CHAPTER 2
Modeling Microbehavioral Decisions: Economic Perspectives

An individual makes many decisions during his/her lifetime in the form of a choice from multiple discrete alternatives (McFadden, 1984, 1999a). In many of these decisions, a chosen alternative determines the path and economic outcome of the individual’s life over a long time horizon. For example, an individual makes a choice decision on which university she/he will attend to earn a degree. A woman makes a decision on whether she/he will enter into a labor market or work at home. One makes a choice of which city she/he will live for her/his life. One decides whether she/he will take a bus or a train to the workplace for daily commutes. Microeconometrics is a field of statistics which quantitatively explains individuals’ choices using a probabilistic theory (Train, 2003; Cameron and Trivedi, 2005).

In choosing one of the many alternatives, an individual relies on an indicator which informs her of the final outcome of the choice. This may be the total discounted net return expected from the selected alternative in the long term. She will choose the alternative which earns her the highest net return among all the alternatives available. An indicator should be defined in the broadest sense to include all the possible outcomes of the decision that are valued by an individual.

Of the many choice decisions that an individual makes, some decisions are a participation decision, that is, a decision on whether one will participate in a certain market (or group) or not. An individual will decide to enter the market if the total net return from the market participation is expected to exceed a reference value which is unique to the decision maker. In a situation where there are multiple alternatives from which an individual can choose, she/he will choose one option only if the total discounted net return from the alternative of choice would exceed those expected from the other available alternatives.

In environmental and natural resource studies, discrete choice decisions of individuals have been treated as a key factor in explaining market and environmental outcomes (Freeman, 2003; Mendelsohn and Olmstead, 2009). For example, a hedonic property method explains the variation in property values by, inter alia, individuals’ varied preferences and choices of a certain
environmental quality such as cleaner air free of smog. Similarly, a hedonic wage method explains the variation in observed wages by, \textit{inter alia}, individuals’ varied preferences and choices of job-related risks and compensations. Nevertheless, modeling probabilistic choices of individuals have been set aside as secondary in the past environmental and natural resource studies. Instead, the focus of the literature laid on the variation of prices or wages.

In the environmental and natural resource literature, microdecisions of individuals have become a major field of scientific inquiry through the heated debates on whether and how societies can adapt to global warming challenges (Seo, 2013b, 2014a, c). Early studies argued that the magnitude of damage from global warming will depend on whether, how, and how easily farmers will adapt to global climate changes (Rosenberg, 1992; Mendelsohn, 2000; Hanemann, 2000). The seminal paper by Mendelsohn et al. (1994) showed empirically that the impact of climate warming by about 2–3°C may not harm the American agriculture if farmers adapt by substituting inputs and switching customary practices.

However, adaptation strategies were never studied or quantified for a decade since the seminal paper until, Seo and Mendelsohn (Seo, 2006; Seo and Mendelsohn, 2008a) presented an empirical adaptation model using African farmers’ choices of household animals in response to climatic conditions in the continent. The authors reported that African farmers will switch from cattle and chickens to more heat tolerant livestock species of goats and sheep when climate becomes hotter. The authors also found that African farmers switch from cattle and sheep to goats and chickens when precipitation increases due to global warming.

The initial model of microadaptations to global warming has been further developed since then to explain a variety of agricultural systems: a crops-only, a mixed crops-livestock, a livestock-only, irrigated agriculture, rainfed agriculture (Seo, 2010a, b, 2011a). The adaptation model has been further advanced to include all natural resource intensive enterprises. That is, forest-based activities, which constitute a major fraction of the South American rural economy such as a crops-forests, a crops-livestock-forests, and a forests-only enterprise are explicitly integrated into the model structure (Seo, 2012a, b).

This book describes the literature of microbehavioral econometric methods that is pertinent and therefore can be applied to the research endeavors on a large array of environmental and natural resource problems that face today’s societies. The book elaborates economic and behavioral theories, developments of microbehavioral models, and applications to
empirical environmental and natural resource data. The present author integrates multiple disciplines of research such as climate science, environmental and ecological science, economics and finance, econometrics, and statistics to put forth the literature of microbehavioral econometric methods for environmental and natural resource studies.

Empirical applications of the microbehavioral models are presented in Chapters 4–7 with the rural households’ environmental and natural resource decisions collected in a large number of low-latitude developing countries in three continents. The surveys of household decisions were taken from Africa, Latin America, and South Asia (Seo and Mendelsohn, 2008b; Seo et al., 2009; Seo, 2016). In Africa, eleven countries were included: Burkina Faso, Senegal, Niger, Ghana from West Africa; Cameroon from Central Africa; Nigeria from North Africa; Ethiopia, Kenya from East Africa; Zimbabwe, Zambia, South Africa from Southern Africa. Household surveys from Latin America were collected from seven Latin American countries: Argentina, Brazil, Chile, Uruguay from the Southern Cone region; Ecuador, Colombia, Venezuela from the Andean region. For South Asian studies, agricultural data from Sri Lanka and India are used.

An agricultural and natural resource manager chooses a portfolio of farm products she/he manages given climatic and geographic conditions. A large number of crops are planted around the world (Reilly et al., 1996; Mata et al., 2001). In addition, there are many different types of crops. Some of the major grain crops are maize, wheat, rice, barley, millet, and sorghum. Some of the major bean crops are soybeans, legumes, pulses, and lentil. Some of the major root crops are potatoes, sweet potatoes, cassava, carrots, and radish. Some of the major oil seeds are sunflower, canola, mustard seeds, and sesame seeds. Some of the major vegetables are lettuce, spinach, tomatoes, egg plants, Chinese cabbage, onions, green onions, garlic, pepper, cucumber, zucchini, and broccoli. Other specialty crops include sugarcane, sugar beet, tobacco, ginseng, etc.

Besides the large portfolio of crops which has received dominant attention from agricultural as well as development researchers at the expense of other salient rural activities, an agricultural and natural resource manager most often owns domesticated animals, that is, livestock (Nin et al., 2007; World Bank, 2008). Major animals raised by farmers are beef cattle, dairy cattle, goats, sheep, chickens, pigs, horses, ducks, and turkeys. Other animals include donkeys, dogs, camels, Asian water buffalo, beehives etc. Some of these animals are a ruminant. Some farmers sell livestock products such as eggs, wool, meat, milk, cheese, butter, skins, and others.
In the United States, 53% of farms own at least some livestock while livestock management accounts for 49% of agricultural income (USDA, 2007). In Africa and South America, more than two thirds of the farms own at least some livestock (Seo and Mendelsohn, 2008a; Seo et al., 2010). In South America, almost 15% of the total farms are a specialized livestock farm while only 3–4% farms in Sub Saharan Africa are a livestock-only farm (Seo, 2010a, b). Of the total agricultural lands, pastures used for livestock are four to eight times larger than the croplands in South American countries (Baethgen, 1997; WRI, 2005).

Besides a large number of crops and animals, the pool of portfolios held by natural resource managers includes forest-based portfolios. The income earned from forests and forest products accounts for 22% of rural income in South and Central America (Peters et al., 1989; Vedeld et al., 2007). The forest income is earned from sales of wild foods such as mushroom, tree fruits, fuel wood, fodder, timber, grass/thatch, wild medicine, and others. Nontimber forest products are many and diverse including fruits, nuts, plants, resins, barks, and fibers.

In South America, the forest-covered ecosystem, defined as >50% forest cover, is a dominant ecosystem accounting for 44% of the total land area (WRI, 2005). In South America, 19% of the total farms have forest-based activities: 10% of the farms are a crops-livestock-forests enterprise, 8% a crops-forests enterprise, and 1% is a forests-only farm (Seo, 2012b). Common trees in South America are palm, cacao, cashew, mango, pineapple, citrus, banana, shea nut, apple, Kola, peach, almond, prune, apricot, avocado, cherry, hickory, eucalyptus, lemon, and Brazil nuts (Seo, 2012a). Other common farm trees include coffee, gum acacia in the Sahel; date, persimmons, papaya, guava, guanabana, tea, coconut, chestnut, oak, nut pines, and rubber in South and East Asia (Seo et al., 2005; Seo, 2010c). Besides being sources of income and livelihoods of rural managers, forests provide a sink for Carbon dioxide in the atmosphere as well as settlements for birds and animals (Houghton, 2008; Convention on Biological Diversity, 2010).

Table 2.1 summarizes key features of agricultural and natural resource enterprises that are held in low-latitude developing countries across the world. Arable and permanent crop lands account for 7–8% of the total land area in Sub Saharan Africa and South America. The 35% of the total land area in Sub Sahara is permanent pasture while the 29% of the total land area in South America is permanent pasture. The farms that own some livestock account for 49% in the United States, but about 70% farms own livestock in South America and Sub Sahara. Almost 20% of the farms in South America own livestock only. In South America, about 13% of the rural farms own forests and forest products.
### Table 2.1 Key statistics on natural resource enterprises in low-latitude countries

<table>
<thead>
<tr>
<th>Major products</th>
<th>Crops</th>
<th>Animals</th>
<th>Forests</th>
</tr>
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<tbody>
<tr>
<td>Grains (maize, wheat,</td>
<td>Grains (maize, wheat, rice, barley, millet, sorghum); Bean crops</td>
<td>Livestock: Beef cattle, dairy cattle, goads</td>
<td>Palm, cacao, cashew, mango, pine-apple, citrus</td>
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<tr>
<td>rice, barley, millet,</td>
<td>(soybeans, legumes, pulses, lentil); Root crops (potatoes, sweet</td>
<td>chickens, pigs, turkey, donkey, ducks,</td>
<td>banana, sheanut, apple, Kola, peach, almond,</td>
</tr>
<tr>
<td>sorghum)</td>
<td>potatoes, cassava, carrots, radish); Oil seeds (sunflower, canola,</td>
<td>horses, dogs, beehives, llama, etc.</td>
<td>prune, apricot, avocado, cherry, hickory,</td>
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<tr>
<td></td>
<td>mustard seeds, sesame seeds); Vegetables (lettuce, spinach, tomatoes,</td>
<td>Livestock products: Wool, eggs, milk,</td>
<td>eucalyptus, lemon, Brazil nuts, coffee, gum</td>
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<td></td>
<td>egg plants, Chinese cabbage, onions, green onions, garlic, pepper,</td>
<td>butter, cheese, hides.</td>
<td>acacia date, persimmons, papaya, guava,</td>
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<tr>
<td></td>
<td>cucumber, zucchini, Kale, broccoli); Other specialty crops</td>
<td></td>
<td>guanabana, tea, coconut, chestnut, oak,</td>
</tr>
<tr>
<td></td>
<td>(sugarcane, sugar beet, tobacco, ginseng, gourds).</td>
<td></td>
<td>rubber, nut pines, pear, Korean dogwood,</td>
</tr>
<tr>
<td>Land use</td>
<td>Arable and permanent cropland accounts for 8% of total land area in</td>
<td>Permanent pasture accounts for 35% of total land area in South America and 18% of the total land area in Sub Sahara.</td>
<td>13% of rural farms in South America.</td>
</tr>
<tr>
<td>percent- ages</td>
<td>Sub Sahara and 7% in South America.</td>
<td></td>
<td></td>
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<tr>
<td>Ownership</td>
<td>95% in Sub Saharan African rural farms. 80% in South American rural farms.</td>
<td>49% of the US farms. About 70% of Sub Saharan farms. About 70% of South American farms.</td>
<td>22% of rural household income South and Central America.</td>
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<tr>
<td>percent- ages</td>
<td></td>
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<tr>
<td>Income percent- ages</td>
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</tbody>
</table>

Note: Data sources are WRI (2005), USDA (2007), Seo (2015a).
From a large number of products and portfolios, a rural manager chooses a portfolio which is composed of any of the products explained earlier (Seo, 2015a). A portfolio of choice can be either a specialized portfolio or a diversified (mixed) portfolio. For example, a farmer may choose a portfolio composed of some crops and some animals. Or, she/he may choose a portfolio composed of some crops, some animals, and some trees. Alternatively, one may choose to specialize in one of these categories of assets, that is, a crops-only, a livestock-only, a forests-only enterprise.

In this particular classification system, the following family of portfolios constitutes the choice set of the rural managers:

- Portfolio 1: A crops-only enterprise;
- Portfolio 2: A livestock-only enterprise;
- Portfolio 3: A forests-only enterprise;
- Portfolio 4: A crops-forests enterprise;
- Portfolio 5: A crops-livestock enterprise;
- Portfolio 6: A livestock-forests enterprise;
- Portfolio 7: A crops-livestock-forests enterprise.

The first three portfolios are a specialized portfolio and the latter four portfolios are a diversified portfolio across the three types of assets. It is important to note that diversification is an economic decision which is driven by a motive to deal with risk in returns (Markowitz, 1952; Tobin, 1958). That is, one will choose a diversified portfolio if and only if it gives a higher return than the other specialized portfolios, conditional on the same risk. Equivalently, a farmer will choose a diversified portfolio if and only if it has a lower risk than the other portfolios, conditional on the same return.

Further, diversification is a different behavior from selection or choice. That is, diversification is another dimension of microbehavioral decisions made by individuals. Whereas selection is a behavior to choose one asset, diversification is a behavior to choose a pool of assets. Therefore, a decision maker must consider, among other things, correlations among the assets in the pool in the ways they react to a shock, complementarity of inputs across the assets, and dietary demands for foods.

In agricultural and natural resource industries, a diversification decision can arise for many reasons. For example, a farmer may decide to diversify across crops and animals, so that she/he can graze farm animals when croplands are left fallow in an effort to improve the quality of soils of the croplands during the fallow period. A farmer may diversify across crops and animals since the total profit earned from the diversified portfolio is higher than either of those earned from specialized portfolios in either crops or livestock.
Besides diversification across multiple asset types, that is, crops, livestock, or forests, diversification can take place within each of the seven enterprises. In a crops-only portfolio, for example, a farmer may use inter‐cropping or crop rotations, both of which are widely practiced by the farmers across the world. It is commonly believed that diversification through these practices increases the total production and return from the given land (Zilberman, 1998).

A natural resource manager chooses only one of the seven enterprises, as will be formally explained later, in order to earn the highest return, given external conditions, considering the characteristics of risks. Conditional on the choice of one of these enterprises, she/he will make further decisions on the levels of numerous inputs, outputs, farm practices to maximize the profit in the long‐term (Seo, 2006, 2015a, b).

If the external condition, for example, a climate system, were to be altered, yields and profitabilities of the seven natural resource enterprises would be changed. These changes would occur through physical changes in Carbon Dioxide concentration in the atmosphere, average temperature, average rainfall, temperature variability, rainfall variability, and shifting seasons (Schlesinger, 1997; Tubiello and Ewert 2002; Ainsworth and Long, 2005; Denman et al., 2007; Hahn et al., 2009). Indirectly, an alteration in the climate system leads to changes in disease occurrences and prevalence which affect animal and plant productivities (Ford and Katondo, 1977; Fox et al., 2012) or influence changes in insects, pests, and weeds (Porter et al., 1991; Ziska 2003).

The changes in yields and returns of the enterprises would be varied across the enterprises. Therefore, a natural resource manager should be allowed in the microbehavioral models to make switch decisions simultaneously on enterprises, production inputs such as labor and capital, production practices, and outputs. To put it differently, the microbehavioral econometric framework which will be presented shortly must capture a full array of adaptations across the enterprises as well as within each enterprise.

Let the observed profit (\(\pi\)) from enterprise 1 by an individual manager \(n\) be written as a function of exogenous factors as follows (McFadden, 1999a; Train, 2003):

\[
\pi_{ni} = X_{ni} \xi_i + \varphi_{ni}.
\]  

(2.1)

In the reduced form equation above, \(X\) is a vector of explanatory variables that determine the profit from enterprise 1. The second term on the right‐hand side is an error term which is assumed to be a white noise. This reduced form equation exists in certain conditions, for example, if there is no selectivity in enterprise 1.
However, since the profit data are only available when enterprise 1 is chosen, the latent (true) profit may differ from the observed profit. Let the latent profit \( \bar{\pi} \) from enterprise \( j \) by an individual manager be written as a function of exogenous factors as follows:

\[
\bar{\pi}_{nj} = Z_{nj} \zeta_j + \eta_{nj}, \quad j = 1, \ldots, J. \tag{2.2}
\]

In the earlier equation, \( Z \) is a vector of explanatory variables that determine the profits of not only enterprise 1, but also all the other enterprises. The second term on the right-hand side is an error term which is again assumed to be a white noise. Note that \( \bar{\pi} \) is latent, therefore, not observable by a researcher or a resource manager. Therefore, we cannot estimate Eq. (2.2) directly.

Researchers are often concerned with estimating Eq. (2.1) by employing a proper statistical procedure (Greene, 2011). The difficulty arises because, since the profit data of enterprise 1 are available only if that enterprise is chosen, the observed profit data and the latent profit data must be correlated. The estimation of Eq. (2.1) therefore must correct for the correlation that arises from a selection process from multiple alternatives. Otherwise, estimated parameters of Eq. (2.1) will be biased and inconsistent (Heckman, 1979).

In an optimization problem over a long time horizon such as a natural resource manager’s optimization decisions under global warming, the profit measure in the left-hand side of Eq. (2.1) is a profit measure over a long time horizon. Such a measure has been a signature feature of the climate change economics literature. Land rent is an annual profit of a farm and land value is defined as the discounted present value of the infinite stream of land rents in the future with flexible discount rates (Ricardo, 1817; Fisher, 1906, 1930; Mendelsohn et al., 1994; Seo, 2015b).

For the purpose of estimating Eq. (2.1) consistently, let’s assume the classical error term for Eq. (2.1) for the moment, given \( X, Z \). That is, it has a zero mean and homoscedastic as follows (Bourguignon et al., 2004):

\[
\begin{align*}
E(\varphi_{n1} \mid X_n, Z_n) & = 0, \\
Var(\varphi_{n1} \mid X_n, Z_n) & = \sigma^2. \tag{2.3}
\end{align*}
\]

The profit data for enterprise 1 are observed only if this enterprise is chosen by an individual manager from the pool of available enterprises. Enterprise 1 will be chosen only if the latent profit from this enterprise exceeds those from all the other enterprises (For simplicity, from now on
we will drop the subscript indicating an individual manager as long as there is no ambiguity in reading the equations). That is,

$$\tilde{\pi}_1 - \tilde{\pi}_k > 0, \forall k \neq 1.$$  

(2.4)

The probability of enterprise 1 to be chosen by an individual manager is then expressed as follows:

$$P_1 = P[\tilde{\pi}_1 > \tilde{\pi}_k, \forall k \neq 1]$$

$$= P[Z\zeta_1 + \eta_1 > Z\zeta_k + \eta_k, \forall k \neq 1]$$

$$= P[\eta_k < Z\zeta_1 - Z\zeta_k + \eta_1, \forall k \neq 1].$$  

(2.5)

This probability can be solved into a succinct form if we assume a certain distribution for the error term. Let \((\eta_j)’s be identically and independently Gumbel distributed after spatial resampling (Anselin, 1988; Case, 1992; Seo, 2011b). This is so called Independence from Irrelevant Alternatives (IIA) hypothesis to which we will come back again later in this chapter. A rationale and procedure for spatial resampling will be given in the next chapter.

Then, the probability of enterprise 1 to be chosen by an individual manager is written in a succinct form as a Logit (McFadden, 1974):

$$P_1 = \frac{\exp(Z\zeta_1)}{\sum_{j=1}^{J} \exp(Z\zeta_j)}.$$  

(2.6)

That the Logit formula in Eq. (2.6) is handily derived from the Gumbel distribution is intuitively clear, given that the third line in Eq. (2.5) is simply the cumulative distribution of the Gumbel distribution. The Gumbel distribution is defined by the following cumulative distribution function \((G)\) and the density function \((g)\):

$$G(\eta) = \exp(-e^{-\eta}),$$

$$g(\eta) = \exp(-\eta - e^{-\eta}).$$  

(2.7)

The sample log-likelihood function is defined as follows:

$$LL = \sum_{n=1}^{N} \sum_{i=1}^{I} d_{ni} \cdot \ln P_{ni}$$  

(2.8)

where \(P_{ni}\) is defined by Eq. (2.6) and \(d_{ni}\) is an indicator function whose value equals 1 if the farm household chose alternative \(i\) or zero otherwise.
The parameters \( (\zeta_j, j = 1, \ldots, J) \) are estimated using a Maximum Likelihood method by maximizing the log-likelihood function in Eq. (2.8). A nonlinear iterative optimization technique such as a Newton–Raphson method is used to find the estimated parameters which maximize the log-likelihood function (Johnston and DiNardo, 1997). The Newton–Raphson method, as in many other optimization techniques, calculates the Score matrix and the Hessian matrix from the log-likelihood function and uses them to find the shortest distance to climb to a certain target level of the log-likelihood function.

The vector \( Z \) is a set of explanatory variables in the determination of the profits earned from managing natural resources. In the studies of global warming and climatic changes, primary variables in this vector are climate variables. The climate of a given farming region is identified by climate normals such as a temperature normal or a precipitation normal. For example, a precipitation normal is a 30 year average precipitation of a given region (IPCC, 2014). Note that a climate normal is different from a yearly weather variable.

The distinction between climate and weather is a key concept for understanding individuals’ behaviors in response to climatic changes. The distinction is clear in the comparison between annual rainfall and a 30 year average rainfall. An amount of precipitation fluctuates interannually (Rosenzweig et al., 2001). A heavy rainfall year is often followed by a low rainfall year which is again often followed by a high rainfall year. A natural resource manager makes numerous decisions to cope with the amount of rainfall in a specific year. At the same time, a natural resource manager makes many decisions to deal with the long-term average rainfall, that is, rainfall normals.

The decisions to cope with climate normals are by and large different from the decisions to cope with the weather in a specific year. The responses to the weather in a specific year are likely to be dependent upon the decisions taken to cope with a long-term weather pattern, that is, climate normals. Researchers should be careful in defining climate variables which must not be confused for annual weather (Seo, 2013b).

Another aspect of climate and weather is seasons. In capturing behavioral decisions of individuals in response to climate conditions, definition of seasons matters. Many economic activities are seasonally arranged: crops are planted in spring, grown in summer, harvested in autumn, and stored in winter. The climate change impact and adaptation literature has relied on multiple definitions of seasons. A traditional four-season approach is widely used: spring, summer, autumn, and winter (Mendelsohn et al., 1994). In the tropical countries, two seasons were used: summer and winter (Seo and
Mendelsohn, 2008a, b). In the monsoon climate regime, two seasons were used: monsoon period and nonmonsoon period (Seo, 2016).

In the Southern Hemisphere, a summer season corresponds approximately to a winter season in the Northern Hemisphere which falls upon Dec., Jan., and Feb. (Kurukulasuriya et al., 2006; Seo and Mendelsohn, 2008a). As an example, summer precipitation in the Southern Hemisphere can be defined as follows. With $PR^s_t$, being average precipitation for season $s$ and year $t$:

$$PR_{sum} = \sum_{t=1}^{30} (PR^{Dec}_t + PR^{Jan}_t + PR^{Feb}_t) / 30 \times 3.$$  

Instead of using seasons as described earlier, agronomic or statistical crop studies often rely on the concept of growing degree days (Schenkler et al., 2006; Schlenker and Roberts, 2009; Deschenes and Greenstone, 2007). The concept of growing degree days builds upon several key assumptions: (1) there is a base temperature below which the organism does not grow; (2) the growth rate increases with temperature above the base temperature; (3) growth and development of crops are closely related to daily temperature mean accumulations above the base temperature.

Formally, the growing degree days (GDD) is defined as follows:

$$GDD = \frac{TE_{max} + TE_{min}}{2} - TE_{base}$$  

where $TE_{max}$ is maximum daily temperature and is set equal to 86°F when temperatures exceed 86°F, $TE_{min}$ is the minimum daily temperature and is set equal to 50°F when temperatures fall below 50°F, and $TE_{base}$ is the base temperature for the organism (US EPA 2014).

The GDD concept is useful for understanding crop growth. One of the original uses of the GDD concept was characterization of corn development. Corn (maize) has a base temperature of 50°F and each corn hybrid has a certain GDD requirement to reach maturity. Those varieties grown in the central Corn Belt in the United States require anywhere from 2,100–3,200 GDD depending on the hybrid. The GDD requirement varies across the varieties and the crops. In addition, the GDD requirement event of the same crop variety varies across the crop growing regions. Hence, the GDD concept is less meaningful in microbehavioral studies, which are concerned on the whole range of portfolios farmers hold, not a single grain crop.

Besides climate variables, the vector $Z$ includes other determinants of farm profit and choices such as soils, topography, hydrology, household
characteristics, market access, and country-specific variables (Seo and Mendelsohn, 2008b, Seo 2012c). A dominant soil type in any given region of the world is available from the FAO (Driessen et al., 2001; FAO, 2003). Elevation data are available from the Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) dataset developed by the United States Geological Survey (USGS) and the National Geospatial-Intelligence Agency (NGA) (Danielson and Gesch, 2011). The elevation data are constructed from a large number of source data sets which are often available at 1 arc-second resolution. Hydrology data capture the amounts of seasonal waterflows and the amounts of seasonal runoffs in a given region, which are available from, for example, the University of Colorado hydrology model (Strzepek and McCluskey, 2006). Accessibility to the markets is measured by a travel time or a travel distance to a major city or a major port for purchases of inputs or sales of products, which are available from the World Bank spatial dataset constructed from the World Bank Project on Africa Infrastructure and Country Diagnostic (AICD) (World Bank, 2009a). Detailed explanations of these nonclimate explanatory variables will be given in the application chapters of the book, that is, Chapters 4–7.

A natural resource manager, having chosen an enterprise, say enterprise 1, chooses the bundle of inputs and outputs at the same time to maximize the profit earned from the chosen enterprise over a long time horizon. A researcher who attempts to estimate the profit function of enterprise 1 using the observed profit data of the enterprise and the other observed data of the explanatory variables may estimate the following equation:

$$\pi_{n1} = X_n \hat{\xi}_1 + \nu_{n1}.$$  \hspace{1cm} (2.11)

This is the same equation as in Eq. (2.1) except the error term which can be defined by a concerned researcher more generally than the error term in Eq. (2.1). That is, the researcher may assume $\nu_{n1}$ to have the following general variance-covariance matrix structure with heteroscedastic or autocorrelated error terms:

$$COV[\nu] = COV[\nu_1, \nu_2, \ldots, \nu_J] = \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \ldots & \sigma_{1J} \\ \sigma_{21} & \sigma_{22} & \ldots & \ldots \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{J1} & \sigma_{J2} & \ldots & \sigma_{JJ} \end{bmatrix} \hspace{1cm} (2.12)$$
However, any specification from the whole variety of specifications that is contained in Eqs. (2.11) and (2.12) will end up with a bias due to the selection process involved in estimating Eq. (2.11). That is to say, regardless of how general the specification of the covariance matrix is, a researcher cannot avoid the fundamental problem that the error term in Eq. (2.11) must be correlated with the error term in the selection equation, that is, Eq. (2.2). When selectivity is present, a direct estimation of the outcome equation results in biased parameter estimates (Heckman, 1979, 2000).

To see concretely what the problem is, let’s assume that the error term in Eq. (2.11) and the error term in Eq. (2.2) have the following correlation structure:

\[
\text{Corr}[\eta, \nu] = \begin{bmatrix}
\text{Corr}(\eta_1, \nu_1) \\
\text{Corr}(\eta_2, \nu_1) \\
\vdots \\
\text{Corr}(\eta_j, \nu_1) \\
\vdots \\
\text{Corr}(\eta_J, \nu_1)
\end{bmatrix} = \begin{bmatrix}
\omega_1 \\
\omega_2 \\
\vdots \\
\omega_j \\
\vdots \\
\omega_J
\end{bmatrix}, \text{with } \omega_j \neq 0, \forall j. \tag{2.13}
\]

Then, the error term in Eq. (2.11) can be rewritten instead by \( \eta_j \)’s:

\[
\nu_1 = \omega_1 \cdot \eta_1 + \omega_2 \cdot \eta_2 + \cdots + \omega_j \cdot \eta_j + \cdots + \omega_J \cdot \eta_J. \tag{2.14}
\]

Therefore, the estimated equation in Eq. (2.11) is not unbiased, therefore not consistent under the general structure of \( \eta \) distribution. That is to say,

\[
E[\nu_1] \neq 0. \tag{2.15}
\]

The same conclusion can be drawn to the estimation of the profit function of the other enterprises. When selection is an economic decision, the outcome function of the selected alternative cannot be estimated in an unbiased way. Note that the value of the expectation in the above equation can be either positive or negative since the correlation coefficient \( \omega_j \) can be either negative or positive. This means the outcome equation can be biased either downward or upward.

Is there a way to estimate without bias the outcome equation of the selected alternative? This is the question that James Heckman asked and provided an answer, for which the Nobel Prize in Economic Science was awarded in the year 2000, along with Daniel McFadden (Heckman, 2000). In the Heckman’s seminal paper, the choice decision was dichotomous.
Heckman provided a selection bias correction method for the estimation of the women’s wage function in which there are two groups of women: those work at home and those who are paid wages for the jobs they are employed.

In the Heckman problem where the choice is yes/no, the correlation matrix in Eq. (2.13) has only one element which can be identified. Then, a selection bias can be expressed in a simple manner by capturing the single correlation term. Since the Heckman method is also important in a multinomial choice setting to be described later in this chapter, the present author will write down the Heckman problem and method in the following, which can be based on a slightly revised version of Eq. (2.1) and Eq. (2.2):

\[
\pi_{n1} = X_n \xi_n + \nu_{n1}. \tag{2.1*}
\]

\[
\bar{\pi}_{nj} = Z_n \zeta_j + \eta_{nj}, \quad j = 0 \text{ or } 1. \tag{2.2*}
\]

Equations marked with (*) denotes the revised version of Eq. (2.1) and (2.2).

The selection bias correction term for the Heckman binomial problem is derived from the following manipulations:

\[
E[\nu_1 | \bar{\pi}_1 > 0] = E[\nu_1 | Z_1 \xi_1 + \eta_1 > 0] = E[\nu_1 | \eta_1 > -Z_1 \xi_1]. \tag{2.16}
\]

If \( \nu_1 \) and \( \eta_1 \) are uncorrelated, the selection bias term in the above equation is equal to zero. However, since the two error terms are correlated, Eq. (2.17) can be written as follows using the inverse-mills ratio \( \lambda_1 \) (Greene, 2011):

\[
E[\nu_1 | \bar{\pi}_1 > 0] = \omega_1 \cdot \sigma_{\nu_1} \cdot \lambda_1(\alpha_{\eta_1}) \tag{2.17}
\]

where
\[
\lambda_1(\alpha_{\eta_1}) = \frac{\phi(Z_1 \xi_1 / \sigma_{\eta_1})}{\Phi(Z_1 \xi_1 / \sigma_{\eta_1}). \tag{2.18}
\]

A consistent estimation of Eq. (2.1)* in the Heckman problem takes the following form with the white-noise error term \( \tau_{n1} \):

\[
\pi_{n1} = X_n \xi_n + E[\nu_{n1} | \bar{\pi}_{n1} > 0] + \tau_{n1} \tag{2.19}
\]

\[
= X_n \xi_n + \omega_1 \cdot \sigma_{\nu_1} \cdot \frac{\phi(Z_1 \xi_1 / \sigma_{\eta_1})}{\Phi(Z_1 \xi_1 / \sigma_{\eta_1})} + \tau_{n1}. \tag{2.20}
\]
In a multinomial choice setting, there are $J-1$ correlation terms. Therefore, the correction of selection bias becomes more complicated as all these terms should be part of the selection bias correction.

In a polychotomous (multinomial) choice setting, the Dubin-McFadden method is known to provide a selection bias correction that outperforms other methods such as the Lee’s or the semi-parametric Dahl’s method (Dubin and McFadden, 1984; Schmertmann, 1994; Bourguignon et al., 2004). The Dubin-McFadden method outperforms the other methods because it allows for a more flexible correlation structure than the other methods (Lee, 1983; Dahl, 2002). For instance, the Lee’s method assumes the same correlation coefficient among all the alternatives in the choice set.

The Lee’s method is a generalization of the Heckman method to a multinomial choice situation and assumes the following highly restrictive correlation structure:

$$\text{Corr}[\eta_j, \nu_1] = \omega, \quad \forall j. \quad (2.21)$$

This restrictive correlation structure means that the selection bias term can be expressed as a single parameter, as in the Heckman method for a binomial choice situation (Lee, 1983; Bourguignon et al., 2004).

$$E[\nu_1 | \varepsilon_1 = \text{Max}(\tilde{\pi}_j - \bar{\nu}_1) < 0, \Gamma] = \omega \cdot \sigma_{\nu_1} \cdot \frac{\phi(J_{\varepsilon_1}(0 | \Gamma))}{F_{\varepsilon_1}(0 | \Gamma)}. \quad (2.22)$$

Note the similarity between Eq. (2.22) and Eq. (2.17). In the Eq. (2.22), $F$ is a cumulative distribution of $\varepsilon_1$, $\Gamma$ is the vector of explanatory variables, and $J$ is a transformation of $F$. In the next chapter, we will revisit this equation and the Lee’s method. For now, it is sufficient to note that the Lee’s method is a generalization of the Heckman method to the multinomial choice situations and is a restrictive model because it assumes implicitly that all correlations among the alternatives in the choice set are identical.

Dubin and McFadden (1984) suggested an alternative method which does not impose such a restrictive assumption on the correlation structure. Instead, they assumed the following linearity condition with all the unique correlation parameters included in the equation:

$$E(\nu_1 | \eta_1, \ldots, \eta_j) = \sigma_{\nu_1} \sum_{j=1}^{J} \omega_j (\eta_j - E(\eta_j)), \quad (2.23)$$

with $\sum_{j=1}^{J} \omega_j = 0$,

where $\omega_j = \text{corr}(\nu_1, \eta_j)$. 

Eq. (2.23) can be simplified and rewritten as follows:

\[ E(\nu_1 | \eta_1, \ldots, \eta_J) = \sigma_v \sum_{j=2}^{J} \omega_j (\eta_j - \eta_i). \]  

(2.24)

If the choice model is the multinomial Logit model as in Eq. (2.6), the expectation of the term in the parenthesis on the right-hand side of the Eq. (2.24) can be derived as follows:

\[ E(\eta_j - \eta_i | \pi_i > \max_{j \neq 1} \pi_j, \Gamma) = \frac{P_j \cdot \ln P_j}{1 - P_j} + \ln P_j, \quad \forall j \neq 1. \]  

(2.25)

Then, the conditional long-term profit for enterprise 1 can be estimated consistently after correcting for selection biases (the second term on the right hand side below) with the white-noise error term (\(\delta_1\)) as follows:

\[ \pi_1 = X\xi_1 + \sigma_v \sum_{j \neq 1}^{J} \omega_j \left[ \frac{P_j \cdot \ln P_j}{1 - P_j} + \ln P_j \right] + \delta_1. \]  

(2.26)

Note that there are \(J - 1\) selection bias correction terms in the outcome equation in Eq. (2.26) of enterprise 1. Similarly, there will be \(J - 1\) selection bias correction terms in the outcome equation of any of the other enterprises. This is in contrast to the generalized Heckman method, that is, the Lee’s method, which has only one selection bias correction term for any of the outcome equations.

The sign of each of the selection bias correction terms will reveal the sign of the correlation coefficient between the corresponding two alternatives. This is because \(\sigma\) is always positive while \(\omega_j\) can be positive or negative. A positive estimate of the selection bias correction term (\(\sigma \omega_j\)) will mean that the correlation between \(\eta_j\) and \(\nu_i\) is positive. A negative estimate of the bias correction term will mean that the correlation between the two error terms is negative.

The estimated bias correction terms tell important economic stories. A negative estimate for the selection bias correction term in Eq. (2.26) for alternative \(j\) means that an error term, which increases the choice of alternative \(j\), will decrease the long-term profit of alternative 1. On the other hand, a positive estimate for the selection bias correction term for alternative \(j\) means that an error term which increases the choice of alternative \(j\) will increase the long-term profit of alternative 1.
To be more concrete, let’s say that alternative 1 is a specialized enterprise in crops, alternative 2 is a mixed enterprise of crops and animals, and alternative 3 is a specialized enterprise in animals. Let’s assume that we estimated Eq. (2.26) for enterprise 1. Then, there are two selection bias correction terms in the estimated function: one for the mixed enterprise and the other for the specialized enterprise in animals. A negative selection bias correction term that belongs to enterprise 2, if assumed so, would mean that an error term that increases the adoption of the mixed enterprise would decrease the profit of the crops-only enterprise. Similarly, a positive selection bias correction term that belongs to enterprise 3, if assumed so, would mean that an error term that increases the adoption of the specialized enterprise in animals increases the profit of the specialized enterprise in crops.

This again means that, if these parameter estimates are assumed, a farm that is more likely to choose a mixed crops-livestock enterprise has a lower crops-only enterprise profit. Similarly, a farm that is more likely to choose a specialized livestock enterprise has a higher crops-only enterprise profit. This is of course if these farmers were to be managed for the crops-only enterprise instead.

The outcome (profit) equations for the other enterprises are estimated in the same manner. In total, there will be \( J \) conditional outcome (profit) equations to be estimated. It is extremely important not to miss the feature that a microbehavioral econometric methodology enables researchers to model component systems of the whole system. Let’s say the whole system here is the natural resource system. The whole system comprises numerous natural resource enterprises that are mutually exclusively and exhaustively defined. The seven portfolios introduced in the beginning of this chapter is one such categorization of the natural resource system.

In the microbehavioral econometric methodology described up to now, two sets of equations are estimated simultaneously: the set of choice equations and the set of outcome equations. When there are \( J \) alternatives in the choice set to choose from, \( J \) outcome equations should be estimated. Note from Eqs. 1 and 2 that the vector of explanatory variables (\( Z \)) in the choice equations is different from the vector of explanatory variables (\( X \)) in the outcome equation.

In estimating the system of equations, the set of choice equations should be identified from the set of outcome equations (Koopmans, 1949; Fisher, 1966; Manski, 1995). In a nonparametric identification strategy which is most often used by researchers, the vector of explanatory variables in the choice equations should include the subset of explanatory variables that are
significant variables for choices among the alternatives but do not affect the outcome (profit) equations. The identification variables should enter only the choice equations and be dropped from the outcome equations.

The identification problem arises when you observe a person and her mirror image at the same time (Manski, 1995). The two objects move at the same time. Does a person cause the mirror image to move? Does the mirror image cause the person to react? You cannot identify one from the other.

In the research contexts, the identification problem occurs when a researcher attempts to estimate $J$ behavioral functions when there are in fact more than $J$ behavioral relations that bring about the $J$ behavioral functions (Johnston and DiNardo, 1997). The $J$ behavioral functions must be identified by employing an identification strategy.

To understand this, let’s examine the estimation problem of market demand. A researcher observes only one market data of the numbers of a product sold and prices sold of the product. In Fig. 2.1, an example scatter plot of market data of observed prices and quantities sold of the item is drawn.

A researcher observes the changes in the price over time and the changes in the quantity sold over time. This plot puts together price data and

![Figure 2.1 Observed market data on prices and quantities sold of a product.](image)
quantity data in one space. From the plot, a researcher can identify neither the demand function nor the supply function of the product, although each point in the plot has been determined in the market by the demand and the supply at that point of time. The researcher does not see either a downward sloping demand curve or an upward sloping supply curve in Fig. 2.1.

In order to identify either equation, the researcher needs to know more about changes in the markets, for example, changes in income, changes in other prices, and changes in demographics. For example, one way to identify the demand equation from the above plot is to analyze changes in the equilibrium points during the time period when the demand curve has remained stable. By tracing the changes in the equilibrium supply points along the stable demand curve, one will be able to establish the demand equation. When the demand curve is shifted to another line due to, for example, changes in income level, she/he can estimate another demand curve for the time period when the demand curve remains stable.

Alternatively, the demand equation (or the supply equation) can be identified in the system of equations by adding an explanatory variable that is unique to the demand equation (or the supply equation). For example, an income variable can enter the demand equation and a price of an important input for the product can enter the supply equation. This process prevents the demand equation from being determined by the supply equation, and vice versa.

Let \( Q_D \) be the demand amount, \( Q_S \) be the supply amount, and \( x \) and \( y \) are two explanatory variables that determine both dependent (outcome) variables. Let’s suppose that a researcher estimates the following structural equation with the classical error terms, \( \epsilon_D \) and \( \epsilon_S \):

\[
Q_D = \alpha_D + \beta_1 x + \beta_2 y + \epsilon_D,
\]
\[
Q_S = \alpha_S + \phi_1 x + \phi_2 y + \epsilon_S.
\]  

(2.27)

Since the researcher observes only the quantities sold at certain prices, there is only one quantity at one transaction point, that is, \( Q = Q_D = Q_S \). Given the data points in Fig. 2.1, neither of the two equations in Eq. (2.27) can be estimated. A change in one explanatory variable in the supply function also causes a change in the demand function. That is to say, the demand equation is unidentified, so is the supply equation.

An identification of the demand equation can be achieved nonparametrically (Johnston and DiNardo, 1997). Let \( z \) be an independent variable
which influences the demand function, but not the supply function. Then
the following system of equations can be estimated:

\[ Q_D = \alpha_D + \beta_1 x + \beta_2 y + \beta_3 z + \epsilon_D, \]
\[ Q_S = \alpha_S + \phi_1 x + \phi_2 y + \epsilon_S. \]  
(2.28)

The system of equations in Eq. (2.28) is said to be exactly identified,
which occurs when \( J - 1 \) identification variables are entered in the system of
\( J \) equations. In simple terms, when there are two equations to be estimated,
one unique variable identifies one equation and therefore the other equa-
tion too. The system of equations can be over-identified or under-identified
when the number of identification variables \( (NI) \) satisfies the following
equations:

Over-identified if \( NI > J - 1 \);
Under-identified if \( NI < J - 1 \).  
(2.29)

Getting back to the microbehavioral model in Eq. (2.2) and Eq. (2.26),
there are \( J \) alternatives to choose from in the choice model as well as \( J \)
outcome equations. Choices of enterprises influence profits earned from
enterprises while profits of enterprises influence choices. To exactly iden-
tify the choice equations from the outcome equations or vice versa, there
should be \( J - 1 \) identification variables.

The \( J - 1 \) identification variables will be chosen so that they affect
the choice of an individual agent from the pool of options, but do not affect
the long-term profits of the options that are chosen. To give an example, the
present author will build a microeconometric model outlined so far for
the study of agricultural systems, which is presented in Chapter 4 of this
book. In the first stage of the model, an individual agents’ choice of one
of the three agricultural systems is modeled: a crops-only, a livestock-only,
a mixed. In the second stage, land value of one of the systems is estimated
after correcting for selection biases. The choice equations were identified
using two identification variables. One was the topographic variable indi-
cating whether the terrain was flat or not. Another was the distance to the
nearest coast (Seo, 2010b, 2015b).

The chosen identification variables were effective in explaining the
choice of agricultural systems in the past studies. That is, a farmer is more
likely to choose a livestock-only system in a flat terrain than the other
systems. Also, a farmer is more likely to choose a crops-only system if the
farm is located near the coast due to export considerations, for example,
refrigeration costs of livestock products (Seo, 2010b, 2011b). The identification variables turned out insignificant in explaining the land values of these systems of agriculture with other explanatory variables controlled.

From the choice probabilities estimated in Eq. (2.6) and the conditional long-term profit equations estimated in Eq. (2.26), a researcher can estimate the expected profit from natural resource enterprises at the microlevel. This is done by multiplying the probability of each enterprise to be adopted to the conditional profit of that enterprise, repeating the procedure for all the enterprises in the model, and summing these products across all the natural resource enterprises in the model. Formally, let $C$ be the vector of climate variables and $\Pi$ be expected long-term profit. Then, the expected long-term profit for farm $n$ is written as follows:

$$\Pi_n(C) = \sum_{j=1}^{J} P_{nj}(C) \cdot \pi_{nj}(C).$$  \hspace{1cm} (2.30)

Note that the $\Pi$ is not observed by a researcher, nor by a manager. It is the welfare measure pertinent to each microagent. It is the expected profit given the full array of enterprises available as an option to each agent. It is the weighted sum of all enterprise unbiased profits using the estimated probabilities of adopting enterprises.

The change in this welfare measure, $\Delta \Pi$, resulting from a change in the climate vector from $C_0$ to $C_1$ can be measured as the difference in the expected profit before and after the change:

$$\Delta \Pi_n = \Pi_n(C_1) - \Pi_n(C_0).$$  \hspace{1cm} (2.31)

The change in the welfare measure in Eq. (2.31) captures both the changes in adoption probabilities of natural resource enterprises and the changes in the conditional profit equations of all the enterprises (Seo, 2013b, 2014c). That is, the microbehavioral models can capture both changes in systems or enterprises as well as changes in economic activities within each of the systems. This can be clarified by rewriting Eq. (2.31) using individual components:

$$\Delta \Pi_n = \sum_{j=1}^{J} P_{nj}(C_1) \cdot \pi_{nj}(C_1) - \sum_{j=1}^{J} P_{nj}(C_0) \cdot \pi_{nj}(C_0).$$  \hspace{1cm} (2.32)

Note that all the components in the above welfare equation, if climate is shifted, contribute to the change in the total welfare. In the flow diagram
in Eq. 2.33, a change in climate leads to simultaneous changes in the choice probabilities, changes in the conditional profits, and the cross-products of the two terms (denoted as * below). All these changes lead to the change in the welfare of the microagent:

\[
\Delta C \rightarrow \begin{bmatrix}
\Delta P_{n1} & \Delta P_{n2} & \ldots & \Delta P_{nj} \\
\Delta \pi_{n1} & \ast & \ast & \ast \\
\Delta \pi_{n2} & \ast & \ast & \ast \\
\vdots & \vdots & \vdots & \vdots \\
\Delta \pi_{nj} & \ast & \ast & \ast 
\end{bmatrix} \rightarrow \Delta \Pi_n. \quad (2.33)
\]

A microbehavioral model can be contrasted with a so-called “black box” model in which these changes are all implicitly included. Let \( \vartheta_n \) be land value observed at the microagent level, that is, farm \( n \). The value of this captures the highest income that can be earned over time at the farm given climate and soil conditions. A researcher can estimate the land value function using climate (\( C_n \)) and other exogenous factors (\( M_n \)) as explanatory variables as follows:

\[
\vartheta_n = \theta \left( \frac{C_n}{w_n}, \frac{M_n}{w_n} \right) + O_n. \quad (2.34)
\]

All the variables are weighted by \( w_n \). This equation is known as the Ricardian model (Mendelsohn et al., 1994; Deschenes and Greenstone, 2007). A full explanation and analysis of the Ricardian model will be given in Chapter 5, which is one of the primary subjects of this book. The Ricardian model itself or the conceptual basis of the model has been applied widely across the world from the United States to India, Canada, Sri Lanka, Africa, Brazil, South America, China, and Mexico (Mendelsohn et al., 1994; Kumar and Parikh, 2001; Reinsborough, 2003; Seo et al., 2005; Schenkler et al., 2005; Kelly et al., 2005; Kurukulasuriya et al., 2006; Seo and Mendelsohn, 2008b; Sanghi and Mendelsohn, 2008; Wang et al., 2009; Mendelsohn et al., 2010). The Ricardian model is also applied to the panel data of US agriculture with time-varying random effects (Massetti and Mendelsohn, 2011).

The strength of the Ricardian model arises from its conceptual foundation which allows for all adaptive changes to be captured in the model.
The model was developed more than two decades ago in response to agro-economic crop models which did not allow for a large number of adaptive measures that farmers routinely take to cope with natural changes (Adams et al., 1990; Rosenzweig and Parry, 1994; Parry et al., 2004; Butt et al., 2005). However, the Ricardian model does not reveal any of the adaptation changes embedded in the model. They are implicit in the model (Seo and Mendelsohn, 2008a).

The microbehavioral model introduced in this book makes adaptation strategies taken by the natural resource managers which are implicitly included in the Ricardian model explicit. To be more concrete, an operation of Eq. (2.6) reveals changes in individuals’ adoptions of enterprises as a climate condition is altered. This is achieved while not compromising the capability of the model to encompass a full array of adaptation behaviors in the model. That is, an operation of Eq. (2.26) will capture the full range of adaptation strategies in the corresponding natural resource enterprise.

Given this background on the Ricardian model, Eqs. (2.6, 2.26, and 2.31) can be understood to be tools that unlock the Ricardian black box which contains the full range of adaptation activities. In the above-presented microbehavioral model framework, some adaptation strategies are explicitly modeled while other adaptation strategies are implicitly included. The changes in choices of natural resource enterprises are modeled as an explicit adaptation strategy in the model described in this chapter.

What are the implicit adaptation strategies in the microbehavioral model of this chapter? All other adaptation strategies besides the choices of enterprises are implicit. For example, individuals’ choices of crops or crop varieties are included implicitly (Seo and Mendelsohn, 2008c). A farmer can switch animals, for example, from cattle to goats and sheep in a hotter temperature regime or from cattle and sheep to goats and chickens in a wetter climate regime (Seo and Mendelsohn, 2008a). A farmer can adopt an irrigation system as an existing climate regime becomes drier or hotter or more variable (Seo, 2011a). A farmer more likely chooses a mixed portfolio of crops and livestock in order to cope with a hotter or drier climate (Seo, 2010a, 2010b). Similarly, a farmer may change many of cropping and animal husbandry practices including crop rotations, fertilization, chemical uses, farming machines, intercropping, sprinkling, shades, barns, and feedlots in order to cope with numerous climate-related risks (Hahn, 1981; Ruttan, 2002; Mader and Davis, 2004; FAO 2009). A farmer can also adopt a new variety of crops or livestock species which are
more heat tolerant or drought resistant (Evenson and Gollin, 2003; Zhang et al., 2013).

That these adaptation strategies are implicitly included in the microbehavioral model presented in this chapter does not mean that one cannot model these adaptation strategies explicitly. As the above referred articles indicate, these strategies can be modeled as an explicit adaptation strategy by developing an apposite model structure. The upshot is that microbehavioral econometric methods are excellent tools that enable environmental and natural resource researchers to examine and quantify the behaviors of individuals observed in the markets and the rural operations. Using these tools, a researcher can model the full range of adaptation strategies explicitly and show quantitatively the impact of each of these adaptation strategies on the microagent’s ability to deal with external changes in the environment and nature.

The Eq. (2.32) can capture the impact of a climatic change on an individual with full adaptation strategies employed by the microagent accounted for. A critique, however, can be leveled that a rural manager may not be able to switch from one enterprise to another in response to a climate change from $C_0$ to $C_1$ for various reasons (Hanemann, 2000). For example, a farmer may be a subsistence farmer who does not have means and finance to adjust from one enterprise to another enterprise which calls for a substantial investment of capital. In the market economy, she/he may be able to loan money to make adaptive changes and pay back at later years. Let’s say that such a financial system is not available, nor is any similar kind of banking systems (World Bank, 2008, 2009b). Then, she/he may end up with the current system unchanged even if the climate is altered.

The microbehavioral econometric models in this chapter have the flexibility to capture such constraints that are faced by decision makers (Seo, 2010b). Let’s call this situation a constrained optimization case. In this constrained optimization case, the impact of a climatic change can be calculated by, for example, fixing choice probabilities:

$$
\Delta \tilde{\Pi} = \sum_{j=1}^{J} P_j (C_0) \cdot \pi_j (C_1) - \sum_{j=1}^{J} P_j (C_0) \cdot \pi_j (C_0).
$$

(2.35)

In the above equation, a decision-maker sticks to the adoption probabilities of the enterprises that are currently existent even if the climate is altered from $C_0$ to $C_1$. That is, she/he does not make any switch to another enterprise although the climate has changed. In the constrained optimization
case, the impact of a climatic change would turn out to be severer than that in the full optimization case captured in Eq. (2.32). Formally,

\[ |\Delta \hat{\Pi}_n| \geq |\Delta \Pi_n|. \quad (2.36) \]

Behavioral and psychological factors that constrain an optimization decision of an individual decision-maker has been an important research field in both economics and psychology since the seminal work by Kahneman and Tversky (1979, 1984) for which the Nobel Prize was awarded in 2002. The seminal papers were directed to the psychological barriers that force an individual to make a seemingly irrational decision. They argued that individuals have a different attitude toward winning and losing in a gamble situation. An individual has a distinct value function and there is a shifting critical value at which attitudes of a decision-maker diverge.

The degree of dominance of psychological factors varies across the range of choices to be made and the situations in which the choices are put into. The psychological factors may not matter much to individuals’ decisions with regard to global warming. The rationale for this is that an individual’s decision is not motivated by a single year outcome in the global warming case. One must consider long-term changes in the climate and the effects of such changes on her/him in the long-term. That is, one should consider not just a single outcome, but more than a decade long outcomes. A rational decision is more likely to be expected in decisions with regards to global warming and climate change.

On the other hand, behavioral and psychological factors have been reported to have a powerful sway in market indices of stocks, commodities, and real estates, causing the great depression in the 1930s as well as the great recession in the 2000s (Galbraith, 1954; Shiller, 2003, 2005, 2014). Behavioral and psychological elements set forth irrational exuberance among market participants, which lead to a bubble for a sustained period of time after which it bursts eventually, leaving painful experiences to a large fraction of individuals in the society of losses, bankruptcies, foreclosures, and debts. A market bubble arises from the interactions among market participants through which a success story spreads rapidly with envy and exaggeration.

In the economics of global warming, irrationality and/or a bubble can play an important role occasionally. For example, a farmer’s high profit from a certain crop, say, garlic, in a certain year may influence the whole village to decide to plant garlic the next year, causing a price drop in a local market
due to excess supply. However, it is not easy to imagine that such behavioral factors strongly sway agricultural market prices of an entire country, given information and extension services available. A fuller description of the theory and applications of the behavioral economics and finance which is beyond the scope of this chapter will be taken up in Chapter 7.

The uncertainty on the estimated welfare change in Eq. (2.32) can be quantified by the size of standard error and the confidence interval constructed using the standard error. Since it is difficult to estimate parametrically the standard error of the estimate in Eq. (2.32) due to numerous terms of probabilities and profits involved in the equation, one should prefer to proceed nonparametrically. That is, one can bootstrap the result by calculating the bootstrap standard error (Efron, 1979, 1981).

The bootstrap method interprets the sample data that is available to a researcher as one representation of the population or the universe. A researcher resamples the original sample to obtain a bootstrap sample and she/he repeats the resampling for a sufficiently large number of times (B) (Andrews and Buchinsky, 2000). The resampling is done randomly or based on alternative assumptions of the distribution of the sample data (McFadden, 1999b). The number of observations in each bootstrap sample can be the same as N, the number of data points in the original sample, or a different number. From each of the B samples, one can obtain the estimate of the impact in Eq. (2.32):

\[ \{ \Delta \Pi^B_1, \Delta \Pi^B_2, ..., \Delta \Pi^B_B \}. \]  

(2.37)

From the impact estimates in Eq. (2.37) obtained from the B bootstrap samples, the researcher can calculate the mean (\( \mu \)) and the standard deviation (\( \sigma \)) of the estimates. Then, the 95% confidence interval of the impact estimate can be provided as follows, with \( P(|x| \geq Z_{0.025}) = 0.05 \):

\[ \left( \mu_{\Delta \Pi}^B - z_{0.025} \cdot \sigma_{\Delta \Pi}^B, \mu_{\Delta \Pi}^B + z_{0.025} \cdot \sigma_{\Delta \Pi}^B \right). \]  

(2.38)

The same bootstrap procedure can be used to calculate the 95% confidence intervals of the probability estimates in Eq. (2.6) and the conditional profit estimates in Eq. (2.26). Formally, the confidence intervals for \( P_i \) and \( \pi_i \) can be constructed as follows:

\[ \left( \mu_{P_i}^B - z_{0.025} \cdot \sigma_{P_i}^B, \mu_{P_i}^B + z_{0.025} \cdot \sigma_{P_i}^B \right) \]  

(2.39)

\[ \left( \mu_{\pi_i}^B - z_{0.025} \cdot \sigma_{\pi_i}^B, \mu_{\pi_i}^B + z_{0.025} \cdot \sigma_{\pi_i}^B \right). \]  

(2.40)
The Eqs. (2.31) and (2.32) make it possible for a researcher to measure the impact of climate change—or other environmental changes—on the welfare of an individual enterprise. A remaining question that needs to be addressed is how to capture a climate system and identify the changes in a climate system (Le Treut et al., 2007). Earlier in this chapter, the present author explained the differences between climate and weather. The author also explained the ways to capture a climate system using climate normals. A climate normal is defined as the 30 year average of temperature or precipitation.

One may argue that this question falls on the realm of science, not economic models (IPCC, 2014; Gordon et al., 2000; Schmidt et al., 2005). The question is one of the key economic questions with regard to global warming and climate changes. Economists have labored painstakingly to identify the most pertinent climate characteristics that determine behavioral decisions of individuals (Mendelsohn et al., 1994; Schenkler et al., 2006; Deschenes and Greenstone, 2012; Welch et al., 2010; Lobell et al., 2011; Seo, 2012c, 2016).

A climate system can be defined in more than one ways. For example, we may define the climate system by characteristics of risk and variability in yearly weather variables. Indeed, climate scientists have increasingly focused on climate risks and extremes, shifting away from the efforts to quantify changes in the average climate, that is, climate normals. Climate scientists have warned the world of the possibilities of increased risks associated with global warming, for example, more frequent extreme weather events, more destructive hurricanes, and disruptions in rainfall patterns in major farming areas, and abrupt climatic shifts (Easterling et al., 2000; IPCC 2001, 2012; Emanuel, 2005; Tebaldi et al., 2007; UNFCCC 2009; Rahmstorf and Coumou, 2011; Hansen et al., 2012; NRC 2013; Titley et al. 2016). Economists are debating about the existence of a climate threshold beyond which a climatic shift turn quickly into a global catastrophe (Weitzman, 2009; Nordhaus, 2011). Changes in climate risk and variability will lead to major changes in yields of plants and crops (Aggarwal and Mall, 2002; Porter and Semenev, 2005). Some argue that agriculture will be severely harmed if climate thresholds for major staple crops were to be crossed (Schlenker and Roberts, 2009).

The microbehavioral econometric methods introduced in this book provide an outstanding scientific framework to model and explain changes in individuals’ behaviors in response to changes in risk factors caused by a climatic shift (Seo, 2012c). In making everyday decisions, an individual takes risk, whether small or large, as a fact of life. Always people are forced to make decisions under uncertainty and in consideration of risks involved.
Naturally, economists have long delved into decision-making under risks when financial returns are concerned (Fisher, 1930; Markowitz, 1952; Tobin, 1958; Fama, 1970; Arrow, 1971; Arrow and Fisher, 1974; Kahneman and Tversky, 1979; Shiller, 2003, 2014). Agricultural economists have studied farm management decisions under various farm risks including weather risks (Udry, 1995; Zilberman, 1998; Kazianga and Udry, 2006; Wright, 2011; Sumner and Zulauf, 2012).

Climate risk is a new type of risk that confronts environmental and natural resource managers now and in the future. A rigorous study of climate risk and strategies to cope with it has begun only recently (Reilly et al., 1996; Easterling et al., 2007; Seo, 2012c, 2014b, 2015c, 2016; Bakkensen and Mendelsohn, 2015; Kala, 2015). Nevertheless, characteristics and alterations of climate risks have received substantial attention from researchers in some communities of the globe. The multidecadal swings in precipitation in the Sahelian region over the past millennium are one of the best known examples of climate risk, which is attributed to changes in the ocean known as the Atlantic Multidecadal Oscillation (Janowiak, 1988; Hulme et al., 2001; Shanahan et al., 2009). Another example is the El Nino Southern Oscillation (ENSO) that alternates multidecadally over the Pacific Rim countries, affecting rainfall patterns, droughts, and wild fires (Ropelewski and Halpert, 1987; Curtis et al., 2001).

Many studies of agricultural development in Africa have focused on understanding the weather risks to farmers in Africa (Udry, 1995; Kazianga and Udry, 2006). It should be emphasized once again that climate risk is not the same phenomenon as weather risk. A rural village, which is visited from time to time by a weather shock such as a severe drought or an intense rainfall can still be said to be a low climate risk zone if the number of weather shocks over many decades turn out to be smaller in the village than in the other villages. A high climate risk village is one in which weather shocks occur more frequently and more surprisingly from a sustained period of time, for example, 30 years.

From this point on, the present author explains three indicators of climate risk that affect agricultural and natural resource enterprises: coefficient of variation in precipitation, diurnal temperature range, and monsoon variability index. The risk in the climate regime that an individual farmer faces takes the form of either temperature risk or precipitation risk or both.

A long-term risk in a rainfall regime can be captured by the degree of dispersion in precipitation amounts over a long time period.
of Variation in Precipitation (CVP) is a measure of precipitation dispersion over a defined period of time that is independent of the absolute amount of measurement. A seasonal CVP is defined as an average of corresponding monthly CVPs, with $PR_{kj}$ being monthly precipitation in month $j$ and year $k$ and $\bar{R}_j$ being a 30 year average rainfall for month $j$:

$$\text{CVP}_j = \frac{\bar{R}_j}{\bar{R}_j}$$

where

$$\bar{\sigma}_j = \sqrt{\frac{\sum_{k=1}^{K} (PR_{kj} - \bar{R}_j)^2}{(K - 1)}}.$$

(2.41)

The seasonal CVPs are measured from the many decades’ data on monthly precipitation normals. A global database of the seasonal CVPs is, for example, constructed from many decades’ weather observations, that is, for the 40 year period from 1961 to 2000, at more than 26,000 ground weather stations scattered all parts of the world (New et al., 2002).

The CVP measure is found to be effective in capturing a climate system in the regions where multidecadal and cyclical fluctuations in precipitation exist due to either changes in ocean circulations or other reasons. The seasonal CVPs in Sub Saharan Africa are found to correlate well with the cyclical multidecadal fluctuations in the Sahelian region which are dominated by the Atlantic Multi-decadal Oscillation (Seo, 2012c). The precipitation fluctuations in South American countries caused by the ENSO cycles are explained well by the seasonal CVPs in the continent (Seo, 2014b).

Table 2.2 summarizes the distribution of annual CVP across the Agro-Ecological Zones (AEZ) of Sub Saharan Africa. There are 16 AEZs in the continent according to the AEZ classification system proposed by the Food and Agriculture Organization (FAO) based on the concept of the Length of Growing Periods for crops which is again defined by soil and climate conditions of a spatial location (Dudal, 1980; FAO, 2005; Seo et al., 2009; Seo, 2014a).

The table reveals that the lowland dry savannah zones and the lowland semiarid zones exhibit the highest CVPs, 198% and 226% respectively. The two zones are located in the Sahelian region which lies just below the Sahara Desert. In the desert zones, the CVP is 144%. On the other hand, humid zones have the lowest CVPs. Highland humid forest zones and mid-elevation humid forest zones exhibit 69% of the CVP (Seo, 2012c).

As reported in the earlier referenced articles, the variation in the CVP across the continent leads to drastically different farming decisions made
by rural natural resource managers. In the high CVP zones of Sub Saharan Africa, farmers more often diversify their portfolios into a varied array of crops and animals than the farmers in the low CVP zones do. The high CVP zones therefore show a higher rate of adoption of the mixed system of agriculture.

Another major climate risk variable is a Diurnal Temperature Range (DTR). Scientists are concerned that global warming will unfold with more frequent extreme temperature occurrences. Extreme temperature events are, inter alia, an extremely hot day, an extremely cold day, and a more volatile temperature (IPCC, 2001, Tebaldi et al., 2007). The increases in the intensities and frequencies of these extreme temperature events lead to an increase in the long-term range between daily maximum temperature and daily minimum temperature, that is, the DTR. The changes in the DTR would affect natural resource managers through the changes in growing periods for crops and changes in the frequency and severity of a heat wave event or a cold spell event (Easterling et al., 2000; FAO, 2005; Schlenker and Roberts, 2009; US EPA 2014).

Table 2.2  CVPs across the AEZs in Sub Saharan Africa

<table>
<thead>
<tr>
<th>AEZs</th>
<th>Number of sampled households</th>
<th>Mean</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert</td>
<td>193</td>
<td>144.8</td>
<td>51.7</td>
</tr>
<tr>
<td>High elevation dry savanna</td>
<td>75</td>
<td>97.5</td>
<td>14.9</td>
</tr>
<tr>
<td>High elevation humid forest</td>
<td>224</td>
<td>69.1</td>
<td>14.1</td>
</tr>
<tr>
<td>High elevation moist savannah</td>
<td>135</td>
<td>90.1</td>
<td>15.1</td>
</tr>
<tr>
<td>High elevation semi-arid</td>
<td>20</td>
<td>99.8</td>
<td>0.001</td>
</tr>
<tr>
<td>High elevation subhumid</td>
<td>153</td>
<td>77.9</td>
<td>16.7</td>
</tr>
<tr>
<td>Lowland dry savannah</td>
<td>1395</td>
<td>198.4</td>
<td>34.5</td>
</tr>
<tr>
<td>Lowland humid forest</td>
<td>1061</td>
<td>71.3</td>
<td>12.5</td>
</tr>
<tr>
<td>Lowland moist savannah</td>
<td>826</td>
<td>148.1</td>
<td>34.0</td>
</tr>
<tr>
<td>Lowland semi-arid</td>
<td>1272</td>
<td>226.2</td>
<td>21.7</td>
</tr>
<tr>
<td>Lowland subhumid</td>
<td>299</td>
<td>84.2</td>
<td>13.9</td>
</tr>
<tr>
<td>Mid-elevation dry savanna</td>
<td>195</td>
<td>145.8</td>
<td>41.8</td>
</tr>
<tr>
<td>Mid-elevation humid forest</td>
<td>291</td>
<td>68.5</td>
<td>13.3</td>
</tr>
<tr>
<td>Mid-elevation moist savannah</td>
<td>1086</td>
<td>185.5</td>
<td>41.3</td>
</tr>
<tr>
<td>Mid-elevation semi-arid</td>
<td>27</td>
<td>156.5</td>
<td>33.1</td>
</tr>
<tr>
<td>Mid-elevation subhumid</td>
<td>381</td>
<td>89.9</td>
<td>29.7</td>
</tr>
</tbody>
</table>
The daily temperature range is measured by the DTR. The DTR data are provided as a monthly average DTR (New et al., 2002). The average monthly DTR in a spatial location for the 40 year period, a DTR normal, can be constructed by averaging the 40 year monthly DTR data. Let $TE_{\text{max}}$ be a daily maximum temperature, $TE_{\text{min}}$ a daily minimum temperature, $j$ an index for day, $m$ for month, and $k$ for year. Then, the DTR normal for month $m$ is defined as follows:

$$DTR_m = \frac{\sum_{k=1}^{K} \sum_{j=1}^{J} (TE_{k,m,j,\text{max}} - TE_{k,m,j,\text{min}})}{J \times K}$$

(2.42)

where $J = \text{number of days per month}, K = 40 \text{ years}$.

The DTR normal captures temperature volatility over a sustained period of time. Table 2.3 summarizes the seasonal DTR normals across the major land covers in South America. The classification of major land covers is based on satellite imageries and an extensive collection of ground-level studies of land uses, which is available at the Goddard Institute for

<table>
<thead>
<tr>
<th>Major land covers</th>
<th>Summer DTR (°C)</th>
<th>Winter DTR (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cold-deciduous forest, with evergreens</td>
<td>13.12</td>
<td>8.6</td>
</tr>
<tr>
<td>Tall/medium/short grassland, &lt; 10% woody cover</td>
<td>7.16</td>
<td>11.48</td>
</tr>
<tr>
<td>Tall/medium/short grassland, shrub cover</td>
<td>12.05</td>
<td>9.92</td>
</tr>
<tr>
<td>Tall/medium/short grassland, 10–40 % woody cover</td>
<td>10.19</td>
<td>14.62</td>
</tr>
<tr>
<td>Meadow, short grassland, no woody cover</td>
<td>10.86</td>
<td>11.09</td>
</tr>
<tr>
<td>Subtropical evergreen rainforest</td>
<td>12.05</td>
<td>11.74</td>
</tr>
<tr>
<td>Tall grassland, no woody cover</td>
<td>13.63</td>
<td>11.19</td>
</tr>
<tr>
<td>Temperate/subpolar evergreen rainforest</td>
<td>12.81</td>
<td>7.99</td>
</tr>
<tr>
<td>Tropical evergreen rainforest</td>
<td>9.67</td>
<td>11.05</td>
</tr>
<tr>
<td>Tropical/subtropical broad forest</td>
<td>9.85</td>
<td>11.38</td>
</tr>
<tr>
<td>Tropical/subtropical drought-deciduous forest</td>
<td>9.41</td>
<td>11.93</td>
</tr>
<tr>
<td>Xeromorphic forest/woodland</td>
<td>12.04</td>
<td>9.92</td>
</tr>
<tr>
<td>Xeromorphic shrubland/dwarf shrubland</td>
<td>13.9</td>
<td>12.01</td>
</tr>
<tr>
<td>Water</td>
<td>8.12</td>
<td>7.58</td>
</tr>
</tbody>
</table>
Space Studies (GISS) at the National Aeronautic and Space Administration (NASA) or other similar space programs (Matthews, 1983).

The DTR is high in the xeromorphic forests, tall grasslands with no woody cover, and cold-deciduous forests. In these land covers, summer DTR exceeds 13°C. The DTR is lowest in the water body such as coastal zones, rivers, and lakes. Winter DTR is highest in the grasslands with 10–40% woody cover and lowest in the temperate evergreen forests (Seo, 2014b).

In Sub Saharan lowlands, temperature volatility expressed as the DTR is highest in the lowland arid zones and the lowland semiarid zones which fall most notably upon the Sahelian region. The volatility of temperature is lower in the humid zones of Sub Sahara and in the lowland humid zones (Seo, 2012c).

A third climate risk indicator is identified from a unique regional climate system known as a monsoon. The monsoon is a regional climate phenomenon which is salient in South Asia including Sri Lanka, India, and Thailand (IPCC, 2014). It is characterized by an exceptionally heavy rainfall during a monsoon season and a scarcity of rainfall during a nonmonsoon season (Meehl and Hu, 2006; Goswami et al., 2006; IITM, 2012). Evidently, a monsoon-driven precipitation pattern dominates agricultural activities in these South Asian countries. That is, almost every crop varieties must be harvested before or early in the monsoon season. Otherwise, all left on the fields will be swept away. Growing crops is virtually impossible in a severe monsoon season.

In Table 2.4, the average monsoon season rainfall and the average non-monsoon season rainfall in each state of India for the 40 year period from 1971 to 2010 are summarized. The 40 year rainfall record indicates that the monsoon season, that is, the heaviest rainfall months of the year, ranges from Jun. to Sep. while the nonmonsoon season falls on Dec., Jan., and Feb. In the Gujarat state, the monsoon season rainfall reaches 2126 mm/month, but the nonmonsoon season rainfall drops precipitously to 22 mm/month. In the state of Karnataka, the monsoon season rainfall is as high as 3356 mm/month but the nonmonsoon season rainfall is as low as 44 mm/month. In Goa, the monsoon rainfall is 5661 mm/month while the nonmonsoon rainfall is 17 mm/month. On the other hand, in the State of Tamil Nadu, the monsoon rainfall is 790 mm/month relative to 430 mm/month for the nonmonsoon season, a much milder transition from one season to another (Seo, 2016).

To identify the risk characteristics of the monsoon climate system, a Monsoon Variability Index (MVI) is created as follows. In the first step,
based on the 40 year period (from 1971 to 2010) monthly weather data compiled by a weather agency, the ratio of a monsoon season rainfall ($PR_i^M$) over a nonmonsoon season rainfall ($PR_i^{NM}$) for each year ($t$) is calculated:

$$\Phi_t = \frac{PR_i^M}{PR_i^{NM}}. \quad (2.43)$$

In the second step, the coefficient of variation in this ratio for the 40 year period which is defined to be the MVI is calculated:

$$\sum = \sigma^M(\Phi_t)/\bar{\Phi}. \quad (2.44)$$

Table 2.4 Indian monsoon and nonmonsoon season rainfall by State

<table>
<thead>
<tr>
<th>State and union territories</th>
<th>Average monsoon precipitation (mm/month)</th>
<th>Average nonmonsoon precipitation (mm/month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Andhra Pradesh</td>
<td>1393</td>
<td>113</td>
</tr>
<tr>
<td>Assam</td>
<td>3610</td>
<td>204</td>
</tr>
<tr>
<td>Bihar</td>
<td>2550</td>
<td>116</td>
</tr>
<tr>
<td>Chhattisgarh</td>
<td>2699</td>
<td>99</td>
</tr>
<tr>
<td>Goa</td>
<td>5661</td>
<td>17</td>
</tr>
<tr>
<td>Gujarat</td>
<td>2126</td>
<td>22</td>
</tr>
<tr>
<td>Haryana</td>
<td>1192</td>
<td>143</td>
</tr>
<tr>
<td>Jharkhand</td>
<td>2732</td>
<td>151</td>
</tr>
<tr>
<td>Karnataka</td>
<td>3356</td>
<td>44</td>
</tr>
<tr>
<td>Kerala</td>
<td>4616</td>
<td>195</td>
</tr>
<tr>
<td>Madhya Pradesh</td>
<td>4706</td>
<td>234</td>
</tr>
<tr>
<td>Maharashtra</td>
<td>1810</td>
<td>67</td>
</tr>
<tr>
<td>Manipur</td>
<td>3097</td>
<td>177</td>
</tr>
<tr>
<td>Meghalaya</td>
<td>3610</td>
<td>204</td>
</tr>
<tr>
<td>Mizoram</td>
<td>3097</td>
<td>177</td>
</tr>
<tr>
<td>Nagaland</td>
<td>3097</td>
<td>177</td>
</tr>
<tr>
<td>Odisha</td>
<td>2855</td>
<td>114</td>
</tr>
<tr>
<td>Punjab</td>
<td>1340</td>
<td>222</td>
</tr>
<tr>
<td>Rajasthan</td>
<td>1078</td>
<td>44</td>
</tr>
<tr>
<td>Tamil Nadu</td>
<td>782</td>
<td>435</td>
</tr>
<tr>
<td>Tripura</td>
<td>3097</td>
<td>177</td>
</tr>
<tr>
<td>Uttar Pradesh</td>
<td>2042</td>
<td>129</td>
</tr>
<tr>
<td>West Bengal</td>
<td>3008</td>
<td>161</td>
</tr>
<tr>
<td>Dadra and Nagar</td>
<td>2126</td>
<td>22</td>
</tr>
<tr>
<td>Daman and Diu</td>
<td>2126</td>
<td>22</td>
</tr>
</tbody>
</table>
The MVI ($\sum$) is a measure of variability in the ratio $\Phi$, independent of the long-term average where $\sigma^w$ is the standard deviation in the 40 year rainfall data of the ratio in Eq. (2.43). The MV Index is not a risk measure for a single year. It is a measure of variability (risk) for a 40 year time period, a climate risk normal.

The MVI is a key indicator which encapsulates a monsoon climate risk and has the power to explain South Asian farmers’ decisions in response to the monsoon climate system. This point can be elucidated by Fig. 2.2, which plots the numbers of goats per farm across Indian States against the MVI values defined in Eq. (2.44). Overlaid to the two-dimensional plot is the log-linear relationship between the two measures. The estimated relationship shows that South Asian farmers increase the number of goats owned as the MVI increases. This behavioral response is of course an endeavor by the farmers to deal with an increase in climate risk.

The three indicators—CVP, DTR, and MVI—introduced in this chapter capture a riskiness in the climate system as well as uncertainty in the system. As the value of one of these indicators increases, a climate-related uncertainty becomes amplified. Changes in choices and resultant long-term profits from the decisions made in the face of the changes in these risk indicators would capture adaptation strategies adopted by the individual farmers in order to reduce the harmful effects and take advantage of beneficial effects.

Figure 2.2 Distribution of goats owned over monsoon variability index.
In applying the microbehavioral econometric methods to the environmental and natural resource problems, identification of an indicator(s) of the external factor of concern is a crucial statistical procedure. The identification problem has long been regarded as one of the pillar areas of biological, environmental, and ecological statistics. Notwithstanding, this literature has in general made microbehavioral implications from proposed and conventional indicators a secondary consideration (Gregoire and Valentine, 2004). The three indicators of climate risk are, by contrast, developed in order to reveal microbehavioral decisions and consequences that are induced by external changes.

There is a greater understanding among concerned researchers that the microbehavioral econometric methods elaborated thus far depend critically on the reliability and accuracy of available climate and climate risk data. However, it has turned out to be a no minor scientific task (Le Treut et al., 2007). Climate scientists have measured climate variables through observed data from either ground weather stations dispersed around the world or Earth-orbiting satellites (Basist et al., 1998; New et al., 2002). A high resolution data on climate, soils, and geography can play a prominent role in capturing numerous microbehaviors taken by individuals (Adams et al., 2003; Mendelsohn et al., 2007; Fisher et al., 2012; Seo, 2013a).

This completes the presentation of the microbehavioral econometric methods from the perspectives of economic motives and behavioral decisions. In the next chapter, we will continue our journey with an alternative presentation of the microbehavioral econometric methods from the perspectives of the mathematical and statistical considerations and sophistications that go into the microbehavioral models applied to a large variety of unique problems.

**Exercises**

1. Referring to the microbehavioral econometric model framework presented in this chapter, explain that nonmarket benefits and costs of economic decisions can be accommodated handily in this framework. Explain what nonmarket benefits and costs are pertinent to agricultural and natural resource managers.

2. Referring to the Heckman selection bias correction term for a binomial choice situation, prove that the parameter estimates of the model are attenuated by correcting the selection bias. In other words, show that, using a simple model of selectivity, the OLS estimates overestimate the treatment effect. Explain the implications of this attenuation in terms of the magnitude of the impact of a change in climate on the outcome (profit) variable.
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