have been attributed as a possible explanation for the input choices of producers. Nevertheless, the importance of risk preferences in the production choices of producers is still uncertain (Just and Pope, 2003). There are many alternative explanations (fixed inputs, imperfect capital markets, intertemporal financial policies, among others) for why producers may be expected to behave in an apparently risk averse manner. In the Machakos region of Kenya in this study many farms do not use fertilizer to grow maize. They might be expected to use fertilizer assuming simple profit maximization. The low use of fertilizer may be explained by risk aversion. It also could be explained by insufficient transportation infrastructure (Omamo, 1998), imperfect access to capital (Murton 1999), and high transaction costs (Renkow et al., 2004).

In two separate studies both Arrow (1965) and Pratt (1964) independently derived coefficients for relative and absolute risk aversion. The Arrow-Pratt absolute risk aversion coefficient is defined as:

$$AP(W) \equiv -\frac{u''(W)}{u'(\mathrm{W})}$$

with u' defined as $\frac{\partial u}{\partial W}$ and u'' as $\frac{\partial^2 u}{\partial \mathrm{W}^2}$ with respect to wealth (W). The unit-free relative risk aversion coefficient is defined as:

$$R(W) \equiv -W\frac{u''(W)}{u'(\mathrm{W})} \equiv W * AP(W).$$

Larger values of AP or R imply a greater degree of absolute or relative risk aversion. Measuring wealth can be problematic because it is both hard to elicit accurate statements of personal wealth as well as difficult to measure when observed. One way to avoid this is to use the partial risk aversion coefficients:

$$P \equiv -M\frac{u''(M+W)}{u'(M+\mathrm{W})} \equiv M * AP(M+W)$$

defined instead in terms of the returns (M).

This study draws upon the work of other researchers to calibrate the relevant risk aversion range. Binswanger (1980) conducted a series of experimental lotteries in rural India which found that most participants were either “intermediately” or “moderately” risk averse. The experimental lottery had different choices available to the respondents which corresponded with different payoff schemes. Binswanger repeated the experimental lottery with different levels of payoffs while preserving the same ratios of returns associated with each choice. This design allowed the relative value of the expected return of a risky choice to remain constant while observing different risk attitudes at different levels resulting from changing the size of the payments. With the largest possible lottery reward, at 4.5% of average annual earnings, participants' risk attitudes became less heterogeneous and more strongly risk averse.

Within studies to estimate R, the choice of W is neither obvious nor trivial. In Binswanger's earlier study (1980) he uses the partial risk aversion measurement. In a follow up study (1981) he calculates relative risk aversion measurements for the same data. Assuming that AP(M+W) is approximately the same as AP(W), the difference between the two methods is the choice of the multiplier M or W. Meyer and Meyer (2005) discusses the problem of multiplier choice as being often ignored or overlooked by researchers when comparing risk aversion estimates across studies. They demonstrate that the choice of multiplier can substantially alter risk aversion estimates. Binswanger (1980) finds most values of P fall in the range of 0.5 to 1.5. In a follow up study (1981) he finds R estimates to range from 2 to 16,000.

The Machakos study uses seasonal crop returns to calculate P. These returns are much greater relative to the certainty equivalents of lottery values M used to estimate P in Binswanger's 1980 study. They are also substantially less than the estimates for total wealth W used to estimate R in Binswanger's 1981 study. Therefore, the sensitivity analysis presented in this study uses a mix of values between R and P with a range of 0.5

to 5.0 and refers to it as R[2]. Goodwin (2009) surveys a number of risk aversion estimates by other researchers and finds that an R of 1.0 is appropriate for agriculturalists in the United States.

The structure of risk preferences within this study refers to the categories of risk structures potentially possessed by producers. These categories define constant, decreasing, and increasing absolute risk aversion as $\frac{\partial AP}{\partial W} = 0, \frac{\partial AP}{\partial W} < 0,$ and $\frac{\partial AP}{\partial W} > 0$ respectively. Likewise they define constant, decreasing, and increasing relative risk aversion as $\frac{\partial R}{\partial W} = 0, \frac{\partial R}{\partial W} < 0$, and $\frac{\partial R}{\partial W} > 0$ respectively. There is some discussion over the importance of these risk preference structures. Lence (2009) presents a thought experiment from which he concludes that the attention given to estimating flexible functional forms capable of measuring risk preference structure simultaneously with technology is misplaced and yields functional form estimates that "bear no resemblance to the true parameters". A number of other researchers observed that for the most part[3], individuals with different structures of risk preferences, but the same level of risk aversion, made almost identical portfolio decisions (Černý, 2004; Kallberg and Ziemba, 1983, p. 1257), indicating again that the structural of risk preferences is less important than the level of risk aversion.

Under risk aversion, producers make decisions based upon the ex-ante expected utility of production choices. A production option has an expected utility of U defined as:

[2] An R of 5 is much the same in tested producer behavior as an R of 10 or greater in this application.
[3] Černý (2004) found so long as investments did not involve very large and skewed risks.

$$U \equiv \mathrm{E}\big(u(y(x) - cx)\big).$$

There are many potential expected utility functions that could be used. Goodwin (2009) takes one approach to estimating expected utility. He constructs a distribution of utilities and takes the expected mean utility of that distribution. He is able to use this flexible approach to find expected utility values associated with different levels of risk aversion given different distributions of returns. For simplicity, flexibility, and in response to available data, this study uses Saha's (1997) mean-standard deviation utility (MSU) framework. Let μ be defined as mean returns, τ defined as standard deviation of the stochastic temporal returns, and θ and γ defined as risk attitude parameters. MSU is defined as:

$$MSU \equiv \mu^{\theta} - \tau^{\gamma}.$$

A number of researchers have used MSU to estimate risk aversion parameters (Isik and Khanna, 2003; Toledo and Engler, 2008). However, it is not clear in these studies how to relate the econometrically estimated MSU risk parameters across studies. In Chapter 3 this thesis presents a framework for translating MSU risk preferences into the common unit free measurement for relative risk aversion (R).

Ecosystem Services

The United Nations Millennium Ecosystem Assessment (2005) defined ecosystem services (ES) as "the benefits people obtain from ecosystems." They found that of the 24

ES observed during the report, 15 of them were being degraded or used unsustainably. In agriculture, ES are the most important public good that farmers can supply (Antle and Capalbo, 2003). The mitigation of anthropologic climate change has become an increasingly important ES. In a recent full report the Intergovernmental Panel on Climate Change (2007) found that the "warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice and rising global average sea level." Increased awareness and concern for climate change increases the likelihood that governments will (or will continue to) take actions intended to decrease the level of greenhouse gasses in the atmosphere. A United Nations Food and Agricultural Organization report (2008) suggests that the large scale and rapid change in government policies to encourage the use and production of liquid bio-fuels was in part motivated by efforts to mitigate climate change. Currently the U.S. congress is considering the Waxman-Markey bill that provides domestic farmers with subsidies for low-carbon agricultural practices and aims at establishing a national cap-and-trade system for CO2 similar to the current system in Europe (Broder, 2009).

Carbon sequestration refers to the quantity of additional carbon above the base practice that is captured and stored by use of carbon sequestration practices. There are a number of recognized ways of sequestering carbon from the atmosphere, including but not limited to geological carbon sequestration as well as terrestrial carbon sequestration (TCS). Research indicates that TCS has the potential to provide a low cost alternative to emissions reductions and other options to offset emissions (Lubowski et al., 2006). With a large quantity of land mass and much room for soil quality improvement, the developing world is likely to have high *technical* potential for TCS. The technical potential refers to the total additional amount of carbon that can be sequestered in soils through use of carbon sequestration practices. The *economic* potential on the other hand refers to the level of addition carbon sequestered given a range of ecosystem service payment levels that is consistent with the expected market value of carbon sequestration. The economic potential for TCS, at incentive payments levels typically modeled, is likely to be less than the technical potential due to the high cost of sequestering carbon in degraded soils, as well as a number of factors common to the developing world (imperfect capital markets, poor institutional structures, political instability, etc.). As the price of carbon sequestration increases, the economic potential for carbon sequestration asymptotically approaches the technical potential (Antle, 2009). This is illustrated in the following figure.

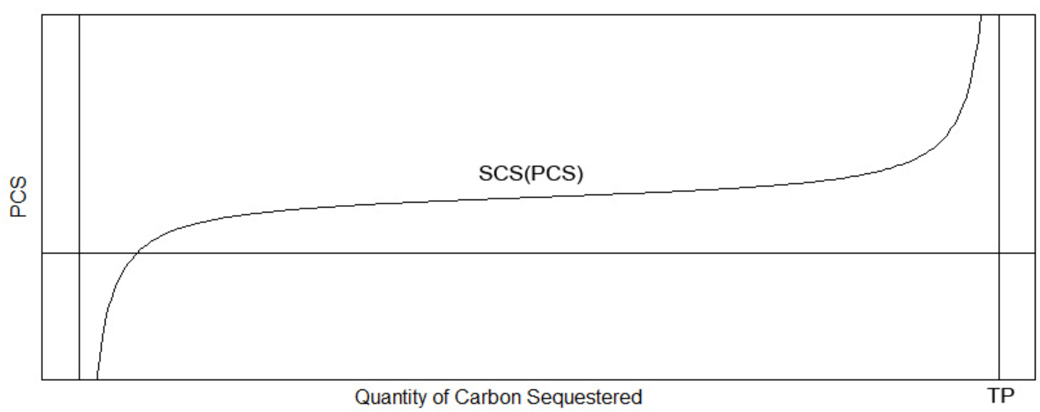

Figure 3: The economic potential analogous to the supply of carbon sequestered (SCS) asymptotically approaches the technical potential (TP) as the price of carbon sequestered (PCS) gets large.

As of yet, TCS has not been widely recognized in the context of international agreements such as the Kyoto Protocol. The behavior of agricultural producers has the potential to influence long term stocks of carbon within soils and therefore should be included as a way for nations to earn marketable carbon credits. One way for farmers to sequester carbon is by managing their fields differently, resulting in increases in the biomass in soils (Lal and Bruce, 1999). Currently, “strategies to increase the soil carbon pool include soil restoration and woodland regeneration, no-till farming, cover crops, nutrient management, manuring and sludge application, improved grazing, water conservation and harvesting, efficient irrigation, agroforestry practices, and growing energy crops on spare lands” (Lal, 2004). It is possible that additional low cost strategies will be developed as wide-scale establishment of carbon markets provide monetary incentives for innovation.

Overcropping has been shown to reduce soil organic carbon level by as much as 50-70% in some nations (Lal and Bruce, 1999). Deforestation and soil degradation aggravates the problem of global industrial carbon emissions and has been estimated by the Intergovernmental Panel on Climate Change (1995) to account for 20% of the annual increase in radiative forcing. Without some kind of unanticipated structural change, soil degradation in developing nations is predicted to steadily increase, leading to declining levels of productivity as well as increasing rates of total crop failure (Lal, 2000).

Soil organic carbon levels can be increased with the adoption of appropriate management practices (Batjes, 2001). There is the potential for a contract system to reward farmers for changing their base system of practices to a TCS system of practices.

Through a TCS payment program, Antle and Stoorvogel (2008) suggest greenhouse gas emissions could be mitigated, rural poverty in developing nations could be alleviated, and agricultural sustainability enhanced. They warn however that ecosystem services payment are “not a panacea”.

This study uses a hypothetical TCS payment program that rewards farmers based upon the expected TCS provided. It is not possible to know how much TCS actually would actually be provided on any given site ex-ante if a TCS system was used. Antle et al. (2003) find that a payment in exchange for expected carbon sequestered could be effective if the costs of quantifying actual services provided were large. However, Antle and Diagana (2003) point out that the lack of well defined property rights and poor financial institutions can pose significant issues in designing soil carbon contracts for farmers in developing nations.

In the absence of a contract payment scheme, farmers will make production system choices that maximize their personal utility resulting in an underproduction of socially valued TCS. Without a payment scheme, farmers do not internalize the willingness to pay of society for the TCS they could supply. To increase the level of TCS production above the private equilibrium, farmers must be induced to change behavior. One way to achieve the social optimum would be through governmental regulation. Another would be to provide farmers an incentive payment for providing TCS. Theory and experience suggests that an incentive payment program would be a more efficient way of encouraging farmers to increase their supply of TCS (Ellerman, 2006).

Following Antle (2009), a farmer using system a has returns each period t equal to $\Pi(p_t,z)$ with p_t equal to the price vector at period t with z indexing the choice between the base system a and the alternative system b. Let total seasonal periods be T and the discount factor in period t be Δ_t. The net present value NPV of system a for the risk neutral producer is:

$$NPV(a) \equiv \sum_{t=1}^{T} \Delta_t \, E\big(W(p_t, a)\big).$$

Let the alternative system that sequesters carbon be b, the payment be g_t and the seasonal adjusted fixed cost of changing between systems be F_t. The NPV for a risk neutral producer b is:

$$NPV(b) \equiv \sum_{t=1}^{T} \Delta_t \; E(W(p_t, b) + g_t - F_t).$$

For the producer, when $NPV(b) > NPV(a)$ the farmer enters the contract and does not enter it otherwise. For the purpose of policy analysis it is useful to consider the special case where $\Delta_t = \Delta$, $p_t = p$, $g_t = g$, $F_t = F$ for all time periods. In that case, the decision to switch to a carbon sequestration system for the risk neutral producer occurs when:

$$E(W(p, b) + g - F) - E\big(W(p, a)\big) > 0$$

for all t. Under the MSU framework in which expected utility is characterized by mean returns $\mu(p_t, z, t)$, temporal standard deviation $\tau(p_t, z, t)$, and risk attitude parameters θ_t and γ_t f Paustian et al., 2000or each production period t. For the risk averse producer, the decision to switch between systems is based upon expected utility. The risk averse producer has the present values (PV) for the separate production systems defined as:

$$PV(a) \equiv \sum_{t=1}^{T} \Delta_t\, MSU(\mu(p_t, a, t), \tau(p_t, a, t), \theta_t, \gamma_t)$$

and

$$PV(b) \equiv \sum_{t=1}^{T} \Delta_t\, MSU(\mu(p_t, b, t) + g - F, \tau(p_t, b, t), \theta_t, \gamma_t).$$

As with the RN producer, the RA producer uses system b when $PV(b) > PV(a)$. With RA producers, the special case occurs where $\Delta_t = \Delta, p_t = p,\ g_t = g,\ \mu(p_t, z, t) = \mu_z,\ \tau(\bar{\Pi}(p, z, t)) = \tau_z,\ \theta_t = \theta, F_t = F$ and when $\gamma_t = \gamma$ for all t. In this case the seasonal decision to switch to the alternative system occurs when

$$MSU(\mu_b + g - F, \tau_b, \theta, \gamma) - MSU(\mu_a, \tau_a, \theta, \gamma) > 0.$$

Under risk aversion the carbon supply curve in figure 3 is not only a function of differences between μ_a and μ_b but also differences in τ_a and τ_b and how they are valued based on the producer risk preference parameters θ and γ. Within this seasonal production framework, ecosystem services can also be expressed as an average level of carbon per season sequestered (e_s). Let SC_T defined as the soil carbon at the last time period using the TCS practice, SC_0 as soil carbon at the first time period, T_T as the last seasonal time period, and T_0 as the initial seasonal time period. A seasonal level of average soil carbon sequestered using the alternative practice can be found with $e_s = (SC_T) - SC_0)/(T_T - T_0)$. A carbon payment g in each production period may induce producers to switch from their base practice to the alternative practice that supplies an average TCS of e_s.

Several recent studies have looked at the potential for the supply of terrestrial carbon sequestration by farmers in both developing and developed nations (Lal, 1998; Lal, 2000; Paustian et al., 2000; Lal, 2004; Antle and Valdivia, 2006; Antle and Stoorvogel, 2008). Pendell et al. (2007) model the supply of TCS in Kansas under risk. However, none of these empirical studies has incorporated risk preferences in the estimation of the supply of TCS in developing nations.

Graff-Zivin and Lipper (2008) present a model of carbon sequestration with risk preferences and examine the comparative statics associated with marginal changes. They find that the supply of carbon is positively correlated with the price of carbon sequestration. They also find that the supply of carbon sequestration is ambiguously correlated with risk aversion levels. Increased risk aversion has two competing effects. Risk averse producers favor carbon sequestration systems because higher soil carbon levels decrease the volatility of returns. Conversely, risk averse producers shy away from carbon sequestration production systems because the associated technology tends to increase the volatility of returns. Thus, risk averse producers will favor carbon sequestration systems more than risk neutral producers when the volatility reduction effect of increased carbon in soils dominates. In contrast, risk averse producers will be less likely to use carbon sequestration technology than risk neutral producers when the volatility increasing effect of sequestration technology dominates.

Minimum Data Framework

The Minimum Data (MD) is a spatially explicit modeling approach for the supply of ecosystem services characterized by opportunity cost. The MD approach can be done with the kinds of secondary data currently available in many parts of the world. While not having the complexity of more heavily data dependent models, it is intended to provide a framework for analysis that is sufficiently accurate to be useful to policy makers within a timeframe relevant for policy making. The MD approach is a freely available and transparent framework that is publicly accessible.

The MD approach has been used to model the supply of a variety of ecosystem services, including the supply of carbon (Antle and Valdivia, 2006; Antle and Stoorvogel, 2008), the supply of water (Immerzeel et al., 2008), and the supply of wetland habitat (Nalukenge et al., 2009). This study provides a framework for which researchers who would like to model ecosystem services with the MD approach can incorporate risk aversion preferences. The MD analysis presented in this study draws upon other models and data such as the DSSAT cropping model, historic weather information, soil quality survey data, and experimental studies to calibrate the Machakos, Kenya application.

CHAPTER 3

THEORETICAL FRAMEWORK

This chapter builds on the Minimum Data (MD) approach by incorporating risk averse producer behavior. Like the original MD approach, the goal is to develop a model that is sufficiently accurate to be useful to policy makers and that can be implemented with currently available data. The model presented here uses a mean-standard deviation utility function (MSU) proposed by Saha (1997). This chapter presents a framework for calibrating the MSU risk aversion population parameters in terms of the common measurement for relative risk aversion (R). This framework is used in Chapter 4 to translate risk aversion preferences measured by other researchers into MSU preferences.

The analysis is designed to represent a population of agricultural producers. Each producer has risk attitudes and a site-specific distribution of returns. These characteristics are spatially distributed throughout the region. Each individual evaluates the short term expected utility from each production choice and chooses the system with the highest expected utility. Expected utility is determined by expected returns, the temporal variance of these returns, and risk preferences. Temporal variance measures the variation of returns at an individual site over time, while spatial variation refers to the variation in returns across sites at one point in time.

Following Antle and Valdivia (2006), farmers within the region potentially produce ecosystem services (ES) through the choice of their production systems. In this study, farmers using higher levels of fertilizer and manure will sequester more carbon in their soil. Without a positive price for terrestrial carbon sequestration (TCS), farmers will use inputs to maximize their expected utility level as a function of crop returns. When farmers are offered an incentive payment (g) for TCS, they incorporate this incentive into the choice of production system. The MD framework assumes that the model parameters remain constant over the timeframe of the study. If a producer chooses a system at a level of ecosystem service payments during one production period, it is assumed that the producer uses the same system the next period if offered the same payment.

Basic Setup

Table 1: Basic definitions.

$z =$	indexes production systems.
$i =$	indexes producers.
$\pi_{zi} =$	net returns for producer i using system z.
$\mathrm{P} =$	the probability density function for π_{zi}.
$\mu_{zi} =$	mean returns for system z on site i.
$\tau_{zi}^2 =$	the temporal variance for system z on site i.
$\omega_i =$	a vector of site-specific parameters.
$S(\omega) =$	the probability density function for ω.
$\mu_z =$	the mean of μ_{zi} in the population.
$\sigma_z^2 =$	the variance of μ_{zi} in the population.
$\tau_z =$	the mean of τ_{zi} in the population.

Table 2: Basic relationships.

$$\pi_{zi} \sim \mathrm{P}(\pi|\omega_i, z)$$

$$\mu_{zi} \equiv \mu(\omega_i, z) \equiv \int \pi \mathrm{P}(\pi|\omega_i, z) d\pi$$

$$\tau_{zi}^2 \equiv \tau^2(\omega_i, z) \equiv \int \left(\pi - \mu(\omega_i, z)\right)^2 \mathrm{P}(\pi|\omega_i, z) d\pi$$

$$\mu_z \equiv \int \mu(\omega, z) S(\omega) d\omega$$

$$\sigma_z^2 \equiv \int (\mu(\omega, z) - \mu_z)^2 S(\omega) d\omega$$

$$\tau_z \equiv \int \tau(\omega, z) S(\omega) d\omega$$

$$r(g) \equiv \frac{1}{n} \sum_{j=1}^{n} C_j\,(g)$$

Original Minimum-Data Approach

Table 3: Original MD section definitions.

$g =$	an incentive payment per hectare.
$U_i =$	the expected utility function for producer i.
$C_i =$	a vector of system choices with i equal to 1 when farmer i chooses to use system b and equal to 0 otherwise.
$r =$	adoption rate per head.
$n =$	the total number of producers in the simulation.

The MD approach examines a population of agricultural producers who make choices between a base system a and an alternative system b. Each producer chooses a production system based on their expected utility function (U_i) which, under risk neutrality, is monotonically dependent upon mean returns μ_{zi}. Assuming the cost of switching between systems is zero, an economically rational producer i will choose to use system b over a if $U(\mu_{ai}) - U(\mu_{bi}) < 0$ or equivalently if $\mu_{ai} - \mu_{bi} < 0$. Returns by system over time are assumed constant and the choice of systems is at an equilibrium level.

By choosing the alternative system, producers can supply ecosystem services for which, initially, they are not rewarded. An incentive payment per hectare of g has the potential to influence economically rational producers to switch from system a to b. With a payment of g, producer i will choose system b if $U(\mu_{ai}) - U(\mu_{bi} + g) < 0$. With $C(g)$ a vector of producer choices equal to 1 if system b is used, the rate of adoption of the alternative system given any level of payment g is $r(g) \equiv \frac{1}{n}\sum_{j=1}^{n} C_j\,(g)$.

Minimum Data Risk Aversion

Risk aversion enters the model through the utility function of the producer. The minimum data risk aversion (MDR) approach assumes an individual's expected utility function can be expressed as a function of the first two moments of the distribution of net returns. This is equivalent to assuming that the distribution of net returns is a member of a location-scale family of distributions (Meyer, 1987). With parameters θ and γ, the expected utility function is characterized by $U(\mu_{zi}, \tau_{zi}, \theta, \gamma)$, and the producer will use system *b* if $U(\mu_{ai}, \tau_{ai}, \theta, \gamma) - U(\mu_{bi} + g, \tau_{bi}, \theta, \gamma) < 0$. $C(g)$ and $r(g)$ are defined as in the original MD for the MDR approach using the new specification for U. Note that, in general, the expected utility function parameters are specific to an individual and would be indexed by *i*, but in the analysis in this study all decision makers are assumed to have the same utility functions. If ecosystem service payments are certain and only enter the mean returns part of the utility function then the ratio of expected utility under risk neutrality to that of expected utility under risk aversion converge to one as g approaches infinity. In other words as the size of risk free payments become larger, the difference in expected producer behavior gets small[4] . If, in contrast, ecosystem payments are dependent upon the levels of ecosystem services supplied and risky, then it is uncertain whether the behavior of the risk neutral producer and the risk averse producer will converge as payments get large[5].

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[4] $\lim_{g\to\infty} \frac{MSU(\mu_{zi}+g, \tau_{zi}, \theta_i, \gamma_i=0)}{MSU(\mu_{zi}, +g\ \tau_{zi}, \theta_i, \gamma_i)} = \lim_{g\to\infty} \frac{(\mu_{zi}+g)^{\theta_i-1}}{(\mu_{zi}+g)^{\theta_i} - \tau_{zi}^{\gamma_i}} = 1$

[5] $\lim_{g\to\infty} \frac{MSU(\mu_{zi}+g, \tau_{zi}+\tau_g(g), \theta_i, \gamma_i=0)}{MSU(\mu_{zi}+g, \tau_{zi}+\tau_g(g), \theta_i, \gamma_i)} = \lim_{g\to\infty} \frac{(\mu_{zi}+g)^{\theta_i-1}}{(\mu_{zi}+g)^{\theta_i} - (\tau_{zi}+\tau_g(g))^{\gamma_i}}$ ...does not necessarily converge.

Expected Utility Model

Table 4: Expected utility section definitions.

θ and $\gamma =$	population risk preference parameters.
$\upsilon =$	the ratio of γ to θ and can be written $\upsilon \equiv \frac{\gamma}{\theta}$.
MSU =	the mean-standard deviation utility function.
$A =$	the MSU risk aversion measure.
Sign =	equal to 1 or -1 when its argument is positive or negative respectively.
Abs =	the absolute value function.
DARA =	decreasing absolute risk aversion.
CARA =	constant absolute risk aversion.
IARA =	increasing absolute risk aversion.
DRRA =	decreasing relative risk aversion.
CRRA =	constant relative risk aversion.
IRRA =	increasing relative risk aversion.

This study uses a mean-standard deviation utility function (MSU) to represent producers' preference orderings over risky outcomes. The MSU assumes that expected utility can be expressed as:

$$MSU(\mu_{zi}, \tau_{zi}, \theta, \gamma_i) \equiv {\mu_{zi}}^{\theta} - {\tau_{zi}}^{\gamma} \; with \; \theta > 0, \gamma \geq 0.$$

In MSU, risk neutrality occurs when $\gamma = 0$. Under MSU, the mean-standard deviation model is a special case that occurs when $\theta = \gamma = 1$. It is worth noting that MSU is not well defined when μ_{zi} is negative and θ is not an integer. Also, when μ_{zi} is negative and θ an even number, expected utility is not monotonically increasing in μ_{zi} as would be expected for rational behavior. In addition, it no longer preserves the ordinal system for a rational producer. To avoid this problem, this study uses the following alternative specification of the MSU model that is identical to Saha's specification when $\mu_{zi} > 0$, and is well-defined and monotonic in μ_{zi} when $\mu_{zi} < 0$.

$$MSU_A(\mu_{zi}, \tau_{zi}, \theta_i, \gamma_i) \equiv sign(\mu_{zi}) \cdot abs(\mu_{zi})^{\theta_i} - \tau_{zi}{}^{\gamma_i}$$

According to Saha, MSU exhibits decreasing, constant, and increasing absolute risk aversion when $\theta > 1, \theta = 1,$ and $\theta < 1$ respectively. Likewise with $\upsilon \equiv \frac{\gamma}{\theta}$ decreasing, constant, and increasing relative risk aversion occur when $\upsilon > 1, \upsilon = 1,$ and $\upsilon < 1$ respectively.

Table 5: Risk preference structures under MSU.

	DRRA	CRRA	IRRA
DARA	$\upsilon_i < 1, \theta_i > 1$	$\upsilon_i = 1, \theta_i < 1$	$\upsilon_i > 1, \theta_i > 1$
CARA	$\upsilon_i < 1, \theta_i = 1$	$\upsilon_i = 1, \theta_i = 1$	$\upsilon_i > 1, \theta_i = 1$
IARA	$\upsilon_i < 1, \theta_i < 1$	$\upsilon_i = 1, \theta_i > 1$	$\upsilon_i > 1, \theta_i < 1$

With decreasing, constant, and increasing absolute risk aversion (DARA, CARA, IARA).
With decreasing, constant, and increasing relative risk aversion (DRRA, CRRA, IRRA).

(1) $$A(\mu_{zi}, \tau_{zi}) \equiv -\frac{\partial U}{\partial \tau_{zi}} \left(\frac{\partial U}{\partial \mu_{zi}}\right)^{-1} \equiv \left(\frac{\gamma}{\theta}\right) \mu_{zi}{}^{1-\theta} \tau_{zi}{}^{\gamma-1}.$$

Following the well-known Arrow-Pratt measure of risk aversion, Saha defines the MSU risk aversion measure as A (equation 1). The important attributes of A include: risk aversion, neutrality, and affinity when $A > 0, A = 0,$ and $A < 0$ respectively. The magnitude of A for positive values reflects higher levels of risk aversion. Decreasing, constant, or increasing absolute levels of risk aversion occur when the sign of $\partial A / \partial \mu < 0, = 0,$ or > 0 respectively.

Relative Risk Aversion

Table 6: Definitions for the relative risk aversion section.

$u_i(W) =$	the utility function for producer i.
$\pi_{it} =$	the mean returns across systems for producer i at time t and is defined as $\pi_{it} \equiv \frac{1}{2}(\pi_{ait} + \pi_{bit})$.
$\mu_i =$	the mean returns across time and systems for producer i and is defined as $\mu_i \equiv \frac{1}{2}(\mu_{ai} + \mu_{bi})$.
$\mu =$	the mean returns across systems for the entire population and is defined as $\mu \equiv \frac{1}{2}(\mu_a + \mu_b)$.
$\tau =$	the mean temporal standard deviation across systems and individuals for the entire population and is defined as $\tau \equiv \frac{1}{2}(\tau_a + \tau_b)$.
$E=$	the expected value function.
$AP =$	the Arrow-Pratt absolute risk aversion coefficient defined as $AP \equiv -\frac{u''}{u'}$.
R =	the Arrow-Pratt relative risk aversion coefficient and is a unitless measure of risk aversion defined as $\mathrm{R} \equiv WAP = -W\frac{u''}{u'}$.

In order to use the risk preferences estimated by researchers not using MSU, it is possible to relate the MSU parameters to the AP and R using a second-order approximation of the utility function. The individual's utility function u_i can be expressed as a Taylor series expansion around μ_{zi} as $u(\pi_{it}) \equiv u(\mu_i) + \frac{u'}{1!}(\pi_{it} - \mu_i)^1 + \frac{u''}{2!}(\pi_{it} - \mu_i)^2 + \cdots$. By setting the higher-order derivatives of u equal to zero, $u(\pi_{it}) = u(\mu_i) + \frac{u'}{1!}(\pi_{it} - \mu_i)^1 + \frac{u''}{2!}(\pi_{it} - \mu_i)^2$ and taking the expected value yields $E(u_{it}) = U(\mu_i) + \frac{U'}{1!}E(\pi_{it} - \mu_i)^1 + \frac{U''}{2!}E(\pi_{it} - \mu_i)^2$ which simplifies to $U_i = U + \frac{U''}{2}\tau_i^2$. By partial differentiation and dropping the derivatives of U_i greater than two: $\frac{\partial U}{\partial \mu_i} = U_i'$ and $U_i'' = 2\frac{\partial U}{\partial \tau_i^2}$.

Since we are looking at only the estimated parameters for the entire population's risk preferences, we will replace individual means (μ_i) with the population mean (μ) and individual temporal standard deviations squared (τ_i^2) with population mean temporal standard deviations squared (τ^2). Now $U' = \frac{\partial U}{\partial \mu}$ and $U'' = 2\frac{\partial U}{\partial \tau^2}$. Looking at the MSU estimator using population averages for returns and average temporal standard deviation $MSU \equiv \mu^{\theta} - \tau^{\gamma} = \mu^{\theta} - (\tau^2)^{\frac{\gamma}{2}}$ given standard deviations τ_{zi} are always positive, average standard deviations τ must also always be positive. U' and U'', as approximated by a second order Taylor series expansion can be defined as:

(2) $$U' = \frac{\partial U}{\partial \mu} = \theta \mu^{\theta - 1}$$

(3) $$U'' = 2\frac{\partial U}{\partial \tau^2} = 2(-\frac{\gamma}{2}(\tau^2)^{\frac{\gamma}{2}-1}) = -\gamma \tau^{\gamma - 2}$$

To solve for AP_U and P_U, substitute equations 2 and 3 into the equations for AP and R:

$$AP_U \equiv -\frac{U''}{U'} \equiv -\left(-\gamma \tau^{\gamma-2}\left(\theta \mu^{\theta-1}\right)^{-1}\right) = \frac{\gamma}{\theta} \mu^{1-\theta} \tau^{\gamma-2}$$

(4) $$R_U \equiv -\mu \frac{U''}{U'} \equiv -\mu \left(-\gamma \tau^{\gamma-2}\left(\theta \mu^{\theta-1}\right)^{-1}\right) = \frac{\gamma}{\theta} \mu^{2-\theta} \tau^{\gamma-2}$$

Saha's risk aversion measure (A) is equivalent to AP_U when multiplied by the inverse of the measure for temporal standard deviation $AP_U = A \cdot \frac{1}{\tau}$. Likewise R_U is $A \cdot \frac{\mu}{\tau}$. By using estimates of R from other studies, it is possible to determine corresponding values of θ and γ. By imposing the restrictions for CARA ($\theta = 1$) and CRRA ($\theta = \gamma$), it is possible to find single point estimate for each value of R. With these restrictions R_U

simplifies to $R_U(\gamma) \equiv \gamma\mu\tau^{\gamma-2}$ and $R_U(\gamma) \equiv \mu^{2-\gamma}\tau^{\gamma-2}$ for CARA and CRRA respectively. Risk preferences structures that are neither CARA nor CRRA can be found by assigning values for υ and solving for values of θ and γ.

CHAPTER 4

DATA AND EMPIRICAL FRAMEWORK

This study uses summary statistics taken from Machakos, Kenya. These statistics are estimated from detailed survey data to represent the types of secondary data that are typically available in many parts of the world. The survey population statistics data are used to parameterize the MDR analysis.

This chapter describes the Machakos study region of Kenya, an agricultural production region typical in the developing world. The results of this analysis could have much wider implications for poor farmers in the developing world. The data from the Machakos region is used to construct the sensitivity analysis that looks at the importance of risk in predicting producer behavior when offered a carbon contract. This chapter also presents the risk aversion preference values used in the sensitivity analysis and translated from levels of relative risk aversion (R) by the method illustrated in Chapter 3.

Machakos, Kenya

The Machakos study region is important because it is representative of the conditions faced by many agricultural producers in developing nations. The population is Machakos averages about one dollar a day, which is a common measure for absolute poverty. In 2005, one billion people in developing nations lived on approximately one dollar a day (Ravallion et al., 2008). Machakos is also important because it is experiencing the population growth problems endemic to much of the developing world.

In Machakos, high population growth and the practice of dividing land inheritances between sons has resulted in increased use of soil mining agricultural practices (Hamilton, 2000) and increased poverty. A solution that promises to curb the rapid soil degradation, decrease poverty, sequester carbon in Machakos has the potential to have wider applicability throughout the developing world.

Southeast of Nairobi, the Machakos study area is made up of three districts and covers approximately 20,000 km^2. The climate is semi-arid and has two growing seasons with low average and highly variable rainfall. The soil generally suffers from low rates of phosphorus, nitrogen, and organic matter. The soil has low infiltration rates and is prone to erosion. Farms are classified primarily as substance-oriented with a mix of both livestock and crops. The primary staple crop is maize and can be sold for cash. Farmers also grow a wide variety of subsistence crops such as vegetables, fruits, and tubers. The area suffers from extensive soil erosion in the mid-20^{th} century and is now terraced with the assistance of government programs. The data obtained from studies conducted between 1997 and 2001 covered six villages, 120 families, and detailed the inputs and outputs of nearly 2700 fields. Following Antle and Stoorvogel (2008) the carbon contracts modeled "require farmers to utilize minimum amounts of organic fertilizer (600 kg/ha/season) and mineral fertilizer (60 kg/ha/year)." A more in-depth description of the area and data can be found in Antle and Stoorvogel (2008) and more details of the data in Jager *et al.* (2001) and Gachimbi *et al.* (2005).

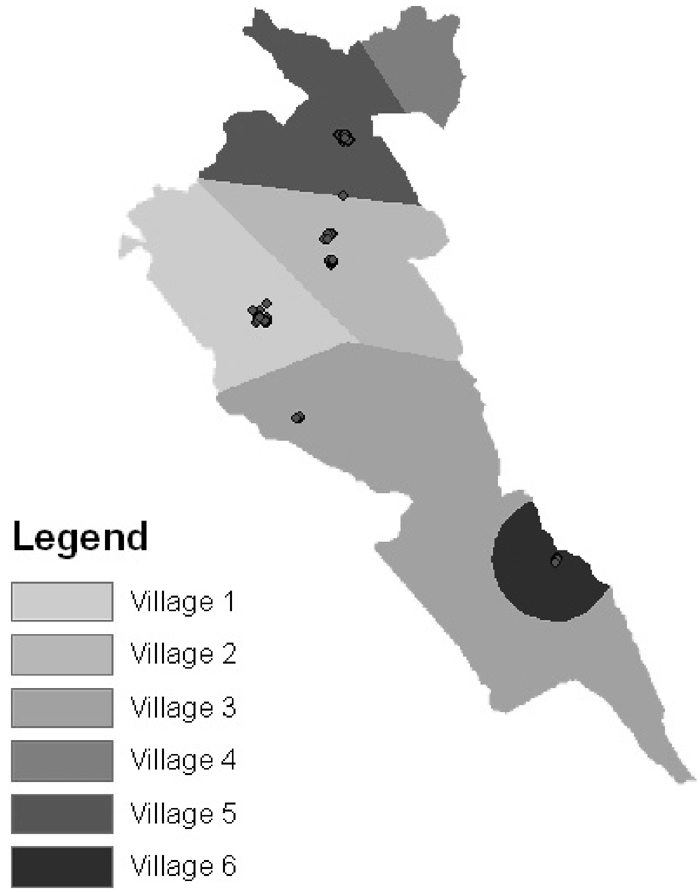

Figure 4: A map of the Machakos study region. The points are survey sites used to estimate the average production temporal variance in villages. Village four has no survey sites in the temporal estimation.

Data for MDR Implementation

Table 7: Definitions for the MDR implementation section.

$TCV_z =$	the average temporal coefficient of variation (TCV) due to weather given fixed management for system z.
$SCV_z =$	the spatial coefficient of variation (SCV) for system z.
MTCV =	a scalar multiplier for TCV_b.
MSCV =	a scalar multiplier for SCV_b.

Summary statistics for the base system are calculated for the subset of the population which uses minimal fertilizer and manure inputs. Expected yield increases under the carbon contract scenario are calculated by a combination of crop and econometric models based on both the direct expected yield increase due to higher input usage as well as the expected yield increase due to the more input intensive management system. The increased cost of the alternative system, the contract scenario, was calculated by the additional costs of the inputs based on market value estimates of input costs.

The Machakos data were collected in six villages judged to be representative of the region. Each of these villages has unique characteristics that have been statistically estimated and are used to parameterize the MDR study. Table 8 and table 9 show the mean net seasonal return per hectare in Kenyan shillings for the base system and the contract system, for each of the activities: a subsistence intercrop, maize, beans, and vegetables. Within the MD framework endogenous choices for land area allocated to activity within systems are not possible. However, the typical share of land area devoted to each activity is statistically estimated for the base system. This analysis uses that share of activities in the base system and assumes it is constant across systems. It also assumes that individual producers all share the same allocation of activities. The share of land area to different activities across systems can be found in table 10. The shares and spatial variation for the base system are also used for the contract system in the results presented here. The total system expected returns by system (μ_z) for each village are calculated by multiplying the returns for each activity by its share and summing across village, as seen in table 15.

Table 8: Base system seasonal returns (Kenyan shillings*).

Village	Intercrop	Maize	Beans	Vegetables
1	7033	6390	16849	0
2	1888	4543	16849	0
3	8828	12695	16849	0
4	6547	5819	6887	0
5	18712	38828	31210	14852
6	8449	2147	0	6428
Mean	8576	11737	14774	3547

* Approximately 75 Kenyan shillings to 1 U.S. dollar.

Table 9: Contract system seasonal returns (Kenyan shillings*).

Village	Intercrop	Maize	Beans	Vegetables
1	10533	28399	20558	0
2	-71	17444	22108	0
3	16052	41740	19447	0
4	28173	14008	7253	0
5	16694	48421	39482	25699
6	22140	1384	0	16171
Mean	15587	25233	18141	6978

* Approximately 75 Kenyan shillings to 1 U.S. dollar.

Table 10: Share of land using each activity (percent).

Village	Intercrop	Maize	Beans	Vegetables
1	18	38	44	0
2	60	38	2	0
3	29	63	8	0
4	36	48	16	0
5	14	62	6	18
6	13	26	0	62
Mean	0.28	0.46	0.13	0.13

Table 11: Spatial coefficient of variation for both systems (percent).

Village	Intercrop	Maize	Beans	Vegetables
1	51	83	21	0
2	48	104	21	0
3	57	87	31	0
4	88	101	19	0
5	17	17	23	39
6	60	23	100	52
Mean	54	69	36	15

The spatial coefficient of variation by activity is used to calculate the spatial standard deviation for each system in each village. Spatial standard deviations are calculated as follows.

$$Spatial\ standard\ deviation_a = SCV_a * \mu_a$$

$$Spatial\ standard\ deviation_b = SCV_b * \mu_b * MSCV$$

In addition to the MD's data requirements, MDR requires estimates for the temporal standard deviation τ_z and the population risk preferences θ and γ. The range of risk preferences used in the sensitivity analysis is calculated using the method described in Chapter 3 from a range of estimates of R calculated by other researchers. The estimates for temporal standard deviation are calculated by simulating the DSSAT crop models for maize and beans using historic weather patterns spanning thirty years. The temporal standard deviation over the thirty years was calculated on 67 fields in the survey villages where site-specific soil data were collected. Historic weather data was used as an input in crop models to simulate a time series of yields for each site and each production system. The temporal standard deviations and mean yields per site were calculated and translated into temporal coefficient of variation estimates for each site. In each of the study villages, TCV_z was calculated based on the average TCV_z across sites. One village (Village 4) had no sampled fields, the TCV_z for that village was estimated by averaging the TCV_z for the other 5 villages. Due to data limitations, the intercrop and vegetable crops were assumed to have the same temporal variation as beans.

The crop model simulations show that the temporal variance of maize in the contract scenario is around twice that of the base scenario, whereas the variance for beans is little changed. This is consistent with the fact that maize is much more vulnerable to the droughts that frequently occur in Machakos than the other crops. It is reasonable to assume that the intercrop yield follows a pattern similar to beans because it is made up of a diverse mix of drought-tolerant crops including pigeon pea. The vegetable crop is irrigated so it also should not be as vulnerable to drought as maize.

Table 12: Base system temporal coefficient of variation (percent).

Village	Intercrop	Maize	Beans	Vegetables
1	61	23	61	61
2	36	20	36	36
3	24	21	24	24
4	38	21	38	38
5	42	20	42	42
6	30	21	30	30
Mean	38	21	38	38

Table 13: Contract system temporal coefficient of variation (percent).

Village	Intercrop	Maize	Beans	Vegetables
1	61	43	61	61
2	36	42	36	36
3	24	49	24	24
4	39	43	39	39
5	41	41	41	41
6	30	42	30	30
Mean	39	43	39	39

These estimates for temporal coefficient of variation based on weather variation may be either low or high estimates of total average temporal variation. Other potential sources of variation may contribute to, or reduce, the total variation - depending upon the sign of the correlation of the unobserved variation and that due to weather. With that in mind, a parameter M is introduced as a scalar multiple for the average temporal coefficient of variation. Individual τ_{zi} are calculated on a per site basis as follows:

$$\tau_{ai} = TCV_a * \mu_{ai}$$

and

$$\tau_{bi} = TCV_b * \mu_{bi} * MTCV.$$

Note that τ is calculated from τ_{zi} as derived by the definitions in Chapter 3 in tables 2 and 6. R values are chosen from ranges of values estimated by other researchers as discussed in Chapter 2. θ and γ are solved for from τ and μ by the method illustrated in Chapter 3 (equation 5). The resulting risk aversion parameters calculated for M of 1, 1.5, and 2 and R of 0, .5, 1, .15, 2, and 5 are displayed in the following table:

Table 14: Risk aversion parameters with MTCV=1.

Model	R	θ	γ	ARA	RRA	υ
RN	0.0	1.00	0.00	CARA	DRRA	0.00
CARA	0.5	1.00	0.83	CARA	DRRA	0.83
CARA	1.0	1.00	0.90	CARA	DRRA	0.90
CARA	1.5	1.00	0.94	CARA	DRRA	0.94
CARA	2.0	1.00	0.97	CARA	DRRA	0.97
CARA	5.0	1.00	1.06	CARA	IRRA	1.06
CRRA	0.5	2.70	2.70	DARA	CRRA	1.00
CRRA	1.0	2.00	2.00	DARA	CRRA	1.00
CRRA	1.5	1.59	1.59	DARA	CRRA	1.00
CRRA	2.0	1.30	1.30	DARA	CRRA	1.00
CRRA	5.0	0.38	0.38	IARA	CRRA	1.00
DRRA	0.5	2.46	2.44	DARA	DRRA	0.99
DRRA	1.0	1.82	1.80	DARA	DRRA	0.99
DRRA	1.5	1.44	1.43	DARA	DRRA	0.99
DRRA	2.0	1.18	1.17	DARA	DRRA	0.99
DRRA	5.0	0.33	0.33	IARA	DRRA	0.99
IRRA	0.5	2.96	2.99	DARA	IRRA	1.01
IRRA	1.0	2.19	2.21	DARA	IRRA	1.01
IRRA	1.5	1.74	1.76	DARA	IRRA	1.01
IRRA	2.0	1.43	1.44	DARA	IRRA	1.01
IRRA	5.0	0.42	0.42	IARA	IRRA	1.01

Absolute risk aversion (ARA) categories are decreasing, constant, or increasing (DARA, CARA, IARA) and relative (RRA) and categories (DRRA, CRRA, IRRA).

Carbon sequestration rates estimation under the contract scenario are taken from the DSSAT model. The important values for the model by system and village are summarized in the following table.

Table 15: Village level summary statistics.

Maize	Village 1	2	3	4	5	6
Area (Ha)	465	926	298	1436	390	331
Base System Seasonal						
Expected Returns (Kenyan shillings**)	11052	3237	11905	6251	31216	5588
TCV_a* (percent)	38	22	19	27	24	26
SCV_a* (percent)	58	81	66	82	15	50
Contract System Seasonal						
Expected Returns (Kenyan shillings**)	21715	7060	32581	17951	39326	13139
TCV_b* (MTCV=1) (percent)	42	42	39	35	37	29
SCV_b* (MSCV=1) (percent)	68	105	72	81	15	57
MgC*** Sequestered per hectare	0.16	0.13	0.15	0.13	0.16	0.14

*Calculated for a covariance across activities within the system of 0.5.
** Approximately 75 Kenyan shillings to 1 U.S. dollar.
*** Megagram of carbon (MgC) equivalent to 1000 kilograms or one metric tonne.

The expected returns in the contract scenario are in general between two and three times those of the base system (table 15). There is both a higher SCV and higher TCV for the contract system. The increase in SCV is driven by maize having a higher SCV and being a more important crop with respect to expected returns in the contract system. The higher TCV is a result of maize having a higher TCV in the contract scenario.

Software for MDR Model Implementation

In order to construct the following MDR analysis, it was necessary to build upon the preexisting software design of the MD approach. Changing the original software was relatively straightforward process. Integrating new inputs within the program and managing the increased complexity was more difficult. One of the primary goals of the MD approach has been to provide analysis tools that are both easy to use and accessible. To this end the MD approach is available in both SAS and Excel formats. Continuing in this tradition MDR has been written in both SAS and the open source statical programming package R and will be publicly available in the near future. The translation of rates from levels of relative risk aversion (R) to MSU θ and γ required the programming of a small additional piece of software that solved non-linear equations conditional upon the structure of risk preferences. This software will be included in the MDR release. Publicly released versions of the software will soon be available online.

CHAPTER 5

RESULTS

This chapter presents a sensitivity analysis, demonstrating the ability of the minimum data risk aversion (MDR) approach to capture a wide range of results driven by four different key elements: risk aversion level, temporal variation, risk preference structure, and spatial variation. This chapter uses the method illustrated in Chapter 3 to calculate relative risk aversion measurements (R) estimates under MSU and construct a range of potential supply curves. This sensitivity analysis is implemented for risk neutral and risk averse producers who have relative risk aversion coefficients of 0.5, 1.0, 1.5, 2.0, and 5.0. The risk aversion parameters for R approximated under MSU are estimated under the method illustrated in Chapter 3 (equation 5) and presented in Chapter 4 (table 14). These MSU risk aversion parameters are estimated at a MTCV of unity and used consistently throughout all of the following analysis.

The first section presents a sensitivity analysis in which results are presented at different levels of temporal coefficient of variation for the contact system as a result of modifying the scalar MTCV. This section assumes the risk preference structure of producers is constant absolute risk aversion (CARA). The next section presents the results as functions of different risk preference structures under the assumption that the multiplier for the spatial coefficient of variation for the contact system (MSCV) is one. The next section tests the effects on the results of varying MSCV while assuming CARA. An important driving factor throughout the sensitivity analysis is the assumption that carbon payments are risk free. This assumption drives the finding that at all levels of risk aversion and at all tested risk preference structures, the expected behavior of the risk averse producers tends to converge on the expected behavior of risk neutral producers as carbon sequestration payments become sufficiently large.

Temporal Coefficient of Variation Scalar

MTCV is a scalar on the temporal coefficient of variation TCV for the contract scenario. As MTCV gets larger (smaller) the riskiness of the contract scenario increases (decreases). The level of TCV for both the base scenario as well as the contract scenario is estimated by crop model simulations driven by weather variation. Figure 5 and table 16 show the change in estimated participation rates at different levels of R using initial levels of TCV. In the figures presented in this chapter, the square symbol curves are always the risk neutral scenario (RN) while the curves expanding away from it represent R at the levels of 0.5, 1.0, 1.5, 2.0, and 5.0. The R of 5.0 is easily identifiable as the curve farthest from the RN curve.

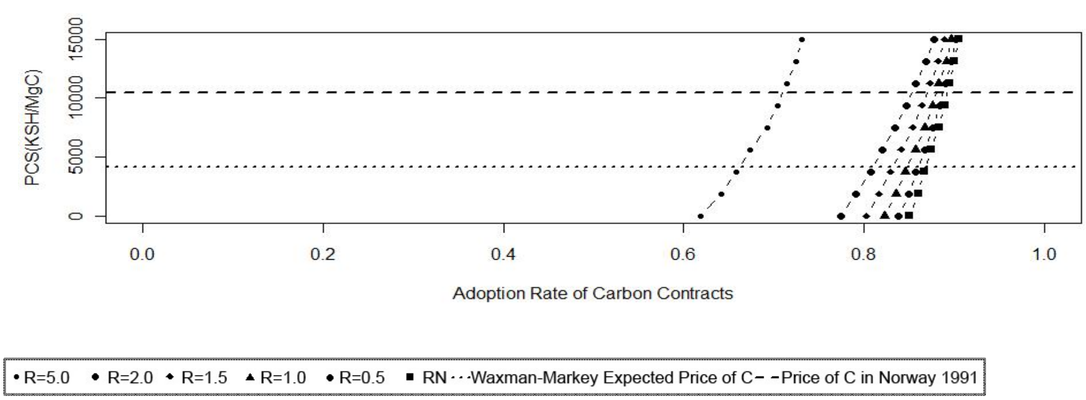

Figure 5: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

At an MTCV of 1 at all levels of risk aversion, the adoption rate of carbon contracts increases as the price of carbon sequestration[6] (PCS). In figure 5 this is seen as curves with positive slopes. There are two different horizontal lines on the figure. The lower dotted line is representation of the average expected PCS that would result if congress were to pass the Waxman-Markey bill in its present form as estimated by the Environmental Protection Agency of the U.S. [7] (2009). The PCS in Norway in 1991 is based on a carbon emissions tax that was in place in 1991. It was much higher than the price of carbon found in the current European trading market. However, if the curbing of carbon emissions were to result in the implementation of geological sequestration practices, the price of 185 U.S. dollars per MgC might be low. In table 16, the PCS is listed on the topmost row while contract participation under each level of R corresponds with each row. Table 16 presents the same information as figure 5. In table 16, carbon contract participation increases at all levels of risk aversion as the carbon price increases and can be seen as the increase in contract participation rates from any lower price column (to the left) to a higher price column (to the right).

At an MTCV of 1 the contract scenario is riskier in terms of both TCV (table 15, Chapter 4) as well as in average temporal standard deviation. This leads the contact scenario to have a lower expected participation rate under all levels of R than for the RN scenario. Under an MTCV of 1 at all levels of moderate to low risk aversion (R between

[6] In the Machakos application the price of carbon sequestration (PCS) is the price of ecosystem services (g).

[7] This paper uses a value of 55 U.S. dollars per MgC. The Environmental Protection Agency of the U.S. report lists the expected price of CO_2 as ranging from 13 to 17 U.S. dollars. The average is 15 U.S. dollars. C reductions can be translated in equivalent weight to CO_2 reductions at a ratio of 11/3 which yields 55 U.S. dollars per MgC. To approximate into Kenya shillings this paper assumed 75 KSH to 1 U.S. dollars.

0.5 and 2) the difference between the expected participation rates under RN are small (at most 8 percentage points at a PCS of zero).

Table 16: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
CARA	1.0	0.82	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CARA	1.5	0.80	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89
CARA	2.0	0.77	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88
CARA	5.0	0.62	0.64	0.66	0.67	0.69	0.70	0.71	0.72	0.73

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

As the PCS increases the difference between the RN scenario and the RA scenario becomes very small (at most 2 points at a price of 15,000 Kenyan shilling, approximately 200 U.S. dollars[8]). The extreme risk aversion scenario (R=5.0) is slightly different. At a price of zero, the difference between it and the contract scenario is 23 points and converges to a difference of 17 points as the price of carbon increases to 15,000 Kenyan shillings. This convergence is driven by the assumption that the carbon payment is risk free.

[8] In 1991, Norway taxed C emissions at a rate of 185 U.S. dollars per MgC (Herzog, 2001). The tax was dropped to 140 U.S. dollars per MgC in 2000. The tax is typical of the costs associated with alternative methods of sequestering carbon.

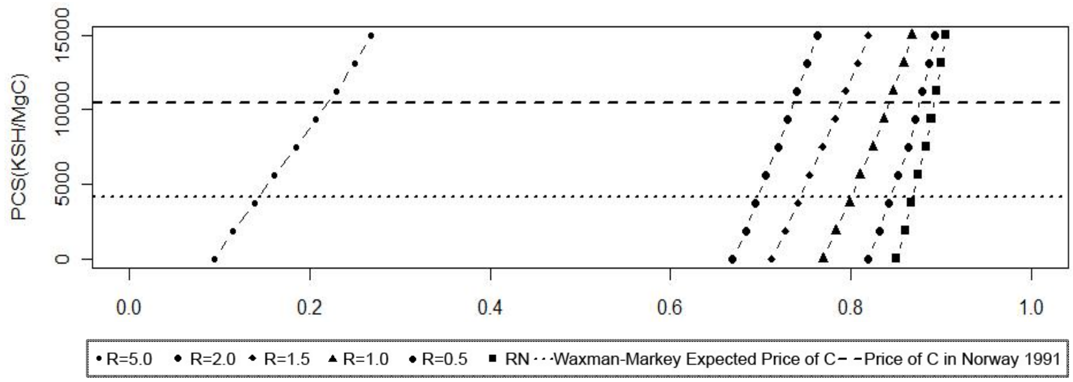

Figure 6: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1.5 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Given these results, if we assume that producers have low to moderate risk aversion ($R \leq 2.0$) and MTCV is equal to 1, then it appears that excluding risk aversion preferences does not substantially bias the results. However, a number of factors could increase carbon contract riskiness (uncertainty about carbon rates, policy risk, contract default, etc.) are not included explicitly in this analysis. These factors would increase the riskiness of the contract scenario and are simulated by increasing the size of the scalar MTCV. Figure 6 and table 17 show the effect of risk aversion with an MTCV of 1.5. An MTCV of 1.5 is equivalent to assuming that the riskiness of the contract scenario due to unknown factors is proportionate to one half that of weather variation (if correlation of weather and unknown factors is 1). Or that total variation of the contract scenario is one and a half that of the estimated weather variation. This assumption is obviously problematic, but is useful in showing that accounting for risk aversion is more important when the riskiness of one system is substantially larger than that of the alternative system.

Table 17: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1.5 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89	0.89
CARA	1.0	0.77	0.78	0.80	0.81	0.82	0.84	0.85	0.86	0.87
CARA	1.5	0.71	0.73	0.74	0.75	0.77	0.78	0.79	0.81	0.82
CARA	2.0	0.67	0.68	0.69	0.71	0.72	0.73	0.74	0.75	0.76
CARA	5.0	0.09	0.12	0.14	0.16	0.19	0.21	0.23	0.25	0.27

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

At a MTCV of 1.5 (figure 6 and table 17), the differences between the RN scenario and the RA scenario are much more pronounced than at a MTCV of 1. At a low level of risk aversion (R=0.5) the difference between RN and RA is still small (at most 3 percentage points). However as risk aversion increases the differences between the RN and RA scenarios are accentuated with an extreme risk aversion (R=5.0) having substantially different results. As with an MTCV of 1, adoption rates at all levels of risk aversion converge - or begin to converge - with the RN scenario as the PCS. This indicates that if the PCS is expected to be high and if risk aversion is expected to be moderate to low ($R \leq 1.5$) then the RN model for contract participation is adequate (with at most 8 points difference at a price of 15,000 Kenyan shillings[9]).

[9] Approximately 200 U.S. dollars.

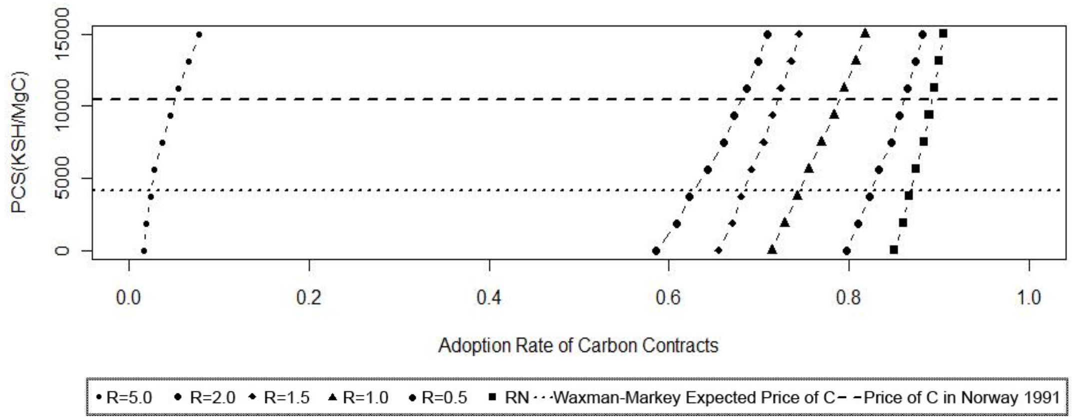

Figure 7: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

The results of an even more extreme level of riskiness (MTVC = 2) associated with the contract scenario is presented in figure 7 and table 18. As with the difference between and MTCV of 1 and 1.5, a MTCV of 2 decreases participation rates at all levels of risk aversion and correspondingly increases the difference between the RA scenarios and the RN scenario. As with MTCV of 1 and 1.5 the difference in adoption between the RA scenarios and the RN scenario decrease as the price of carbon increases. One notable difference between an MTCV of 1.5 and 2 is in the expected participation rates under extreme risk aversion (R=5.0). With an MTCV of 1.5, contract participation rates are .09 and increase to .27 as the price of carbon increases from zero to 15,000 Kenyan shillings. However at an MTCV of 2, contract participation is initially at .02 and only increases to .08 as the price increases. This indicates that the effects of extreme risk aversion are so strong at an MTCV of 2 that even large potential payoffs from carbon contracts have little power to change carbon contract participation.

Table 18: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.80	0.81	0.82	0.83	0.85	0.86	0.86	0.87	0.88
CARA	1.0	0.71	0.73	0.74	0.75	0.77	0.78	0.79	0.81	0.82
CARA	1.5	0.66	0.67	0.68	0.69	0.71	0.71	0.72	0.74	0.74
CARA	2.0	0.58	0.61	0.62	0.64	0.66	0.67	0.69	0.70	0.71
CARA	5.0	0.02	0.02	0.02	0.03	0.04	0.05	0.06	0.07	0.08

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

For the sake of completeness, this analysis also presents the results from an MTCV of .5. This would mean that the carbon contracts in terms of TCV are less risky. Results are presented in figure 8 and table 19. In contrast to the previously presented figures, the RN scenario is the leftmost curve while the extreme risk aversion scenario is the rightmost curve. This indicates that due to risk aversion the contract scenario has a higher participation rate. However, the differences in contract participation between the RA scenarios and RN scenario are very small at all levels (at most 3 percentage points).

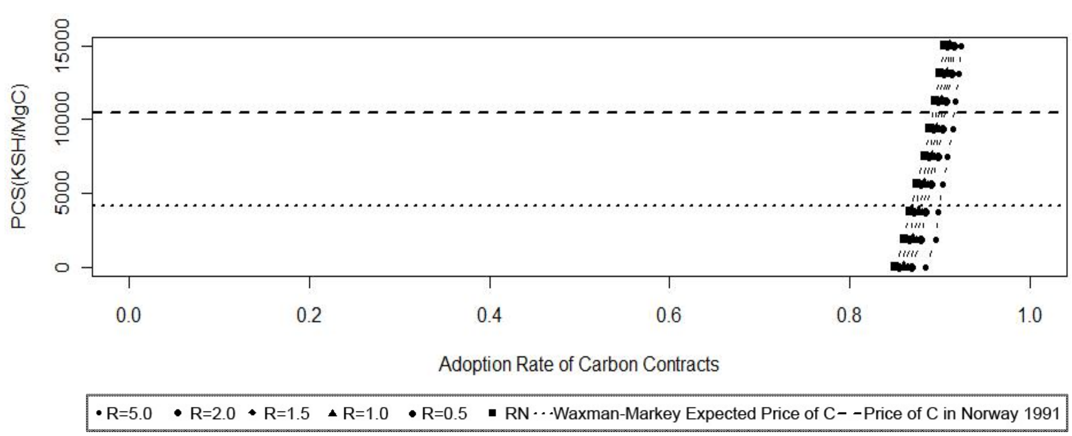

Figure 8: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=.5 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 19: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=.5 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.85	0.87	0.87	0.88	0.89	0.89	0.90	0.90	0.91
CARA	1.0	0.86	0.87	0.88	0.88	0.89	0.90	0.90	0.91	0.91
CARA	1.5	0.86	0.87	0.88	0.89	0.89	0.90	0.90	0.91	0.91
CARA	2.0	0.87	0.88	0.88	0.89	0.90	0.90	0.91	0.91	0.92
CARA	5.0	0.88	0.89	0.90	0.90	0.91	0.91	0.92	0.92	0.92

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

It is unlikely that an MTCV of .5 would be typical of the Machakos study. It is more likely that a representative MTCV would be between 1 and 2. As MTCV increases (decreases), the riskiness of the contract scenario, the importance of including risk aversion increases (decreases). At all levels of MTCV the difference in participation rates between the RN scenario and RA scenarios decreases as the price of carbon increases. This indicates that there is a reasonable combined range of RA levels and riskiness levels with a high carbon price for which RA can be safely excluded from the analysis without substantially biasing the results. However even this result might be biased since it is driven by the implicit assumption within the MDR framework that the carbon sequestration payoff is risk free. If the carbon payoff is also risky, there is no expectation that the RN scenario and the RA scenarios will converge. That said, even given a risk free contract scenario, there is a substantial range of RA levels combined with MTCV levels for which the inclusion of RA changes the expected level of carbon contract participation and cannot be excluded without biasing the results.

The Structure of Risk Preferences

This section presents results driven by varying the structure of risk preferences. Four different risk preferences are tested: constant absolute risk aversion (CARA), constant relative risk aversion (CRRA), decreasing relative risk aversion (DRRA), and increasing relative risk aversion (IRRA). These different structures of risk preferences are examined at an MTCV of 1 and 2 and an R of 0.5, 1.0, 1.5, 2.0, and 5.0.

The following figure 9 and table 20 show different contract participation rates at different payment levels under CARA and an MTCV and MSCV of 1. The same levels of MTCV and MSCV are examined in figure 10 and table 21 under the assumption that producers risk preferences exhibit CRRA. Visually, figure 10 is very similar to figure 9. Likewise, table 21 is almost identical to table 20 to within one point for all adoption rates except with regards to the extreme risk aversion scenario (R=5.0) in which there is at most an 8 point difference driven by the structure of risk preferences. At the high carbon price of 15,000 Kenyan shillings, the largest difference between CARA and CRRA is only percentage 4 points. At lower levels of R, the difference in expected participation rates at different risk structures is tiny. This supports the proposition that for the most part risk aversion levels are a more important predictor of producer behavior than the structure of risk preferences.

Table 20: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
CARA	1.0	0.82	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CARA	1.5	0.80	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89
CARA	2.0	0.77	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88
CARA	5.0	0.62	0.64	0.66	0.67	0.69	0.70	0.71	0.72	0.73

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

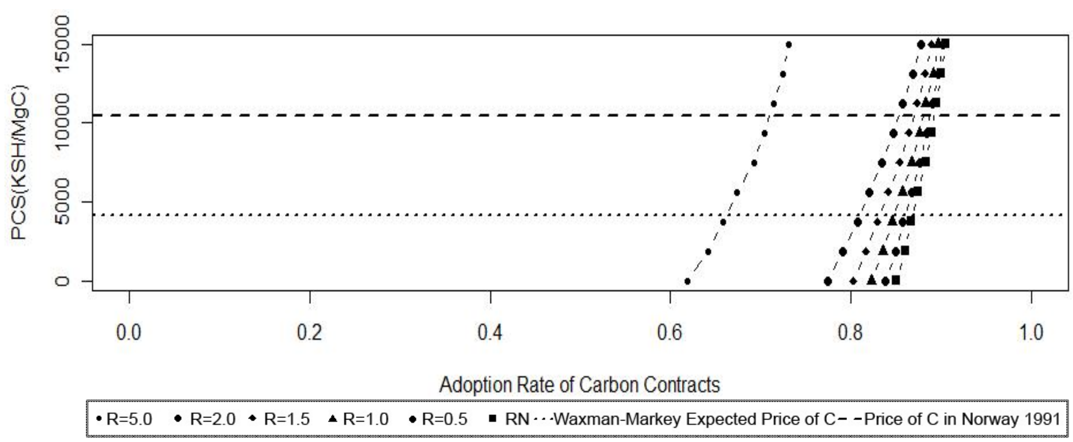

Figure 9: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 21: Contract adoption rates under constant relative risk aversion (CRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CRRA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
CRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CRRA	1.5	0.81	0.82	0.83	0.84	0.86	0.87	0.87	0.88	0.89
CRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
CRRA	5.0	0.54	0.57	0.59	0.61	0.63	0.65	0.66	0.68	0.69

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant relative risk aversion (CRRA) and risk neutrality (RN).

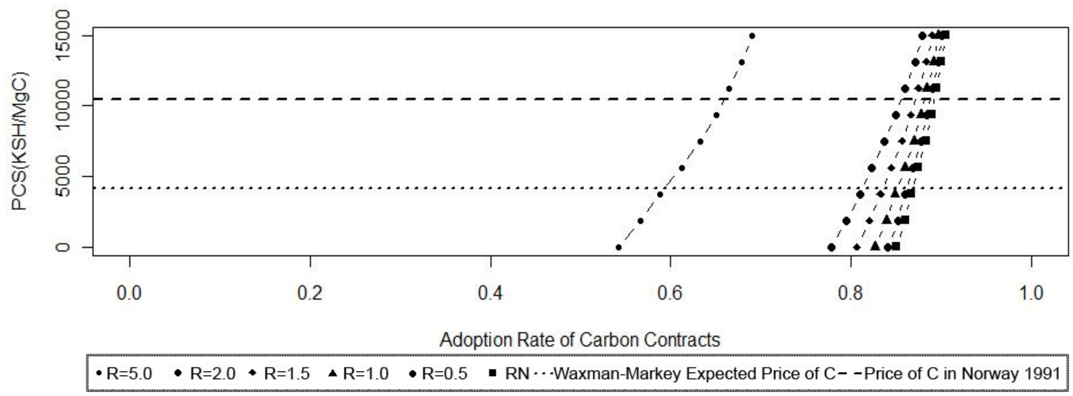

Figure 10: Contract adoption rates under constant relative risk aversion (CRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Figure 11 and table 22 presents the results assuming decreasing relative risk aversion (DRRA). Figure 12 and table 23 presents the results assuming increasing relative risk aversion (IRRA). These results are almost identical to those of CRRA. The difference between CRRA and IRRA, as well as DRRA, is a linear difference in υ of 1 percentage point (in table 14). It is possible therefore that there are other values of risk preferences that yield the same level of R, while producing more pronounced difference between CRRA and DRRA or IRRA.

Table 22: Contract adoption rates under decreasing relative risk aversion (DRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
DRRA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
DRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
DRRA	1.5	0.81	0.82	0.83	0.84	0.86	0.87	0.87	0.88	0.89
DRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
DRRA	5.0	0.53	0.55	0.58	0.60	0.62	0.64	0.65	0.67	0.68

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are decreasing relative risk aversion (DRRA) and risk neutrality (RN).

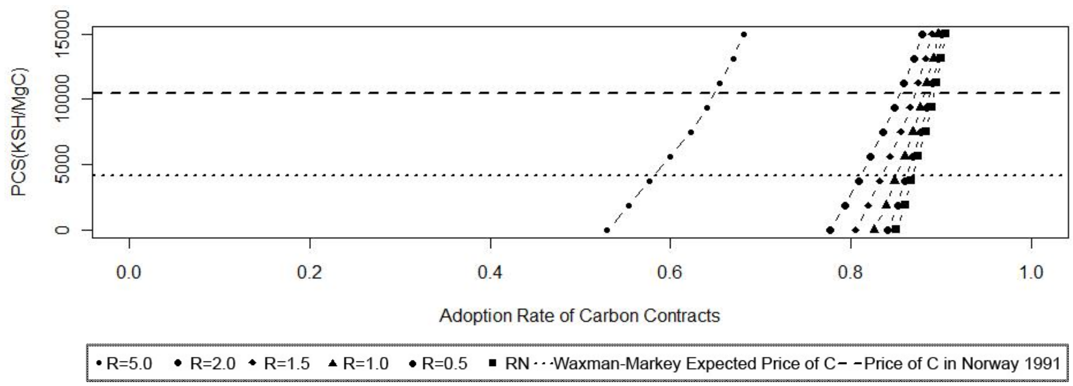

Figure 11: Contract adoption rates under decreasing relative risk aversion (DRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 23: Contract adoption rates under increasing relative risk aversion (IRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
IRRA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
IRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
IRRA	1.5	0.81	0.82	0.83	0.84	0.86	0.87	0.87	0.88	0.89
IRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
IRRA	5.0	0.54	0.56	0.59	0.61	0.63	0.65	0.66	0.68	0.69

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are increasing relative risk aversion (IRRA) and risk neutrality (RN).

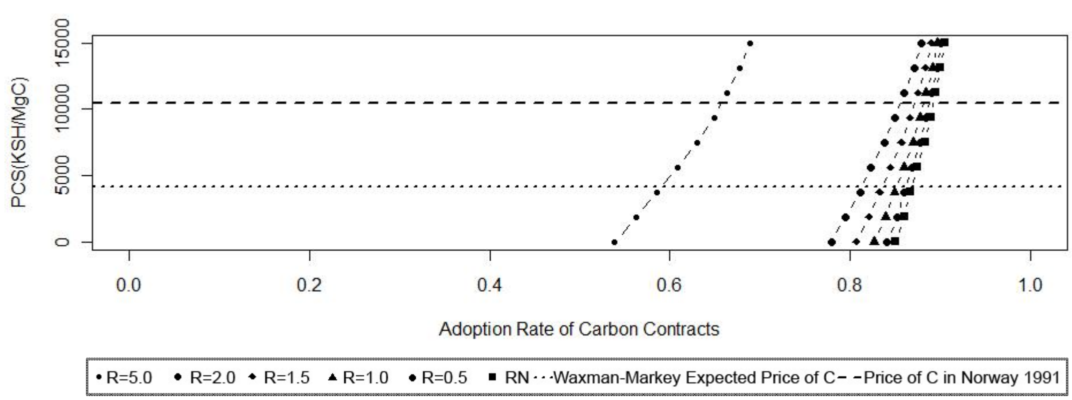

Figure 12: Contract adoption rates under increasing relative risk aversion (IRRA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 24 shows the difference in participation rates at different levels of R 1, 2, and 5 with an MTCV of 1. All structures of risk aversion produce almost identical results so long as R is less than 5. As noted previously, the results tend to converge as the PCS gets large.

Table 24: Contract adoption rates with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
CARA	1.0	0.82	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
DRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
IRRA	1.0	0.83	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CARA	2.0	0.77	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88
CRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
DRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
IRRA	2.0	0.78	0.79	0.81	0.82	0.84	0.85	0.86	0.87	0.88
CARA	5.0	0.62	0.64	0.66	0.67	0.69	0.70	0.71	0.72	0.73
CRRA	5.0	0.54	0.57	0.59	0.61	0.63	0.65	0.66	0.68	0.69
DRRA	5.0	0.53	0.55	0.58	0.60	0.62	0.64	0.65	0.67	0.68
IRRA	5.0	0.54	0.56	0.59	0.61	0.63	0.65	0.66	0.68	0.69

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are absolute decreasing, constant, or increasing (DARA, CARA, IARA) and relative decreasing, constant, or increasing (DRRA, CRRA, IRRA).

The following figures and tables presents the same results, but with a MTCV of 2 while MSCV remains at 1. Figure 13 and table 25 show the results of CARA with a MTCV of 2. Figure 14 and table 26 assume CRRA. When compared with figure 11 and table 25, diverge at a price of zero, while producing almost identical results as the price of carbon reaches the high price of 15,000 Kenyan shillings. At its most extreme (a price of zero), the difference between CARA and CRRA is at most 13 percentage points (R=2.0).

Table 25: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.80	0.81	0.82	0.83	0.85	0.86	0.86	0.87	0.88
CARA	1.0	0.71	0.73	0.74	0.75	0.77	0.78	0.79	0.81	0.82
CARA	1.5	0.66	0.67	0.68	0.69	0.71	0.71	0.72	0.74	0.74
CARA	2.0	0.58	0.61	0.62	0.64	0.66	0.67	0.69	0.70	0.71
CARA	5.0	0.02	0.02	0.02	0.03	0.04	0.05	0.06	0.07	0.08

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk aversion categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

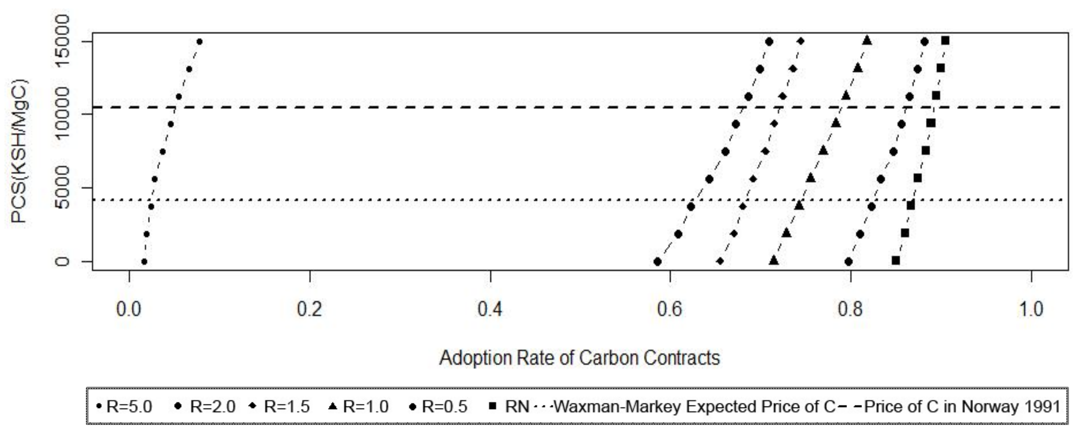

Figure 13: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 26: Contract adoption rates under constant relative risk aversion (CRRA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CRRA	0.5	0.69	0.71	0.73	0.75	0.76	0.78	0.79	0.81	0.82
CRRA	1.0	0.63	0.66	0.67	0.69	0.70	0.71	0.73	0.74	0.74
CRRA	1.5	0.56	0.60	0.62	0.64	0.67	0.68	0.69	0.71	0.72
CRRA	2.0	0.45	0.49	0.52	0.56	0.59	0.62	0.64	0.66	0.68
CRRA	5.0	0.04	0.04	0.04	0.05	0.06	0.07	0.08	0.09	0.10

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant relative risk aversion (CRRA) and risk neutrality (RN).

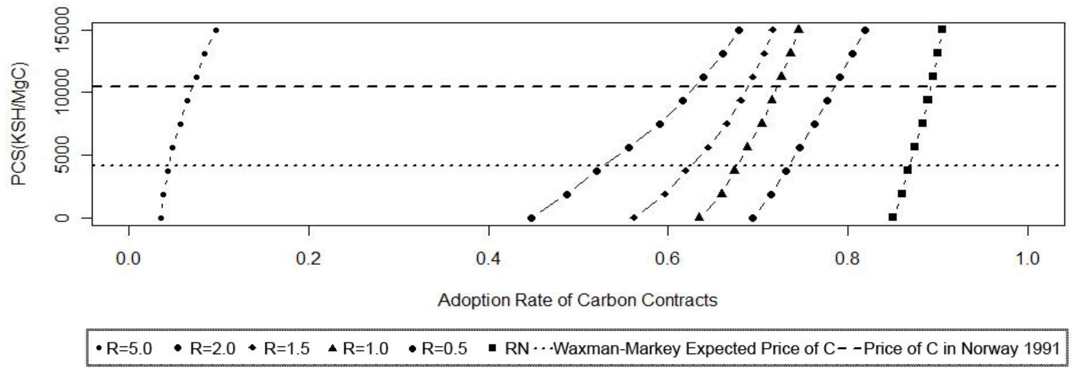

Figure 14: Contract adoption rates under CRRA with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 27: Contract adoption rates under decreasing relative risk aversion (DRRA)with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
DRRA	0.5	0.72	0.74	0.75	0.77	0.78	0.80	0.81	0.82	0.84
DRRA	1.0	0.66	0.68	0.69	0.70	0.71	0.73	0.74	0.75	0.76
DRRA	1.5	0.61	0.63	0.65	0.66	0.68	0.69	0.70	0.71	0.72
DRRA	2.0	0.53	0.56	0.58	0.61	0.63	0.65	0.67	0.68	0.70
DRRA	5.0	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.08	0.10

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant relative risk aversion (DRRA) and risk neutrality (RN).

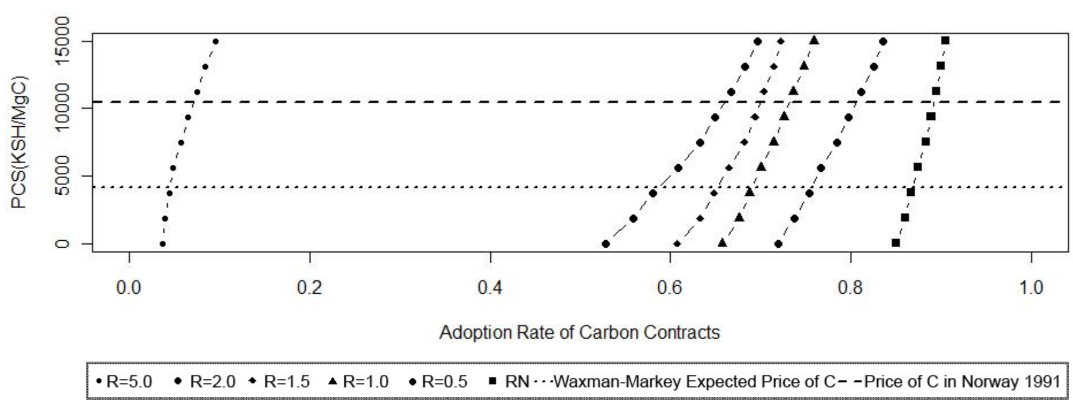

Figure 15: Contract adoption rates under decreasing relative risk aversion (DRRA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Figure 15 and table 27 present the results of assuming DRRA, while figure 16 and table 28 present IRRA. The difference between CRRA and DRRA is that CRRA has lower levels of contract participation generally at all price levels. However, the difference appears to be small (less than 8 points at most at all levels). IRRA is interesting because it is the risk preference structure for which there is the highest average change in participation rates due to an increase in price at all risk aversion levels.

Table 28: Contract adoption rates under increasing relative risk aversion (IRRA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
IRRA	0.5	0.58	0.65	0.69	0.71	0.73	0.74	0.76	0.77	0.79
IRRA	1.0	0.50	0.55	0.60	0.64	0.67	0.69	0.71	0.72	0.73
IRRA	1.5	0.42	0.46	0.50	0.54	0.58	0.62	0.64	0.67	0.69
IRRA	2.0	0.33	0.36	0.39	0.43	0.47	0.51	0.54	0.57	0.60
IRRA	5.0	0.03	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.09

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are increasing relative risk aversion (IRRA) and risk neutrality (RN).

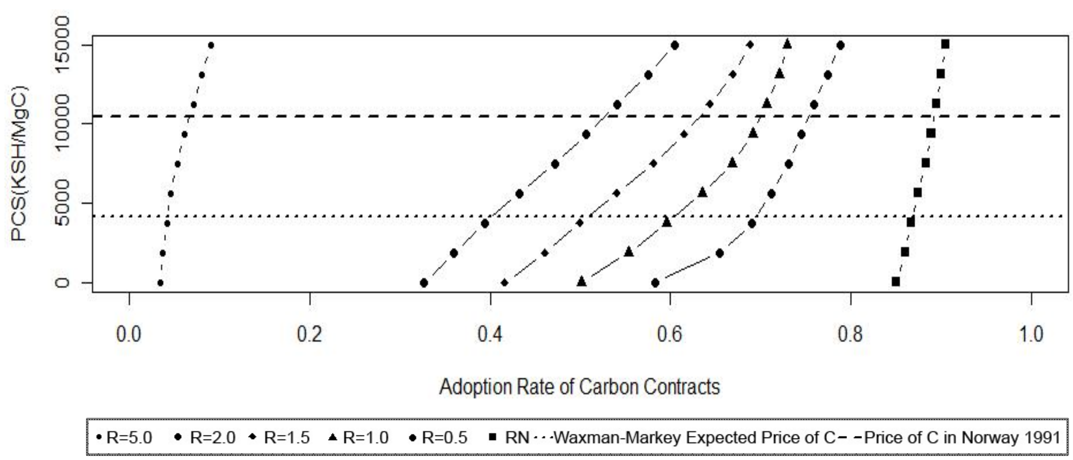

Figure 16: Contract adoption rates under increasing relative risk aversion (IRRA) with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 29: Contract adoption rates under different risk preference structures with MTCV=2 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
CARA	1.0	0.71	0.73	0.74	0.75	0.77	0.78	0.79	0.81	0.82
CRRA	1.0	0.63	0.66	0.67	0.69	0.70	0.71	0.73	0.74	0.74
DRRA	1.0	0.66	0.68	0.69	0.70	0.71	0.73	0.74	0.75	0.76
IRRA	1.0	0.50	0.55	0.60	0.64	0.67	0.69	0.71	0.72	0.73
CARA	2.0	0.58	0.61	0.62	0.64	0.66	0.67	0.69	0.70	0.71
CRRA	2.0	0.45	0.49	0.52	0.56	0.59	0.62	0.64	0.66	0.68
DRRA	2.0	0.53	0.56	0.58	0.61	0.63	0.65	0.67	0.68	0.70
IRRA	2.0	0.33	0.36	0.39	0.43	0.47	0.51	0.54	0.57	0.60
CARA	5.0	0.02	0.02	0.02	0.03	0.04	0.05	0.06	0.07	0.08
CRRA	5.0	0.04	0.04	0.04	0.05	0.06	0.07	0.08	0.09	0.10
DRRA	5.0	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.08	0.10
IRRA	5.0	0.03	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.09

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are absolute decreasing, constant, or increasing (DARA, CARA, IARA) and relative decreasing, constant, or increasing (DRRA, CRRA, IRRA).

Estimated adoption rates at the R levels of 1.0, 2.0, and 5.0 at a MTCV of 2 are presented in table 29. In table 24, which assumed a MTCV of 1, there was almost no difference in adoption rates at any R less than 5.0. In table 29, differences in adoption rates driven by different structures of risk are much more pronounced at low to moderate R levels. These differences are most extreme at an R of 2.0 with CARA and IRRA in which the expected participation rates have a 25 percentage point spread. IRRA is also interesting because it is often hypothesized that individuals have IRRA and DARA.

The results of this section show that consistent with Lence (2009) the structure of risk preferences are generally not as important as risk aversion levels when risks are not very large and skewed (table 25). However, when risks are large and skewed the structure of risk preferences can have high potential explanatory power (table 29).

Spatial Coefficient of Variation Scalar

This section presents a sensitivity analysis with respect to a multiplier on the spatial coefficient of variation (MSCV). In other sections, the MSCV is equal to 1 and the SCV for both systems are very close in most of the villages (table 15). By decreasing (increasing) the SCV of any system, the distribution of expected returns of that system correspondingly tightens (expands). The following sensitivity analysis will demonstrate the effect on expected producer behavior of varying the spatial distribution of returns of the contract system. This simulation assumes producer risk preference structures are CARA and an MTCV of 1.

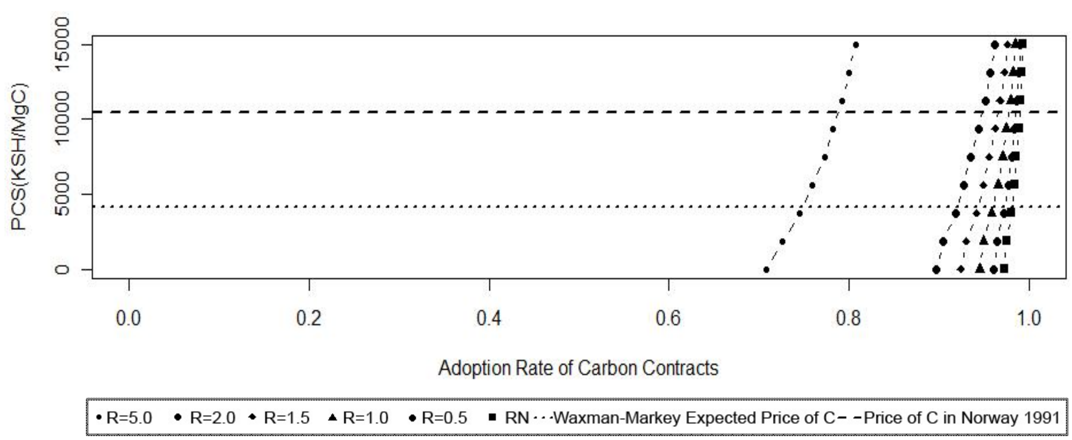

Figure 17: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=.5 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 30: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=.5 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.97	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.99
CARA	0.5	0.96	0.96	0.97	0.98	0.98	0.98	0.99	0.99	0.99
CARA	1.0	0.94	0.95	0.96	0.96	0.97	0.97	0.98	0.98	0.98
CARA	1.5	0.92	0.93	0.94	0.95	0.96	0.96	0.97	0.97	0.98
CARA	2.0	0.90	0.90	0.92	0.93	0.93	0.94	0.95	0.96	0.96
CARA	5.0	0.71	0.73	0.75	0.76	0.77	0.78	0.79	0.80	0.81

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

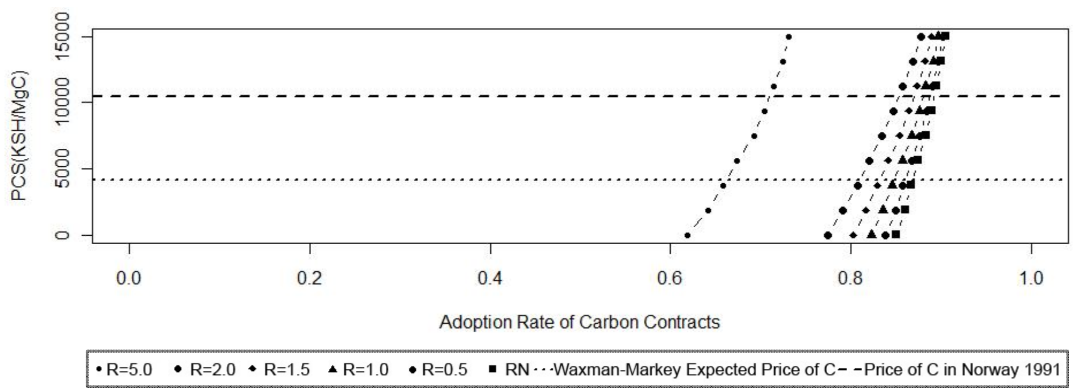

Figure 18: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 31: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.85	0.86	0.87	0.87	0.88	0.89	0.89	0.90	0.90
CARA	0.5	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90	0.90
CARA	1.0	0.82	0.84	0.85	0.86	0.87	0.88	0.88	0.89	0.90
CARA	1.5	0.80	0.82	0.83	0.84	0.85	0.86	0.87	0.88	0.89
CARA	2.0	0.77	0.79	0.81	0.82	0.83	0.85	0.86	0.87	0.88
CARA	5.0	0.62	0.64	0.66	0.67	0.69	0.70	0.71	0.72	0.73

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

Table 32: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1.5 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.74	0.75	0.76	0.76	0.78	0.78	0.79	0.79	0.80
CARA	0.5	0.73	0.74	0.75	0.76	0.77	0.77	0.78	0.79	0.80
CARA	1.0	0.72	0.73	0.74	0.75	0.76	0.77	0.78	0.78	0.79
CARA	1.5	0.71	0.72	0.73	0.74	0.75	0.76	0.77	0.78	0.79
CARA	2.0	0.69	0.70	0.71	0.72	0.74	0.74	0.76	0.77	0.78
CARA	5.0	0.55	0.57	0.58	0.60	0.61	0.62	0.63	0.64	0.65

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

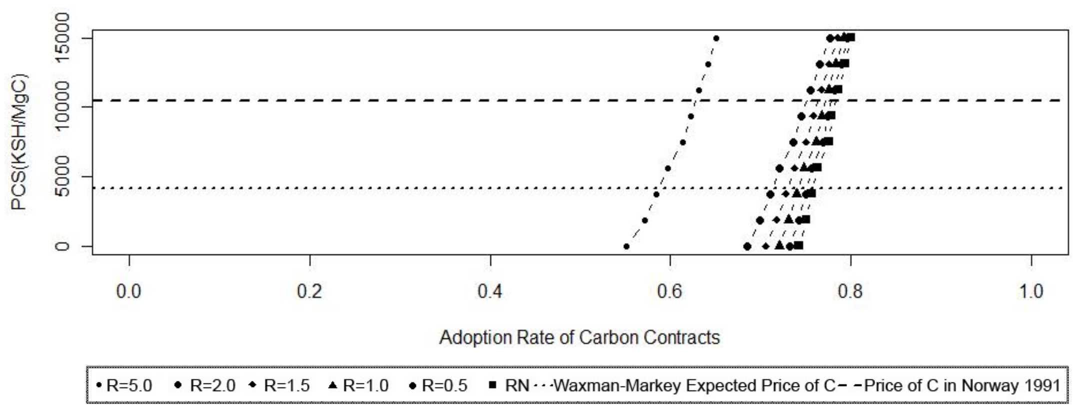

Figure 19: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=1.5 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

Table 33: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=2 under different levels of relative risk aversion (R).

PCS (Kenyan shillings*)		0	1875	3750	5625	7500	9375	11250	13125	15000
RS	R									
RN	0.0	0.68	0.69	0.69	0.70	0.71	0.71	0.72	0.72	0.73
CARA	0.5	0.67	0.68	0.69	0.69	0.70	0.71	0.71	0.72	0.73
CARA	1.0	0.66	0.67	0.68	0.68	0.70	0.70	0.71	0.71	0.72
CARA	1.5	0.65	0.66	0.67	0.68	0.69	0.69	0.70	0.71	0.72
CARA	2.0	0.64	0.65	0.66	0.66	0.68	0.68	0.69	0.70	0.71
CARA	5.0	0.51	0.53	0.54	0.55	0.57	0.57	0.58	0.59	0.60

*The price of carbon sequestration (PCS) is defined in terms of Kenyan shillings per MgC with approximately 75 Kenyan shillings to 1 U.S. dollar. Risk structure (RS) categories are constant absolute risk aversion (CARA) and risk neutrality (RN).

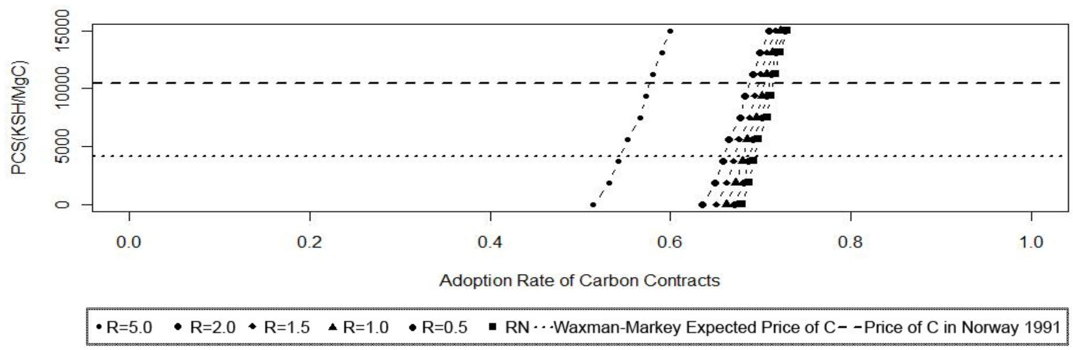

Figure 20: Contract adoption rates under constant absolute risk aversion (CARA) with MTCV=1 and MSCV=2 under different levels of relative risk aversion (R). The price of carbon sequestration (PCS) labeled Waxman-Markey is based on the average price calculated by the Environmental Protection Agency of the U.S. (2009) if the current version of the bill were passed. The PCS in Norway in 1991 is based upon an emissions tax that has since been decreased (Herzog, 2001).

As MSCV for the contract scenario increases from .5 to 2, the area of overlap in expected returns from the two scenarios increases. This causes the entire distribution of the base scenario to converge on the mean of the contract scenario. If MSCV gets large enough, contract participation at all plausible payment levels converges to on fifty percent adoption rate[10]. The underlying logic is that site specific characteristics (given a large enough spatial variation) make the contract scenario so profitable - or so unprofitable - that no reasonable size carbon payment could induce a producer to change systems. Figure 21 maps the two different distributions and their overlap. The distribution to the left is the base scenario and the right as the contract scenario. Going from the left figure to the right figure in each panel shows the change in the distribution of the contract scenario as MSCV increases. The scale remains constant with respect to the base scenario distribution in figure 18. Figure 22 shows identical information, except that the scale changes compensating scale for expanding domain and contracting range of the contract system. In figure 21, as MSCV increases, the distribution of the base scenario of returns

[10] I found this to the case at an MSCV of 100 though a lower value would no doubt find this result as well.

relative to the contract scenario tightens and moves towards the center of the distribution of returns of the contract scenario. This is the driving force behind the producer behavior simulated previously in this section.

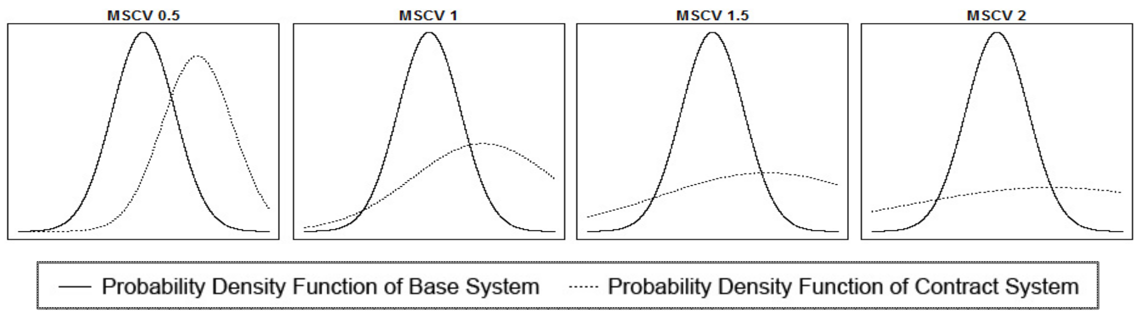

Figure 21: The mean returns of the base scenario are lower than the distribution of returns from the contract scenario. The different plots vary MSCV left to right from .5 to 2. This figure holds the focus on the base scenario constant.

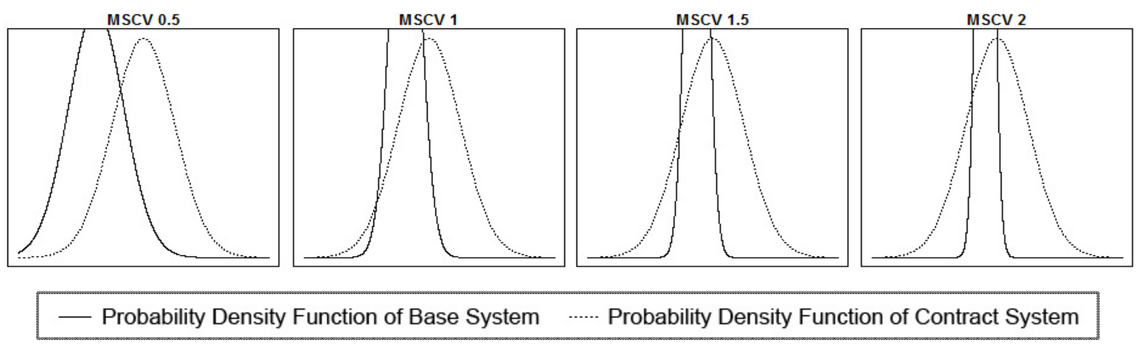

Figure 22: The mean returns of the base scenario are lower than the distribution of returns from the contract scenario. The different plots vary MSCV left to right from .5 to 2. This figure holds the focus on the contract scenario constant.

It is not certain what the most appropriate MSCV would be. As discussed in Chapter 4, the spatial coefficients of variation used in this analysis to set up the base level (MSCV=1) were taken from surveys of the region and were assumed to be constant across systems for the same activity. It is not obvious why the base system would have different spatial variation than the contact system. However as shown above, the results of MDR are highly responsive to the degree of spatial variation[11] of the contract scenario.

Summary

This chapter presents a sensitivity analysis of the range of potential results of the MDR approach in the Machakos study region. A range of values for relative risk aversion are used as inputs that simulate a series of supply curves for risk neutral and risk averse producers under different scenarios. By introducing a multiplier for the contract system's temporal coefficient of variation (MTCV), the sensitivity analysis indicates that risk preferences become more important for decision makers when the difference in riskiness between the contract scenario and the base scenario becomes more pronounced. For the majority of cases examined, the riskiness of the contract scenario was greater than that of the base scenario and risk averse producers were shown to have lower contract adoption rates than risk neutral producers. In the cases when MTCV equaled 1, there was little difference in producer behavior at low to moderate levels of risk aversion ($R \leq 2.0$) and risk neutral producers. As MTCV increased, the level of risk aversion became an increasingly important predictive element until, at an extreme with an MTCV and an R of 5.0, risk aversion and the riskiness of the contract scenario was so great that the even the largest potential incentive payment tested had little power to change the behavior of producers.

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[11] For all analysis in this paper the spatial correlation across systems is assumed to be .75 while the spatial and temporal correlation across activities is also assumed to be .75.

This chapter also examined the effects of different risk preference structures while maintaining the same level of R. Risk preference structures were examined at two different levels of MTCV. At an MTCV of 1, risk preference structure seems to be of little importance. Adoption rates of risk averse producers varied little from the risk neutral case at low carbon payment levels and all but disappeared as the payment size increased. In the case of extreme risk aversion (R = 5.0), adoption rates did differ noticeably (9 points between CARA and DRRA) but converged somewhat (to 5 points) as the price of carbon rose. This indicated that at relatively low levels of riskiness, as well as moderate levels of risk aversion, risk preference structures are less important than the level of risk aversion. This results is consistent with the findings of a number of other researchers (Černý, 2004; Kallberg and Ziemba, 1983, p. 1257; Lence, 2009)

At a MTCV of 2, risk preference structures become more important in predicting adoption rates. There is as much as a 25 point difference between CARA and IRRA (at R=2.0) at a carbon price of zero. As the price of carbon increases to a maximum of 15,000 Kenyan shillings (about 200 U.S. dollars), the difference in adoption rates drops to 11 points. Yet, in the majority of cases, the difference in adoption rates given different preference structures is slight. This indicates that the structure of risk aversion preferences can be important in MDR, given reasonably high levels of riskiness as well as a low enough price of carbon. However, given a low enough levels of riskiness, low enough levels of risk aversion, or high enough expected price of carbon sequestration, risk preference structures do not seem to be important.

This chapter also addresses the potential for the spatial variation of the contract system to be less than or greater than that of the base system through different levels of spatial coefficient of variation multiplier (MSCV). At a MSCV of .5 the supply curves for all risk aversion levels move uniformly to the right. This is driven by the separate spatial distribution of expected returns having little overlap. As MSCV increased to 2 the adoption rate of the contract scenario shifted left towards the 50 percent adoption rate at all levels of risk aversion.

This chapter shows that the MDR framework is capable of capturing a wide range of potential producer behaviors given different levels of risk aversion, different risk preference structures, different levels of spatial variation, and different contract payments. All of these factors can be shown to be potentially important predictive elements. When risk is relatively large, the level and structure of risk aversion becomes important. However as risk free carbon sequestration payments become large enough, even extremely risk averse producers can be influenced to change behavior. Spatial variation, while an important element of the model does not directly interact with the other elements of the sensitivity analysis.

There are a number of potential explanations for why producers in developing nations diverge from expected profit maximization. Many of these explanations impose constraints on the physical limitation of the producers, such as insufficient transportation infrastructure (Omamo, 1998), imperfect access to capital (Murton 1999), and high transaction costs (Renkow et al., 2004). However risk aversion offers a possible explanation which is based on the personal preferences of producers. This study shows that so long as there is more stochastic temporal variation than that associated with the weather (MTCV$\geq$1.5), risk aversion is one potential explanation for why producers systematically diverge from expected profit maximization.

CHAPTER 6

CONCLUSION

The minimum-data approach (MD) of Antle and Valdivia (2006) seeks to provide a means of modeling ecosystem supply by producers that is sufficiently accurate to be useful to policy makers. This study generalizes the MD approach by incorporating producer risk aversion preferences in the minimum-data risk aversion approach (MDR). The MDR approach uses Saha's (1997) flexible mean-standard deviation utility (MSU) function to model producer risk preferences. It presents a framework for translating the unit-free risk aversion preferences measured by other researchers into the MDR framework. This study presents a sensitivity analysis of the Machakos region of Kenya using a range of estimates for risk aversion preferences taken from other researchers. Machakos, Kenya is a unique region to study because producers in Machakos face similar conditions encountered by as many as a billion extremely poor people in developing nations (Ravallion et al., 2008).

Agricultural producers in Machakos have the ability to influence the global stock of public ecosystem services through their actions. Currently, no reward system provides incentives to farmers in developing nations for taking actions that decrease atmospheric green house gas levels by increasing the stock of carbon in their soils. Given the establishment of a global carbon emissions trading market and the option of terrestrial carbon sequestration credits as a valued commodity, there exists the potential for a government or private contracting agency to provide fiscal incentives for farmers to produce ecosystem services. Such an incentive program would have the potential of not only mitigating carbon emissions, but also helping address the issue of extreme poverty faced by many poor agriculturalists in developing nations. It would also help provide a pathway to increasing sustainability of agricultural production in developing nations.

This study presents a sensitivity analysis that finds a range of results produced by varying key elements of the model: price of carbon sequestered, risk aversion level, temporal variation, risk preference structure, and spatial variation. The study finds that when risks are low and risk aversion levels are small, the difference between the risk neutral producers assumed in the original MD approach and those in the MDR approach is small. However, as risk of the contract system increases and risk aversion levels increase, the inclusion of risk preferences begins to have an important effect on the simulated contract participation. This study also tests the importance of risk preference structure. It finds that all of the risk preference structures tested produce similar results when risks are small. When risks are large, risk aversion preference structure is more important. Consistent with the findings of other researchers, the level of risk aversion seems to be a more important predictive element than the structure of risk preferences.

This analysis finds that for all levels of risk aversion and risk aversion structures, the expected behavior of risk averse producers converges with the expected behavior of risk neutral producers as the price of carbon sequestration gets large enough. This result is driven by the assumption that the carbon contract payment is a constant, risk-free payment. At large payment levels, there is little difference in expected producer behavior driven by risk aversion. The sensitivity analysis also presents results based on varying the spatial variation of returns across producers. As the spatial variation of returns for the contract scenario increase, other parameters in the model become less important. As spatial variation gets large enough, the individual expected returns of the contract system become so large that no reasonable contract payment could induce producers to change from the base system to the contract system.

The sensitivity analysis uses a range of risk aversion levels typically measured in the populations in developing nations. Assuming total temporal stochastic variation is at least one and a half that of the simulated weather variation, the sensitivity analysis shows that risk aversion could potentially explain why a large number of producers systemically diverge from expected profit maximization. Other possible explanations for producers diverging from expected profit maximization include production constraints in the form of imperfect capital markets, high transaction costs, imperfect input or output markets, among others.

In conclusion, it is possible to include risk aversion into the minimum-data framework and to parameterize the model based on risk aversion levels found by other researchers. This study finds that the inclusion of risk preferences is important when modeling the supply of ecosystem services and when risks and risk aversion levels are large. In the case of the Machakos study region of Kenya the inclusion of risk preferences has the potential to resolve the disconnect often observed between expected behavior under simple profit maximization and the observed behavior of producers who are likely to be risk averse and face significant production risk.

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