AN ABSTRACT OF THE DISSERTATION OF

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Transforming to a sustainable agricultural production system requires optimizing both socio-economic and environmental outcomes and tracking their interactions. In the assessment of agricultural production systems, analysis should consider both a bottom-up linkage (from the farm to market) and a top-down linkage (from market to farm) to reflect interactions across scales. However, farm-level *ex-ante* economic impact assessment either does not account for market-level aggregate responses which can overestimate the economic potential of new technology,, or requires a large amount of detailed data and complex structures to reflect cross-scale interactions. In order to support evidence-based policy decision making, there is a clear need for a quantitative method that can provide timely accurate predictions by considering price endogeneity while keeping biophysical and socio-economic heterogeneity.

This dissertation provides an integrated farm-level *ex-ante* impact assessment model to examine direct supply responses and price feedback effects (i.e. impacts of indirect supply responses) of new technology through estimating population-level

adoption rates. The model explicitly shows how market equilibrium changes in response to collective adoptions, as well as how these changes in equilibrium determine the effects of new technology on economic and environmental outcomes.

Chapter 2 reviews the two strands of economic literature, *ex-ante* farm impact assessments and market equilibrium models, to identify important research gaps and highlight methodological challenges. Scale differences between farm and market create difficulties in analyzing indirect supply responses by using computationally feasible models with available data. Therefore, a theoretical framework integrates farm profit maximization with partial market equilibria by formulating adoption rates as a function of output prices. Next, this dissertation presents an empirical method that incorporates the price-endogenous adoption rate and its impacts on economic and environmental outcomes.

The methodology presented in this dissertation applies to both price and policy simulation setting. The first empirical application examines the impacts of supply responses to a new biofuel crop, *Camelina sativa*, in a wheat production system in the Pacific Northwest of the United States. Results indicate that high relative profitability of the alternative farming system is essential to boost adoption rates. Price scenario simulation demonstrates that the indirect supply responses affect farms' adoption decisions. This in turn reduces the potential improvements in environmental quality and income equality from the new biofuel crop. The second application investigates how output market changes, due to the introduction of new direct payment programs affect the economic feasibility of an alternative grain crop, soybean, in the rice industry in South Korea. The analysis shows that the adoption rate is likely to vary with policy scenarios, but aggregate responses play an important role in evaluating the impacts of the policy interventions.

Findings of this dissertation have implications for forward-looking assessments that provide information for decisions on policy-making and project feasibility. In order to achieve economically profitable and environmentally sustainable agricultural systems, multi-scale and multi-dimensional consideration can play an important role in predicting more accurate synergies or trade-offs of farm level agricultural activities and policy interventions. The magnitude of indirect supply responses are largely determined by the relative prices of competing crops and relevant economic parameters. These findings also demonstrate the importance of addressing potential price endogeneity in policy analysis, especially where a regional or population scale policy is likely to change market supply or demand by aggregate responses.

Price-Endogenous Farm Technology Adoption and Ex-Ante Economic Impact Assessment

by
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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Seojin Cho, Author

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Chapter 1 Introduction

The demand for sustainable agricultural systems has been increasing due to rising global average temperature, degrading environment, and depleting natural resources (United Nations, 2015). The need for sustainable agricultural systems has been a driving force to develop tools for a better understanding of synergies or trade-offs between agronomic, environmental, and socioeconomic outcomes of agricultural production. (Fleming & Adams, 1997; E. Hochman & Zilberman, 1978; Just & Antle, 1990; Sala et al., 2015; Thornton & Herrero, 2001; van Ittersum et al., 2008).

The progress of assessment tools has been accompanied by an increasing emphasis on quantitative *ex-ante* analysis of sustainable farming systems to improve the efficiency of policy design and implementation. In the literature, the term ‘farming system’ tends to encompass technology adoption to refer to the interactions of the biophysical environment and economic behavior associated with overall farm activities (Antle et al., 2017). The difficulty in tracking interactions mentioned above is in the evaluation of farm-level decisions that will affect or be affected by more aggregate level changes (Kanter et al., 2018). For example, changes in technology (i.e. output or input use) can influence both demand and supply of agricultural commodities and consequent changes in prices will affect income and decision making.

Several previous studies thus far have linked across scales to provide accurate estimates of impacts of interest and its interactions between society, economy, and environment (Polasky et al., 2008; Rosenzweig et al., 2016; Valdivia et al., 2012).

However, difficulties arise when an attempt is made to implement policy analysis because previous methods do not meet the limited timeline and data conditions frequently encountered in policy analysis. High-resolution biophysical and economic data are rarely available to support policy decision making in a timely manner (Antle & Valdivia, 2006). Furthermore, the previous research models require a large amount of detailed data and complex structure to reflect interactions (Berger, 2001; X. Chen & Önal, 2012; Mérel & Bucaram, 2010). Therefore, a major challenge in modeling is how to capture essential interactions while building models that are computationally feasible to implement with available data.

The main objective of this dissertation is to provide a quantitative method, TOA-MDE (Trade-Off Analysis Multi-Dimensional Equilibrium impact assessment), that establishes a linkage between farm-level optimization and market-level changes using parsimonious model structures and readily available data. This methodology can provide timely, sufficiently accurate economic analysis that measures the price-endogenous adoption rates in a farm-level *ex-ante* impact assessment.

The TOA-MDE model identifies how farm optimization interacts with market changes through population-level adoption rates. Adoption decisions at farm-level are made by their profit maximization given market and policy conditions. However, adoption decisions can be affected by aggregate responses by collective adoptions which can cause changes in supply. These feedback effects through market changes are defined as indirect supply responses in this dissertation. The adoption rates are represented as a function of market prices to reflect indirect supply responses. This specification allows this study to iteratively solve structural models consisting of three different levels: farm profit maximization, population adoption rates, and multi-output market equilibria.

This model integration makes a noteworthy contribution to an *ex-ante* policy analysis literature by filling the research gaps such as inconsistency of modeling assumptions. The assumption of farm-level *ex-ante* impact assessment takes price as given, so adoption mechanisms neglect the indirect supply responses (Claessens et al., 2008; Robinson et al., 2014). In contrast, aggregated models take adoption as exogenous, thus failing to capture farm heterogeneity (Auffhammer & Schlenker, 2014; Robinson et al., 2016). More importantly, these assumptions, at each scale, are inconsistent with the assumption in technology adoption literature that farm profit maximization reflects a reduction in output price by supply responses (Foster & Rosenzweig, 2010). As such, a methodology that this dissertation suggests contributes to forward-looking assessments by providing a multi-scale approach that reflects cross-scale interactions while keeping heterogeneity of farms.

The dissertation is organized as follows. Chapter 2 reviews two strands of economic literature and describes a theoretical model and an empirical method. The first part of the review revolves around the economic impact assessment of technological improvements in agriculture and how these assessments evaluate multi-dimensional interactions. The second part of the literature review focuses on market equilibrium models that analyze the impacts of interest through the operation of output and input markets. Following this literature review, this chapter discusses how this dissertation contributes to a more comprehensive understanding toward sustainable agricultural systems by considering impacts of indirect supply responses on farms' adoption decisions.

In the second half of chapter 2, I describe the theoretical framework and empirical method of an integrated adoption decision with farm profit maximization and a partial market equilibrium. First, I present a three-level theoretical model that consists of three-level specifications by output prices: farm profit maximization, population adoption rates, and market equilibria. With the possibility of indirect supply responses, this model shows the impacts of price changes by output expansion on farm adoption decisions. Second, I show empirical integration of *ex-ante* technology impact assessment models, TOA-MD (trade-off analysis multidimensional impact assessment), and a partial market equilibrium model and illustrate model specification and parameterization.

Next, the prior model and method are used in two applications to examine the impact of supply responses of adopting sustainable farming systems on farm population adoption rates. The third chapter of my dissertation outlines how price changes affect indirect supply responses and quantify those impacts using data from a wheat production system in the Pacific Northwest of the United States. I estimate the price-endogenous adoption rates of a new biofuel crop, *Camelina sativa* under the various price combinations. Simulation results demonstrate that a falling price by output expansion can shrink the adoption rates and also potential improvements of environmental quality from the new farming system.

Chapter 4 presents another application of TOA-MDE to evaluate indirect supply responses to new policy interventions. The methodology is applied to the context of the rice industry in South Korea where agricultural policies intensify a structural rice oversupply problem. I evaluate the economic viability of another grain crop, soybean, with a new direct payment program to increase domestic grain production and reduce unwanted oversupply of rice. Results reveal that the changes in supply by the new direct payment program is not enough to address rice oversupply issue, but new policy could improve income equality between large and small farms. However, price changes by increased soybean production decrease the predicted income increase of small farms by crop diversification.

The final chapter summarizes findings and discusses the methodological and empirical implications of the method that this dissertation suggests. This dissertation extends the trade-off analysis of economic impact assessment by filling the gaps where adoption-driven market changes affect farm adoption decisions. For more accurate *ex-ante* assessment, the analysis of agricultural production systems aimed at win-win outcomes must consider the price feedback effects and its impacts on economic and environmental outcomes.

Chapter 2 Methodology

2.1 Introduction

This chapter reviews and discusses the economic literature and introduces the theoretical framework and empirical methodology of this dissertation. This chapter begins with the summary of extensive literature on the economic impact assessment of farm technology and market equilibrium models and discussing the need for multi-scale approaches to navigate various interactions of economic and environmental outcomes of farm technology adoption.

Next, the general methodology of this dissertation is presented for evaluating economic feasibility of new technology that accounts for indirect supply responses in agriculture. A structural model that consists of farm, population, and market reflects the impacts of collective adoptions on market equilibrium and farm adoption decisions. In this theoretical step, the farm profit maximization, population adoption rates and market equilibria are represented as a function of output price. This specification enables this model to transmit collective adoptions to changes in market equilibrium and farm adoption decisions.

Finally, an empirical method is described to estimate adoption rates of new technology and its impacts on market and adoption decisions. In particular, the design of a simulation experiment shows how a farm level impact assessment model incorporates a partial market equilibrium model with model specification and parameterization. This simulation design gives flexibility for evaluation of indirect supply responses under different price and policy scenarios.

2.2 Review of Modeling

Growing interest in sustainable agriculture systems has been a driving force to develop tools for evaluating the impact of economic and environmental factors and their interactions between farm management decisions and agricultural commodity markets. Public policy objectives, such as Sustainable Development Goals and limiting global warming to less than 2°C, have strengthened the relevance and the importance of multi-scale and multi-dimensional assessment (Antle & Stöckle, 2017).

Economic impact assessment (EIA) models have been used to evaluate impacts of major changes by technology, climate, and policy on economic, social and environmental outcomes (Dey et al., 2010; Thornton & Herrero, 2001). However, past farm-level studies required a large amount of detailed data and complex structures to combine models at market-level to make prices endogenous (Auffhammer & Schlenker, 2014; Jones et al., 2017). Thus, a conceptual and analytical challenge of farm-level *ex-ante* EIA approach is to fully reflect adaptive feedbacks of farmers' decision making with less data and simpler structures.

Market equilibrium (ME) models are used to analyze the impacts of major changes on agricultural commodities and inputs markets and differentiate their welfare impacts between consumers and producers. Since ME models require an aggregation based on the behavior assumptions of "representative agent", models above the regional or national level lose site-specific and farm heterogeneity in data. Thus, ME models cannot represent disaggregate factors, such as soils or climate and their interactions with agricultural production systems.

Clearly, there is a trade-off in modeling between keeping heterogeneity and aggregating information. However, transforming to a sustainable agricultural system requires optimizing agronomic, environmental and socio-economic outcomes which create the potential for trade-offs and synergies. Thus, a multi-scale approach is necessary to better understand and navigate the myriad interactions between multiple outcomes while keeping heterogeneity. Below is a review of modeling using EIA approaches and ME models to then discuss why establishing a linkage of ME models with farm-level EIA approaches is essential.

2.2.1 Economic Impact Assessment (EIA)

Economic impact assessment (EIA) modeling is a quantitative method to evaluate the efficiency of agricultural investment as well as its economic and environmental consequences. This assessment tool provides essential information for estimating how agricultural systems have performed in the past (*ex-post*) and will perform under plausible future conditions (*ex-ante*) (Jones et al., 2017). Likewise, there are a variety of approaches that can be used in economic impact assessment. But no single approach can be a comprehensive tool, because the impact assessment is performed for a policy or project in the specific regional, economic or societal context under data and budgetary constraints (Gasparatos & Scolobig, 2012). Here, I briefly review three assessment approaches that have been applied in agricultural, environmental, and energy economics: benefit-cost analysis, integrated assessment modeling, and indicator-based approach.

Benefit-cost analysis has been widely used in prioritizing policy alternatives by choosing one with the highest value of net benefits. In principle, it is possible to measure and evaluate the relevant market outcomes (e.g. the value of production) and non-market outcomes (e.g. the value of social, environmental benefit and costs) in a monetary unit. But it is challenging to quantify non-market outcomes in monetary value and aggregate benefits and costs with adequate scientific data. Another problem of benefit-cost analysis is that the evaluation of market and non-market outcomes does not provide distributional impacts of each policy option.

Furthermore, benefit-cost analysis is not sufficient to represent the interdependency of agricultural supply responses and its biophysical feedback. Therefore, trade-off analysis was developed as a more inclusive approach to evaluate potential outcomes including interactions among factors from multiple dimensions (Kanter et al., 2018). The modeling approach of trade-off analysis can be divided into two categories based on what research emphasizes; 1) representing environmental and economic processes (Integrated assessment model) or 2) comparing information from a greater number of dimensions (Indicator-based approach).

First, integrated assessment models portray agricultural processes by the formal linkage of economic models and biophysical models. This integration allows models to simulate the farmers' decision making by incorporating the economic behavior with bio-physical and environmental factors. Therefore, the research process can be extended to a combination of crop production, livestock management, and even landscape, national level of those models to represent whole agricultural production systems (Jones et al., 2017).

Several integrated assessment models have been developed along with economic simulation models. van Wijk et al. (2014) reviewed a range of different approaches that simulated the farmers' responses to the environmental processes: Positive Mathematical Programming (PMP) model calibrates the supply response of farmers by crop-specific elasticities of supply (Mérel & Bucaram, 2010) by incorporating cropping patterns under expected crop prices (X. Chen & Önal, 2012); Agent-based model calibrates the structure of aggregate supply response with interactive human behaviors and biophysical, environmental processes (Berger, 2001).

Second, indicator-based approaches represent multi-dimensional measurements into a single unit as an indicator. In tradeoff analysis, economic, environmental and social outcomes can be quantified as an indicator that is used to assess trade-offs or synergies (Capalbo et al., 2017). Kanter et al. 2018 summarized the five types of indicators that have been used to analyze sustainable agricultural systems: agriculture, environment, biodiversity, human well-being, and food security. Once the value of these indicators is estimated, trade-offs are evaluated by comparing indicators under different scenarios. This chapter has described the EIA approach and the chapter that follows moves on to Market Equilibrium model.

2.2.2 Market Equilibrium (ME) Model

Unlike the impact assessment model which characterizes the farm- and site-specific heterogeneity to represent economic behavior, the market equilibrium (ME) model solves a market equilibrium to evaluate welfare implications of exogenous changes. That is, markets are cleared, implying prices are endogenous in the model. In the market equilibrium model, exogenous changes are transmitted through the changes in prices to the market participants.

In economic theory, there are two types of market models: Partial Equilibrium (PE) models and General Equilibrium (GE) models. These two models differ from their scope, in how they represent supply and demand in markets. PE models focus on a particular sector or are extended to at most multiple output and input markets, while other sectors are assumed to be exogenous. Robinson et al. (2014) divided PE model into two groups depending on how they treat the supply-side specification. The first group of models, which is called shallow structural models, specifies input demand and output supply only with prices. This type of PE model does not include details about economic behavior or technology in optimization. The second group of models is a deep structural model which explicitly optimizes maximizing behavior with technology constraints. Likewise, PE models focus more on the specification of the agriculture sector to investigate the operation of commodity markets, not economic-wide feedback across sectors.

In contrast to PE models, the GE models represent the whole economy, emphasizing the interactions between sectors or populations. Most GE models are implemented as computable general equilibrium (CGE) models: for example, GTAP (Global, Trade Analysis Project[1]), DART (Dynamic Applied Regional Trade[2]), and

[1] https://www.gtap.agecon.purdue.edu/models/current.asp accessed 03/17/2020
[2] https://www.ifw-kiel.de/institute/research-centers/the-environment-and-natural-resources/articles/dynamic-applied-regional-trade-model-dart/ accessed 03/17/2020

LEWIE (Local Economy-wide Impact Evaluation[3]). Some general equilibrium models at the national or global level allow crop productivity to be endogenously determined by prices. These models are more suitable for scrutinizing paths of exogenous impacts across sectors where shocks on the output market affect farmers' input choice and its feedback leads to change in the output market.

The issue about choosing between PE and GE models is essentially an empirical question (Robinson et al., 2014). This decision largely depends on whether the ignoring feedback effects, between sectors or supply chains from economic activities, will lead to inaccurate results or not. For example, if a researcher wants to capture direct and indirect market interactions or estimate income effects throughout the economy, the analysis will benefit from the GE model framework. On the other hand, if a researcher focuses on the detailed specification of agricultural technology (e.g. linking land and yields to agronomy analysis), rather than economic-wide scenario analysis, PE models will provide a better structure. A summary of the main characteristics of each approach and the need for linkage of two approaches are provided in the next chapter.

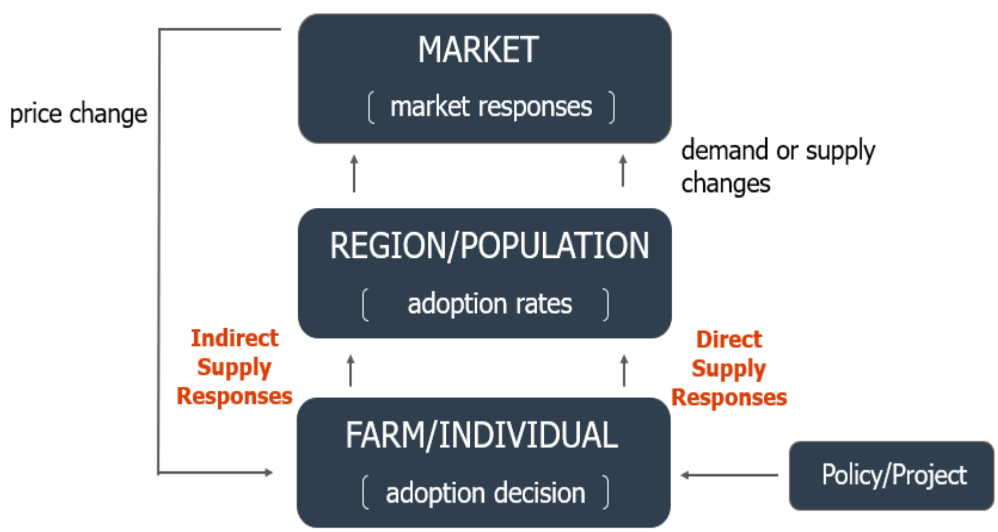
2.2.3 Linking *Ex-Ante* Economic Impact Assessment of Farm Technology Adoption with a Market Equilibrium Model

As mentioned above, in ex-ante policy analysis, a key focus of the economic impact assessment is to predict the supply responses regarding farmer's decisions. However, at aggregate level, supply responses mean that multiple individual decisions could affect or be affected by agricultural commodity and input markets (Just &

[3] https://globalmigration.ucdavis.edu/research/economy-wide-impact-evaluation accessed 03/17/2020

Huffman, 1992). Figure 2.1 shows these two directions of responses if there is an exogenous shock (i.e. government intervention, international policy change). Agricultural policies and government interventions can directly affect the farmers' adoption decisions (i.e. direct supply response). At the same time, a falling output price, caused by an increase in supply, will reduce farmers' incentives to adopt a new farming system (i.e. indirect supply response). The rest of this section reviews how EIA and ME models treat supply responses and then discusses the need of integrating two model approaches.

Figure 2.1 The Illustration of Farm Supply Responses in Technology Adoption



ME models have assessed at least local or regional level of welfare change through the impact on output and input markets, thus prices are endogenous. But these models are highly aggregated or, at least, need local or regional level of aggregation. This implies it is hard to link directly to biophysical processes that depend on site-specific, disaggregate data. Aggregated data cannot represent farm-level heterogeneity that may affect adoption; therefore, adoption becomes exogenous in national or global level production estimation (Auffhammer & Schlenker, 2014; Robinson et al., 2014).

Conversely, farm-level ex-ante impact assessment can precisely navigate interactions among economic, social, and environmental factors at a disaggregate level, requires detailed data and complex model structures. In ex-ante analysis, highly detailed biophysical and economic data are not available for new technologies and prices are treated as given. This type of adoption analysis neglects indirect supply responses in the model. For example, productivity growth by technology adoption is exogenous and shifts the yield or supply function (Robinson et al., 2014). But this assumption is inconsistent with literature in technology adoption assuming that adopting new technology is determined by farm profits and other factors influencing adoption behavior. Since the output expansion from increasing productivity lowers the output price in the market and may also affect input prices, impacts of technology adoption are not fully exogenous.

Likewise, ignoring indirect supply responses may lead to inaccurate prediction of adoption because of falling output price by aggregate supply responses. However, an implementation of analysis of fully adaptive responses with less data and model structures is methodologically challenging because of spatial scale differences between farm/household level and aggregate level. Thus, a main challenge in modeling is how to accurately predict population-level adoption while maintaining models feasible to implement with available data.

It is acknowledged that the technology diffusion process is influenced by various factors. Analyses including adaptive feedback are well documented in literature associated with production uncertainty, network effects, or behavior economics (Just and

Pope 1979; Berger 2001; Streletskaya et al. 2020). However, it is costly and time-consuming in simulating how the adoption process happens with detailed data at the policy-making stage. For the purpose of informing timely policy decision making, It is more adequate to suggest a method that estimates the upper bound of economic feasibility along with a market change with available data.

2.3 Theoretical Framework

The goal of this section is to develop a conceptual framework to link a microeconomic model that formulate the adoption rate of heterogeneous farm population from farm profit maximization to a partial market equilibrium model. In this model, the market equilibrium adoption rates will be represented by endogenous output prices associated with alternative farming systems impacting output markets. It is assumed that farmers are risk-neutral and maximize expected profit.

2.3.1 Farm Profit Maximization

This model considers farmer's choice between two farming systems $h = 1,2$ denoted as systems 1 and 2 in a given geographic region. The system 1 refers to the current farming system and the system 2 is an alternative farming system which incorporates new technology into the farming system 1. In the empirical implementation of the model the system 2 can introduce a new crop, input, or farm management practice.

The production function of crop $i = 1, \dots, I$ at site $j = 1, \dots, J$ for system h is $q_{ij} = f_i(\mathbf{v}_{ij}, \mathbf{e}_j; h)$ where $\mathbf{v}_{ij}$ the vector of variable inputs and $\mathbf{e}_j$ is a vector of biophysical characteristics of the site. The corresponding profit function is $\pi_{ij} =$

$\pi_i(p_{ij}, \mathbf{w}_{ij}, \mathbf{e}_j; h)$ with expected output price, p_{ij}, and input price vector, $\mathbf{w}_{ij}$. Define the indicator function δ_{ij} such that $\delta_{ij} = 1$ if the ith crop is grown at location jth and zero otherwise. The land-use decision on site j is represented by

$$\max_{(\delta_{ij,} \cdots, \delta_{Ij})} \sum_{i=1}^{I} \delta_{ij} \pi_i(p_{ij}, \boldsymbol{w}_{ij}, \mathbf{e}_j; h)$$

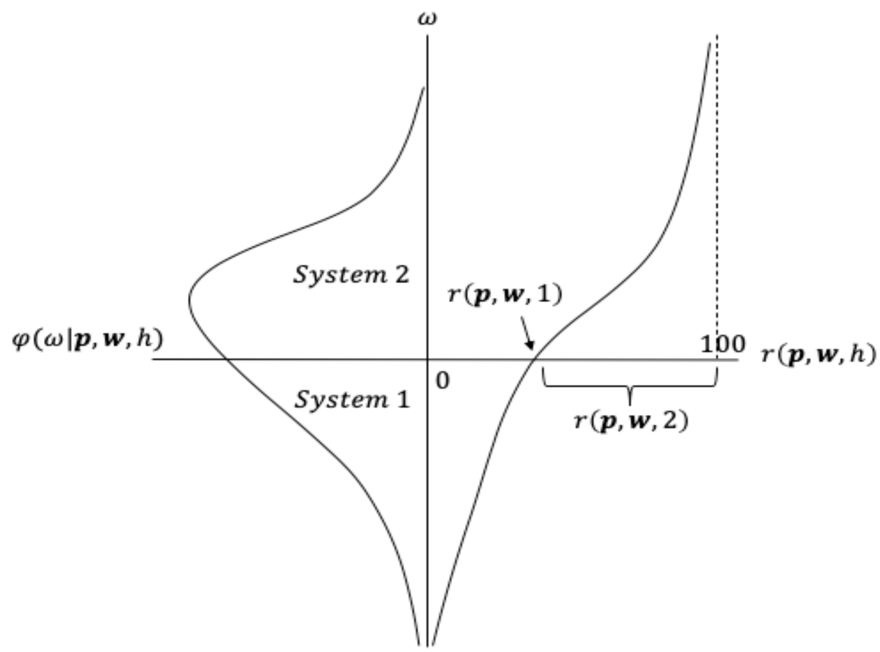
The solution of land-use decision takes the form of a discrete step function, $\delta_{ij}^* = \delta_i(p_{ij}, \boldsymbol{w}_{ij}, \mathbf{e}_j; h)$. The farm $n = 1, \ldots, N$ has J_n units of land where $J = \sum_{n=1}^{N} J_n$. Total land units of crop i for farm n is $a_i^n(p_{ij}, \boldsymbol{w}_{ij}, \mathbf{e}_j; h) = \sum_{j=1}^{J_n} \delta_{ij}^* * a_j$ where land unit j is a_j hectares. The land allocation shares are $s_i^n(p_{ij}, \boldsymbol{w}_{ij}, \mathbf{e}_j; h) = a_i^n / A^n$ where total land of farm is $A^n = \sum_{i=1}^{I} a_i^n$. Farm's expected profits of crop i are $v_i(\boldsymbol{p}, \boldsymbol{w}; h) = \sum_{j=1}^{J_n} \pi_{ij}$ where $\boldsymbol{p}$ is output price vector and $\boldsymbol{w}$ input price matrix. The farm's total expected profits can be represented with land allocation share:

$$v^n(\boldsymbol{p}, \boldsymbol{w}; h) = \sum_{i=1}^{I} \{s_i^n * v_i(\boldsymbol{p}, \boldsymbol{w}; h)\} \tag{1}$$

2.3.2 Farming System Choice and Adoption Rates

Equation (1) provides a farm expected profits for farming system h, so the comparison of system performances can show the farm's choice on the farming systems. The farmer decides whether to adopt a new farming system based on their expected net gains of switching systems. Net gains can be measured by the differences between expected profits of each farming system: $\omega^n(\boldsymbol{p}, \boldsymbol{w}) = v^n(\boldsymbol{p}, \boldsymbol{w}; 2) - v^n(\boldsymbol{p}, \boldsymbol{w}; 1)$. The alternative farming system will be adopted when system 2 gives more expected profits, i.e. $\omega^n(\boldsymbol{p}, \boldsymbol{w}) > 0$.

Figure 2.2 Derivation of Adoption Rates from the Spatial Distribution of Net Gains Adapted from Antle and Valdivia (2006)



For convenience, the spatial distribution of expected net gains is represented a continuous density function defined as $\varphi(\omega|\boldsymbol{p}, \boldsymbol{w})$. The percentage of farms with $\omega^n(\boldsymbol{p}, \boldsymbol{w}) > 0$ is interpreted as the adoption rate of the new farming system and is calculated as the area under the distribution of net gains: $r(\boldsymbol{p}, \boldsymbol{w}, 2) = 100 \int_0^\infty \varphi(\omega|\boldsymbol{p}, \boldsymbol{w}) d\omega$ (Figure 2.2). Therefore, if the alternative farming system does not provide higher profitability to most farms, adoption rates can be very low. For example, high crop prices that are produced in system 1 or high cost of production for system 2 can aggravate the relative profitability of alternative farming systems. The right side of

Figure 2.2 is a cumulative distribution of net gains. The share of farms using system 1 is $r(\boldsymbol{p}, \boldsymbol{w}, 1) = 100 - r(\boldsymbol{p}, \boldsymbol{w}, 2)$.

Figure 2.3 Effect of the Mean of Net Gains on the Adoption Rates (*r*)

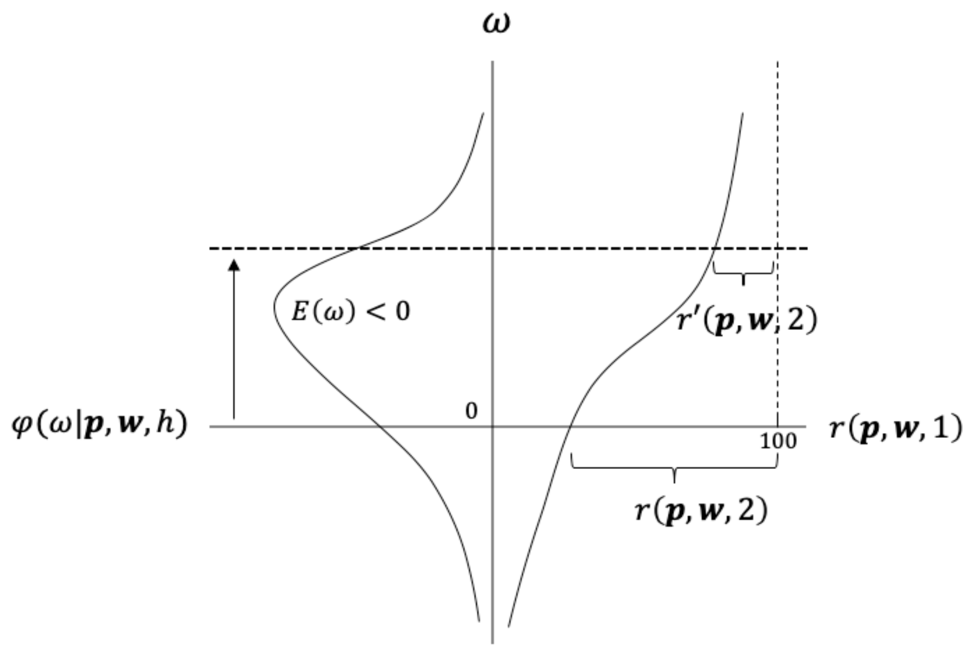


Figure 2.3 shows that the shape of the adoption curve is determined by the form of the distribution of net gains and the point where the distribution meets the x-axis. Accordingly, where the mean of net gains ($E(\omega)$) located significantly affects the adoption rates. For example, in Figure 2.3, the horizontal axis moves to the right side of the distribution of net gains. Mathematically, this shift implies the mean is less than zero ($E(\omega) < 0$). Under normality assumption, more than half of farms have higher expected profits from current farming systems. Thus, the corresponding adoption rates, $r'(\boldsymbol{p}, \boldsymbol{w}, 2)$, are in the range from 0% to 50%.

2.3.3 Market Equilibria

The objective of this section is to quantify the impacts of output price changes on the adoption rates among farms at a given region. For simplicity, crop 1 is assumed as a widely produced staple crop and crop 2 is an alternative crop that can be a newly introduced crop in subregion or another crop promoted by policy. In order to focus on indirect supply responses of output price change, it is assumed that crop prices are endogenously determined. The market demands of staple crop (crop 1) and alternative crop (crop 2) are not affected by each other. Factor prices are exogenously determined.

With this setup, only crop 1 is grown in farming system 1, whereas system 2 includes both crops 1 and 2. Given input prices, the output prices are adjusted in the market after the introduction of alternative farming system (system 2). These market changes will induce changes in expected farm profits of both farming systems. Output prices and farm adoption rates can be iteratively solved until market equilibria is obtained. This economic process makes farm adoption rates endogenous to output prices affected by the new farming system and policy interventions. To represent this endogeneity, the aggregate supply function is specified as a function of adoption rates in the market model.

Define the population mean output supply function of crop i for each farming system as $y_i^*(p_i, \mathbf{w}_i; h)$. The aggregate output supply for crop 1 can be represented as a function of the adoption rates of system 2, $r(\boldsymbol{p}, \boldsymbol{w}, 2)$:

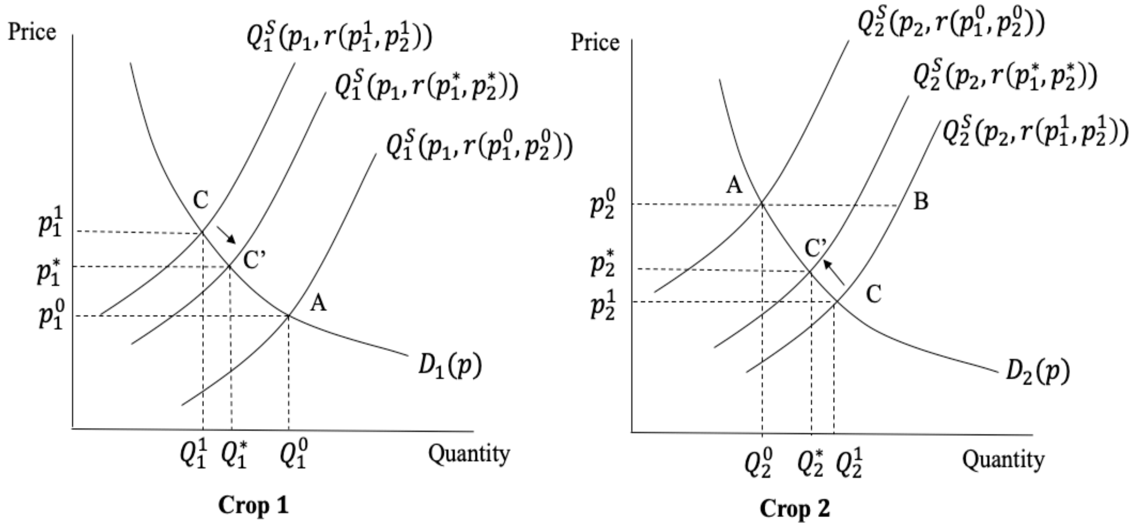
$$Q_1^s(p_1, r(\boldsymbol{p})) = \left\{\left(1 - \frac{r}{100}\right) \cdot N \cdot y_1^*(p_1, \mathbf{w}_1; 1)\right\} + \left\{\frac{r}{100} \cdot N \cdot y_1^*(p_1, \mathbf{w}_1; 2)\right\} \quad (2)$$

Since crop 2 is only in system 2, the aggregate output supply function for crop 2 is $Q_2^s(p_2, r(\boldsymbol{p})) = r/100 \cdot N \cdot y_2^*(p_2, \mathbf{w}_2; 2)$.

The farm production technologies are assumed to satisfy standard assumptions thus the output supply function is an increasing function of price ($\partial Q_i^s/\partial p_i > 0$). The aggregate supply of crop 2 is an increasing function of adoption rates ($\partial Q_2^s/\partial r > 0$) and adoption rate is an increasing function of price of crop 2 ($\partial r/\partial p_2 > 0$). The market demand is defined as $Q_i^D = D_i(p_i)$ and demand is assumed to have downward sloping curve ($D_p < 0$). The market equilibrium condition is then defined as $Q^D = Q^S$.

Figure 2.4 shows the impacts of adopting the alternative farming system on the market equilibrium of both crop markets. To simplify the presentation, the aggregate supply function and adoption rates are represented as a function of the market crop price (p_i). The supply curve for crop 2 is $Q_2^S(p_2, r(p_1^0, p_2^0))$ with initial market equilibrium prices and adoption rates. If the crop 2 is newly introduced in this region, $r(p_1^0, p_2^0)$ starts from zero. Initial equilibria are at point A. A new equilibrium will be achieved at price p_1^* and p_2^* when supply and demand are met in both markets at adoption rate $r(p_1^*, p_2^*)$.

Figure 2.4 Market Equilibria with Adoption of Crop 2



We can define function $r(p_1^*, p_2^*)$ using an iterative analysis. Market equilibrium will change in response to crop introduction or policy intervention that increases aggregate output of crop 2. The new adoption rate ($r(p_1^0, p_2^0)$) shifts the supply curve rightward from $Q_2^S(p_2, r(p_1^0, p_2^0))$ to $Q_2^S(p_2, r(p_1^1, p_2^1))$, because of excess supply (point B). At adoption rate $r(p_1^1, p_2^1)$ the market equilibrium moves to the point C with price p_2^1 and p_1^1. However, at C, due to the lower price of crop 2 ($p_2^1 < p_2^0$) and higher price of crop 1 ($p_1^1 > p_1^0$), the incentives to produce crop 2 is reduced. This iteration between adoption rate and price continues until new market equilibrium prices, p_2^* and p_1^*, are achieved. At the same time, the lower adoption rates shift the supply function inward to a stable market equilibrium at point C' where $r(p_1^0, p_2^0) < r(p_1^*, p_2^*) < r(p_1^1, p_2^1)$.

It is important to note that price responsiveness (i.e. elasticities) influences the magnitude of shifts in supply, resulting in a change in market equilibrium. The introduction of crop 2 leads to a rightward shift in the supply curve and the magnitude of the price change depends on two types of relative elasticities: First is the relative elasticity of demand compared to supply of crop 2. An increase in quantity supplied is larger when a demand curve of crop 2 is less elastic, reducing market equilibrium price more. Second is demand and supply elasticities of crop 2 relative to those of crop 1. For example, less elastic demand of crop 1 leads to a higher equilibrium price of crop 1 which decreases farmers' incentives more to adopt the new farming system.

In addition, these implications from price responsiveness also show when supply responses do not affect market equilibrium and farm's adoption decisions. If the region or population size is small relative to a large market, changes in output by their adoption don't change output price. In other words, if farmers in a given region are price-takers, the equilibrium prices are $p_1^0 = p_1^*$ and $p_2^0 = p_2^*$. Thus, there are no price feedback effects on adoption.

2.4 Empirical Method

2.4.1 Regional Integrated Assessment (RIA)

The empirical method is motivated from the Regional Integrated Assessment (RIA) developed by the Agricultural Model Intercomparison and Improvement Project (AgMIP, www.agmip.org). The RIA approach presented in Antle et al. (2015) was developed to evaluate to climate impact and adoption. Here this study utilize a similar approach to evaluate technology adoption and impacts.

The RIA methodology has its foundation in simulation experiments. Existing and prospective agricultural systems are characterized by identifying the key system components and influential factors affecting system performance. This characterization incorporates the relevant environmental, socio-economic and regional factors. This process enables researchers to link different dimensions related to the farming system such as results from global modeling to the regional analysis or biophysical information to the economic analysis. For example, in chapter 3, results from crop model simulations and LCA analysis are utilized to project crop yields and the net greenhouse gas emissions associated with the environmental performance of each system and the price scenarios are developed from the price projection of global economic models.

Impact assessment using RIA evaluates the system performance responding to system changes for adaptation to policy or climate change. Through existing systems, The characterization of farming systems identifies the key system components and influential factors affecting system performance. This information is utilized for defining the simulation experiments to analyze the effectiveness of the adoption. It means the simulation is used to assess how changes in system components and exogenous factors affect the system performance.

RIA uses information from multiple disciplines to include the relevant environment, socio-economic and regional factors. It uses the variability of several models to estimate the plausible range of impacts. For example, climate data can be used as the input data in the crop model to estimate projected yield. The results from the global economic model can be used to generate projected price and cost for simulation. More information on the RIA approach can be found in Antle et al. (2015).

RIA can be implemented using the TOA-MD model by incorporating price effects of supply shifts with the *ex ante* evaluation of technologies. The important implication of the TOA-MD model is to reflect heterogeneity of the farm population with a relatively small number of parameters. This model is built on statistical methods developed in recent decades in the statistics and econometrics literature for analysis of changes in technologies or government programs, *holding constant the economic environment defined by prices and costs of production.* In the analysis of agricultural production systems, this implies that the observed distributions of yields and costs of production are used in the analysis. However, when prices change, farmers modify their management practices which change yields and costs of production.

Tradeoff Analysis Market Equilibrium (TOA-ME) model adds market equilibrium layer to the TOA-MD model to respond to the need for timely analysis using available data (Antle et al., 2014; Valdivia et al., 2012). This model, first, reflects biophysical, environmental and economic processes based on farming systems within a population of heterogeneous farms. It uses low moments of outcome distribution, thus data requirements for out-of-sample analysis (e.g. *ex ante* evaluation) are low. At the same time, TOA-ME model incorporates market adjustments that occur in response to a change in policy or technology.

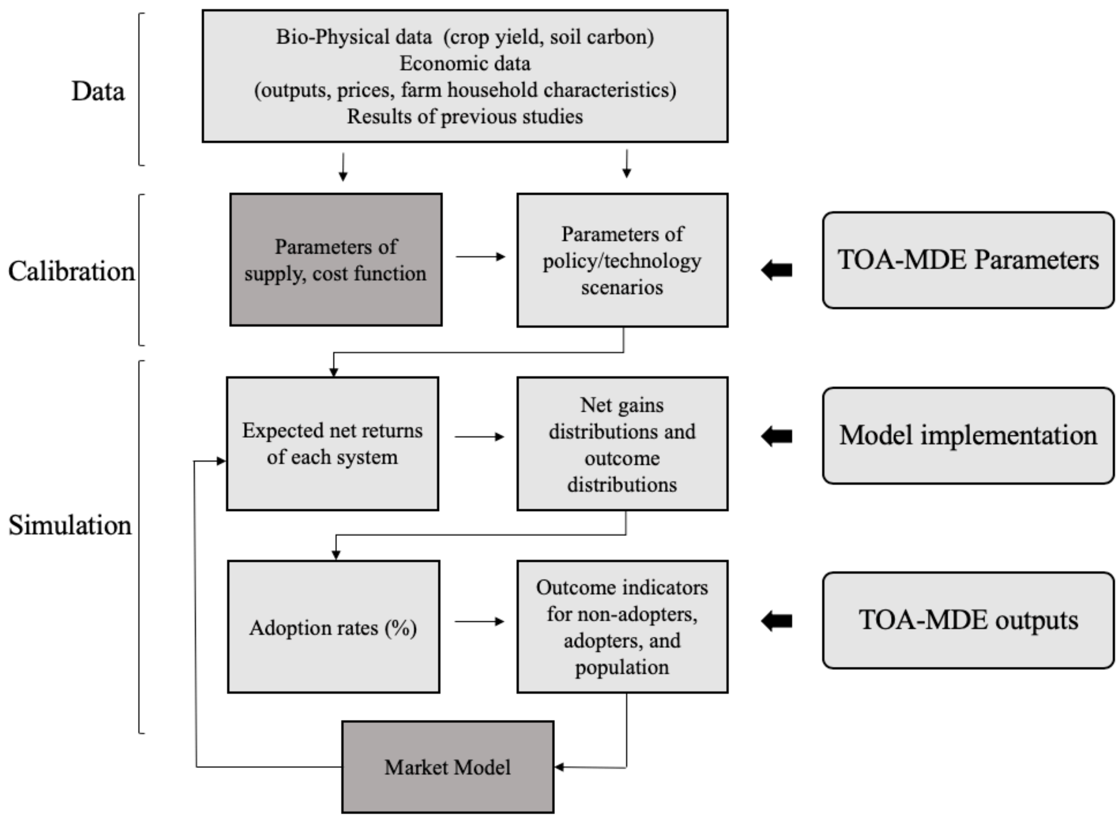
TOA-ME model is conducted as a two-stage analysis. First, the output (i.e. adoption rates) was driven by an impact assessment model, TOA-MD, assuming no market response. For the second stage, estimated and calibrated parameters are used to derive output supply function and information about demand function which is estimated or provided in the model. The model solves market equilibrium simultaneously and re-runs the impact assessment model with a new equilibrium point**.** The model solves the first stage again with a new equilibrium price. However, since the market equilibrium adoption rate is solved in a different stage, TOA-ME cannot determine an equilibrium price directly from technology adoption. For assessing adaptive effects from technology adoption, price and quantity in supply function should be specified by technology adoption. Therefore, the main objective of section below is to provide a new empirical approach that incorporates price changes directly from adopting new technology through RIA approach.

2.4.2 Farm Impact Assessment: TOA-MDE model

This dissertation suggests a new version of model TOA-MDE (TOA-MD Equilibrium impact assessment) that simulates the adoption rate as a function of market equilibrium output prices as described in section 2.3.3 above. As in the RIA approach, the analysis of farming system change is carried out in later chapters under a range of prices and policy scenarios to explore uncertainty in future economic conditions. Figure 2.5 shows the description of the TOA-MDE model along with the flow of simulation experiments. In order to link the TOA-MD model to a partial market equilibrium model, the additional steps for simulation experiments, darker grey boxes in figure, were added. The document for simulation programming is available in Appendix C.

The simulation method begins with the characterization of current and alternative farming systems. Given biophysical, environmental and economic information of each farming system, the parameterization is based on a MD (Minimum-Data) approach (Antle & Valdivia, 2006; Claessens et al., 2008). The MD approach uses available data (i.e. ‘average’ or ‘representative’ data from previous studies, government data such as census, or data from farm survey) for parameterizing the spatial distribution of net returns by using low order moments (e.g. mean, standard deviation). Through this approach, the competing agricultural activities are characterized with underlying biophysical and economic process. Using readily available data, this approach can provide timely and sufficiently accurate information for policy decision making.

Figure 2.5 The Flow of Economic Simulation Experiments of TOA-MDE



The simulation model calculates parameter values and predicts the proportion of farms that adopt the new system. As described in previous section, the adoption rates are affected by the shape of the distribution of net gains, $\varphi(\omega|\boldsymbol{p}, \boldsymbol{w}, \boldsymbol{h})$. The TOA-MD model assume that ω is distributed in the population and specifies it by using the mean expected net returns of each farming system: $\mu_v(\boldsymbol{p};h) = \sum_i (p_{hi}y_{hi} - c_{hi})$ where p is output price, y mean output, and c mean production costs for each crop i over system h. With given prices and quantities, the mean of net gains can be represented as $\mu_\omega(\boldsymbol{p}) = \mu_v(\boldsymbol{p},1) - \mu_v(\boldsymbol{p},2)$. In other words, the TOA-MD model does not change the level of output and cost by aggregate feedback from the market.

Another key parameter of $\varphi(\omega|\boldsymbol{p})$ is variance: $\sigma_\omega^2(\boldsymbol{p}) = \sigma_v^2(\boldsymbol{p},1) + \sigma_v^2(\boldsymbol{p},2) - 2\rho_v\sigma_v(\boldsymbol{p},1)\sigma_v(\boldsymbol{p},2)$ where $\sigma_v^2(\boldsymbol{p};h)$ is the variance of expected profits of system h and ρ_v correlation between expected profits of system 1 and system 2 (i.e. *between-system correlation*). The yield variance and covariance between expected profits are assumed to be fixed as given from the data, because the parameterization of supply and cost functions does not change the level of mean output and costs. Furthermore, the yield variability depends on biological factors and farming practices that two systems are using.

The share of land, s_{ih} for crop i and system h is used to determine how the farming system is composed of each activity (Antle et al, 2010). The expected profits for the system h is $\mu_v(\boldsymbol{p};h) = \sum_i s_{ih}(p_{hi}y_{hi} - c_{hi})$ where $\sum_i s_{ih} = 1$ for each system $h = 1,2$. Accordingly, the variance of net gains become $\sigma_v^2(\boldsymbol{p};h) = \sum_i s_{ih}^2\,\sigma_{ih}^2 - 2\sum_{i\neq z} s_{ih}\,s_{zh}\rho_{izh}\sigma_{ih}\sigma_{zh}$ by assuming σ_{ih}^2 is the variance of returns to crop i and system h and the ρ_{izh} is the correlation coefficient between net returns to crop i within each system h (i.e. *within-system correlation*).

The functional form and parameters in supply and cost functions can be determined depending on each case of empirical applications as well as methods for parameter estimation in this dissertation. A calibration method is used to estimate parameter values of supply and cost functions. The advantage of calibration method is the data requirements are less demanding than traditional econometric estimation and other simulation methods. The generalized production function is specified with a Cobb-Douglas functional form. This specification permits this approach to have algebraic tractability and the expositional ease because of its self-dual property.[4] The full mathematical presentation of the model can be found in Appendix A.

The model calibrated as follows. First, the production function of each crop is specified in Cobb-Douglas form under an assumption of competitive output and input markets. Second, the short-run return to scale ($\boldsymbol{\gamma}$) of each crop is calibrated by a cost-share of the given crop and system. Third, intercepts of supply and cost functions is calibrated followed by the calibration of the short-run return to scale ($\boldsymbol{\gamma}$). This calibrated model represents the farm's expected profits of each farming system as a function of price, implying output price changes are now reflected in the farm's expected profits in simulation.

The distribution of net gains involving multiple activities can be generalized by specifying individual activities with land allocations. If the data is available for estimating reduced-form crop share equation, land allocation can be endogenous in the simulation model (Fezzi & Bateman, 2011). For this dissertation, the analysis is restricted

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[4] The corresponding cost function can be represented by the production function's coefficients and functional form.

to use average or representative data in order to keep the usefulness of MD approach for limited data conditions.

Whereas parameterization (upper gray box in Figure 2.5) specifies adoption rates as a function of endogenous output price, the lower gray box shows how adoption rates link to the aggregate output supply of each crop. After estimating adoption rates, the TOA-MDE model solves market equilibria with given the market demand and supply parameters (lower dark gray box in Figure 2.5). Market demand and supply functions for crop i are specified in linear form (Table 2.1). The aggregate market demand and supply function are defined as $Q_i^d = \alpha_i^d + \beta_i^d p_i$ and $Q_i^s = \alpha_i^s + \beta_i^s p_i$ for each crop i, with market equilibrium condition: $Q_i^d = Q_i^s$ for all i. Table 2.1 shows this partial market equilibrium model and equilibrium conditions. New market equilibrium leads to changes in expected profits of each farming system and this change adjusts adoption rates. This process solves equilibrium price and adoption rates interactively.

Table 2.1 Specification of Market Supply and Demand for Crop *i*

	Accounts	Equation
Supply (Q_i^s)		
	Beginning stocks (BS)	$BS_i = a_{i1}^s + b_{i1}^s p_i$
	Production (S)	$S_i = a_{i2}^s + b_{i2}^s p_i$
	Imports (IM)	$IM_i = a_{i3}^s + b_{i3}^s p_i$
	$Q_i^s = \alpha_i^s + \beta_i^s p_i = (a_{i1}^s + a_{i2}^s + a_{i3}^s) + (b_{i1}^s + b_{i2}^s + b_{i3}^s) p_i$	
Demand (Q_i^d)		
	Domestic utilization (DU)	$DU_i = a_{i4}^d + b_{i4}^d p_i$
	Exports (EX)	$EX_i = a_{i5}^d + b_{i5}^d p_i$
	Ending stocks (ES)	$ES_i = a_{i6}^d + b_{i6}^d p_i$
	$Q_i^d = \alpha_i^d + \beta_i^d p_i = \left(a_{i4}^d + a_{i5}^d + a_{i6}^d\right) + (b_{i4}^d + b_{i5}^d + b_{i6}^d) p_i$	
Market clearing condition for crop i: $BS_i + S_i + IM_i = DU_i + EX_i + ES_i$		

2.4.3 Price Endogenous Adoption Rates and Outcome Indicators

As shown above, the TOA-MD model specifies parameters of outcome distribution (mean, variance, and correlation) and this feature allows the model to estimate both economic (i.e. profits) and non-economic (i.e. soil quality) outcome indicators (Figure 2.5). The outcome indicators distinguish between an adopter, which benefits from the changes in the farming system, and a non-adopter, that adheres to the current farming system, to avoid a reduction in profits. In this section, price endogenous adoption rates are linked to changes in the outcome indicators by the new farming system in the TOA-MDE model.

The outcome distribution is a mixture of two farming systems' outcome, which will be a different distribution from the case where only system 1 is available. This approach imitates what would be observed if farms using system 2 were assigned into a 'treated' group in controlled experiments. The difference between mean values of the two systems can be interpreted as the average treatment effects as in the econometric policy evaluation literature (Heckman & Vytlacil, 2007). The formal illustration is shown in Appendix B.

The indirect supply responses can affect the magnitude of changes in environmental outcomes by the new farming system. The introduction of a new farming system and its adoption result in the changes in market equilibrium. New equilibrium price and adoption rates lead to a different spatial distribution of environmental outcomes, especially when the new production system is associated with management practices that generates improved environmental outcomes.

The introduction of new farming system impacts environmental performance that could affect all farms in the region. If the new system facilitates environmentally friendly management practices, higher adoption will result in a collective increase in environmental quality of the region (i.e. positive relationship between adoption rates and environmental outcomes). However, reduction of adoption rates due to indirect supply responses shrinks environmental outcomes that could have been achieved at initial adoption rates.

2.5 Conclusions

This section shows how this dissertation fits and contributes to economic literature on farm technology adoption by reviewing farm-level impact assessments and market equilibrium models. The scale difference of these two literature generates a methodological challenge that is likely to need integrated models to achieve both keeping farm heterogeneity and aggregating information for policy decisions. Therefore, the theoretical framework and the empirical method developed in this dissertation link farm profit maximization with market equilibrium through population level adoption rates.

The methodology gives two important implications. First the price responsiveness influences the magnitudes of supply shifts which determine how much indirect supply responses affect farm adoption. Second, the linkage of the farm-level impact assessment and market equilibrium analysis in the simulation design allows me to evaluate the impacts of new technology or policy introduction on economic and environmental outcomes with possible market equilibriums.

Chapter 3 Empirical Application 1: Adoption of a Biofuel Crop in Dry-land Wheat Farming System in U.S. Pacific Northwest

3.1 Introduction

The Paris Accord of the UNFCCC 21st Conference of the Parties (COP21) asks the agriculture industry to respond to the need for mitigating greenhouse gas emissions and shifting petroleum-based energy systems to bio-based energy systems. However, recent research has shown that the temperature goal is unachievable with existing practices and mitigation technology of current agriculture systems (Wollenberg et al., 2016). Additionally, the demand for high emission reductions could result in the substitution of food production with biofuels, and in the expansion of biofuel production into environmentally sensitive lands.

Previous studies have shown that incorporating a biofuel crop could contribute to limiting greenhouse gas emissions and also increasing farm income. However, land use competition between food and biofuel could result in price volatility, which makes the economic feasibility of this system sensitive to crop prices (G. Hochman et al., 2008; Lotze-Campen et al., 2014). It would thus be of interest to investigate how price changes affect the performance of the alternative farming system that could contribute to achieving the temperature goal and improving farm profitability.

The empirical application in this chapter evaluates the short-term economic benefits of incorporating an oilseed crop, *camelina sativa,* into a wheat production system in the Pacific Northwest (PNW) of the United States. *Camelina* is known as a well-adapted crop in the dryland farming system and it can be used for food oil, biodiesel, and jet fuel (Wysocki et al., 2013).[5] The wheat-based farming system in the PNW has been economically productive even with soil erosion and little crop diversification (Schillinger and Papendick 2008). Farmers in this region are being challenged to simultaneously address long-term risks, such as climate change and environmental conservation, and near-term improvements in farm profitability and market diversification (Pan et al., 2017). A growing interest in home-grown bio-jet fuel in the PNW region and increasing demand for domestic biodiesel production can provide an opportunity for the PNW to address both these short-term and long-term challenges (Reimer & Crandall, 2018; Smith et al., 2017).[6]

This analysis contributes to several strands of literature. First, this research provides the out-of-sample *ex-ante* simulation method that includes indirect supply responses from farmers' adoption decisions through price changes. One difficulty of out-of-sample impact assessment is to parameterize the model which depends on the underlying physical process and behavioral responses (Auffhammer & Schlenker, 2014). Conventional econometric estimation is not able to evaluate new farming systems that have not been observed historically in terms of economic variables. In contrast, my analysis characterizes a new biofuel crop production through crop model simulations, field experimental data, observed properties of current practices, and calibrated economic

[5] It is not used for edible oil yet, but recent approval for oilseed meals in the EU and the US shows the potential of its utilization, especially for animal meal by-product (Colombini et al. 2013). U.S. Environmental Protection Agency (EPA) qualifies *camelina* oil as biomass-based diesel, renewable diesel, jet fuel that can be traded on the market (Approved Pathways for Renewable Fuel https://www.epa.gov/renewable-fuel-standard-program/approved-pathways-renewable-fuel last accessed 9/13/19).

[6] U.S. Energy Information Administration: https://www.eia.gov/todayinenergy/detail.php?id=39292# last accessed 09/13/19

parameters. This modeling approach allows me to estimate price-endogenous adoption rates while keeping heterogeneous characteristics of the farm population.[7]

Second, this research enriches the quantitative analysis of current trade disputes by examining the impacts of potential policies and market shifts on a biofuel crop adoption. Previous studies have suggested that a supportive policy environment is crucial to maximizing profitability and productivity when incorporating *camelina* into wheat cropping systems in the PNW (Antle et al., 2019; Reimer & Zheng, 2017). But little empirical study has been offered along with price changes associated with trade disputes and possible domestic policies.

Third, I consider interactions between economic and environmental responses to farming system change: how the interactions between farm decisions and market responses affect environmental outcomes. I include no-till adoption sequestering additional carbon in the soil as a management option. Building on previous work, this research is one of the first to link site-specific life cycle analysis (LCA) to economic impact assessment (Antle et al., 2019). In addition to outputs from crop model simulations, projected crop yields, carbon sequestered in the soil, and the net greenhouse gas emissions associated with current and alternative farming systems are used collectively to evaluate both the economic and environmental performance and interactions between economic and environmental outcomes.

[7] It is worth noting that this analysis quantifies adaptive feedback effects from farming system changes rather than finding a linkage at economy-wide perspectives or a feedback mechanism. Analyses including adaptive feedback are well documented in the literature with associated production uncertainty, network effects, or behavior economics (Berger, 2001; Just & Pope, 1979). However, one of the goals of farm-level *ex-ante* impact assessment is to estimate the economic feasibility for timely assessment during the policy design stage (Alston & Norton, 1995; Claessens et al., 2008). Thus, it is adequate to suggest a method that estimates the upper bound of economic feasibility along with a market change in the *ex-ante* analysis.

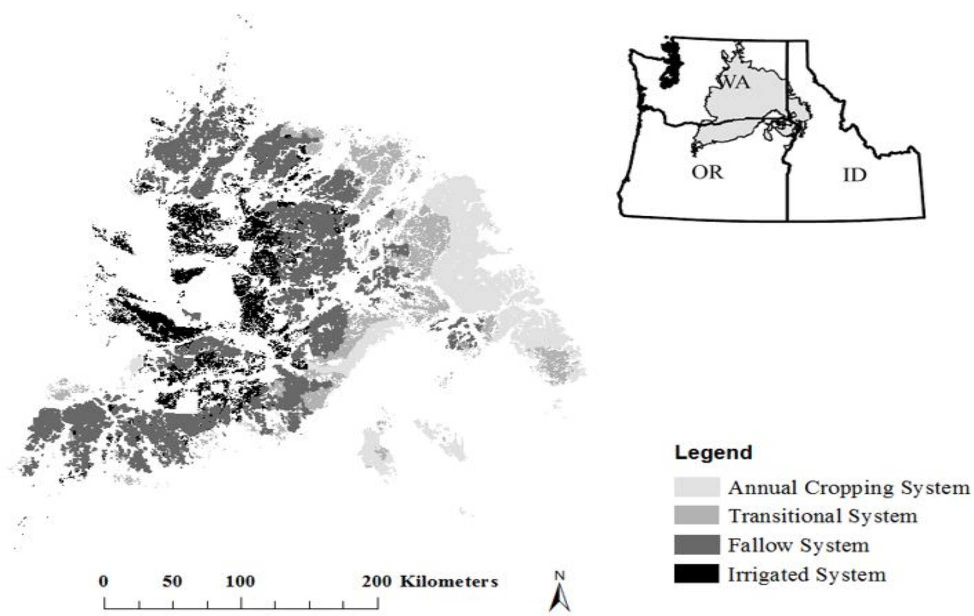
The final contribution of my analysis is to examine the distributional effects of indirect supply responses on farm income. One of the major findings in technology adoption literature is farm income is positively correlated to adoption: the farmers who already have higher profits are more likely to adopt new technology (Foster & Rosenzweig, 2010). Therefore, a lower price by new technology could aggravate profits among those farmers who use old technology. The TOA-MD model, based on a parsimonious model (Antle, 2011), can estimate various treatment effects motivated from the econometric policy evaluation literature (Heckman & Vytlacil, 2007), using outcome distributions associated with adopters and non-adopters. Relative to this model, my main contribution is to reflect price feedback on the distributional impacts of the new farming system. My method can predict the effect of indirect supply responses on the income distribution. The rest of this chapter is organized as follows: Section 3.2 describes data and summary statistics, section 3.3 parameterization, section 3.4 simulation scenarios. section 3.5 presents the simulation results and section 3.6 discusses and concludes this economic analysis.

3.2 Study Area and Data

The study area is the Pacific Northwest in the U.S. across Oregon, Washington, and Idaho (Figure 3.1). The rain-fed, large-scale, wheat-based system has dominated the region for decades. However, changes in commodity and conservation policies, the trade disputes, commodity price fluctuations, and climate change are all concerns to farmers in the region, especially farms that are primarily dependent on income from wheat.

The classifications of the PNW farming system were based on the characterization of (Huggins et al., 2015). Figure 3.1 shows the spatial distribution of rain-fed cereal-cropping systems in the PNW as three categories: The annual cropping of winter and spring wheat with summer, mainly legume, crops; the winter wheat-fallow system (WWF); and the transitional wheat system rotating winter, spring wheat and fallow.

Figure 3.1 Wheat-Based System in Pacific Northwest (ID Idaho, OR Oregon, WA Washington state) Source: Huggins et al. (2015)



In this study, I focus on the WWF system as the base system (system 1). Farms with the WWF system have the lowest mean revenue among farming systems within this region. But the percentages of wheat revenue in total revenue (about 80%) are the largest, meaning almost all of the farmers' incomes come from wheat production (Table 3.1).

Thus, this system will be more vulnerable than other systems to changes in economic and policy conditions. The WWFC (winter wheat – fallow – *Camelina*) system is considered as an alternative farming system (system 2) of the WWF system. This new system extends crop rotation from 2 to 3 years by including oilseed *camelina* into the WWF system. The WWFC system also incorporates no-till cultivation of wheat and *camelina* that could increase and maintain soil carbon.

Table 3.1 Summary Statistics for U.S. Pacific Northwest Wheat Systems from U.S. Census of Agriculture Data in 2007

Variables	Unit	Annual cropping system		Fallow (WWF) system		Transitional system	
		Large	Small	Large	Small	Large	Small
Winter wheat revenue	$/farm	382,381 (287,558)	79,045 (82,120)	450,697 (329,923)	60,495 (80,593)	367,448 (260,132)	102,253 (108,681)
Total crop sale	$/farm	625,738 (422,181)	124,235 (117,550)	488,281 (344,585)	69,940 (88,934)	488,122 (343,115)	157,360 (154,276)
Share of wheat sale	%	77 (18.5)	81 (24.5)	96 (12.3)	85 (32)	88 (17.3)	70 (32)

Notes: Standard deviations in parentheses

Table 3.2 presents the yield and cost statistics for the farm in each farming system and Table 3.3 shows summary statistics of environmental variables. The data for TOA-MD analysis is stratified into small (about 263 hectare) and large (about 1619 hectare) groups by the median acres of the farm area. The farm-level data of wheat production comes from the 2007 Census of Agriculture, including wheat yield, areas, production cost, and subsidy payments.[8] Reduction in wheat production costs in system 2 is assumed

[8] I use 2007 data because it is more representative of farms in this region due to unusual crop market conditions around 2012.

because fallow costs are removed. The parameterization of the WWFC system including wheat yield and returns to *camelina* is discussed in Antle et al. (2019b)and Capalbo, Antle, and Seavert (2017). *Camelina* production costs are calculated from the field experiment data.[9] Production costs for wheat and camelina in Table 3.2 are variable costs.

Table 3.2 Summary Statistics of WWF and WWFC System: Economic Variables

Farm size		Wheat yield (kg/ha)	Wheat cost ($/farm)	Govt. subsidies ($/farm)	*Camelina* yield (kg/ha)	*Camelina* costs ($/farm)
System 1 (winter wheat – fallow rotation)						
large	Mean	3418	109,848	60,744		
	Std dev	1040	80,038	33,640		
small	Mean	3579	19,691	12,827		
	Std dev	1230	15,861	8,887		
System 2 (winter wheat – fallow – *camelina* rotation)						
large	Mean	2940	73,598	60,744	1345	36,709
	Std dev	770	53,626	33,640	n.a.	
small	Mean	3078	13,193	12,827	1345	5,053
	Std dev	910	10,627	8,887	n.a.	

Note: mean large farm size = 1688 hectare, mean small farm size 291 hectare.

Data of environmental outcomes are results from a DNDC (DeNitrification-DeComposition) model and LCA analysis built upon the previous analysis in Tabatabaie, Tahami, and Murthy (2018) and Antle et al. (2019b). The current cropping system, WWF system, is a net source of greenhouse gas emissions, while the WWFC system has negative greenhouse gas emission. This difference comes from changes in soil organic

[9] Oregon Agricultural Enterprise Budgets, Camelina (Spring) Following Fallow, Direct Seed, Less than 14-Inch Precipitation Zone, https://agsci.oregonstate.edu/sites/agscid7/files/oaeb/pdf/AEB0044.pdf last accessed 05/12/2020

carbon, the emissions from input uses, and management practices, resulting in the lower global warming potential of the WWFC system. The estimates of soil organic carbon was assumed to take about 20 years to be established in DNDC analysis (Tabatabaie et al., 2018).

All market data of wheat and camelina are obtained from Wheat Yearbook and Oil Crops Yearbook published by the United States Department of Agriculture Economic Research Service (USDA ERS, 2018a, 2018b). Since the camelina market is not established, publicly available data on the camelina market is unavailable. Data on canola is used based on their agronomic and use similarities for the market level analysis.[10]

Table 3.3 Summary Statistics of WWF and WWFC System: Environmental Variables

	Soil organic carbon (kg C/ha/3-years)	Soil greenhouse Gas emissions (kg CO2-eq./ha/3-years)	System global warming potential (kg Co2-eq/ha)
System 1 (winter wheat – fallow rotation)			
Mean	-201	813	1810
Std dev	219	827	971
System 2 (winter wheat – fallow – *camelina* rotation)			
Mean	227	-696	841
Std dev	247	965	1144

3.3 Model Parameterization

To implement simulation experiments using the TOA-MD model, I parameterize production function, the distribution of net gains from adoption, and market demand and supply function following the description in chapter 2.3. If the model parameters are

[10] Both are included in Brassicaceae family and oilseeds can be used as biodiesel and byproduct meal for livestock (George et al., 2017; Neibergs et al., 2019). Chen et al. (2015) also used canola price to approximate camelina price because of its strong correlation.

calibrated correctly, the adoption rates and direction of market changes without indirect supply responses is expected to match theoretical expectations and the adoption rates estimated in the TOA-MD model.

Given that there are no counterfactual observations for the WWFC farming system, the supply and cost functions are identified by the calibration method with parameters of production functions. For a crop-share of given crop and system, I use information on crop price, the Census of Agriculture, *camelina* field experiments, and results of LCA analysis. The short-run returns to scale ($\boldsymbol{\gamma}$), the parameter discussed in chapter 2.3.2, is 0.30 for wheat and 0.42 for *camelina*.

Means and variances of net returns of the crops are used to parameterize between- and within-system correlations which determine the shape of the distribution of net gains from adoption *camelina*. The within-system correlation of the WWF system in PNW is 0.11 from the Ag Census. The net returns to *camelina* produced with a wheat-fallow rotation would be highly but not perfectly correlated with returns to wheat-fallow rotation without *camelina*, as suggested by previous analysis on switching from a wheat-fallow rotation to continuous cropping showed the between-system correlation is above 0.8 in Montana (Antle & Valdivia, 2006). I assume between-system correlation is 0.75 as a lower bound in a plausible range of correlations.

To investigate the impacts of the new farming system on output markets, Table 3.4 shows demand and supply quantities and elasticities at the domestic level with a trade component in 2007. The trade of interest is between the U.S. and the rest of the world (ROW). I restrict wheat demand to the white wheat which farmers in the PNW produce the largest amount in the U.S.. Since the *camelina* market is not established yet, I use the canola market to represent the likely properties of the camelina market. I assume *camelina* production from the PNW shifts the supply curve in the U.S. canola seed market, which is also used to produce biodiesel. Since the demand for wheat is food consumption and that of *camelina* is assumed for processing to biodiesel production, the market demand of both crops are independent of each other.

Table 3.4 Market Demand, Supply, and Elasticities

	Accounts	Quantity (1000ton)		Elasticity	
		Wheat	Camelina	Wheat	Camelina
Supply					
	Beginning stocks (BS)	1197	116	0	0
	Production (S)	6020	715	0.43	0.72
	Imports (IM)	2566	963	-0.03	0.02
Demand					
	Domestic utilization (DU)	1858	1157	-0.34	-0.61
	Exports (EX)	4610	466	-0.4	-0.61
	Ending stocks (ES)	1007	173	-0.57	-0.26

Data source: Crop Yearbook from USDA ERS

I use elasticity estimates for specific demand and supply accounts if it is available from existing literature: Production elasticity of wheat (Huang & Khanna, 2010); export demand elasticity for wheat (Reimer, Zheng, and Gehlhar 2012). The supply elasticity for *camelina* production is derived from the calibrated model in Appendix A. This estimate is more representative of farmers' responses for *camelina* than canola production. The other elasticities are estimated by simple OLS regression ($Q_i = k_0 {P_{it}}^{k_{i1}} e^{k_{i2}t} \epsilon_i$) with market level time-series data from USDA ERS. Regression results are presented in the Appendix C.

3.4 Simulation Scenarios

To evaluate the economic feasibility of the WWFC farming system and its market responses, nine price scenarios are simulated. Assumptions about price scenarios are based partly on global model projections and information on research papers, reports, and news articles to represent a plausible range of future price.

The United Nations goal of limiting global average temperature to 1.5 °C requires greenhouse gas mitigation and transition of the energy system to alternative energy sources. The demand for high emission reductions could result in the substitution of food production biofuels and the expansion of biofuel production into environmentally sensitive lands. Price effects can be stronger with limited land expansion and competing for land use with crop production for biofuel (Lotze-Campen et al., 2014). In AgMIP Coordinated Global and Regional Assessments, the range of price increase ranges is in 10 to 20% under scenarios that limit warming temperature to 1.5 ℃ (Ruane et al., 2018). van Meijl et al. (2017) analyzed five global climate and agro-economic models and concluded the climate change, mitigation efforts, or both could increase real producer prices in agriculture. Their result showed projected prices have a general tendency towards 10-25% higher prices.

Potential or ongoing domestic and trade policies are expected to increase the camelina price. The ongoing trade dispute makes producing camelina more attractive to farmers in the PNW. Due to the increasing demand for livestock meal, the share of overall vegetable oil trade is expected to decline in world production (OECD/FAO, 2018)(OECD/FAO, 2018). In 2018, anti-dumping duty (60.44% to 276.65%) was imposed on imported biodiesel from Argentina and Indonesia, two major biodiesel exporters to the U.S. [11] It prevents the U.S. from importing biodiesel from those two countries, leading higher domestic production despite lower consumption in 2018.[12] If the government maintains the policy to strengthen the capacity of U.S. biodiesel production, the demand for oilseed will be increased and thus the price will be increased.

The wheat price is uncertain due to a rapid change in political conditions in wheat major producing regions. In terms of wheat production, the tariff debates in Trans-Pacific Partnership (TPP) are becoming a threat to wheat producers in the PNW. Most of the wheat from the PNW (about 75-90%) is exported and large importers are Asian countries, primarily Japan, Taiwan and South Korea with Japan importing about 20% of the PNW wheat production. Producers in the PNW could face increased tariffs and the more competitors such as Canada and Australia.[13] As of writing, the U.S. and Japan agreed with a new tariff rule to lower it to the same level as Canada and Australia.[14] Likewise, the wheat price that the PNW farmers face highly depends on political circumstances in the short term.

Based on the global model price projection and policy conditions, the magnitudes of increasing price are assumed to up to 50%. In order to examine absolute and relative effects of price changes on supply responses, I set additional price scenarios in the range of plus and minus 25% relative to base prices (Table 3.5).

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[11] https://www.federalregister.gov/documents/2018/04/26/2018-08775/biodiesel-from-argentina-and-indonesia-antidumping-duty-orders last accessed 09/13/19

[12] Domestic biodiesel production was 1,596 million gallons in 2017 and 1,857 million gallons in 2018. Consumption was 1,985 million gallons in 2017 and 1,895 million gallons in 2018 (U.S. Energy Information Administration, https://www.eia.gov/totalenergy/data/monthly/#renewable last accessed 09/13/19)

[13] https://www.reuters.com/article/us-trade-tpp/pacific-trade-pact-takes-off-with-tariffs-cut-in-six-nations-idUSKCN1OT00C last accessed 09/13/19

[14] New York Times “Trump Announces a Trade Pact With Japan” last accessed 09/30/19 https://www.nytimes.com/2019/09/25/business/trump-announces-limited-trade-pact-with-japan.html

Table 3.5 Price Simulation Scenarios

Base Price Scenario	Wheat ($265/ton)	*Camelina* ($300/ton)
P1	Base	Base
P2	+25%	Base
P3	+50%	Base
P4	Base	+25%
P5	Base	+50%
P6	-25%	-25%
P7	+25%	-25%
P8	-25%	+25%
P9	+25%	+25%

Base prices come from Crop Year Book (USDA) and Stein et al. (2014)

For all price scenarios, it is assumed that wheat yields are increased 20% due to CO_2 fertilization and corresponding cost of wheat production are 20% higher than those of baseline. This assumption is followed by prior analysis that an increase in yield and output price is likely to raise production costs (Antle et al., 2019).

I also simulate a hypothetical carbon payment associated with the switch to no-till cultivation of wheat. Farmers receive fixed payment for the area of the new farming system in their crop land. I assume that a carbon price of $50/ton based on the EPA estimates of social cost of CO_2 in 2030 in 2007 dollars per metric ton CO_2.[15]

Using data from the LCA analysis, this analysis predicts the changes in carbon in soil and greenhouse gas emissions associated with the change in the system (i.e. environmental outcome distribution). The differences in environmental outcome in each

[15] US Environmental Protection Agency, Climate Change, The Social Cost of Carbon https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html last accessed 05/12/2020

farming system are due to the heterogeneity of yields and cost associated with their different soils, climate and other characteristics represented in parameters in the model.

3.5 Results

3.5.1 Price Endogenous Adoption Rates

The first step in the simulation of the extended model, TOA-MDE, is to compare adoption rates without considering indirect supply responses with results from the original TOA-MD model. The results suggest that at the base price the TOA-MD model predicts adoption rates are 38.93% and 54.82%, respectively, for large and small farms. Adoption rates without indirect supply responses, from the TOA-MDE model, suggest the supply and cost functions are adequately calibrated (large farms: 38.97%, small farms: 54.84%).

Indirect supply responses are obtained by simulating the equilibrium adoption rates and output prices by the price scenarios defined in Table 3.5. Table 3.6 summarizes results from TOA-MDE simulation with price scenarios; adoption rates, equilibrium price, and quantity of wheat and *camelina* at each equilibrium point in Figure 2.4 of section 2.2.3. Results show that the changes are consistent with the theoretical expectations. When market equilibrium is considered, the equilibrium adoption rates are less than the initial adoption rates due to the lower *camelina* price caused by the output increase. Hence, after taking indirect supply responses into account (point C versus point C'), the adoption rates are reduced and the equilibrium price of *camelina* increases. In the baseline scenario, 38.97% (54.84%) of large (small) farms would adopt *camelina,* but the lower price reduces the adoption rates to 35.45% (52.99%). This means that the indirect supply responses reduce the adoption rates: -3.52 percent point (-9.03%) for large farms and -1.85 percent point (-3.37%) for small farms. The changes in equilibrium price and quantity for wheat are not substantial, because the proportion of production from the PNW compared to domestic production is insufficient to change market condition substantially.

The magnitudes of indirect supply responses vary by farm size and price scenario. The magnitude of reduction in adoption rates by the indirect supply responses is from -2 to -12 percent points for large farms, while those are from -0.5 to -7 percent points for small farms. This result indicates that including *camelina* into the crop rotation is more profitable to small farms. The adoption rates of small farms are higher even in the case of relatively high wheat prices (P2, P3, and P7). However, large farms are more responsive to *camelina* price. The predicted rates of adoption for large farms are higher than small farms only when the relative price of *camelina* is 150% greater than wheat price (P5 and P8). The results also suggest the magnitude of indirect supply responses are larger for large farms under all price scenarios.

Table 3.6 TOA-MD Simulation Results for Adoption of the WWFC System into the WWF System in the U.S. Pacific Northwest

Stratum	Price scenario ($)		At C Adoption rate (r%)	At C P($)	At C Q(ton)	At C’ Adoption rate (r'%)	At C’ P($)	At C’ Q(ton)	Differences of (r-r') (%)
	Winter Wheat								
Large	P1	265		266.52	474,713		266.40	478,388	
Small	P1	265		266.52	67,093		266.40	67,370	
Large	P2	331.25		331.89	495,765		331.87	496,145	
Small	P2	331.25		331.89	69,207		331.87	69,263	
Large	P3	397.5		397.70	502,375		298.76	502,391	
Small	P3	397.5		397.70	70,878		298.76	70,886	
Large	P4	265		267.29	460,460		267.03	465,585	
Small	P4	265		267.29	66,079		267.03	66,441	
Large	P5	265		267.94	447,164		267.60	454,117	
Small	P5	265		267.94	65,094		267.60	65,623	
Large	P6	198.75		200.31	464,731		200.22	467,172	
Small	P6	198.75		200.31	66,290		200.22	66,457	
Large	P7	331.25		331.55	500,803		331.54	500,844	
Small	P7	331.25		331.55	70,201		331.54	70,213	
Large	P8	198.75		201.21	440,546		201.03	445,202	
Small	P8	198.75		201.21	64,426		201.03	64,856	
Large	P9	331.25		332.52	485,906		332.41	487,674	
Small	P9	331.25		332.52	68,099		332.41	68,264	
	Camelina								
Large	P1	300	38.97	282.29	64,320	35.45	283.75	58,505	-9.03
Small	P1	300	54.84	282.29	12,497	52.99	283.75	12,076	-3.37
Large	P2	300	10.79	294.25	17,802	10.25	294.49	16,912	-5.00
Small	P2	300	34.96	294.25	7,968	34.42	294.49	7,844	-1.54
Large	P3	300	1.40	298.75	2,319	1.38	298.76	2,283	-1.43
Small	P3	300	18.56	298.75	4,230	18.48	298.76	4,211	-0.43
Large	P4	375	60.88	340.00	100,497	53.47	344.00	88,258	-12.17
Small	P4	375	65.67	340.00	14,965	62.11	344.00	14,155	-5.42
Large	P5	450	79.75	394.20	131,640	69.88	400.80	115,354	-12.38
Small	P5	450	75.38	394.20	17,169	70.14	400.80	15,985	-6.95
Large	P6	225	54.82	208.23	90,493	51.34	209.22	84,775	-6.35
Small	P6	225	63.60	208.23	14,493	61.95	209.22	14,119	-2.59
Large	P7	225	3.64	223.30	6,003	3.58	223.33	5,906	-1.65
Small	P7	225	25.20	223.30	5,744	25.09	223.33	5,718	-0.44
Large	P8	375	89.14	324.58	147,142	82.53	328.22	136,235	-7.42
Small	P8	375	81.89	324.58	18,662	77.68	328.22	17,702	-5.14
Large	P9	375	24.77	359.64	40,896	22.27	361.02	36,754	-10.09
Small	P9	375	45.84	359.64	10,446	44.23	361.02	10,078	-3.51

To illustrate the implications of not considering indirect supply responses, Figure 3.2 and Figure 3.3 provide a graphical illustration of the adoption rates and equilibrium camelina price measured at each equilibrium point. The price scenarios from P2 to P5 show relative effects of price changes on adoption rates, equilibrium price, and indirect supply responses (Figure 3.2). The indirect supply responses are larger when camelina price is relatively higher than wheat price. Under price scenario 4 (P4), where only camelina price increases by 25%, adoption rates decrease by 12.17 percent points among large farms and 5.43 percent points is reduced for small farms. Likewise, the indirect supply responses of P5, where camelina price is increased by 50%, shows similar results. It implies that the proportional change of the price doesn't affect the magnitudes of indirect supply responses substantially at relatively high price levels of camelina.

Figure 3.3 shows the various combinations of low and high price assumptions for wheat and *camelina*. The results of P7 and P8 suggest the consistent implication for the effect of relative price on adoption rates. One interesting result is the case of low prices for wheat and camelina (P6) shows the higher adoption rates than base and high prices scenarios (P1 and P9, respectively) when the relative price of wheat and camelina is the same for three scenarios. This result reinforces the importance of relative price on overall adoption rates and the role of indirect supply responses.

Figure 3.2 Results of the TOA-MDE for the Price Scenarios (P1-P5)

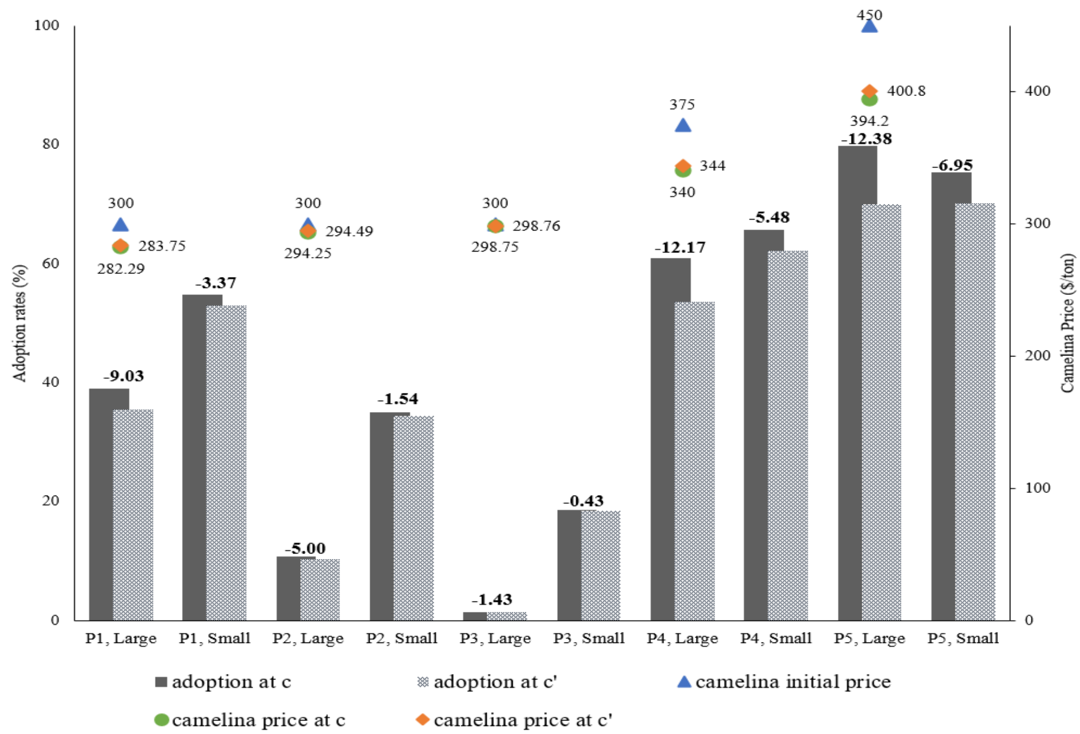
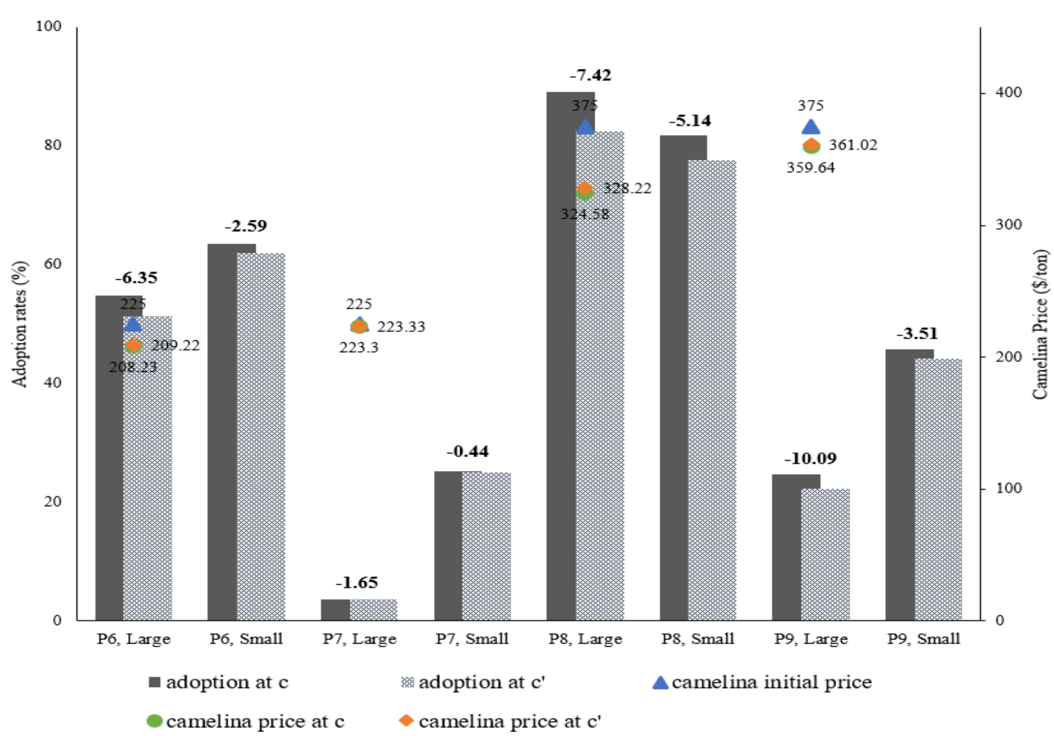


Figure 3.3 Results of the TOA-MDE for the Price Scenarios (P6-P9)



As I carried out the analysis with theoretical assumptions without constraints, the estimates of adoption rates could be interpreted as upper bound estimates, especially given low conventional oil price.[16] Estimates for quantity supplied may not be satisfied for local demand increase, which is consistent with a previous study showing much of increased demand may be satisfied by imports from outside of the PNW. Reimer and Zheng (2017) reported, under business as usual case, a 117,797ton *camelina* demand increase in the PNW for biojet and livestock meal which is about 40,000 tons more than our estimate under the baseline price scenario. Only the estimates of quantity supplied at 50% relatively high *camelina* price (P5 and P8) can satisfy the local demand increase. At least a 30% increase in *camelina* price is required to meet this local demand at the base wheat price; corresponding predicted adoption rates are 56.97% and 63.81% for large and small farms respectively.

3.5.2 Regional Camelina Supply

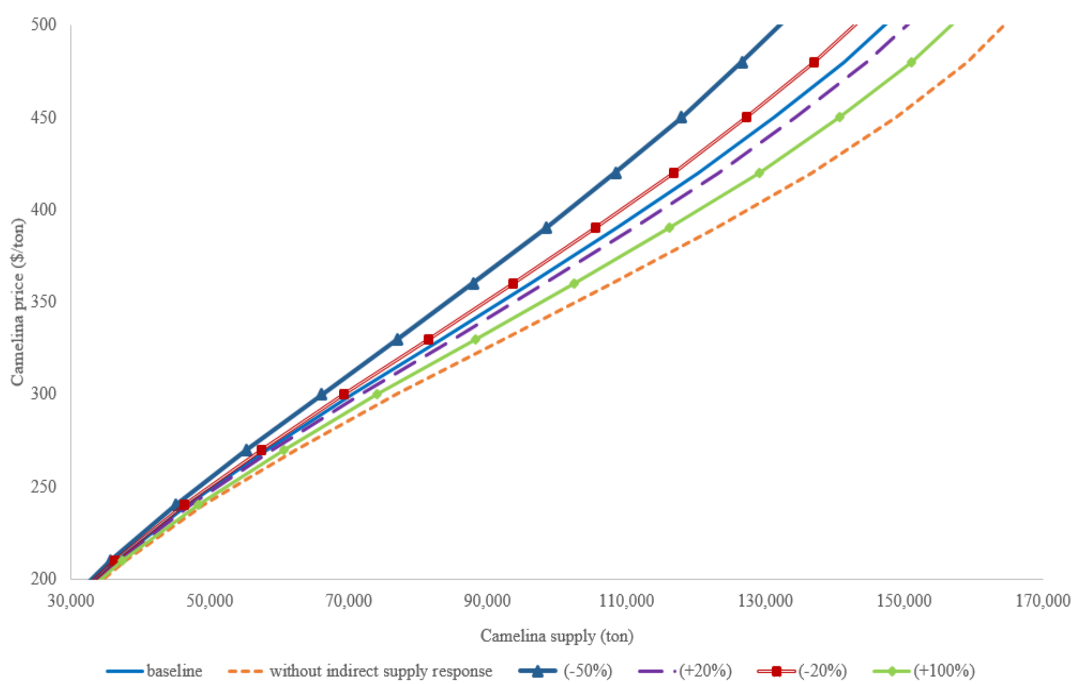
Figure 3.4 shows the regional supply curves of camelina. Wheat price is assumed to be baseline. The supply curves show that the quantity supplied is diminished, when new market equilibrium by indirect supply responses is considered. The rate of decrease in adoption becomes greater as the camelina price increases. This finding can be

[16] The calibrated model could be generalized with various factors that may hamper the adoption of a new biofuel crop, such as risk, transaction costs, financial constraints, and network effects. All of these factors would increase the costs of adoption, resulting in lower adoption rates. Meanwhile, the change in the price of crude oil influences adoption rates due to the substitute relationship between bioenergy and petroleum products. Meanwhile, adoption rates could be low because of less demand of biofuel by low conventional oil price.

explained by the result that large farms are more responsive to the price change, especially at a higher camelina price.

Given that the ex-ante study has substantial uncertainty in the parameters of the model, sensitivity analysis is conducted. The market demand curve could have a strong influence on the magnitude of indirect supply responses, because the extent to which a shift in supply affects equilibrium depends on the shape of the demand curve. This sensitivity analysis investigates how much a change in the price elasticity of camelina demand affects the indirect supply responses.

Figure 3.4 Sensitivity Analysis of *Camelina* Demand Elasticity



I simulate the impacts of a change in the elasticity of market demand on the regional *camelina* supply curve. The four simulations are performed for a range of minus

50%, plus and minus 20%, or plus 100% relative to base elasticity, -1.48 from Table 3.4 to illustrate how the shape of supply curve is impacted by demand elasticity of *camelina*. As discussed in the theoretical model, there is no *camelina* production in this region at the initial equilibrium (point A in Figure 2.4), so the regional supply curve without indirect supply response represents the collection of equilibriums at point C of in section 2.2.2 (i.e. direct supply responses to the introduction of *camelina*).

In Figure 3.4, indirect supply responses are greater with less elastic *camelina* demand, consistent with theoretical expectation that inelastic demand gives more reductions of equilibrium price by rightward supply shift (i.e. output induced by new technology). Indirect supply responses are larger with inelastic *camelina* demand (in the case of -50%), making regional supply curves inelastic.

3.5.3 Impacts on Environmental Outcomes and Farm Income

In order to show the impacts of indirect supply responses on environmental outcomes, the simulation is done using a high *camelina* price scenario (P4). Table 3.7 presents the results including carbon payments associated with the no-till cultivation of wheat and its impacts on environmental quality. The adoption rates are slightly higher with carbon payments because some farms are now more profitable with carbon payment in the WWFC system.

The WWFC system with no-till practice has positive impacts on carbon in the soil, soil emissions of greenhouse gas, and global warming potential of wheat production. The results show adopting camelina and no-till cultivation transits soil to a net sink and global warming potential is also improved substantially. The decrease in adoption rates by indirect supply responses diminishes the magnitudes of these positive environmental outcomes.

Table 3.7 Effects of Supply Responses on Adoption and Environmental Quality

Farm size	Supply responses	Adopters (%)	Change in carbon in soil (%)	Change in soil GHG emissions (%)	Change in GWP of wheat (%)
Large	No	63.26	144.18	-106.71	-24.26
	Yes	55.66	128.01	-92.61	-20.20
Small	No	66.82	151.40	-113.71	-26.51
	Yes	62.18	143.64	-106.94	-24.56

Table 3.8 shows a comparison of the impacts on farm income for both cases, with and without indirect supply responses. Average impact shows a percent of the average profits of the WWFC system to those of the WWF system. The result suggests the farm profits of the WWFC system are higher for small farms, showing new crop rotation improves average income of small farms in the region. Meanwhile, the adopter impact represents a percentage of the average profits adopters would gain if they have the WWF system. This result shows adopters gain 13% and 33% more for large and small farms, respectively, by including *camelina* into their crop rotation. The effect of indirect supply responses on average farm income of the whole farm population is unsubstantial, but the average farm income of adopters differs significantly after adopting *camelina,* especially for small farms (33%; $34,301 to $45,617 per farm).

Fourth, fifth, and sixth columns of Table 3.8 present the effect of indirect supply responses on the change in average treatment effect of the whole farm population and sub-populations (adopters and non-adopters). [17] The average treatment effect refers to the difference between the average farm incomes of the two systems. The size of treatment effects declines after considering indirect supply responses, except non-adopters of large farms. The estimates show that indirect supply responses decrease average treatment effect by $5256 for large farms, $833 for small farms. However, as relative price of *camelina* increases, the effects of indirect supply responses on non-adopters of large farms exceeds that on small farms; for scenario P5 where camelina price is increased by 50%, change in average treatment effects on non-adopters is 67.68% for large farm and 87.20% for small farm. These results indicate that non-adopters can be worse off by indirect supply responses at relatively high *camelina* price level.

Table 3.8 Effects of Supply Responses on Adoption and Farm Income

Farm size	Supply responses	Adopters (%)	Average impact on farm income[a] (%)	Adopter impact on farm income[b] (%)	Change in average treatment effects[c] (%)	Change in average treatment effects on adopters[d] (%)	Change in average treatment effects on non-adopters[e] (%)
Large	No	63.26	101.78	115.23	45.11	87.68	103.00
	Yes	55.66	100.81	113.45			
Small	No	66.82	104.50	135.21	82.24	93.14	98.51
	Yes	62.18	103.76	132.98			

[a] 100* {(mean farm net returns per farm, system 2) / (mean farm net returns per farm, system 1)}
[b] 100* {(adopter mean farm net returns) / (adopter counterfactual mean farm net returns)}
[c] 100*{(average treatment effect with indirect supply responses)/(average treatment effect without indirect supply responses)}
[d] 100*{(average treatment effect on treated (adopters) with indirect supply responses)/(average treatment effect on treated (adopters) without indirect supply responses)}
[e] 100*{(average treatment effect on untreated (non-adopters) with indirect supply responses)/(average treatment effect on untreated (non-adopters) without indirect supply responses)}

[17] Technical definition is found in Appendix B.

3.6 Discussions and Conclusion

Substantial investments in agricultural policies and research have been contributing to a transition to a win-win agricultural system, raising farm incomes and enhancing environmental quality. In other words, developing a win-win scenario requires that quantitative *ex-ante* assessment both addresses farm-scale economic needs and reflects region-wide or market level changes. In this chapter, I extend an *ex-ante* impact assessment model to include interactions across scales by integrating farm-level adoption decisions and aggregate responses. Simulation reveals the supply responses of adopting a new farming system affect the overall adoption rates and reduce the potential environmental improvements and income equality from the new farming system.

Past studies in technology impact assessment required a large amount of detailed data and complex structure to represent adoption rates as a function of output price. [18] Models at the national or global level take adoption rates as given because those models lose farm heterogeneity by aggregation.[19] This analysis keeps the heterogeneity of current and alternative farming systems by formulating an adoption of specific technologies at farm-level while allowing for a relatively simple model structure and a small number of parameters with data available from a secondary source (e.g. census, previous studies, etc.). Therefore, methodology in this research can be replicable to any region where a

[18] For example, the Positive Mathematical Programming (PMP) model calibrates the supply response of farmers by crop-specific elasticities of supply (Mérel and Bucaram 2010) by incorporating cropping patterns under expected crop prices(Chen and Önal, 2012). The agent-based model can calibrate the structure of aggregate supply response with interactive human behaviors (Berger & Troost, 2014), but it requires complex model structures.

[19] Various market equilibrium models at the national or global level allow crop productivity to be endogenously determined by prices. For instance, IMPACT (The International Model for Policy Analysis of Agricultural Commodities and Trade) model, GLOBIOM (Global Biosphere Management Model). But, since these models are highly aggregated or, at least, need some level of aggregation, adoption decision is not represented by farm-level heterogeneity that may affect adoption.

national and local government seeks a new technology adoption when only biophysical and aggregate economic data are available.

Overall results suggest high *camelina* price is essential to boost adoption rates and including *camelina* with no-till management of wheat enhances associated environmental outcomes. These results are consistent with past studies showing the agronomic and economic benefits of introducing *camelina* into the current cropping system in the Northern Great Plains (Obour et al., 2018). An important implication from incorporating the market model is that wheat productivity could be maintained at high levels despite diversifying farming systems with improved soil management practice. On top of not having a substantial reduction in wheat yield biophysically (Tabatabaie et al., 2018), a decrease in aggregate output of wheat is not significant in simulation with the market model.

Another important implication is economic parameters play an important role in determining the size of direct and indirect supply responses. First, price scenarios show how farms react to price change. The small farms, which have low returns from wheat, could gain more benefits from the policy incentives. Second, the magnitude of indirect supply responses is dependent on the relative price of crops rather than the absolute price level. Regardless of the absolute price level, indirect supply responses are large when *camelina* price is relatively higher than wheat price. This result indicates land competition between food and biofuel crops can strengthen price feedback in both markets. Third, the elasticities of each market also affect the size of price feedback effect on adoption rates. With less elastic market demand for new crops, indirect supply responses could reduce the adoption rates.

Viewing the economic feasibility of *camelina* in the PNW through its potential adoption rates strengthens the need for considerable policy interventions given price and market conditions. The implication of my results for policy design is that, first, understanding the interactions between farm-level decisions and market-level responses will give more accurate estimates of adoption rates at the regional level and the magnitudes of changes in economic and environmental outcomes at the disaggregate level (i.e. farm-level economic and environmental outcomes). Furthermore, the welfare gains of the new farming system could be overestimated by not considering indirect supply responses, especially under relatively high *camelina* price conditions. Increasing demand for food and bioenergy increases uncertainty about prices and necessitates accurate adoption estimates reflecting market feedback.

Second, both facilitating market development and high *camelina* price support will be needed to achieve large adoption. Since enhancing the economic benefits of new systems critically depend on favorable economic conditions, policy interventions are necessary to encourage development of the *camelina* market. In order to generate enough profit, higher *camelina* price is required to provide competitive returns of *camelina* to wheat. In addition to addressing the near-term economic needs of farmers, long-term agronomic and economic benefits from the new farming system cannot be maintained without *camelina* market development.

This study assumes that input markets are not shared between productions for grain crop and biofuel crops. However, if crops share inputs for their production, the supply responses from the new farming system can be transmitted from interactions with the input markets. An inelastic labor market, for example, could substantially affect the relative productivity of crops in the market. Exploring aggregate responses with input markets and interactions among markets will be an important topic for future research.

Chapter 4 Empirical Application 2: Impact of Direct Payment Policy on Adoption of Alternative Farming System: Rice Production Systems in South Korea

4.1 Introduction

With an increasing population and changing climate, policy objectives of many countries are primarily focused on achieving both improving productivity and mitigating environmental repercussions. South Korea is one of them because of its low food self-sufficiency rates, increasing temperature, and frequent extreme weather events. The agricultural production systems and policy implementations in South Korea have been centralized in rice and rice farmers. Production of rice contributes about 15% of agriculture and forestry outputs from 2011 to 2015 and about 40% farms mainly produce rice in 2017.[20] Moreover, direct payments to rice farmers account for 80% of the direct payment programs.

Despite significant investments, rice producers in South Korea face environmental and socio-economic difficulties in continuing production. Rice productivity is projected to decrease at around 10% per acre as the temperature rose by 2C° (Calzadilla et al., 2010). In addition to changes in domestic production caused by aging and urbanization, changes in the external environment have strengthened a long-term oversupply of rice. On the demand side, the consumption of rice per person has declined from mid-1980 due to a westernized diet pattern and increasing availability of substitutes. In supply, after expanding rice imports in 2005 and ceasing government purchase, farmers are expected

[20] Data source: Agricultural Production from Korean Statistical Information Service (KOSIS; http://kosis.kr/eng/)

to have responded to lower rice prices by switching their land to other agricultural commodities such as soybeans. However, the Direct Payment Program for Rice Income Compensation has deterred farmers from reducing rice supply, thus becoming a government's financial burden.

In order to address unwanted surpluses of rice and boost farm households income, a revised direct payment program will be enforced in 2020. The recipients of direct payments are extended to all farmers, not just rice, and the intention of the new scheme is to support income of small farms. However, the effect of the new direct payment program on rice production is not clear for two reasons. First, according to the design of the new direct payment program, the money that large-sized rice farms receive will not be changed much, implying low new incentives for crop switching created from new policy. Second, because the new payment program eliminates deficiency payments to rice farmers which cover the loss from lower rice price at harvest time, farmers are expected to be more influenced by market changes. It is unclear to what extent this change can contribute to alleviate structural oversupply of rice. Thus, there is a need for a better understanding of predicted impacts of new direct payments on rice production and farm income.

The objective of this application is to analyze different direct payments scenarios for assessing the economic viability of an alternative farming system that incorporates rice and another grain crop, soybean, in South Korea. The TOA-MDE, farm-level *ex-ante* impact assessment suggested in chapter 2, uses available data to characterize the distributions of net gains from adopting an alternative farming system and evaluates the economic feasibility of farmers' adopting soybeans. The proposed methodology links these farm-level adoption decisions with a partial equilibrium market model, which determines market equilibrium and quantifies how much the changes in markets affect adoption. In other words, in addition to farm's response to new direct payments, the supply responses to price changes by new payment programs are considered in the analysis to assess the possibility of addressing the issue of oversupply.

In this application, soybean is studied because of its growing role in domestic production and food consumption. In South Korea, grain crops, except rice, have low self-sufficiency rates for food consumption but the proportion of food consumption level of soybeans is the largest among grain crops currently cultivated in South Korea. Soybeans have the lowest additional subsidy for switching crops, consequently, the prediction of adopting soybeans will suggest a lower bound of policy impacts with additional crop diversification support on farm income.

The present study makes several contributions to the current literature. First, this is the first *ex-ante* analysis predicting a population level adoption rate in the economic analysis of South Korean agriculture. Much of the literature on South Korean crop production is based on *ex-post* evaluation linking field level responses with a partial or general equilibrium model (Ahn, 2015; Lee & Kim, 2020; Rhew et al., 2017). Such modeling is unsatisfactory to show the effects on whole farm income which is involved with producing multiple agricultural products and actively switching between crops, because models in previous research only take account the interactions between changes in acreages of farms' main crop to market conditions (Cho et al., 2018). In contrast, this analysis simulates farmer's adoption decisions based on the expected farm profits from cropping activities, thus factors affecting crop production can be incorporated into the analysis.

Second, this analysis investigates the distributional impacts of the new payment program on farm income. One criticism of current policy is that the payment does not play a role in income stability for small farms, because the scheme is based on the size of the land on which a farm produced rice. Because one element of a new payment program is fixed for every farm, this income improvement could potentially contribute to the equity among farm households. But to date none has analyzed distributional impacts of the new direct payment program.

Third, this will be the first study to quantify how the recent changes in the direct payment program could lead to more diversified and sustainable farming systems. There is a public consensus that the role of direct payment programs should move from preparing domestic production systems for rice market opening to building a more sustainable agriculture industry and rural area. This quantitative analysis can show whether a new payment program can rationalize its objective to address the payment imbalances among agricultural commodities and maximize the efficiency of resource management in agriculture. Without current government interventions on rice price stabilization, rice is expected to have high price fluctuations even by little quantity changes, so specific focus on the effect of price changes by new direct payment programs on farming system changes is needed (Sagong, 2016).

In the remainder of the chapter, first agricultural policies related to crop production in South Korea are discussed. Second, the study area and data used in this analysis are provided followed by model parameterization. Simulation results and discussions are presented. The final section provides conclusions and policy implications.

4.2 South Korean Rice Production and Agricultural Policies

In line with the green revolution in the 1970s, the agricultural productivity in South Korea has increased to the level of attaining self-sufficiency in rice, the dominant grain crop. However, due to the rapid industrial structure changes and the pressure to open markets for agricultural products, South Korea is experiencing an aging farm household population and a decreasing rice cultivated area. [21] As machinery use has increased from 49.2% (1988) to 98.4% (2018), the labor use has substantially decreased from 34.7 hours/1000m^2 (1995) to 11.7 hours /1000m^2 (2018) of farms. Agriculture's share in GDP and employment have been declining but the pace of these changes are much faster than other countries.[22] These rapid changes have caused a growing concern about maintaining the status quo labor force in agricultural activities and production potential of agriculture in the long term. Moreover, the proportions of non-agricultural incomes are increasing and the income gap between urban and rural areas has widened due to rising labor and other management costs.[23]

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[21] The rice farm population over 65 years old has increased from 16.2% in 1995 to 44.7% in 2018. Meanwhile, the rice cultivated area has decreased from 1,262,000 hectare in 1987 to 738,000 hectare in 2018. Data source: Cultivated Land Area by Crops and Farm Household Economy from KOSIS http://kosis.kr/eng/

[22] Agriculture's share in GDP decreased from 24.9% (1970) to 1.8% (2016) along with share in employment decreased 50.4% (1970) to 4.9% (2016). The years from 40% of agriculture's share in GDP to 7% were taken for 96 years for the U.S. and 73 years for Japan, while 26 years for South Korea. That of employment from 40% to 7% were taken for 53 years for the U.S. and 31 years for Japan, while 14 years for South Korea. Data source: OECD Data and Ministry of Agricultural Food and Rural Affairs of South Korea.

[23] Data source: Price/Household Income and Expenditure from KOSIS. http://kosis.kr/eng/

The interesting feature of Korean agriculture is in the importance of rice production, although rice consumption has been decreasing more than a reduction of production since early 1990s (Table 4.1). Rice production accounts for half of cultivated land and 56.6% farms produce rice in 2017.[24] Due to its large proportions in the agriculture industry, income stabilization of rice farmers is an important political issue. The rice direct payments currently in effect have two elements: fixed and variable direct payment schemes. Fixed portion of the scheme is paid according to the size of the rice area to stabilize the farmers' income regardless of market conditions. On the other hand, a variable direct payment scheme can be regarded as a deficiency payment which compensates the differences between the predetermined target price and the average producer price of rice at the harvest time. Because this payment raises the rice price above the market price, a variable part of the current payment could encourage production.

Table 4.1 Rice Supply and Demand by Year

Year	1965	1970	1980	1996	2000	2005	2010	2015	2018
Supply[1]	6772	8084	6468	5469	6092	6042	6212	5553	6258
Domestic Production	3501 (51.7)	3939 (48.7)	5136 (79.4)	4695 (85.8)	5263 (86.4)	5000 (82.8)	4916 (79.1)	4241 (76.4)	3972 (63.5)
Imports	-	-	-	115 (2.1)	107 (1.8)	192 (3.2)	307 (4.9)	438 (7.9)	398 (6.4)
Demand[1]	3995	5005	5402	5225	5114	5210	4707	4199	4816
Food consumption[2]	3771 (95.3)	4254 (85.0)	5057 (93.6)	4778 (91.4)	4425 (86.5)	3815 (73.2)	3678 (78.1)	3239 (77.1)	3161 (65.6)

Data Source: Korea Rural Economic Institute (2019)
Note: Unit (1000ton)
Parentheses represents proportion
[1]The differences between supply and demand are ending stock
[2]Demand for processed food is excluded

[24] Data source: Cultivated Land Area by Crops from KOSIS. http://kosis.kr/eng/

A key debating point is whether current direct payments affect production decisions both intensively and extensively (i.e. coupling effects) which ultimately contribute to the structural oversupply of rice. Given the profit maximization assumption, both fixed and variable payment schemes can influence farmer's decision making. Increased farm income by fixed payments can distort their production decision (i.e. wealth effects). The coupling mechanism of variable payments are more straightforward because policy design of this scheme is directly based on the farm's production level (i.e. insurance effects).

A large body of literature has investigated the degree of production coupling for decoupling payment programs aiming farm income stabilization. Studies in the U.S. have indicated that the impacts of direct payments on production decisions are limited. Young and Westcott (2000) examines direct and indirect impacts of U.S. farm programs on agricultural production and trade. Various domestic agricultural support programs augment or offsets its impacts on production, affecting planting decisions and distorting U.S. exports. Goodwin and MiIshra (2006) analyzed the distortionary effects of decoupled payments but the impacts are not significant. Bhaskar and Beghin (2009) reviewed the literature on decoupling of farm programs and pointed out that farm programs have small coupling impacts except the impact on land values.

The coupling effects of direct payments have been extensively investigated in the rice production system of South Korea. Sagong (2007) argued government intervention by direct payments is effective in preventing a price decrease due to oversupply. Ahn (2015) reported that variable direct payments to rice farmers have very limited impacts on rice acreage regardless of farmers' anticipation of rice price. Rhew, Kim, and Seo

(2017) also argued that effects of direct payments on production are negligible and price support by direct payments offsets supply reduction by crop conversion. Although previous studies have not reached a consensus about the coupling mechanism of direct payment, to some extent they agreed that the rice payment scheme has resulted in farms' low responsiveness to price decrease.

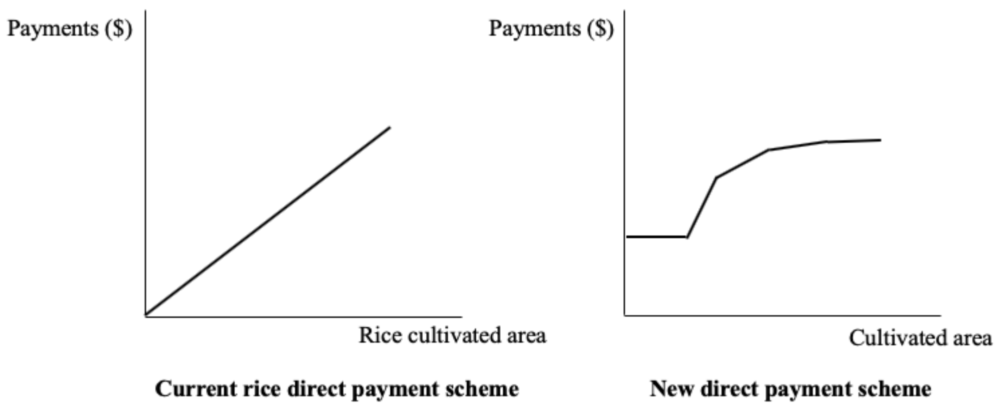
In addition to economic research, practical problems have reinforced the need for redesigning payment programs. Since the current system is paid based on the size of cultivated area, the efficiency of resource allocation and equity issues between large and small farms have emerged. Another equity issue among rice and other crops has risen because a large proportion of direct payment budget was paid to rice farmers.[25] Due to long-term oversupply, the amount of direct payments was close to the World Trade Organization (WTO)'s Aggregate Measurement Support (AMS) limit and the government's decision not to seek special treatment reserved for developing country by WTO raised questions about the continuity of current payment program.

In 2019, a new direct payment program was passed by the National Assembly to reform the direct payment program which strengthens the public role of agriculture by compensating for the effort on sustainable agriculture production and rural area development. The main changes of this program are, first, farms producing any crops are now eligible to receive payments as an income subsidy and second, the distribution of direct payments now puts more weight on small farms. Figure 4.1 conceptually shows how the structure of payments are changed as cultivated area is increased. The goal of

[25] In 2018, 77.5% of direct payments was paid to rice farmers (KREI, 2018).

these changes are to eliminate unwanted rice supply by coupling effects of direct payments and alleviate income inequality among farms. Addressing equity problems between large and small farms and among agricultural products are expected to reduce the importance of rice in farming systems.

Figure 4.1 Comparison of Payment Schemes



In addition to new direct payments, the Korean government is providing a subsidy to encourage switching crops from rice to other grain crops. This policy had been implemented twice for the purpose of adjusting rice production, in 2003-2005 and 2011-2013, and has been in effect from 2018 to the present. However, these programs have not been able to achieve the target because of the unfavorable market conditions such as high rice price and low rice stock.

Theoretically, the payment program for crop diversification should intensify the switching effects with the introduction of a revised direct payment program. Farmers are expected to respond to low rice prices (from long-term oversupply) and high subsidy (from both new direct payment and switching crop payment) by cultivating other grain crops on their land. However, the effect of these policies on production decisions are not clear. First, as reviewed above, empirical results have shown that there are limited coupling effects from the decoupling payments. Second, it is unclear how the new payment program affects markets of rice and other grain crops. For example, if the rice price drops relatively faster than other grain crops, farmers should respond to these relatively low prices by switching the areas cultivated with these other crops. But it is uncertain how much two types of direct payments affect crop markets and augment crop conversion collectively.

4.3 Data

This analysis uses data from the Agriculture Production Cost Surveys in 2017 collected by the Statistics Korea. This survey data provides detailed information about yields, input use, and other economic variables at farm household level. All provinces except metropolitan city areas were covered in the data set (Figure 4.1). Data used at farm level include crop yields, land areas, and as well as quantities and prices of inputs for calculating farm income (1345 observations).

Market data were available for rice and soybeans in the Grain Food Policy dataset from the Ministry of Agriculture, Food and Rural Affairs (MAFRA) of South Korea. Data used for elasticity estimation were from 1980-2017 and the demand and supply accounts are based on 2017 data. The average annual price comes from Korea Agricultural Marketing Information Service (KAMIS).

Figure 4.2 Study Area, South Korea

More than half of the farm population produce only rice in 2017 but detailed crop mix of the rest of farms is not available. From the data on overall farm population, the farms primarily producing grain crops other than rice are only 8.7% of total farm population. Because the government has promoted large-sized rice farms since early 2000, farms whose major crop is rice have larger farm size than farms mainly producing grain crops or vegetables (Table 4.2). Thus, the potential adopters of interest in this research is farm households who only produce rice (System 1). In order to analyze economic feasibility of crop diversification for mitigating oversupply of rice, it is assumed that farmers who produce soybeans with other crops (rice or vegetables) are using alternative systems (System 2). The number of farm households is set to the farms only producing rice from Agriculture, Forestry and Fishery Survey in 2017 and crop share of system 2 is assumed to be the observed share in data.

Table 4.2 Summary Statistics by Farming Systems in 2017

	Farming System 1				Farming System 2			
	Large		Small		Large		Small	
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev
Area (ha)	3.37	3.69	0.508	0.218	2.834	2.399	0.435	0.274
Rice yield (ton/ha)	7.12	1.26	6.91	1.20	6.30	2.47	6.29	2.71
Rice cost ($/farm)	13926	12668	2884.5	1365.0	10815.7	9805.9	1437.86	2018.72
Govt. Subsidies[1] ($/farm)	4808.72	3933.52	1637.27	3234.23	4805.52	4697.40	1351.98	2154.40
Rice variable direct payment[2] ($/ha)	788	-	788	-	788	-	788	-
Soybean yield (ton/ha)	-	-	-	-	0.59	0.85	0.62	0.93
Soybean cost ($/farm)	-	-	-	-	1318.36	4713.0	426.96	771.31
Pepper yield (ton/ha)	-	-	-	-	1.22	1.50	1.09	1.56
Pepper cost ($/farm)	-	-	-	-	2631.75	3665.98	1977.48	2942.13
Garlic yield (ton/ha)	-	-	-	-	3.26	6.13	3.05	5.91
Garlic cost ($/farm)	-	-	-	-	4122.32	11288	2159.19	4825.85
Onion yield (ton/ha)	-	-	-	-	14.85	26.88	7.98	20.44
Onion cost ($/farm)	-	-	-	-	4697.36	14721	684.16	2263.39
Observations	327		555		188		275	

Source: Agricultural production costs survey
[1]Agricultural economic survey
[2] Grain food policy dataset

Table 4.2 shows summary statistics of each farming system. The farm size is classified as small (less than 1ha) and large (more than 1ha). In calculating per farm cost, I consider variable costs except land and capital rents. The data shows that farms producing only rice have larger farm area and higher yield per hectare. Except for soybeans, large farms have similar or better yield per hectare. The data for agricultural subsidies is obtained from the Agricultural Economic Survey and the Grain Food Policy dataset.

Table 4.3 presents income, labor use, and the average shares of crop land between five crops. About 70% of cultivated area is used for rice production, while small farms are using about 25% of their crop area for rice. This supports that small farms in system 2 spend more production costs on pepper and onion than rice, whereas large farms spend the most on rice production in Table 4.2. Table 4.3 also shows how payoff structures are different between grain crops and vegetable crops. Grain crops, rice and soybeans, use less labor but its absolute level of income is low. Given that the cropping vegetables are labor-intensive, only a small portion of land is suitable for each farm to cultivate vegetables. Consequently, the rice share of large farms are much higher than that of small farms.

Table 4.3 Income, Labor Use, and Average Shares of Crops from Survey Data

	Rice	Soybean	Pepper	Garlic	Onion
Income[1] ($/ha)	5414.5	5471.3	23713	29307	27706
	(100)	(100.1)	(438.0)	(541.3)	(511.7)
Income-Revenue ratio (%)	55.6	69.0	69.3	60.5	61.2
Labor use (hours/ha)	101.9	173.9	1450	1248	1003
Hourly income[2]	53.1	31.46	16.4	23.5	27.6
($/ha)	(100)	(59)	(31)	(44)	(52)
Crop Share					
Large	0.696	0.122	0.044	0.066	0.071
Small	0.264	0.278	0.207	0.159	0.092

Source: Agricultural production costs survey 2017
parentheses represent relative index when rice is assumed as 100.
[1]Income = revenue - management costs that are actually paid for production.
[2]Hourly income = income/labor use

4.4 TOA-MDE Application and Policy Scenarios

To investigate policy issues that have been explored in section 4.2, three scenarios are constructed. The scenario 1 is a base scenario with a current direct payment scheme. The rest of scenarios are set with the new payment program and additional payments for grain crop adoption. The scenario 2 only includes the new agricultural direct payment program. Unlike scenario 1, all farms are assumed to receive direct payment by criteria that the government establishes (Figure 4.1; Table 4.4). For example, a farm having 1 hectare land will receive $2200 and with 2.5 hectare land the payments will be $5160.[26] Scenario 3 is a combination of new direct payments and additional direct payments from switching rice to other grain crops, $2550 per hectare of land. The policy scenario 2 and 3

[26] Farm with 1 hectare: $1200 (until 0.5 hectare) + $1000 (from 0.5~1 hectare)
Farm with 2.5 hectare: $1200 (until 00.5 hectare) + $2000 (from 0.5~2 hectare) + $960 (from 2 ~2.5 hectare)

are compared to the base scenario to quantify how much the new payment program affects adoption and farm income.

Table 4.4 New Agricultural Direct Payment Scheme in South Korea

Farm size	Payments
~0.5 ha	$1200/farm
0.5 ~ 2 ha	$2000/ha
2 ~ 6 ha	$1920/ha
6 ~ 30 ha	$1850/ha

To implement the TOA-MDE model, I parameterize production function and corresponding supply and cost functions as described in chapter 2.2.3. For specification, the Cobb-Douglas production function is calibrated to take advantage from its self-dual property. This calibration method exhibits decreasing short-run returns to scale, implying an upward sloping farm's supply curve and quantity of output is decreasing in input prices. A cost-share of given crop and system is used to calibrate γ which is a short-run return to scale of each crop. Table 4.5 shows the parameter value of γ. For farm level calibration, I used Agricultural Production Cost Survey data that was shown in the previous section.

Table 4.5 Farm-level Model Parameters

	Short-run returns to scale			Between-system correlation	Within-system correlation	
	System 1	System 2				
	Rice	Rice	Soybean		System 1	System 2
Large	0.329	0.285	0.158	0.68	1	-0.2720
Small	0.468	0.313	0.370	0.68	1	0.1652

Another important parameters at farm level are between- and within-system correlation coefficient of expected profits given crop and system. As shown in the chapter 2.2.3, the shape of net gains distribution is affected by these correlation coefficients. Positively correlated estimates are supported by the fact that crop rotation of both systems are similar. Within-system correlation in system 2, on the other hand, has different signs between large and small farms, because these statistics reflect that crop share of large farms is more concentrated on rice.

The market demand, supply, and elasticities are shown in Table 4.6 following market calibration in chapter 2.2.3. A general agreement among researchers in Korea is that the responsiveness of own price change is affected not only by supply-side factors but also by both policy and demand side substantially. Regression using only production side information can distort the estimates of own-price elasticity. Therefore, I used estimates from literature which overcomes this issue (Cho et al., 2018; Rhew et al., 2017). Supply and demand of soybeans for feedstock are excluded. The domestic production of soybeans is used for human food, but large magnitudes of feedstocks in imports and domestic utilization could distort demand and supply curves. Rice is imported but the government controls the amount of rice imports by fixed quota every year. Since the domestic rice price is higher than international rice price, the government limits its import just as imposed by WTO. Therefore, the elasticity of rice imports is assumed zero. Demand side estimates come from OLS regression with lagged price ($Q_i = k_0 P_{i(t-1)}^{k_{i1}} e^{k_{i2}t} \epsilon$ for crop i) and estimation results are in the Appendix C. There has been no export of soybeans and the amount of rice export is less than 0.01% of domestic production. Therefore, exports in equilibrium condition are excluded in simulation.

Table 4.6 Market Demand, Supply and Elasticities

	Accounts	Quantity		Elasticity	
		Rice	Soybean	Rice	Soybean
Supply					
	Beginning stocks (BS)	1747	50	0	0
	Production (S)	4197	75	0.188	0.224
	Imports (IM)	382	279	0	0.16
Demand					
	Domestic utilization (DU)	4436	335	-0.224	-0.368
	Exports (EX)	3	0	0	0
	Ending stocks (ES)	1888	69	-1.09	-0.465

4.5 Results and Discussion

4.5.1 Simulation Results

In the application of the TOA-MDE, the model simulates farm profit maximization, adoption rates, and output market equilibria as described in chapter 2. Table 4.7 presents the initial and equilibrium adoption rates for each policy scenario and a percentage change in adoption by output price changes. The equilibrium adoption rates are less than the initial adoption rates due to the lower soybean price caused by output expansion from collective adoption. Hence, the difference between adoption rates are larger when initial adoption rates are higher.

The results are expected to have low adoption rates under current payment program, because population level data suggests that the total rice cultivated area was reduced by -16,994 hectare (-2.3%) while soybean cultivated area was increased 5,082 hectare (10%) in 2017.[27] For the base scenario, the simulation shows low adoption: 0.05% of large farms and 16.89% of small farms would adopt soybean. This estimate is smaller than the case without any direct payments because the current direct payment is favorable to rice producing farms. Especially, large farms' adoption rates are essentially a corner solution. This result may be explained by the fact that the market price of rice is higher than imported rice because of government policy and the cost structure of rice that is profitable for large sized farms as presented in Table 4.3. Rice farming has a high mechanization rate and low labor use per unit than soybean farming, thus rice is more profitable for farmers with large areas together with high price levels.

New direct payment program increases adoption rates for small farms from 16.87 % to 26.39% at new market equilibrium prices, while those of large farms are reduced from 0.06% to 0.05. The result also shows that adoption rates of small farms are the same with the prediction in the absence of direct payments. These results provide the evidence that the new policy could lead rice farmers to be more responsive to changes in economic factors while improving farm income of small farms: small farms are guaranteed to receive higher fixed payments for all types of crop as shown in Figure 4.1.

[27] Data source: Cultivated Land Area by Crops from KOSIS. http://kosis.kr/eng/

Table 4.7 Policy Simulation Results: Adoption Rates

	Initial adoption rates (%)	Equilibrium adoption rates (%)	Differences
Without payments			
Large	0.13	0.12	-0.01
Small	29.01	26.39	-2.62
Scenario 1: Base			
Large	0.05	0.05	-
Small	18.21	16.87	-1.34
Scenario 2: New Scheme			
Large	0.06	0.05	-0.01
Small	29.00	26.39	-2.61
Scenario 3: New scheme + grain crop payments			
Large	0.58	0.52	-0.06
Small	54.08	48.92	-5.16

The combined new scheme and grain crop payments have highest adoption rates in both large and small farms. The adoption of small farms has increased over twice more than base scenario, but still very low for large farms. Whereas, the results of large farms indicate they have much less incentives to change their cropping system, suggesting additional payments are not enough to reverse relative profitability of rice and soybeans.

Table 4.8 shows how market equilibria are changed under each policy scenario. The equilibria points in the table correspond to the notation in Figure 2.4. As expected, adoption leads to an increase in rice price and an reduction in soybean price. The predicted increase in soybean production under scenario 3 is about 25% of domestic production. This estimate indicates targeting small farms can be enough to address low self-sufficiency of soybeans. But the magnitude of changes in rice production are not sufficient to resolve oversupply problems for all scenarios.

From the results, there are two likely causes why the predicted adoption rates of large farms are low. First, the market price of rice is greatly profitable to large farms, because rice production requires much less labor per hectare than other crops as shown in Table 3. Second, the impacts of rice production control (e.g. grain crop support) can be limited with other government programs as the findings of other studies (Rhew et al., 2017). For example, farms with more than 3 hectares have benefited from government credits and rural development programs to specialize their input use for rice production since 2000. With this support, a relative profitability of new crops is reduced while farmers face higher uncertainty if they grow other crops.

Table 4.8 Policy Simulation Results: Equilibrium Prices and Quantities

		At A[1]		At C[2]		At C'[3]	
		P	Q	P	Q	P	Q
Scenario 1: Base							
Rice	Large	1745.3	1455.8	1758.99	1454.7	1757.91	1454.8
	Small		350.7		321.9		324.3
Soybean	Large	4433.4		4255.14	0.043	4275.59	0.038
	Small				8.62		7.68
Scenario 2: New scheme							
Rice	Large	1745.3	1455.8	1766.75	1454.7	1764.55	1454.8
	Small		350.7		304.9		309.70
Soybean	Large	4433.4		4149.96	0.047	4191.49	0.038
	Small				13.723		11.71
Scenario 3: New scheme + grain crop payments							
Rice	Large	1745.3	1455.8	1786.52	1450.8	1781.60	1451.2
	Small		350.7		265.30		275.7
Soybean	Large	4433.4		3897.17	0.046	4001.60	0.038
	Small				25.59		20.64

Note: Unit ($1000, 1000ton)
[1]At A: Initial equilibrium
[2]At C: Equilibria after adoption
[3]At C': Price endogenous equilibria

4.5.2 Sensitivity Analysis

As with other ex-ante analysis, there is uncertainty in exogenous factors and parameters in the model. Sensitivity analysis on the output prices and crop share is conducted to examine the plausible range of effects from changing cropping systems. As the adoption decision is based on farm income, the sensitivity to output price changes of each crop is considered. Since Korean government announced that they will purchase soybeans produced from adopted farms, I assume the soybean price will not be changed by output expansion from collective adoption.

The results in Table 4.9 show that, as expected, lower rice price and higher soybean price give larger adoption than the estimates under baseline output prices. The predicted rates of small farms are similar by either soybean or rice price changes, while the adoption rates of large farms are still very low with soybean price scenarios. Interestingly, when government purchase fixes soybean price (i.e. soybean price is not decreased by collective adoption), adoption rates are higher at new equilibrium. In other words, rising rice price and holding soybean price lead to a higher adoption due to higher profitability of alternative farming systems.

To investigate whether high domestic rice price limits the impacts of direct payments on crop diversification, rice price is assumed to be the same with imported rice price. Imported rice from the U.S. was about \$ 1.350 per kg, while domestic price was \$1.770 per kg in 2017.[28] With lower rice price and additional support, the proportion of adopted large farms increases substantially to over 15%. This result shows the reason

[28] Data source: Prediction Analysis Reports of Rice Production 2017 from the Department of Agricultural Outlook in Korea Rural Economic Institute https://aglook.krei.re.kr/eng/main/main.do

why adoption of soybean is not economically viable for a large percentage of large farms appear to be the high rice price. One policy implication from these results is that additional support for crop diversification could be effective only with low rice price. Since high adoption of small farms are not enough to mitigate rice oversupply problems as shown in Table 4.7, this implication further supports the idea that the effect of policies for rice production adjustments is very limited with high range of rice price (Sagong, 2016).

Table 4.9 Output Prices Sensitivity Analysis

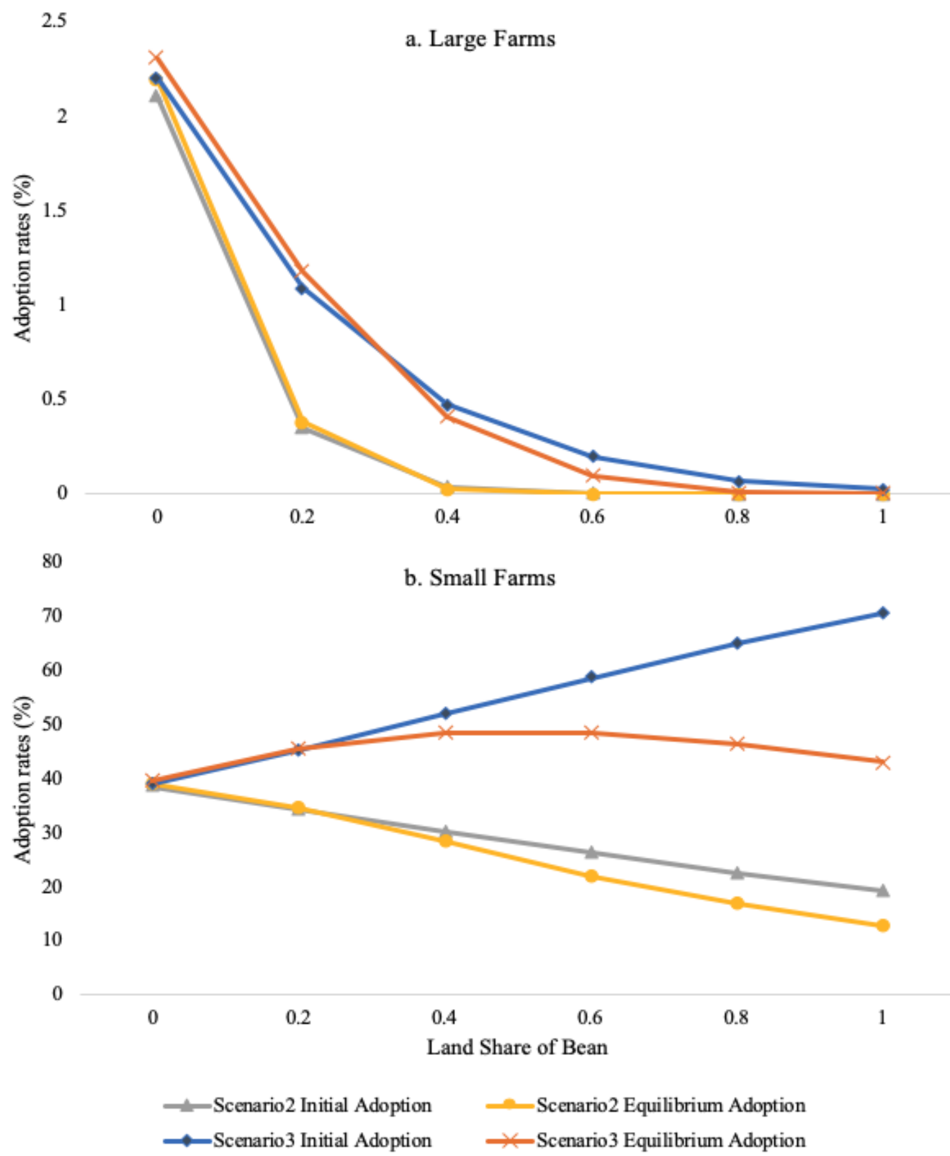
	Initial adoption rates (%)	Equilibrium adoption rates (%)	Differences
Scenario 2: New Scheme			
Rice price -10%			
Large	0.48	0.43	-0.05
Small	39.69	35.66	-4.03
Rice price drops to the level of imported rice			
Large	4.00	3.63	-0.37
Small	54.39	48.56	-5.83
Government purchase soybean at market soybean price			
Large	0.058	0.156	0.098
Small	29.00	39.78	10.78
Government purchase soybean at +10% higher soybean price			
Large	0.106	0.308	0.202
Small	37.03	49.99	12.96
Scenario 3: New scheme + grain crop payments			
Rice price -10%			
Large	3.06	2.85	-0.21
Small	65.34	59.43	-5.91
Rice price drops to the level of imported rice			
Large	15.07	15.29	0.22
Small	77.82	72.14	-5.68
Government purchase soybean at market soybean price			
Large	0.56	0.85	0.29
Small	54.08	57.62	3.54
Government purchase soybean at +10% higher soybean price			
Large	0.92	2.65	1.73
Small	62.73	76.07	13.35

Crop share sensitivity is analyzed to explore how farms allocate land to rice and soybeans in system 2 affects adoption rates. This analysis can give a useful implication for finding target crop shares that can minimize government spending on direct payments. In this analysis, the crop share is exogenous in the model, thus it requires the assumption that changes in the price will not substantially affect the crop share of farm households. This assumption is reasonable for this application, because the price elasticity of the rice area lowers substantially, from 0.2138 to 0.0767, after the current payment scheme is introduced (Park et al., 2010). Furthermore, Cho et al. (2018) shows the rice area doesn't affect the price of other crops.

Figure 4.3 presents the adoption rates of large and small farms as the average proportion of soybean production is increased. The reason why the predicted adoption has positive value at zero share is the profitability of rice production is different between systems. It is apparent that rice is more profitable to large farms, because the proportion of farms that are suitable to adopt soybeans are decreasing as the share of soybeans is increasing. Even though payments for grain crop adoption increase the adoption rates slightly, adding soybeans into their cropping system is barely profitable to large rice producers for all land areas.

On the other hand, about 40% of small farms are predicted to adopt at zero share, implying multi-crop production is more suitable to small farms. With the new payment program, as more area is converted to soybean production, the predicted adoption rates are decreased. Similar to the case of large farms, converting more shares of land to soybeans makes it beneficial to a smaller number of farms. On the other hand, policy scenario 3 which subsidizes soybean producers additionally shows an increase in adoption as more share of land is dedicated to soybeans. However, because higher adoption can result in lower output price, equilibrium adoption rates are dropped with larger share of soybean production.

Figure 4.3 Effects of Changing Average Land Share of Soybean on Adoption



4.5.3 Farming System with Vegetable Crops

Aggregate data for the whole farm population suggests that about 50% of farms grow more than two crops and about 25% of farm households in survey data grow vegetable crops (e.g. pepper, garlic, onion). The South Korean government restricts additional payments for crop diversification to grain crops, because subsidies had increased production resulting in lower prices in 2011. As shown in Table 4.3, since vegetable crops have higher profit margins per hectare than other grain crops except rice, farms producing rice and vegetable crops will respond differently to the new payment policy.

In this subchapter, farming system 1 is redefined as farms producing rice and one vegetable crop among pepper, garlic, onion, while alternative cropping rotation (system 2) has rice, one vegetable crop, and soybean. I assume farms reduce the area for both rice and vegetables and adopt soybeans on that land: the average land share of system 2 is rice 50%, vegetable crop 25%, and soybean 25%.

Table 4.10 presents the simulation results with each three vegetable crops. Overall results show the same patterns as previous analysis. Small farms have higher predicted adoption than large farms and scenario 3 makes more farms profitable to the farming system 2. There are two interesting results: First, the adoption rates of small farms are much higher with garlic or onion. These results reflect the fact that soybean production uses less labor than vegetable crops but have a higher profit margin than rice. Because of this, converting some crop land to soybeans is more profitable to a great number of small farms. Second, the predictions with pepper for large farms are very low. This result may stem from high labor costs of pepper production, hence the profitability of alternative farming with pepper for large farms is very low. As shown in summary statistics, pepper production requires about 200 hours/hectare more than garlic and 400 hours/hectare more than onion. Large farms produce rice more than 80% of land and most of them produce garlic or onion, which require less labor than pepper.

Table 4.10 Simulation Result: Adoption Rates with Vegetable Crops

		Scenario 2: New Scheme	Scenario 3: New scheme + grain crop payments
Pepper	Large	0.001	0.01
	Small	41.37	54.64
Garlic	Large	49.09	64.99
	Small	99.22	99.73
Onion	Large	4.82	11.31
	Small	75.41	84.85

4.6 Conclusion

Farm's supply response and market changes are likely to be important in the policy analysis of farm direct payment programs, because the wealth and insurance effects of decoupled payments can influence farmers' decisions. Also, collective responses can drive not only changes in market supply but also individual responses to policy change. In this application, the TOA-MDE model was used to assess the impacts of a new direct payment program on adopting soybeans as an alternative grain crop in the rice farming system in South Korea. The model is designed to simulate the adoption rates of an alternative crop variety and uses those predictions to assess the effect on the market equilibrium and its feedback effects on farm's decision making under various policy scenarios. This approach offers a flexible framework for evaluating new policies using scarce data and gives timely advice to policy makers for exploring specific policy options.

From the policy simulation a number of conclusions can be drawn. First, adoption of soybeans is economically viable with the new direct payment program for a relatively high percentage of small farms. Second, increased production due to the new program can result in partly offsetting increase in adoption as farmers respond to the lower soybean price. Third, the new direct payment program could improve equity between large and small farms and assist in improving grain crop diversification. Lastly, the new policy as a decoupled income support and additional payments for production adjustment might not be able to address structural rice oversupply problems, unless rice price is decreased substantially.

The analysis in this application does not include other socio-economic factors that can affect farms' adoption decisions. As long as farmers' adaptive feedback is largely dependent on price changes, conventional assumptions on profit maximization are reasonable to provide the upper bound of economic feasibility along with a market change in the *ex ante* analysis. However, the aging of the agricultural population is increasing the preference of crops with low labor input and high mechanization rates such as rice and onions. This change in socio-economic environment will be an important factor for further analysis on the long-term impact of new policy.

Chapter 5 Conclusions

This dissertation provides a method that can evaluate the economic feasibility of a sustainable agricultural system by integrating farm-level ex-ante impact assessment with a partial market equilibrium model. This methodology links models at micro- and macro-level using a multi-scale approach that envelops both disaggregated (individual or farm level) profit maximization to aggregated (regional or domestic) market level changes. The simulation method suggested in this dissertation iteratively solves structural models consisting of three different levels: farm profit maximization, population adoption rates, and multi-output market equilibria. This work explicitly considers the impacts of population-level adoption on market equilibrium and its feedback on farmers' adoption decisions. This method provides a comprehensive understanding of how adoption decisions can affect and be affected by changes in prices and policies by capturing the impacts of indirect supply responses.

The literature review reveals that establishing linkages between farm-level disaggregate models and market-level aggregate models is essential in trade-off analysis to predict more accurate effects of adoptions by capturing their feedback effects. Thus, this dissertation suggests an integrated approach for quantifying the effects of collective adoptions on farm's adoption decision through market changes. The model considers the price changes by output expansions of new technology.

Two empirical applications estimate price-endogenous adoption rates and quantify price feedback effects of collective adoptions. The empirical applications show the differences with and without consideration to indirect supply responses and the importance of price feedback in impact assessment. The first application examines the economic viability of a new biofuel crop, *Camelina Sativa*, in the Pacific Northwest of the United States under various output price scenarios. The second application investigates how the economic potential of crop diversification changes, due to output market changes from the introduction of a new direct payment program in a rice production system of South Korea.

Overall results suggest that output market changes by collective adoption do affect population adoption rates. The magnitudes of changes are largely determined by relative price of competing crops and associated economic parameters. The price-endogenous adoption rates are higher under price conditions which lead to the higher profitability of the alternative crop. However, the size of price feedback effects on the adoption rates are affected by important economic parameters that affect the magnitudes of shifts in supply which ultimately determine where new market equilibrium would be. The results from the analyses indicate that inelastic demand or high crop share reduce market equilibrium price more, resulting in lower adoption rates.

Lower adoption rates by indirect supply responses imply that the spatial distribution of environmental outcomes and distributional impacts on farm income could be over- or under-estimated. For example, in the *camelina* application, the aggregate impacts of adopting new farming systems lead to a decrease in potential improvements of environmental outcomes and non-adopters' welfare. Hence, the market changes as a result of the introduction of a new technology could play an important role in evaluating the impacts of the new sustainable farming system. The importance of this implication depends on which scale the policy targets; in other words, the predicted impacts of indirect supply responses depend on whether aggregate adoptions can change market prices or not. If changes in production from adopters are sufficient to lead to price changes, the welfare and environmental impacts of new technology would be more affected by indirect supply responses.

Insights from this dissertation enhance our understanding of technology improvements in agriculture and their impacts for two reasons: First, supply responses play an important role in evaluating the economic feasibility of a new farming system. In order to achieve win-win, economically profitable and environmentally better, agricultural systems, multi-scale and multi-dimensional consideration can play an important role in predicting more accurate synergies or trade-offs of farm level agricultural activities and more aggregate level changes. Second, the model integration of this dissertation shows a more comprehensive methodology that includes both horizontal (i.e. economic and environmental outcomes) and vertical (i.e. farm - population - market) linkages with less model structures and data requirements. This methodological advantage makes this method applicable to any region where a government seeks a more sustainable agricultural system with sufficiently accurate and timely analysis.

This dissertation has relied on partial equilibrium framework and focused on the output market changes. The indirect supply responses can be transmitted from the changes in input markets from the introduction of new farming systems. For example, an inelastic labor market could substantially affect the relative productivity of crops in the market. Therefore, exploring aggregate responses from input markets and interactions among output and input markets will be an important topic for future research.

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Appendices

Appendix A: Model Calibration - Production Function

In this appendix, I calibrate supply and cost function parameters using Cobb-Douglas production function. Each farm chooses variable input $\boldsymbol{x}$ and quasi-fixed input f to maximize its profit for crop i under system h given input price $\boldsymbol{w}$ and output price $\boldsymbol{p}$. For each system $h = 1,2$, the production function for crop i is

$$y_{hi}(x) = \alpha_{hi0} \prod_{v=1}^{n} x_{hiv}{}^{\alpha_{hiv}} \prod_{t=1}^{T} f_{hit}{}^{\beta_{hit}} \tag{A-1}$$

Where the marginal product of variable input $\boldsymbol{x}$ is

$$y_{hiv} = \frac{\partial y_{hi}(x)}{\partial x_{hiv}} = \alpha_{hiv} x_{hiv}{}^{\alpha_{hiv}-1} \alpha_{hi0} \prod_{t=1}^{n} f_{hit}{}^{\beta_{hit}} \prod_{k \neq v}^{n} x_{hik}{}^{\beta_{hik}} = \frac{\alpha_{hiv}}{x_{hiv}} y_{hi}(x).$$

From the first order condition $\frac{y_{hiv}}{y_{hij}} = \frac{w_{hiv}}{w_{hij}}$ by cost minimization,

$$\frac{w_{hiv}}{w_{hi1}} = \frac{\alpha_{hiv}}{\alpha_{hi1}} \frac{x_{hi1}}{x_{hiv}} \; or \; x_{hiv} = \frac{\alpha_{hiv}}{w_{hiv}} \frac{w_{hi1}}{\alpha_{hi1}} x_{hi1} \tag{A-2}$$

To produce output y_{hi}, substitute (A-2) into production function (A-1)

$$y_{hi}(x) = \alpha_{hi0} \prod_{v=1}^{n} \left(\frac{\alpha_{hiv}}{w_{hiv}} \frac{w_{hi1}}{\alpha_{hi1}} x_{hi1}\right)^{\alpha_{hiv}} \prod_{t=1}^{T} f_{hit}{}^{\beta_{hit}}$$

$$y_{hi}(x) = \alpha_{hi0} F \left(\frac{w_{hi1}}{\alpha_{hi1}}\right)^{\gamma_{hi}} \left[\prod_{v=1}^{n} \alpha_{hiv}{}^{\alpha_{hiv}}\right] \left[\prod_{v=1}^{n} w_{hiv}{}^{-\alpha_{hiv}}\right] x_{hi1}{}^{\gamma_{hi}}$$

$$where \; \gamma_{hi} = \sum_{v=1}^{n} \alpha_{hiv}, F = \prod_{t=1}^{T} f_{hit}{}^{\beta_{hit}} \tag{A-3}$$

Rearranging (A-3) yields

$$x_{hi1}{}^{c}(w,y) = \frac{\alpha_{hi1}}{w_{hi1}}\left(\frac{1}{\alpha_{hi0}F}\frac{W_{hi}}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}} y_{hi}{}^{\frac{1}{\gamma_{hi}}} \tag{A-4}$$

where $W_{hi} = \prod_{v=1}^{n} w_{hiv}{}^{\alpha_{hiv}}$, $A_{hi} = \prod_{v=1}^{n} \alpha_{hiv}{}^{\alpha_{hiv}}$

And substituting back into (A-2) gives conditional input demand function

$$x_{hiv}{}^{c}(w,y) = \frac{\alpha_{hiv}}{w_{hiv}}\left(\frac{1}{\alpha_{hi0}F}\frac{W_{hi}}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}} y_{hi}{}^{\frac{1}{\gamma_{hi}}}. \tag{A-5}$$

Thus, we obtain cost function for crop i under system h

$$C_{hi}(w,y) = \sum_{v=1}^{n} w_{hiv} x_{hiv}{}^{c} = \gamma_{hi}\left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}} y_{hi}{}^{\frac{1}{\gamma_{hi}}}. \tag{A-6}$$

The profit maximization problem of crop i becomes

$$\max \pi(p,w) = p y_{hi} - C_{hi}(w,y). \tag{A-7}$$

The first order condition is

$$p_{hi} - \left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}} y_{hi}{}^{\frac{1}{\gamma_{hi}}-1} = 0. \tag{A-8}$$

Rearranging equation (A-8) gives supply function of crop i

$$y_{hi}(p,w) = p_{hi}{}^{\frac{\gamma_{hi}}{1-\gamma_{hi}}}\left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{-\frac{1}{1-\gamma_{hi}}}. \tag{A-9}$$

From the second order condition,

$$\frac{1-\gamma_{hi}}{\gamma_{hi}}\left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}} y^{\frac{1}{\gamma_{hi}}-2} > 0 \text{ holds if } \gamma_{hi} < 1 \tag{A-10}$$

Therefore, the price elasticity of supply is

$$\frac{\partial y_{hi}}{\partial p_{hi}}\frac{p_{hi}}{y_{hi}} = \frac{\gamma_{hi}}{1-\gamma_{hi}} \tag{A-11}$$

From the derivation, we have unknown parameters $(\alpha_{hi0}, \alpha_{hiv}, \gamma_{hi}, W_{hi}, A_{hi}, F)$.

Assuming output and input market are perfect, the condition $x_{hiv}{}^{c}(w,y) = x_{hiv}(p,w)$ and equation (A-8) gives calibrated $\boldsymbol{\alpha_{hiv}}$ by cost share.

$$\frac{w_{hiv}x_{hiv}}{p_{hi}y_{hi}} = \frac{w_{hiv}x_{hiv}{}^{c}}{p_{hi}y_{hi}} = \frac{w_{hiv}\frac{\alpha_{hiv}}{w_{hiv}}\left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}}y^{\frac{1}{\gamma_{hi}}}}{\left(\frac{W_{hi}}{\alpha_{hi0}F}\frac{1}{A_{hi}}\right)^{\frac{1}{\gamma_{hi}}}y^{\frac{1}{\gamma_{hi}}}} = \boldsymbol{\alpha_{hiv}}$$

From these results, $\boldsymbol{A_{hi}} = \prod_{v=1}^{n}\alpha_{hiv}{}^{\alpha_{hiv}}$, $\boldsymbol{\gamma_{hi}} = \sum\alpha_{hiv} = \frac{\sum w_{hiv}x_{hiv}}{p_{hi}y_{hi}}$. Given the fact that supply represents average output level, I can use observed output data to calibrate intercept of supply function:

observed $\widetilde{y_{hi}} = \widetilde{p_{hi}}^{\frac{\gamma_{hi}}{1-\gamma_{hi}}}\left(\frac{1}{\alpha_{hi0}F}\frac{W_{hi}}{A_{hi}}\right)^{-\frac{1}{1-\gamma_{hi}}}$, then $\frac{1}{\alpha_{hi0}F}\frac{W_{hi}}{A_{hi}} = \tilde{y}^{\gamma_{hi}-1}\widetilde{p_{hi}}^{\gamma_{hi}}$.

Appendix B: Conceptual Framework of Price Endogenous Adoption Rates and Outcome Indicators[29]

In chapter 2, the adoption rate of system 2 is the proportion of farms using system 2 which is represented by the cumulative distribution of net gains (i.e. the differences between expected profits of each farming system).

$$r(\boldsymbol{p}, \boldsymbol{w}, 2) = 100 \int_0^\infty \varphi(\omega|\boldsymbol{p}, \boldsymbol{w}) d\omega$$

The share of farms using system 1 is $r(\boldsymbol{p}, \boldsymbol{w}, 1) = 100 - r(\boldsymbol{p}, \boldsymbol{w}, 2)$.

Since adoption rates are derived from net gains ($\boldsymbol{\omega}$; the differences between net returns of each farming system), its relationship with outcomes of the farming system can be characterized as the joint outcome distribution between $\boldsymbol{\omega}$ and outcome k: $\boldsymbol{\varphi}(\boldsymbol{\omega}, k)$ where outcome k denotes the outcome of the farming system. v and z are its economic and environmental representation. The joint relationship shows the tradeoff between economic and environmental outcome, allowing us to construct impact indicators which quantify the impacts of the new farming system on the whole population. In the process of deriving impact indicators, specific groups (in this chapter, $\boldsymbol{\omega} > 0$ for $h = 1$ and $\boldsymbol{\omega} < 0$ for $h = 2$) are defined so that the adoption process can be linked to outcome distribution.

The integration of joint distribution, $\boldsymbol{\varphi}(\boldsymbol{\omega}, k)$, conditional on farming system and price gives the marginal outcome distribution $\chi(k|p, h, \Theta)$ where Θ is a vector of

[29] The theoretical background and more detailed discussions can be found in Antle 2011; Antle, Stoorvogel, and Valdivia 2014.

exogenous variables. The outcome distribution for the entire population can be represented as a mixture of $\chi(k|p,h,\Theta)$ with adoption rates.

$$\chi(k|p,\Theta) = r(p,1)\chi(k|p,1,\Theta) + r(p,2)\chi(k|p,2,\Theta) \qquad \text{(B-1)}$$

The population-level indicator I_k with system h is defined by using $\chi(k|p,h,\Theta)$ and the range of the variable considered $\iota(k)$ (e.g. $\iota(v) = pq - c(q)$ where q is expected output, $c(q)$ is cost of production).

$$I_k(p,h,\Theta) \equiv \int \iota(k)\chi(k|p,h,\Theta)dk \text{ where } k = v,z \qquad \text{(B-2)}$$

Combining (B-1) and (B-2) gives the impact indicators for the entire population:

$$I_k(p,\Theta) = r(p,1)I_k(p,1,\Theta) + r(p,2)I_k(p,2,\Theta) \qquad \text{(B-3)}$$

The outcome from treatment in the treated and untreated sub-population in the 'treatment effect' literature corresponds to the impact indicators. The conditional mean of outcome k is given ω and normality assumption

$$\mu_k(\omega,h) = \frac{\mu_k(h) + (\omega - \mu_\omega)\sigma_k(h)\theta_k(h)}{\sigma_\omega} \qquad \text{(B-4)}$$

where $\mu_k(h)$ is the unconditional mean of outcome k for system h, μ_ω mean of ω, σ_k standard deviation of k, θ_k correlation between outcome $k(h)$ and ω, and σ_ω standard deviation of ω. The averages of the truncated distribution of ω for each system is

$$\mu_\omega(h) = \mu_\omega - (-1)^h\sigma_\omega\lambda(h) \qquad \text{(B-5)}$$

where $\lambda(a,h) = \frac{\phi^*[\frac{a-\mu_\omega}{\sigma_\omega}]}{r(h,a)}$, the inverse Mill's ratio for the truncated distribution of ω associated with each system for a standard normal density ϕ^*, adoption threshold a. Thus, the means of the truncated outcome distributions for each system are

$$\mu_k(h,a) = \mu_k(h) - (-1)^h \sigma_k(h)\theta_k(h)\lambda(a,h) \qquad \text{(B-6)}$$

From this unconditional means for each system, the average treatment effect for the entire population is $ATE_k = \mu_k(2) - \mu_k(1)$. The counterfactual mean is derived from the expectation of distribution of outcome for the other system:

$$\widetilde{\mu_k}(1,a) = \mu_k(2) - \sigma_k(2)\theta_k(2)\lambda(a,1) \qquad \text{(B-7)}$$

$$\widetilde{\mu_k}(2,a) = \mu_k(1) - \sigma_k(1)\theta_k(1)\lambda(a,2) \qquad \text{(B-8)}$$

Taking the (B-6) ~ (B-8), average treatment effects on the treated is $ATT_k = \mu_k(2,a) - \widetilde{\mu_k}(2,a)$, while the average treatment effects on the untreated is $ATU_k = \widetilde{\mu_k}(1,a) - \mu_k(1,a)$.

Appendix C: Document SAS Source Code of the TOA-MDE model

The TOA-MDE model shown in Chapter 2 is designed to link *ex-ante* farm level impact assessment, TOA-MD, and a partial market equilibrium model. This appendix presents the SAS source programming code of the TOA-MDE model showing how this model incorporates changes in output prices. The TOA-MDE programming coding is based on "TOA-MD 7.0: Parsimonious Technology Adoption and Impact Assessment" (available at https://tradeoffs.oregonstate.edu/). The following code uses the empirical application of the rice production system in South Korea presented in Chapter 4.

In order to link the TOA-MD model to a partial market equilibrium model, a macro simulation was created within the TOA-MD software (Figure 2.5). Therefore, the TOA-MDE program can be divided into two parts: 1) Initial adoption rates and 2) Macro simulation. The first stage 'Initial adoption rates' is the part where the programming is based on the TOA-MD model. At this stage, the model optimizes farm expected profits and calculates adoption rates by comparing two farming systems under each price and strata. The macro simulation, which is new in the TOA-MDE model, reads the initial equilibrium adoption rates and output prices from the previous stage and iteratively solves farm expected profits, equilibrium adoption rates, output prices until it converges.

1) Input variables

The table below shows the input variables that is used in the TOA-MDE model.

Table C.1 Variable Names Used in SAS Source Code

Variable	Description
$PChi$	Price of crop i system h ($/ton)
$SCENARIOi$	Price scenario of crop i (%)
$YChi$	Yield of crop i system h (ton/year)
$SVhi$	Standard deviation of yield for crop i, system h (ton/year)
$CChi$	Variable costs of crop i system h ($/ton/year)
$FChi$	Fixed costs of crop i system h ($/ton/year)
$WChi$	Weight (crop share) of crop i system h
$NUMFARM$	The number of farms
E_BEGSTi	Elasticity of crop i's beginning stock
$BEGSTi$	Beginning stock of crop i (ton/year)
E_PRODi	Elasticity of crop i's domestic production
$PRODi$	Domestic production of crop i (ton/year)
E_IMi	Elasticity of crop i's imports
IMi	Imports of crop i (ton/year)
$E\_DOMESTICi$	Elasticity of crop i's domestic utilization
$DOMESTICi$	Domestic utilization of crop i (ton/year)
E_EXi	Elasticity of crop i's export
EXi	Export of crop i (ton/year)
E_ENDSTi	Elasticity of crop i's ending stock
$ENDSTi$	Ending stock of crop i (ton/year)

2) Initial adoption rates

In this stage, the TOA-MDE model chooses Cobb-Douglas functional form and the program uses the calibrated estimates in Appendix A. The functional form can be specified in a different way by its application. Once the model input data and merge parameter files, the adoption rates are calculated by each price and strata loop.

```
/*Begin price loop */
do P=1 to PT;
PNO=P; *RENAME PRICE LOOP NUMBER;
SET PRICE POINT=P;
```

```
/* Begin tradeoff loop */
do TP=1 to NT;
TNO=TP; *RENAME TRADEOFF LOOP NUMBER;
set trade point=TP;

/* Begin STRAT Loop */
do REGNO = 1 to NREG;
REGN=REGNO;
set PROD_C point=REGN;
set STD_C point=REGN;
set VCOST_C point=REGN;
set FCOST_C point=REGN;
set PRICE_C point=REGN;
set WEIGHT_C point=REGN;
set WEIGHT_ES point=REGN;
set ES point=REGN;
set FARM point=REGN;
set RHO point=REGN;
set DEMAND point=REGN;

****** CROP RETURNS ******;

* NOTATION: SYSTEM/CROP/INPUT;
*** SYSTEM 1 - CALCULATES NET RETURNS WITH SUPPLY AND COST FUNCTIONS
/*PRICE SCENARIO*/;
cp11=(SCENARIO1/100)*PC11;
P12=(SCENARIO2/100)*PC12;
P13=(SCENARIO3/100)*PC13;
P14=(SCENARIO4/100)*PC14;
P15=(SCENARIO5/100)*PC15;
P16=(SCENARIO6/100)*PC16;
P17=(SCENARIO7/100)*PC17;
P18=(SCENARIO8/100)*PC18;

campri=cp11;
delst1=1;
fbegst1=prod1/10;

do until (ptest<.1);
fbegst1=fbegst1+delst1;
BEGST1_L2=E_BEGST1*fBEGST1/campri; *Beginning stock slope;
BEGST1_L1=fBEGST1-BEGST1_L2*campri; *Beginning stock intercept;
PROD1_L2=E_PROD1*PROD1/campri; *production slope;
PROD1_L1=PROD1-PROD1_L2*campri; *(production+camelina) intercept;
IM1_L2=E_IM1*IM1/campri; *import slope;
IM1_L1=IM1-IM1_L2*campri; *import intercept;
DOMESTIC1_L2=E_DOMESTIC1*DOMESTIC1/campri; *domestic use slope;
DOMESTIC1_L1=DOMESTIC1-DOMESTIC1_L2*campri; *domestic use intercept;
EX1_L2=E_EX1*EX1/campri; *export slope;
EX1_L1=EX1-EX1_L2*campri; *export intercept;
ENDST1_L2=E_ENDST1*ENDST1/campri; *ending stock slope;
ENDST1_L1=ENDST1-ENDST1_L2*campri; *ending stock intercept;
TSUPPLY110=BEGST1_L1+PROD1_L1+IM1_L1; *total supply intercept;
TSUPPLY120=BEGST1_L2+PROD1_L2+IM1_L2; *total supply slope;
TDEMAND110=DOMESTIC1_L1+EX1_L1+ENDST1_L1; *total demand intercept;
```

```
TDEMAND120=DOMESTIC1_L2+EX1_L2+ENDST1_L2; *total demand slope;
newpri=(TDEMAND110-TSUPPLY110)/(TSUPPLY120-TDEMAND120); *calibrated
price where TS=TD;
ptest=100*abs(newpri-campri)/campri;
if newpri>campri then delst1=fbegst1/100;  * if price too high,
increase begst;
if newpri<campri then delst1=-fbegst1/100; * if price too low, reduce
begst;
end;
P11=newpri;
P21=newpri;

* ZERO INPUT COSTS; *TO PREVENT MATH FAILURE;
IF VC111=0 then VC111=1; IF VC112=0 then VC112=1; IF VC113=0 then
VC113=1; IF VC114=0 then VC114=1;
*WHEN PC=0 OR YC=0; *TO PREVENT MATH FAILURE;
IF PC11=0 THEN PC11=1; IF YC11=0 THEN YC11=1;
*ZERO VARIABLE COSTS; *TO PREVENT MATH FAILURE;
IF CC11=0 THEN CC11=1;

/*COBB-DOUGLAS PARAMETERS*/

GAMMA11 = CC11/(PC11*YC11);
GAMMA13 = CC23/(P13*YC23);
IF GAMMA11=1 THEN GAMMA11=0.99;
IF W11=0 THEN W11=1; IF W12=0 THEN W12=1; IF W16=0 THEN W16=1;

*SUPPLY AND COST FUNCTION;
alpha11= ((YC11)**(GAMMA11-1))*(P11**(GAMMA11));
alpha13= ((YC23)**(GAMMA13-1))*(P13**(GAMMA13));

supply11=alpha11**(-1/(1-GAMMA11))*P11**(GAMMA11/(1-GAMMA11));
supply13=alpha13**(-1/(1-GAMMA13))*P13**(GAMMA13/(1-GAMMA13));

IF PC11=1 AND CC11=1 THEN SUPPLY11=1;

COST110 = GAMMA11*((ALPHA11)**(1/GAMMA11))*(SUPPLY11**(1/GAMMA11));
ACOST11=COST110-CC11;
COST11=COST110-ACOST11;

COST230 = GAMMA13*((ALPHA13)**(1/GAMMA13))*(SUPPLY13**(1/GAMMA13));
ACOST13 = COST230-CC23;
COST13 = COST230-ACOST13;

*REVERSE BACK TO ZERO SUPPLY IF NO SUPPLY;
IF SUPPLY11=1 THEN SUPPLY11=0;
IF COST11=1 THEN COST11=0;
IF GAMMA11=0.99 THEN GAMMA11=0;

* NET RETURNS system 1;
NR11 = P11*SUPPLY11-COST11-FC11;
NR12 = (PC12*YC12 - CC12 - FC12/SPATH);
NR13 = (PC13*YC13 - CC13 - FC13/SPATH);
NR14 = (PC14*YC14 - CC14 - FC14/SPATH);
NR15 = (PC15*YC15 - CC15 - FC15/SPATH);
```

```
NR16 = (PC16*YC16 - CC16 - FC16/SPATH);
NR17 = (PC17*YC17 - CC17 - FC17/SPATH);
NR18 = (PC18*YC18 - CC18 - FC18/SPATH);

IF NR17<=0 THEN NR17=0;

NR1=WC11*NR11+WC12*NR12+WC13*NR13+WC14*NR14+WC15*NR15+WC16*NR16+WC17*NR
17+WC18*NR18;

* VARIANCE SYSTEM1;
V11=SC11**2;
V12=SC12**2;
V13=SC13**2;
V14=SC14**2;
V15=SC15**2;
V16=SC16**2;
V17=SC17**2;
V18=SC18**2;

SV1=(V11*WC11**2+V12*WC12**2+V13*WC13**2+V14*WC14**2+V15*WC15**2+V16*WC
16**2+V17*WC17**2+V18*WC18**2)+ 2*(RHOC1)
      *(WC11*SC11*WC12*SC12+WC11*SC11*WC13*SC13+WC11*SC11*WC14*SC14
      +WC11*SC11*WC15*SC15+WC11*SC11*WC16*SC16+WC11*SC11*WC17*SC17+WC11
*SC11*WC18*SC18
      +WC12*SC12*WC13*SC13+WC12*SC12*WC14*SC14+WC12*SC12*WC15*SC15+WC12
*SC12*WC16*SC16
      +WC12*SC12*WC17*SC17+WC12*SC12*WC18*SC18+WC13*SC13*WC14*SC14+WC13
*SC13*WC15*SC15
      +WC13*SC13*WC16*SC16+WC13*SC13*WC17*SC17+WC13*SC13*WC18*SC18+WC14
*SC14*WC18*SC18
      +WC14*SC14*WC17*SC17+WC14*SC14*WC16*SC16+WC14*SC14*WC15*SC15+WC15
*SC15*WC18*SC18
      +WC15*SC15*WC17*SC17+WC15*SC15*WC16*SC16+WC16*SC16*WC18*SC18+WC16
*SC16*WC17*SC17
      +WC17*SC17*WC18*SC18); * VARIANCE OF SYSTEM 1;


* SYSTEM 2 - CALCULATES NET RETURNS WITH SUPPLY AND COST FUNCTIONS;
/*PRICE SCENARIO*/;
*P21=(SCENARIO1/100)*PC21;
CP22=(SCENARIO2/100)*PC22;
P23=(SCENARIO3/100)*PC23;
P24=(SCENARIO4/100)*PC24;
P25=(SCENARIO5/100)*PC25;
P26=(SCENARIO6/100)*PC26;
P27=(SCENARIO7/100)*PC27;
P28=(SCENARIO8/100)*PC28;

campri2=cp22;
delst2=0;
fbegst2=prod2/10;

do until (ptest2<.1);
fbegst2=fbegst2+delst2;
BEGST2_L2=E_BEGST2*fBEGST2/campri2; *Beginning stock slope;
```

```
BEGST2_L1=fBEGST2-BEGST2_L2*campri2; *Beginning stock intercept;
PROD2_L2=E_PROD2*PROD2/campri2; *production slope;
PROD2_L1=PROD2-PROD2_L2*campri2; *production intercept;
IM2_L2=E_IM2*IM2/campri2; *import slope;
IM2_L1=IM2-IM2_L2*campri2; *import intercept;
DOMESTIC2_L2=E_DOMESTIC2*DOMESTIC2/campri2; *domestic use slope;
DOMESTIC2_L1=DOMESTIC2-DOMESTIC2_L2*campri2; *domestic use intercept;
EX2_L2=E_EX2*EX2/campri2; *export slope;
EX2_L1=EX2-EX2_L2*campri2; *export intercept;
ENDST2_L2=E_ENDST2*ENDST2/campri2; *ending stock slope;
ENDST2_L1=ENDST2-ENDST2_L2*campri2; *ending stock intercept;
TSUPPLY210=BEGST2_L1+PROD2_L1+IM2_L1; *total supply intercept;
TSUPPLY220=BEGST2_L2+PROD2_L2+IM2_L2; *total supply slope;
TDEMAND210=DOMESTIC2_L1+EX2_L1+ENDST2_L1; *total demand intercept;
TDEMAND220=DOMESTIC2_L2+EX2_L2+ENDST2_L2; *total demand slope;
newpri2=(TDEMAND210-TSUPPLY210)/(TSUPPLY220-TDEMAND220); *calibrated
price where TS=TD;
ptest2=100*abs(newpri2-campri2)/campri2;
if newpri2>campri2 then delst2=fbegst2/100;  * if price too high,
increase begst;
if newpri2<campri2 then delst2=-fbegst2/100; * if price too low, reduce
begst;
end;
p22=newpri2;

*WHEN PC=0 OR YC=0;  *TO PREVENT MATH FAILURE;
IF PC21=0 THEN PC21=1; IF PC22=0 THEN PC22=1; IF PC23=0 THEN PC23=1; IF
PC24=0 THEN PC24=1; IF PC25=0 THEN PC25=1;
IF YC21=0 THEN YC21=1; IF YC22=0 THEN YC22=1; IF YC23=0 THEN YC23=1; IF
PC24=0 THEN PC24=1; IF PC25=0 THEN PC25=1;
*ZERO VARIABLE COSTS; *TO PREVENT MATH FAILURE;
IF CC21=0 THEN CC21=1; IF CC22=0 THEN CC22=1; IF CC23=0 THEN CC23=1; IF
PC24=0 THEN PC24=1; IF PC25=0 THEN PC25=1;

/*COBB-DOUGLAS PARAMETERS;*/
GAMMA21 = CC21/(P21*YC21);
GAMMA22 = CC22/(P22*YC22);
GAMMA23 = CC23/(P23*YC23);

IF GAMMA21=1 THEN GAMMA21=0.99; IF GAMMA22=1 THEN GAMMA22=0.99;

*SUPPLY AND COST FUNCTION;
alpha21= ((YC21)**(GAMMA21-1))*(P21**(GAMMA21));
alpha22= ((YC22)**(GAMMA22-1))*(P22**(GAMMA22));
alpha23= ((YC23)**(GAMMA23-1))*(P23**(GAMMA23));

supply210=alpha21**(-1/(1-GAMMA21))*P21**(GAMMA21/(1-GAMMA21));
supply220=alpha22**(-1/(1-GAMMA22))*P22**(GAMMA22/(1-GAMMA22));
supply230=alpha23**(-1/(1-GAMMA23))*P23**(GAMMA23/(1-GAMMA23));

*IF PC21=1 AND CC21=1 THEN SUPPLY210=1; IF PC22=1 AND CC22=1 THEN
SUPPLY220=1; IF PC26=1 AND CC26=1 THEN SUPPLY260=1;

COST210 = GAMMA21*((ALPHA21)**(1/GAMMA21))*(SUPPLY210**(1/GAMMA21));
ACOST21 = COST210-CC21;
```

```
COST21 = COST210-ACOST21;
COST220 = GAMMA22*((ALPHA22)**(1/GAMMA22))*(SUPPLY220**(1/GAMMA22));
ACOST22 = COST220-CC22;
COST22 = COST220-ACOST22;
COST230 = GAMMA23*((ALPHA23)**(1/GAMMA23))*(SUPPLY230**(1/GAMMA23));
ACOST23 = COST230-CC23;
COST23 = COST230-ACOST23;

IF SUPPLY210=1 THEN SUPPLY210=0; IF SUPPLY220=1 THEN SUPPLY220=0;
IF SUPPLY230=1 THEN SUPPLY230=0;

* NET RETURNS system 2;
NR21 = P21*SUPPLY210-COST21-FC21;
NR22 = P22*SUPPLY220-COST22-FC22;
NR23 = P23*SUPPLY230-COST23-FC23;
NR24 = (P24*YC24 - CC24 - FC24/SPATH);
NR25 = (P25*YC25 - CC25 - FC25/SPATH);
NR26 = (P26*YC26 - CC26 - FC26/SPATH);
NR27 = (P27*YC27 - CC27 - FC27/SPATH);
NR28 = (P28*YC28 - CC28 - FC28/SPATH);

NR2=WC21*NR21+WC22*NR22+WC23*NR23+WC24*NR24+WC25*NR25+WC26*NR26+WC27*NR
27+WC28*NR28;

* VARIANCE SYSTEM2;
V21=SC21**2;* VARIANCE SYSTEM2, Activity C1;
V22=SC22**2;* VARIANCE SYSTEM2, Activity C2;
V23=SC23**2;* VARIANCE SYSTEM2, Activity C3;
V24=SC24**2;* VARIANCE SYSTEM2, Activity C4;
V25=SC25**2;* VARIANCE SYSTEM2, Activity C5;
V26=SC26**2;* VARIANCE SYSTEM2, Activity C6;
V27=SC27**2;* VARIANCE SYSTEM2, Activity C7;
V28=SC28**2;* VARIANCE SYSTEM2, Activity C8;

SV2=(V21*WC21**2+V22*WC22**2+V23*WC23**2+V24*WC24**2 +
V25*WC25**2+V26*WC26**2+V27*WC27**2+V28*WC28**2) +2*(RHOC2)
    *(WC21*SC21*WC22*SC22+WC21*SC21*WC23*SC23+WC21*SC21*WC24*SC24
      +WC21*SC21*WC25*SC25+WC21*SC21*WC26*SC26+WC21*SC21*WC27*SC27+WC21
*SC21*WC28*SC28
      +WC22*SC22*WC23*SC23+WC22*SC22*WC24*SC24+WC22*SC22*WC25*SC25+WC22
*SC22*WC26*SC26
      +WC22*SC22*WC27*SC27+WC22*SC22*WC28*SC28+WC23*SC23*WC24*SC24+WC23
*SC23*WC25*SC25
      +WC23*SC23*WC26*SC26+WC23*SC23*WC27*SC27+WC23*SC23*WC28*SC28+WC24
*SC24*WC28*SC28
      +WC24*SC24*WC27*SC27+WC24*SC24*WC26*SC26+WC24*SC24*WC25*SC25+WC25
*SC25*WC28*SC28
      +WC25*SC25*WC27*SC27+WC25*SC25*WC26*SC26+WC26*SC26*WC28*SC28+WC26
*SC26*WC27*SC27
      +WC27*SC27*WC28*SC28);

STDR1=SV1**.5; STDR2=SV2**.5;
IF C_UNITS=0 THEN DO; NR1F=NR1; NR2F=NR2; SV1F=SV1; SV2F=SV2; END;

*** NET GAINS AND ADOPTION;
```

```
NR1T=NR1F;
NR2T=NR2F-FCOSTD;
OPPCOST=0; PAY_ES=0; PAY_HA=0; * NOTE OPPCOST IS THE PAYMENT VARIABLE
(PER FARM) TO SIMULATE ADOPTION.;

IF DO_ADOPT=1 THEN OPPCOST=ABS(1+0.5*NR1T+0.5*NR2T)*ADTOP/100;
M12=NR1T - NR2T - OPPCOST; * OPPORTUNITY COST CALCULATION;
VAR1=SV1F;
VAR2=SV2F+VFCOSTD;
STD1=VAR1**.5;
STD2=VAR2**.5;
IF RHO12=1 THEN RHO12=.999999; COV12=STD1*STD2*RHO12;
VAR12=VAR1+VAR2-2*COV12;
SO12=(VAR1+VAR2-2*COV12)**.5; *STD DEV OF OPP COST;
*IF SO12=0 THEN SO12=.000001; *SET ZERO VARIANCE TO SMALL POSITIVE
VALUE, NOTE XLS VERSION SETS RHO12 TO .999999;
Z12=M12/SO12; *NORMALIZED OPPORTUNITY COST;
ADOPT_S=100*PROBNORM(-Z12); *PERCENT OF ADOPTING FARMS;
IF ADOPT_S<0 THEN ADOPT_S=0;
ESERVHA_S=0; ESERV_S=0; * SET ES TO ZERO AS DEFAULT;
ADOPTA_S=ADOPT_S*AREA/100; *ADOPTION AREA FOR ADOPTION ANALYSIS;
ADOPTP_S=ADOPT_S; *PERCENT OF AREA ADOPTING;
ADOPTRA=ADOPT_S*AREA/100; *AREA WEIGHTING FOR AGGREGATION;
ADOPTPRA=ADOPTP_S*AREA/100;

IF HH_SIZE1=. THEN DO; *FIX HH_SIZES FOR OLD DATA FILES;
      HH_SIZE1=HH_SIZE;
      HH_SIZE2=HH_SIZE;
      CVHH1=CVHH;
      CVHH2=CVHH;
      END;

ID=(PNO*1000)+TNO*100; *CREATING ID BY PNO,TNO;
ADOPT_S1=ADOPT_S;
QS1A=((WC11*SUPPLY11*NUMFARM));
QS2A=(NUMFARM)*(WC22*SUPPLY220);

* WRITE VARIABLES TO WORK FILE;
OUTPUT;
END; *STRAT LOOP END;
END; *TRADEOFF LOOP END;
END; *PRICE LOOP END;
RUN;
```

3) Macro simulation

This macro simulation programming is new in the TOA-MDE model. In this stage, farm expected profits, adoption rates, and equilibrium output prices are iteratively solved.

```
%MACRO MARKET_SUPPLY; *MACRO CALCULATING SUPPLY ACROSS STRAT;
DATA AM&I; SET AQ&I;
ADOPT_SP&I=ADOPT_S&I/100; *ADOPTION RATE (PERCENT/100);

QS1P&I=(NUMFARM*(1-
ADOPT_SP&I)*WC11*SUPPLY11)+(NUMFARM*ADOPT_SP&I)*WC21*SUPPLY21&K;
QS2P&I=(NUMFARM*ADOPT_SP&I)*WC22*SUPPLY22&K; *AGG SUPPLY PER STRAT;

RUN;

PROC SQL;  *AGG SUPPLY FOR ALL STRAT
CREATE TABLE AGG_CROP1&I AS
SELECT ID, SUM(QS1P&I) AS SUM_QS1&I
FROM AM&I
GROUP BY ID;
QUIT;
DATA AB&I; MERGE AM&I AGG_CROP1&I; BY ID;
RUN;

PROC SQL;
CREATE TABLE AGG_CROP2&I AS
SELECT ID, SUM(QS2P&I) AS SUM_QS2&I
FROM AB&I
GROUP BY ID;
QUIT;

DATA AQ&J; MERGE AB&I AGG_CROP2&I; BY ID;
RUN;

%MEND MARKET_SUPPLY;

%MACRO ADOPTION; *MACRO CALCUATING ADOPTION RATES;

*SYSTEM 1: SUPPLY, COST, AND NET RETURNS
supply11&I=alpha11**(-1/(1-GAMMA11))*PSTAR1&I**(GAMMA11/(1-GAMMA11));
NEW_COST11&I = -ACOST1
+GAMMA11*((ALPHA11)**(1/GAMMA11))*(SUPPLY11&I**(1/GAMMA11));
NR_NEW11&I = PSTAR1&I*SUPPLY11&I-NEW_COST11&I-FC11;
NR_NEW1&I=WC11*NR_NEW11&I+WC12*NR_12+WC13*NR13+WC14*NR14+WC15*NR15+WC16
*NR16+WC17*NR17+WC18*NR18;

*SYSTEM 2: SUPPLY, COST, AND NET RETURNS
supply21&I=alpha21**(-1/(1-GAMMA21))*PSTAR1&I**(GAMMA21/(1-GAMMA21));
supply22&I=alpha22**(-1/(1-GAMMA22))*PSTAR2&I**(GAMMA22/(1-GAMMA22));
NEW_COST21&I = -ACOST21
+GAMMA21*((ALPHA21)**(1/GAMMA21))*(SUPPLY21&I**(1/GAMMA21));
NEW_COST22&I = -ACOST22
+GAMMA22*((ALPHA22)**(1/GAMMA22))*(SUPPLY22&I**(1/GAMMA22));
NR_NEW21&I = PSTAR1&I*SUPPLY21&I-NEW_COST21&I-FC21;
NR_NEW22&I = PSTAR2&I*SUPPLY22&I-NEW_COST22&I-FC22;
NR_NEW2&I=WC21*NR_NEW21&I+WC22*NR_NEW22&I+WC23*NR23+WC24*NR24+WC25*NR25
+WC26*NR26+WC27*NR27+WC28*NR28;

*ADOPTION RATES
IF C_UNITS=0 THEN DO; NR_NEW2F&I=NR_NEW2&I; END;
```

```
NR_NEW1T&I=NR_NEW1&I - FCOSTD;
NR_NEW2T&I=NR_NEW2&I - FCOSTD; *NET RETURNS OF SYSTEM 2;
IF DO_ADOPT=1 THEN OPPCOST2=ABS(1+0.5*NR1T+0.5*NR_NEW2T&I)*ADTOP/100;
NR_M12&I=NR_NEW1T&I - NR_NEW2T&I - OPPCOST2; * OPPORTUNITY COST
CALCULATION;
VAR1=SV1F;
VAR2=SV2F+VFCOSTD;
STD1=VAR1**.5;
STD2=VAR2**.5;
IF RHO12=1 THEN RHO12=.999999; COV12=STD1*STD2*RHO12;
VAR12=VAR1+VAR2-2*COV12;
SO12=(VAR1+VAR2-2*COV12)**.5;
*IF SO12=0 THEN SO12=.000001;
NR_Z12&I=NR_M12&I/SO12;
ADOPT_S&J=100*PROBNORM(-NR_Z12&I);
IF ADOPT_S&J<0 THEN ADOPT_S&J=0;

%MEND ADOPTION;

%MACRO MARKET_EQM (ITER=50); *MACRO MARKET EQM, MAX ITERATION =20;
%GLOBAL I J K PRE_EQMP60;
%LET I=1;
%LET LEAVE=0;

%DO %UNTIL(&LEAVE=1 OR &J= &ITER.); *DO LOOP FOR ITERATION CALCULATION;
%PUT I=&I; *SHOW 'I'TH ITERATION;
%LET J=%EVAL(&I+1); *TO CREATE (I+1) VARIABLE;
%LET K=%EVAL(&I-1); *TO CREATE (I-1) VARIABLE;

%MARKET_SUPPLY; *GETTING MARKET SUPPLY WITH NEW ADOPTION RATES;

DATA AQ&J; SET AQ&J;

*MARKET CLEARING CONDITION; *BEGST+PROD+IM=DOMESTIC+EX+ENDST;
*RICE;
BEGST1_L2=E_BEGST1*BEGST1/P21; *Beginning stock slope;
BEGST1_L1=BEGST1-BEGST1_L2*P21; *Beginning stock intercept;
PROD1_L2=E_PROD1*(PROD1)/P21; *production slope;
PROD1_L1&I=(PROD1-SUM_QS1A+SUM_QS1&I)-PROD1_L2*P21; *production
intercept; *(production)+(aggregate supply after adoption);
IM1_L2=E_IM1*IM1/P21; *import slope;
IM1_L1=IM1-IM1_L2*P21; *import intercept;
DOMESTIC1_L2=E_DOMESTIC1*DOMESTIC1/P21; *domestic use slope;
DOMESTIC1_L1=DOMESTIC1-DOMESTIC1_L2*P21; *domestic use intercept;
ENDST1_L2=E_ENDST1*ENDST1/P21; *ending stock slope;
ENDST1_L1=ENDST1-ENDST1_L2*P21; *ending stock intercept;
TSUPPLY11&I=BEGST1_L1+PROD1_L1&I+IM1_L1; *total supply intercept;
TSUPPLY12=BEGST1_L2+PROD1_L2+IM1_L2; *total supply slope;
TDEMAND11=DOMESTIC1_L1+ENDST1_L1; *total demand intercept;
TDEMAND12=DOMESTIC1_L2+ENDST1_L2; *total demand slope;
PSTAR1&I=(TDEMAND11-TSUPPLY11&I)/(TSUPPLY12-TDEMAND12); *equilibrium
price where TS=TD;

*BEAN;
BEGST2_L2=E_BEGST2*BEGST2/P22; *Beginning stock slope;
```

```
BEGST2_L1=BEGST2-BEGST2_L2*P22; *Beginning stock intercept;
PROD2_L2=E_PROD2*PROD2/P22; *production slope;
PROD2_L1&I=(PROD2-SUM_QS2A+SUM_QS2&I)-PROD2_L2*P22; *(production + NEW)
intercept;
IM2_L2=E_IM2*IM2/P22; *import slope;
IM2_L1=IM2-IM2_L2*P22; *import intercept;
DOMESTIC2_L2=E_DOMESTIC2*DOMESTIC2/P22; *domestic use slope;
DOMESTIC2_L1=DOMESTIC2-DOMESTIC2_L2*P22; *domestic use intercept;
ENDST2_L2=E_ENDST2*ENDST2/P22; *ending stock slope;
ENDST2_L1=ENDST2-ENDST2_L2*P22; *ending stock intercept;

TSUPPLY21&I=BEGST2_L1+PROD2_L1&I+IM2_L1; *total supply intercept;
TSUPPLY22=BEGST2_L2+PROD2_L2+IM2_L2; *total supply slope;
TDEMAND21=DOMESTIC2_L1+ENDST2_L1; *total demand intercept;
TDEMAND22=DOMESTIC2_L2+ENDST2_L2; *total demand intercept;
PSTAR2&I=(TDEMAND21-TSUPPLY21&I)/(TSUPPLY22-TDEMAND22); *equilibrium
price where TS=TD;

%ADOPTION; *GETTING ADOPTION RATES BY NEW MARKET EQM PRICE;

* ITERATION EXIT RULE;
DIFF&I=ABS(ADOPT_S&J-ADOPT_S&I);
RUN;
DATA AQ&J; SET AQ&J;
      IF DIFF&I<0.0000001 THEN CALL SYMPUTX('LEAVE',1);
      IF LEAVE=1 THEN FIN=I;
RUN;

*SAVE EACH ITERATION RESULTS;
PROC SQL;
CREATE TABLE OUTPUT&I AS
SELECT PNO, STRAT, NR1, QS1P&I, SUM_QS1&I, TSUPPLY11&I, PSTAR1&I,
QS2P&I, SUM_QS2&I, TSUPPLY21&I, PSTAR2&I, NR_NEW2&I, ADOPT_S&J
FROM AQ&J;
QUIT;

DATA OUTPUT&I; MERGE OUTPUT&K OUTPUT&I; BY PNO STRAT;
RUN;

DATA OUTPUT; SET OUTPUT&I; RUN;

%LET I=%EVAL(&I+1); *FOR NEXT ITERATION;
%END; *END DO LOOP;
%MEND MARKET_EQM;

%MARKET_EQM; *EXCUTING MARKET_EQM MACRO;
```

Appendix D: Elasticity Estimates

This section shows the elasticity estimates used in simulation of each empirical application, Chapter 3 and Chapter 4. Table D.1 shows the elasticities that are estimated by OLS regression ($Q_i = k_{i0} {P_{it}}^{k_{i1}} e^{k_{i2}t} \epsilon_i$ for crop i) with market level time-series data from USDA ERS.

Table D.1 Supply and Demand Elasticity Estimates

	Import (IM)	Domestic Utilization (DU)	Export (EX)	Ending Stocks (ES)
Wheat				
Intercept	2.196 (4.243)***	2.210 (19.03)***		2.215 (17.03)***
Price	-0.036 (-0.113)	-0.349 (-2.02)*		-0.566 (-2.93) ***
Trend	0.011 (0.971)	0.008 (2.920)**		0.002 (0.556) *
R^2	0.047	0.227		0.294
Camelina				
Intercept	2.921 (2.599)**	4.036 (7.324)***	3.278 (6.752)***	2.524 (4.426)***
Price	0.022 (0.023)	-0.615 (-1.296)	-0.617 (-1.47)	-0.256 (-0.52)
Trend	0.049 (2.654)**	0.052 (5.745)***	0.027 (3.345)***	0.043 (4.629)***
R^2	0.386	0.678	0.353	0.616

Notes: Standard errors are in parentheses; *,** and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D.2 shows the demand side estimates come from OLS regression with lagged price ($Q_i = k_{i0} + k_{i1} P_{i(t-1)} + k_{i2} t + \epsilon_i$ for crop i) using time-series data from Grain Food Policy dataset in South Korea.

Table D.2 Demand Elasticity Estimates at Year 2017

	Domestic Utilization (DU)	Ending Stocks (ES)
Rice		
Intercept	-0.536 (-3.01) ***	-71259.19 (-1.07)
Price	-25.56 (-2.45) **	-0.798 (-1.39)
Marginal effects	-0.224 (-3.14)***	-1.09 (1.72)*
Trend	56729.87 (2.74) **	36.67 (1.09)
Soybean		
Intercept	-50354.43 (-3.89)***	-0.009 (-0.66)
Price	-0.125 (-3.02)***	-0.025(-0.01)
Marginal effects	-0.368 (-3.01)***	-0.465 (-0.65)
Trend	25.996 (3.99)***	176.909

Notes: Standard errors are in parentheses; *,** and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.