ESSAYS ON OPTIMIZATION MODELING AND RISK MANAGEMENT:

BIOFUEL MANDATE, ETF HEDGING, AND CROP-ZONING POLICY

A Dissertation

by

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ABSTRACT

This dissertation consists of three stand-alone studies concerning applications of optimization modeling in agricultural policy evaluation and applications of copula when considering the tail risk in the energy commodity markets. The first study (Chapter II) extends a mathematical optimization model, FASOMGHG, in evaluating economic and environmental effects from fulfilling the renewable fuel standard (RFS), which mandates increasing amounts of ethanol produced from biomass. As the increase in ethanol production from biomass may lead to land competition between traditional food crops and energy feedstocks, one potential solution to relieve the competition on land resources is to grow cellulosic feedstocks on marginal land. The results from this study suggest that growing energy crops on marginal land could help alleviate some of the pressure on land competition between traditional and energy crops, but could potentially lead to higher GHG emission, soil erosion, and nutrient runoffs.

The second study (Chapter III) examines the usefulness of energy commodity exchange-traded funds (ETFs) in dealing with tail risk in crude oil, gasoline, heating oil, and natural gas markets by analyzing the out-of-sample hedging effectiveness of ETFs and comparing their performance with those of the futures counterparts. The empirical distribution method and kernel copula method are applied to estimate the minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) hedge ratios for both long and short hedgers. The empirical results indicate that the futures contract is a better hedging

instrument for hedging tail risk in the crude oil and heating oil markets whereas the ETF provides better downside risk protection in the gasoline and natural gas markets.

The third study (Chapter IV) analyzes the welfare and land uses associated with an implementation of a Thai crop-zoning policy by constructing a Thai agricultural sector model. The results indicate that the crop-zoning policy has the potential to reduce the government spending incurred from the ongoing price-support program and could lead to increases in production for primary rice, maize, and cassava. Furthermore, the results suggest that the policy would reduce secondary rice and sugarcane production. This coincides with the government's objective of discouraging farmers from growing too much rice that was a result of the government's rice price-support program.

DEDICATION

I dedicate my dissertation to my mother, Sophitha Limprasitkul, and my father, Sukit Arunanondchai. I also dedicate this work to my brother, Nopparat Arunanondchai, and my sister, Chayaporn Arunanondchai. I am grateful for their unconditional support and love.

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Contributors

This work was supervised by a dissertation committee consisting of Dr. David Leatham [advisor], Dr. Bruce McCarl [co-advisor], Dr. Ximing Wu of the Department of Agricultural Economics and Dr. Yong Chen of the Department of Finance.

All work for the dissertation was completed by the student, under the advisement of Dr. David Leatham and Dr. Bruce McCarl of the Department of Agricultural Economics.

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CHAPTER I

INTRODUCTION

Changes in policies and market instruments are likely to alter price volatility and therefore increase the level of market risk faced by commodity producers and market participants. It is essential for policy makers to be able to evaluate the impacts of policy changes and to protect commodity producers and their businesses against any potential price risks that may arise because of policy changes. Mathematical programming is a tool that that policy makers can use for analyzing and quantifying potential economic and environmental impacts of a policy before it is officially implemented. Understanding the true impacts of policy changes would provide policy makers with useful information regarding potential benefits and costs that would affect the economy. This dissertation presents three stand-alone essays related to applications of optimization modeling in policy evaluation and market analysis.

The first essay (Chapter II), “Analysis of Switchgrass Production on Marginal Land in the United States”, analyzes the economic and environmental effects from using marginal agricultural lands in fulfilling the renewable fuel standard (RFS). The RFS in full implementation mandates amounts of ethanol produced from biomass to reach 36 billion gallons. Since the RFS also restricts that the amount of corn based ethanol to 15 billion gallons per year, the remaining balance has to be produced from other feedstocks including cellulosic feedstocks grown on agricultural lands. In turn, this would lead to land competition with traditional food crops. One potential solution to relieve the land competition is to grow cellulosic feedstocks on marginal land. Nevertheless, there are concerns on whether marginal land production is economical and low in environmental impacts. In this study, we employ the Forest and Agricultural Sector Optimization Model (FASOMGHG), a dynamic nonlinear programming, optimization model of US forest and agricultural sector to estimate and project dynamic interactions of all agricultural activities (including production, farm-level management, and emissions). The FASOMGHG model endogenously solves for optimal values of those activities using the objective of maximizing total social welfare.

The second essay (Chapter III), “Dealing with Tail Risks in Energy Commodity Markets: Futures Contracts vs Exchange-Traded Funds”, examines the role of Exchange-Traded Funds (ETFs) in dealing with tail risk in energy commodity markets. Four energy commodities are considered: crude oil, gasoline, heating oil, and natural gas. As the ETFs can be traded in small amounts, the energy commodity ETF can potentially be a valuable tool for hedging against adverse energy price movements. This is examined because several empirical studies have evaluated energy futures hedging performance (see, for example, Alizadeh et al., 2008; Chang et al., 2011; Cotter and Hanly, 2012; Conlon and Cotter, 2013), but there are very few studies on energy commodity ETFs. In order to construct hedged portfolios, the kernel copula method is applied to estimate the minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) hedge ratios for energy commodity users (long hedgers) and producers (short hedgers). By considering both hedger positions, this allows us to evaluate futures contracts and ETFs hedging performance vis-à-vis the hedge positions.

The third essay (Chapter IV), “Analysis of Thai Crop-Zoning Policy” analyzes the welfare and land uses associated with crop-zoning and price support policy in Thailand. To do this a Thai agricultural sector model was developed based on the type of optimization model discussed in McCarl and Spreen (1980). The results from this study can aid policy makers in identifying crops that are most suitable for replacing crops being grown on unsuitable lands.

The findings from the three studies should provide valuable information for practitioners, academics, and policy makers regarding the applications of optimization models in policy evaluation and the applications of copula in risk management.

CHAPTER II

ANALYSIS OF SWITCHGRASS PRODUCTION ON MARGINAL LAND IN THE UNITED STATES

2.1 Introduction

The Renewable Fuel Standard (RFS) program – a federal program under Title II of the Energy Independence and Security Act (EISA) of 2007 – requires increasing volumes of renewable fuels to be blended with US fuels. In particular, the RFS contains a target mandate that US fuels must ultimately contain at least 36 billion gallons of renewable fuels. To date, corn has been the primary US feedstock utilized for ethanol production. However, the EISA imposes a cap on the amount of corn-based ethanol that can be used to satisfy the RFS and the cap essentially equals current production – 15 billion gallons per year (Schnepf and Yacobucci, 2013). This means that the remaining balance of the RFS-qualified ethanol will have to be produced from other feedstocks with crop residues, energy crops, and wood considered to be major potential feedstocks.

As cropland in the United States is essentially fully utilized, growing energy crops for cellulosic feedstocks will likely divert cropland from traditional food/feed production. In particular, increasing energy crop production on cropland would reduce the amount of food/feed that flows into traditional markets, reducing exports and consumption levels. This, in turn, is expected to increase food prices and food insecurity (Runge and Senauer, 2007; Tyner et al., 1979). In addition, higher food prices may lead to development of lands outside the United States, potentially stimulating deforestation or other forms of leakage associated with increases in greenhouse gas (GHG) emissions (Fargione et al., 2008; Murray et al., 2004; Searchinger et al., 2008).

One potential solution to relieve cropland competition is to grow cellulosic feedstocks on marginal land. A 2009 US National Academy report (National Academy of Sciences, 2009) states that: "In contrast, liquid biofuels made from lignocellulosic biomass can offer major improvements in greenhouse gas emissions relative to those from petroleum-based fuels if the biomass feedstock is a residual product of some forestry and farming operations or if it is grown on marginal lands that are not used for food and feed production." Moreover, the report estimated the annual amount of cellulosic biomass that could be produced sustainably at 400 million dry tons under 2008 technology and 550 million under anticipated 2020 conditions. In this context, the report concludes that "croplands would not be diverted for biofuels and land therefore would not be cleared elsewhere to grow crops displaced by fuel crops if growing and harvesting of cellulosic biomass would incur minimal or even reduce adverse environmental effects such as erosion, excessive water use, and nutrient runoff".

Compared to croplands, marginal lands generally have lower moisture, soil nutrient content and fertility. In addition, they are often more fragile in terms of erosion potential and degradation state. Therefore, they are not suitable for growing row crops. However, a number of arguments have been presented that energy crops could be grown on marginal lands. Consider the case of switchgrass. Jensen et al. (2007) argue that switchgrass has the capacity to grow on marginal lands with relatively small amounts of fertilizer and that once planted, it can last more than 10 years with annual harvest. In addition, Lemus et al. (2002); Nabity et al., (2012) assert that growing switchgrass on marginal lands would help improve local water quality and nitrogen use efficiency. Vogel (1996) suggests that switchgrass production helps reduce soil erosion and improve soil organic carbon development, which in turn enhances productivity and environmental quality of the land as well as reduces the effects of droughts and floods. Guretzky et al. (2011) indicates that perennial grass crops have potential to produce ethanol with lower levels of GHG emissions and asserts that switchgrass grown on marginal lands can generate relatively high biomass yield despite lower applications of fertilizer and pesticides. Overall, these studies suggest that growing energy crops on marginal lands will help avoid land competition allowing greater amounts of traditional crops to enter the marketplace while simultaneously improving soil and water quality along with other favorable environmental outcomes.

Several studies on growing cellulosic feedstocks on marginal lands have focused on evaluating environmental (including GHG) impacts, appraising land development costs, and assessing economic feasibility of marginal-land-based ethanol production. These studies report mixed results. For example, Valcu-Lisman, Kling and Gassman (2016) find that restricting biofuel crops to marginal land in Iowa is not likely to yield the highest valued production output and ecosystem benefits. In contrast, Schmer et al. (2008) conduct field studies in Nebraska, North Dakota and South Dakota, and find that switchgrass production on marginal land helps improve soil carbon sequestration. The results from Schmer et al. (2008) suggest that utilizing marginal land to grow native grasses for cellulosic ethanol and bioelectricity have potential to offset as much as 17.2%

of the states' energy consumption while also reducing GHG emissions by 68% relative to gasoline. Nevertheless, none of the prior studies have considered the full market interactions over time among different crops and livestock, and generally focused on small regions.

2.2 Objectives of the Study

This study analyzes the effects of growing energy crops on marginal land on a natural scale considering full market effects and many of environmental effects. More specifically, the study aims to address the following questions:

1) Does growing energy crops on marginal land help relax competition with conventional production across the total domain of US agricultural production?
2) What are the economic and environmental implications of satisfying the cellulosic portion of the RFS mandate with and without the use of marginal land?
3) What is the role of marginal land if rather than meeting the RFS mandates we meet the much smaller cellulosic ethanol projections generated by the Energy Information Agency (EIA)?
4) What happens if the mandates are relaxed – i.e., what is the free market penetration of conventional and cellulosic ethanol?
5) To what extent will expanding the amount of cellulosic biofuel produced reduce the amount of traditional crop production reaching traditional markets and raise crop prices?
6) What is the optimal share of energy crops and crop residues with and without employment of marginal land?

The remainder of this paper is organized as follows. Section 2.3 presents the methodology. Section 2.4 describes marginal land definition, source, and characteristics. Section 2.5 provides an overview of model scenarios. Section 2.6 reports and discusses the model results. Section 2.7 concludes this study.

2.3 Methodology

In this study, the Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG) is employed to estimate and project the US-based implications of meeting the RFS and EIA ethanol projections with and without marginal lands. In particular, this study focuses on the dynamic effects of growing energy crops on marginal land on agricultural commodity prices and production; changes in land management such as tillage management, land-use change, and fertilizer usage; net greenhouse gas emissions; and environmental impacts. The FASOMGHG model (Adams et al., 2005; Beach et al., 2013; Lee et al., 2007; McCarl and Schneider, 2001) endogenously solves for optimal values of all those elements. The dynamic optimization process is done under the assumption of perfectly competitive behavior in the agricultural sector and is simulated by maximizing total social welfare as discussed in McCarl and Spreen (1980). The model imposes constraints on natural resources (including land and labor) as well as accounts for GHG emissions, carbon sequestration, and a number of environmental attributes.

For this particular study, three biofuel production levels are imposed. These are the mandate levels contemplated in:

1) The original Energy Independence and Security Act (EISA) projection (although these are retarded by five years given the slow progress in producing cellulosic ethanol). Under EISA, the level of Renewable Fuel mandated, which is often referred to as RFS2, required the annual use of biofuels to reach 36 billion gallons in 2022 (which we make 2027 in our analysis) with at least 16 billion gallons from cellulosic biofuels, and a cap of 15 billion gallons for corn-starch ethanol.

2) The Annual Energy Outlook (AEO) developed by the US Energy Information Administration (EIA), which contains 1 billion gallons from cellulosic biofuels.

3) A free market projection in the absence of biofuel mandates.

For each projection of biofuel production levels, cases with and without marginal land are considered. Hence, a total of six scenarios are examined: (1) EISA without marginal land (EISA), (2) EISA with marginal land (EISA-ML), (3) AEO without marginal land (AEO), (4) AEO with marginal land (AEO-ML), (5) Free Market without marginal land (FreeMkt), and (6) Free Market with marginal land (FreeMkt-ML). The results from the FASOMGHG model yield projections of cropland used for switchgrass production, crop prices, total ethanol production, GHS emissions, and non-GHG environmental effects under these six scenarios.

2.4 Marginal Land Definition, Source, and Characteristics

In this study, marginal land is classified as cropland pasture – land suitable for crop production but is currently used for pasture. This is defined following the classification used in the USDA Economic Research Service Major Land Use (ERS-MUL) database and the Natural Resources Inventory (NRI). According to the ERS-MLU database, cropland pasture is defined as managed land suitable for crop production (i.e., relatively high productivity) that is being used as pasture. However, the ERS-MLU database lacks a clear distinction between grassland pasture and rangeland, while the NRI defines these as separate land categories.

The FASOMGHG model make use of both the ERS-MLU and NRI databases and avoids overlap between different land use categories by developing a unique hybrid NRI-MLU land categorization system (Beach and McCarl, 2010). This combined NRI-MLU land categorization system provides FASOMGHG with a representation of regional marginal land transition possibilities as well as a consistent accounting of public and private grazing lands. The yield estimates associated with growing switchgrass on marginal land were obtained from the Bio-Based Energy Analysis Group at the University of Tennessee and were those used in the Department of Energy billion-ton study (Yu et al., 2014). These data are only available for the states where the Department of Energy (DOE)'s billion-ton team assumed switchgrass would be able to grow on marginal land – Florida, New York, Wisconsin, Georgia, Louisiana, Virginia, Mississippi, Missouri, Texas, South Dakota, and Wyoming. As the main focus of this study involves an examination of economic and environmental effects of allowing switchgrass to be grown on marginal land instead of on cropland, switchgrass grown on marginal land is assumed to be a perfect substitute for switchgrass grown on cropland in producing feedstocks for cellulosic ethanol.

2.5 Model Scenarios

In this study, six scenarios are constructed based on the three projections: EISA, AEO, and Free Market. To analyze the effects of marginal land under each projection while controlling for other factors, two scenarios – with and without marginal land – are constructed for each projection.

The key differences across the six scenarios are summarized in Table 2.1. For the EISA projection, we follow RFS2 and set the upper limit of annual use of biofuels to reach 36 billion gallons in 2022 with at least 16 billion gallons coming from cellulosic biofuels. For the AEO projection, we follow EIA and set the upper limit of annual use of biofuels to reach 15 billion gallons in 2022 with a lower limit of 1 billion gallons for cellulosic biofuels. Under both EISA and AEO projections, a cap of 15 billion gallons for corn-starch ethanol is also imposed. Lastly, for the free market projection, we do not set any upper or lower limits on the annual use of biofuels and the cellulosic biofuels. That is, under this the free market scenario, we let the model generate the optimal amount of biofuel production endogenously.

Table 2.1. Key assumptions across scenarios

		Scenarios					
		EISA	EISA-ML	AEO	AEO-ML	FreeMkt	FreeMkt-ML
Annual Cellulosic Biofuel Use (Billion Gallon)	Lower Limit	15	15	1	1	-	-
Annual Corn-Starch Ethanol Use (Billion Gallon)	Upper Limit	15	15	15	15	-	-
Marginal Land		No	Yes	No	Yes	No	Yes

2.6 Results and Implications

2.6.1 Switchgrass Production

Under the AEO and Free Market scenarios, there is no switchgrass grown on cropland as sufficient cellulosic feedstocks can be obtained at an apparently lower price relying on crop residues mainly in the form of corn stover. Consequently, no switchgrass is grown on marginal land. On the other hand, under the EISA projection, we find that significant amounts of switchgrass are grown.

The annualized amounts of cropland and marginal land used in growing switchgrass over 2015 to 2045 are estimated as constant annuities at a 4% discount rate under the EISA scenarios are shown in Table 2.2, and the projected amounts of cropland and marginal land used in growing switchgrass in 2030 are reported in Table 2.3.

As can be seen from Table 2.2 and Table 2.3, the amounts of cropland used for switchgrass production are significantly affected by whether marginal land use is allowed. When marginal land is allowed, a significant amount of switchgrass production that is used to be grown on cropland will be shifted to marginal land as it helps reduce pressures

Table 2.2. FASOMGHG results on annualized amounts of land used for switchgrass production

	Land-Used Type	
	Cropland	Marginal Land
Scenario		
EISA	1.933	0.000
EISA-ML	0.506	7.651

Unit: million acres

Table 2.3. FASOMGHG results on amounts of land used for switchgrass production in 2030

	Land-Used Type	
	Cropland	Marginal Land
Scenario		
EISA	3.551	0.000
EISA-ML	1.286	16.320

Unit: million acres

on the use of cropland to meet the RFS2's biofuels mandates. Table 2.2 shows that the annualized amount of 1.933 million acres of cropland that is used for growing switchgrass is reduced to 0.506 million acres once marginal land is allowed. It should be noted that the acreage of marginal land used for switchgrass production is much higher than that of cropland. This finding is consistent with the fact that marginal land has less nutrients than cropland. Furthermore, as cellulosic ethanol production technology advances, we find that more acres of marginal land will be used in 2030 as shown in Table 2.3.

Figure 2.1-2.3 show total cropland used in agriculture under all six scenarios. Under the EISA-ML scenario, over time the amounts of total cropland used will be slightly lower than those under the EISA without marginal land scenario. This indicates that a portion of switchgrass will be moved from traditional cropland to marginal land. From Table 2.4, the cropland released from switchgrass production will then be used to grow other

Table 2.4. FASOMGHG results on annualized amounts of cropland used for corn, soybean, and hay production

	Scenario	
	EISA	EISA-ML
Crops		
Corn	88.703	88.788
Soybean	83.477	83.572
Hay	63.974	64.137

Unit: million acres

Figure 2.1. Projected total cropland used in agriculture under EISA projections

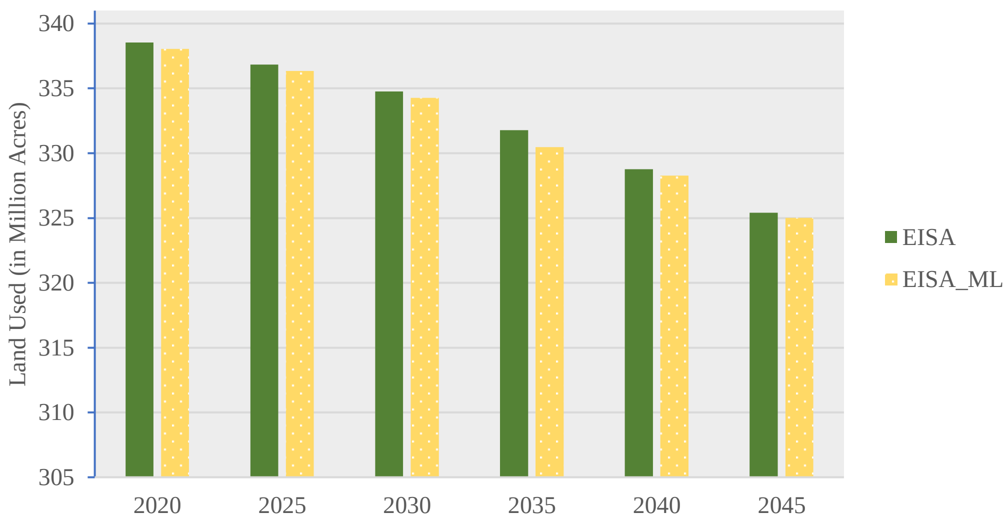


Figure 2.2. Projected total cropland used in agriculture under AEO projections

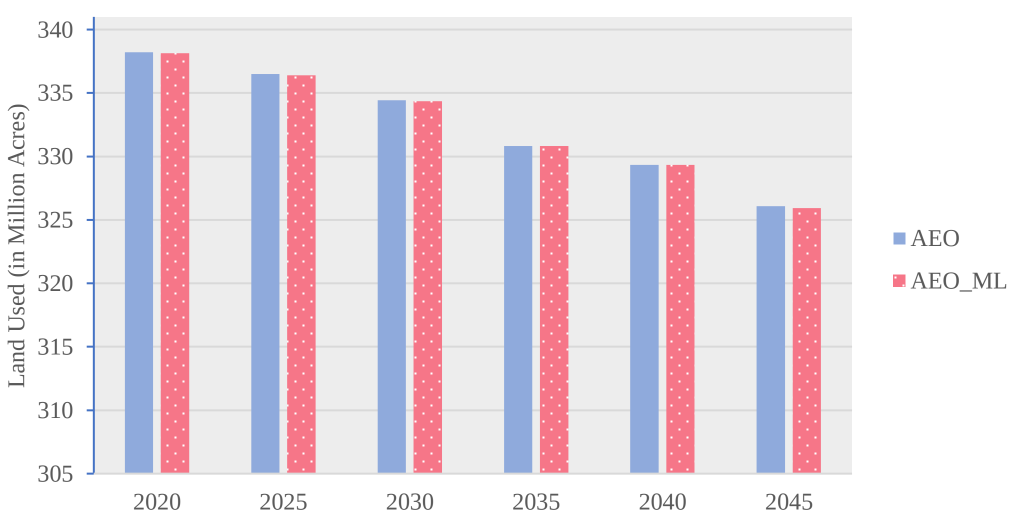
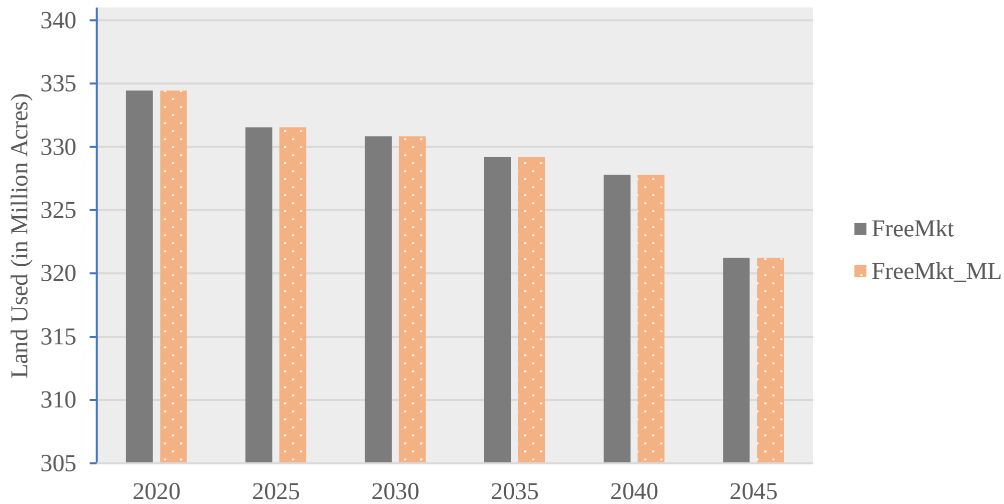


Figure 2.3. Projected total cropland used in agriculture under free market projections



conventional crops, such as corn, soybeans, and hay It should be noted that the declining pattern in land use occurs because we assumed technological advances in the form of yield increases along with land use shifts to non-agricultural uses over time. Figure 2.2 and Figure 2.3 also indicate that the amounts of cropland used under AEO and Free Market projections will not be meaningfully affected by the availability of marginal land.

Figure 2.4 illustrates the shares between conventional croplands and marginal lands for switchgrass production under the EISA-ML scenario. As can be seen from the figure, 100 percent of switchgrass will be grown on marginal lands in 2020 and 2025. In subsequent years (2030-2045), it is projected that a small portion of switchgrass (approximately 5 to 11 percent) will also be grown on cropland. Furthermore, the analysis results show that once switchgrass is allowed to grow on marginal land, not only does switchgrass production increase significantly, but also is widely distributed in multiple states.

Figure 2.4. Land used for switchgrass production under EISA with marginal land scenario

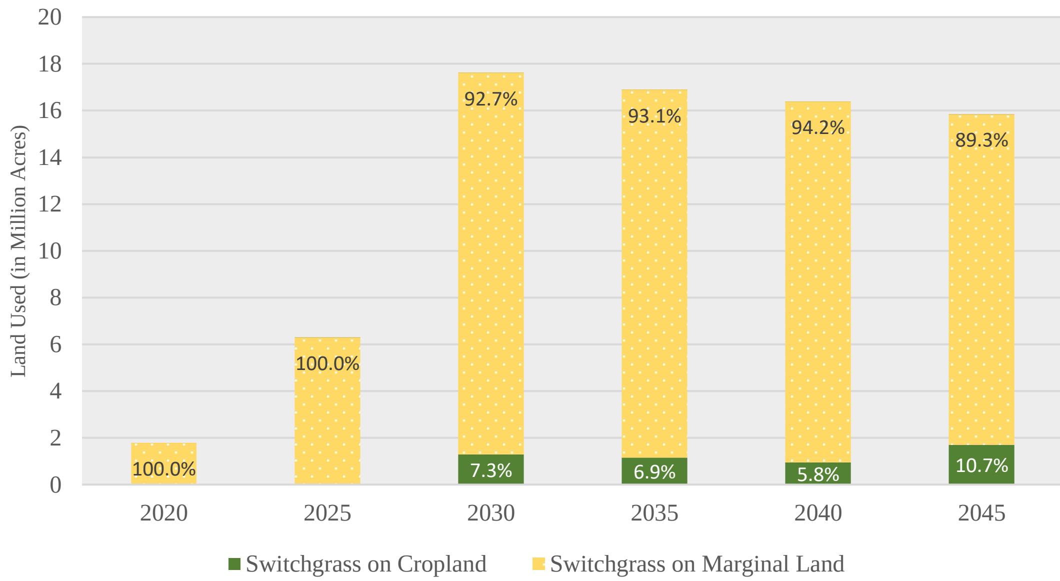


Figure 2.5 and Figure 2.6 show locations and areas where switchgrass will be grown in 2030 under EISA and EISA-ML scenarios, respectively. As we can see, switchgrass would be grown more on marginal land in Missouri and Georgia. This would help release croplands specifically in Texas and Iowa for other conventional crops, such as corn, hay, and so on. Nevertheless, there are costs associated with converting marginal land for growing switchgrass. As a result, the amount of switchgrass on marginal land may not increase dramatically.

Corn, as a major feedstock for ethanol production, is also affected by the introduction of marginal land. Table 2.4 shows that the annualized amount of cropland used for corn production becomes higher once switchgrass is allowed to grow on marginal land. That is, under EISA-ML scenario, cropland that was used to grow the biofuel crop is released to grow other traditional crops.

Figure 2.5. Switchgrass on cropland in 2030 – EISA scenario

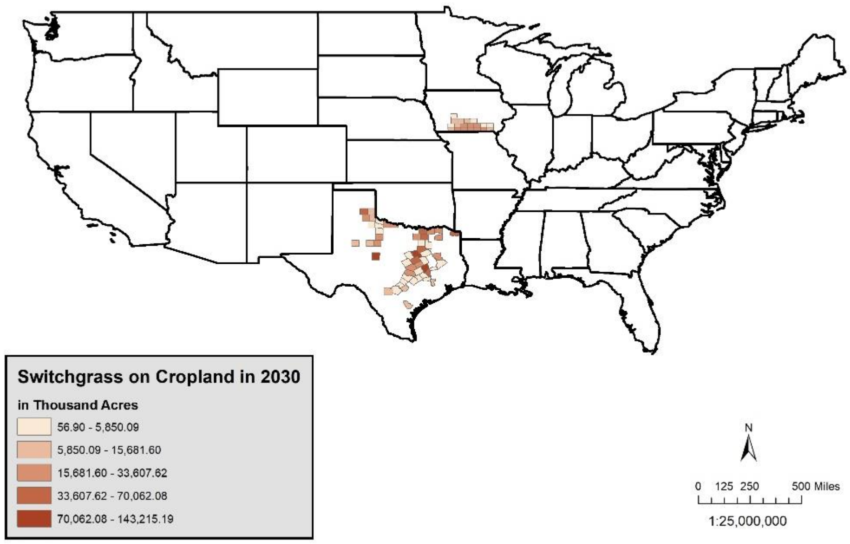


Figure 2.6. Switchgrass on marginal land in 2030 – EISA-ML scenario

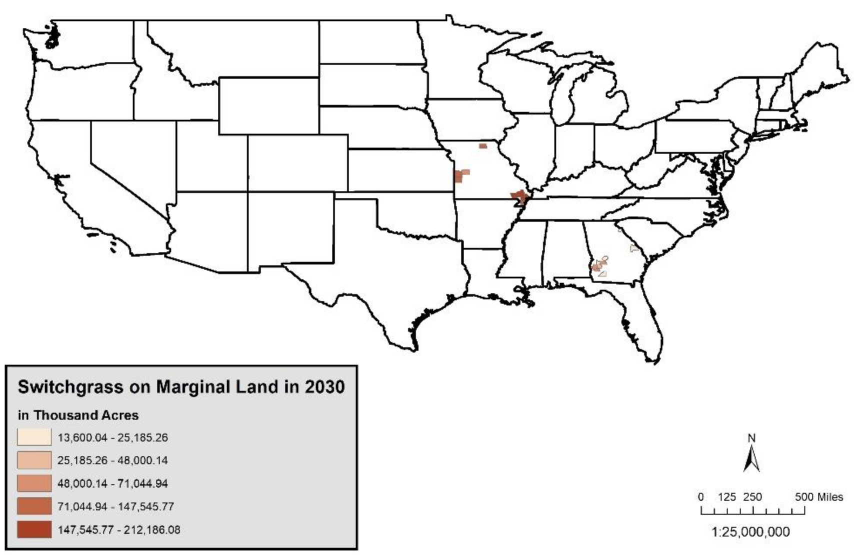


Figure 2.7 and Figure 2.8 suggest that locations where corn will be grown in 2030 across the country under EISA and EISA-ML scenarios are pretty much the same, but more intense under the EISA-ML scenario. Nevertheless, corn production in some states increases significantly after marginal land is allowed to grow switchgrass. Specifically, corn production in California and Louisiana under the EISA-ML scenario is higher than that under the EISA scenario. We can also see a reduction in corn production in some states, such as Wyoming. This can happen since the model take into account the dynamic interaction of multiple crops. Thus, other conventional crops may become more profitable than corn in some states once marginal land is introduced.

Table 2.5 presents estimates of annualized crop prices under both EISA and EISA-ML scenarios. The annualized corn price under the EISA-ML scenario is estimated to be \$2.873 per bushel, which is marginally lower the annualized corn price under the EISA scenario (\$2.896 per bushel). Similar results are observed for the cases of soybeans, sorghum, oats, rye, and canola. Overall, these findings imply that marginal land can help alleviate some of the pressure on land competition between traditional and energy crops although its impact on crop prices is minimal.

Table 2.5. Annualized prices of selected crops

	EISA	EISA-ML
Price		
Corn (\$/bu.)	2.896	2.873
Soybeans (\$/bu.)	10.069	10.045
Sorghum (\$/cwt.)	5.984	5.939
Oats (\$/bu.)	2.385	2.439
Rye (\$/bu.)	7.683	7.774
Canola (\$/bu.)	9.177	9.082

Figure 2.7. Corn on cropland in 2030 – EISA scenario

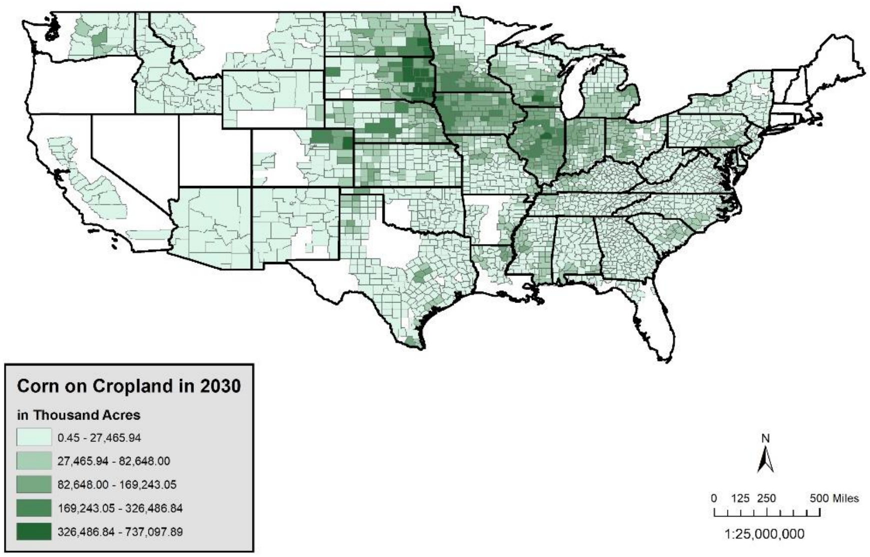
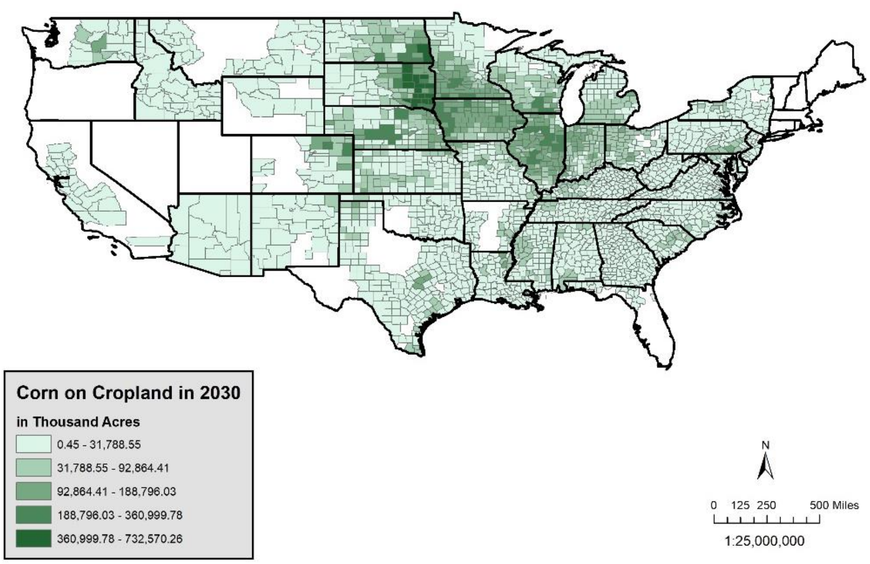


Figure 2.8. Corn on cropland in 2030 – EISA-ML scenario



2.6.2 *Ethanol Production*

Figure 2.9-2.11 show the projected amount of cellulosic ethanol production, crop ethanol production, and total ethanol production (in billion gallons) under four scenarios: AEO, AEO-ML, EISA, and EISA-ML, respectively. Under the free market projection (with and without marginal land), there is no requirement for the minimum amount of cellulosic ethanol produced. As expected, our analysis results indicate that no cellulosic ethanol will be produced under these two scenarios. Under the AEO and AEO-ML scenarios, it is projected that approximately one billion gallons of cellulosic ethanol will be produced during 2020 through 2045. On the other hand, under EISA and EISA-ML, cellulosic ethanol production is projected to increase significantly after 2020 and remains at the mandate level of around 13.7 billion gallons after 2030. With respect to crop ethanol production, it is estimated that about 15 billion gallons of crop ethanol will be produced during 2020 through 2045 under all four scenarios.

Figure 2.9. Cellulosic ethanol production under AEO, AEO-ML, EISA, and EISA-ML scenarios

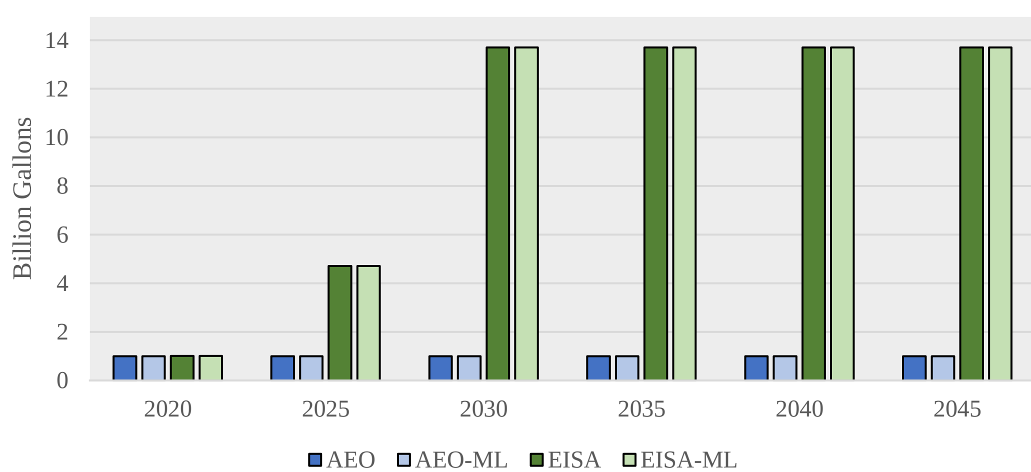


Figure 2.10. Crop ethanol production under AEO, AEO-ML, EISA, and EISA-ML scenarios

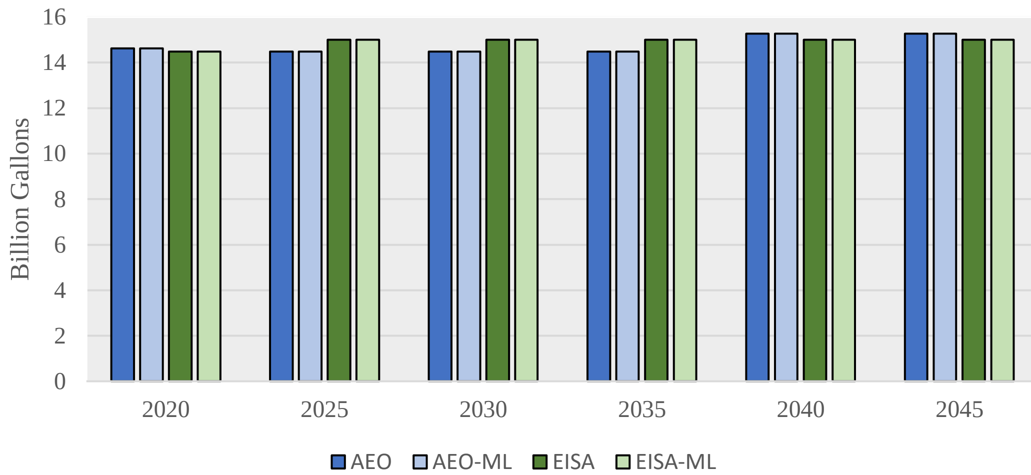
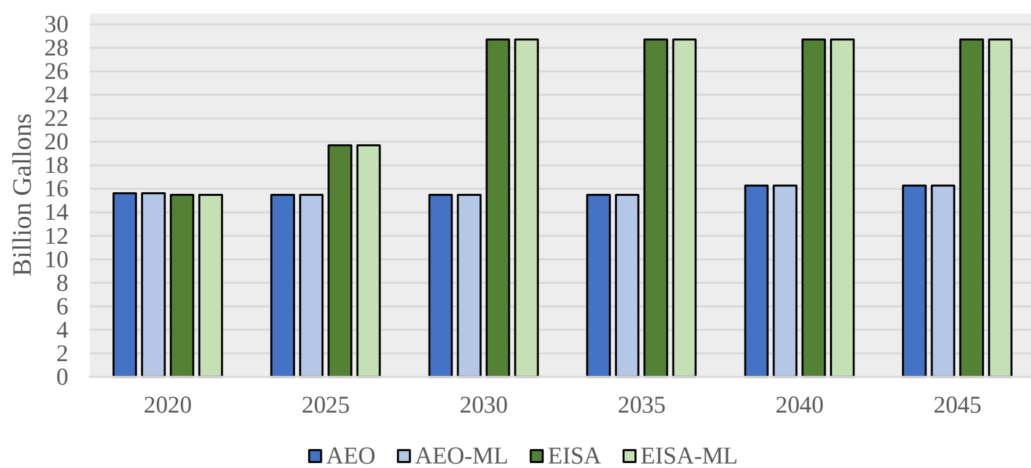


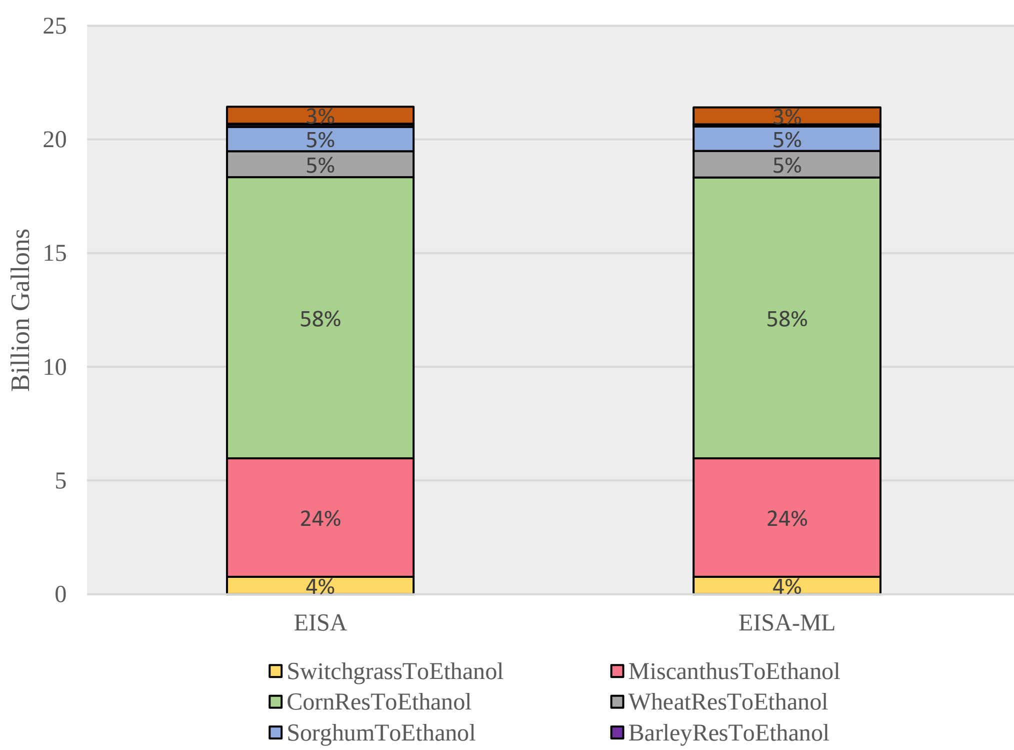
Figure 2.11. Total ethanol production under AEO, AEO-ML, EISA, and EISA-ML scenarios



It should be noted that another major source of cellulosic ethanol other than the agricultural sector is landfill gas. Wastes in landfills, especially the remains of plants processed such as paper contain lignocellulose, which can be broken down into lignin and sugar molecules by using sulfuric acid. The leftover lignin is then burnt to catalyze the fermentation of cellulose into ethanol. While our model takes into account cellulosic ethanol produced from agricultural wastes in the form of corn stover and other crop residues, it does not incorporate ethanol produced from other organic waste in landfills. Therefore, in terms of ethanol production, our model focuses mainly on the contribution from the agricultural sector.

Figure 2.12 presents the annualized amount of cellulosic ethanol produced from different types of feedstocks during 2020 through 2045. The mix of different types of feedstocks remains stable under the EISA projection once marginal land is used to grow switchgrass. As can be seen from the figure, cellulosic ethanol will be produced mainly

Figure 2.12 Feedstock mix to produce cellulosic ethanol under EISA projection



from corn residues. More specifically, corn residues are projected to account for 58 percent of cellulosic ethanol production, while the share of miscanthus is projected to be 24 percent. It should be noted that the projected share of switchgrass used to produce cellulosic ethanol is only 4 percent. This is, nevertheless, expected as corn residues are more cost competitive than switchgrass, and miscanthus yield is almost two times higher than that of switchgrass, hence a better choice. The shares of other ethanol sources such as wheat residues and sorghums are estimated to be about 5 percent. Overall, our results suggest that allowing marginal land for cellulosic feedstock production does not alter the composition of the types of feedstocks contributing to cellulosic ethanol production.

2.6.3 GHG Emissions

An important reason for substituting biofuels for fossil fuels is mainly to offset GHG emissions. Several researchers argue that growing cellulosic crops (namely, switchgrass) on marginal land could help reduce GHG emission if there is no large release of sequestered carbon and if switchgrass sequesters more than traditional crops (Gelfand et al., 2013). Nevertheless, land use changes are inevitable in using marginal land to grow switchgrass. Hence, there will be some carbon, at least initially, released from the land. Moreover, emissions from associated use of fertilizer and harvest or other production machinery, along with the emissions from transportation of feedstock to the bio-refinery, must be taken into account as well.

In this study, total GHG results are compared between the EISA and EISA-ML scenarios. Our results suggest that marginal lands do not reduce net GHG emissions. The amount of GHGs produced under the EISA-ML scenario is higher than the amount generated under the EISA scenario without marginal land. This contradicts the findings of Fargione et al. (2010); Monti et al. (2012); Tilman et al. (2006); and Liu et al. (2017), who report smaller GHG emissions when growing energy crops on degraded or abandoned agricultural land rather than on cropland.

To examine why growing energy crops on marginal lands does not help reduce the net GHG emissions, we decompose the net emissions into several categories. The annualized GHG emissions from various sources under both EISA and EISA-ML scenarios are reported in Table 2.6. The annualized GHG emission offsets from cellulosic ethanol production are estimated to be 33.490 and 33.528 million tons of carbon dioxide equivalents (MMT CO_2e) under the EISA and EISA-ML scenarios, respectively. Another major source of GHG emission offsets is agricultural soil CO_2 sequestration. The offsets contributed from this source are 97.841 MMT CO_2e under EISA scenario.

Table 2.6. Annualized GHG emissions from 2015-2045 (million tons of CO_2e)

	EISA	EISA-ML
Sources of Emission		
Cellulosic Ethanol	-33.490	-33.528
Crop Ethanol	-54.033	-54.032
Biodiesel	-8.766	-8.766
Soil CO_2	-97.841	-96.119
Soil N_2O	7.246	7.388
Fertilizer CO_2	80.336	82.875
Fertilizer N_2O	74.774	76.682
Pasture N_2O	85.837	84.461
Pesticide	8.350	8.389
Fuel	76.867	77.030
Enteric	205.381	204.817
Manure	63.871	63.777
Rice	8.363	8.327
Miscellaneous	1.856	1.856
Total	416.269	420.676

It is initially expected that switchgrass could potentially sequestrate more carbon than traditional row crops, since it has long roots. However, once marginal land is used for growing switchgrass, the amount of CO_2 sequestered in the soil decreases to 96.119 MMT CO_2e. Reduction in soil carbon sequestration is due to more agricultural activities on land and conversion of land in pasture into switchgrass. Moreover, since marginal land has low soil nutrient content and low fertility, more fertilizers are needed in order to increase the yield of switchgrass on marginal land, compared to that used on cropland. Furthermore, the movement of switchgrass to marginal land allows more land to be used in conventional crops, resulting in a net increase in the fertilizer and fuel emissions. Hence, emissions from fertilization, machinery, and transportation of feedstock under the EISA-ML scenario are also higher than those under the EISA scenario.

2.6.4 Non-GHG Environmental Effects

One argument against conventional biofuel production is that growing crops as a bioenergy feedstock could exacerbate both erosion and nutrient runoff. Several studies suggest that growing low-input, perennial grasses such as switchgrass, as a feedstock could potentially reduce such impacts (Campbell et al., 2008; Tilman et al., 2006). Switchgrass could reduce erosion not only due to its presence as a vegetative cover on the soil surface, but due to its network of fibrous roots in surface layers of soil that inhibit erosion (Kort et al., 1998). Moreover, Jensen et al. (2007) assert that planting switchgrass on croplands could reduce soil erosion potential compared to annual row crops, and could potentially provide good forage and habitat for native wildlife. Therefore, in this study, we also investigate a number of other environmental effects including wind and water erosion as well as nitrogen and phosphorus runoff.

Table 2.7 reports the annualized values of wind and water erosion under the EISA and EISA-ML scenarios. As can be seen from the table, the relative changes in wind and water erosion between the two scenarios are negligible. This suggests that the possibility of planting switchgrass on marginal land does not help reduce wind and water erosion effectively. That is, although, from the economic point of view, allowing marginal land for growing switchgrass helps alleviate the pressure from competition for land between food crops and energy crops, in terms of environmental impacts, our results suggest that allowing marginal land for switchgrass production does not help control erosion.

Table 2.7. Annualized values of wind and water erosion (in million tons)

	EISA	
	Without Marginal Land	With Marginal Land
Wind Erosion	540.170	533.511
Water Erosion	788.045	776.131
Total Erosion	1,328.214	1,309.641

In terms of nutrient runoff, we expect that once marginal land is allowed to grow switchgrass, nutrient runoffs will be higher. This occurs because marginal land, which is covered with grass for animal grazing and is generally not fertilized, will then be used to grow switchgrass, resulting in higher fertilizer usage under the scenario with marginal land. Furthermore, as marginal land is used to grow energy crops, more croplands are available for planting other crops. Those croplands are then used to grow other crops that utilize higher amounts of fertilizers than does the switchgrass being replaced. The annualized values of NO3 runoff, Nitrogen loss, potassium runoff, and potassium loss with sediment under the EISA and EISA-ML scenarios are shown in Table 2.8. As expected, the values of all nutrient runoff measures increase when marginal lands are allowed. These findings contradict the National Academy study assertion that utilizing marginal land would help reduce runoff (National Academy of Sciences (U.S.), 2009). The observed results are likely due to both the increased use of marginal land for switchgrass and the increased use of cropland for traditional crops, which shows us that all crop production becomes higher once marginal land is used.

Table 2.8. Annualized values of environmental measures (in million tons)

	EISA	
	Without Marginal Land	With Marginal Land
NO3 Runoff	0.618	0.634
Nitrogen Loss	0.109	0.113
Potassium Runoff	0.075	0.078
Potassium Loss with Sediment	0.135	0.138

2.7 Conclusions

In this study, the economic and environmental effects of growing switchgrass on marginal land were investigated. The Forest and Agricultural Sector Optimization Model with Greenhouse Gases (FASOMGHG) model is employed to estimate and project the US-based implications of meeting the Energy Independence and Security (EISA) and Annual Energy Outlook (AEO) ethanol mandate with and without marginal lands. A free market projection in the absence of biofuel mandates is also considered. Overall, we find positive economic effects but at the cost of negative environmental effects, which contradicts the National Academy study assertion of beneficial environmental effects from utilizing marginal land.

While growing switchgrass on marginal land is not considered to be optimal under the AEO and Free Market projections as cellulosic ethanol. In those cases switchgrass is not found to be economically competitive. However, under the EISA mandate, switchgrass is economic and we find that growing switchgrass on marginal land does reduce land competition pressures. We find that a significant portion of switchgrass production needed to meet the EISA mandate will be shifted to marginal land. In particular, when the model is run allowing switchgrass on marginal land, acres planted to switchgrass on conventional cropland falls. In turn cropland is used to grow other food crops, which in turn helps reduce crop prices and generates benefits for consumers.

In terms of environmental effects, we find that growing switchgrass on marginal land potentially leads to higher levels of net GHG emissions and higher nutrient runoff. This is because CO2 sequestered in the soil is released once marginal land is used for growing switchgrass compared to it staying in pasture. In addition, since marginal land has low soil nutrient content and low fertility, fertilizer is needed and that results in increased nutrient runoff. Additionally GHG emissions from fertilization, machinery, and transportation of feedstock are higher when marginal land is utilized. On the other hand erosion is reduced. These results contradict the National Academy study assertion that biofuels made from cellulosic biomass grown on marginal land can offer major improvements in greenhouse gas emissions and environmental effects relative to those from petroleum-based fuels grown on cropland.

These findings are especially useful for both agricultural producers and policy makers who seek to evaluate benefits and costs of utilizing marginal land for energy crop production. The tradeoff between economic benefits and environmental impacts must be thoroughly taken into consideration.

This study can be extended in several directions. First, the spatial effects of the policy can be investigated further in terms of water quality and quantity used in the agricultural sector. Second, other than land competition, the analysis can be extended to competition in water usage between food and energy crops. Finally, changes in the mix of irrigated crops in total irrigation usage should be examined as a consequence of the RFS2 mandate on biofuels.

CHAPTER III

DEALING WITH TAIL RISKS IN ENERGY COMMODITY MARKETS: FUTURES CONTRACTS VS EXCHANGE TRADE FUNDS*

3.1 Introduction

Given the increase in energy commodity price volatility over the last decade, energy price risk management is becoming increasingly important for both users and producers. Futures contracts are one of the most common derivatives used to reduce exposures to adverse energy price movements. Energy commodity users (producers) can take a long (short) futures market position to lock a near future purchase (sale) price. While the futures contracts offer market participants the ability to hedge against price fluctuations in the energy commodity markets, they may not be a feasible hedging tool for small and mid-sized market participants due to their minimum size. Most futures contracts are too large and expensive for small and mid-sized energy market participants (especially for end-users such as residential consumers, agricultural producers, and small and mid-sized trucking companies)[1].

Alternatively, these market participants can gain exposure to energy price changes by investing in an energy commodity Exchange Traded Fund (ETF), which is designed to track movements in the price of futures contracts. While several empirical studies have

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[1] Note that one futures contract on crude oil, gasoline, and heating oil offered by the Chicago Mercantile Exchange (CME) Group is worth 42,000 gallons (or 1,000 barrels) of crude oil, gasoline, and heating oil, respectively, and one natural gas contract represents 10,000 million British thermal units (MMBtu) of natural gas.

evaluated the hedging performance of energy commodity futures (see, for example, Alizadeh et al., 2008; Chang et al., 2011; Conlon and Cotter, 2013; Cotter and Hanly, 2012), there are very few studies on the hedging effectiveness of energy commodity ETFs.

Murdock and Richie (2008) examined the suitability of the United States Oil Fund as a hedging instrument. Based on the correlation analysis results, they concluded that the Fund is a reasonably good hedging vehicle for crude oil during backwardation, but it may not be an effective hedging tool during contango. Sukcharoen et al. (2015) compare the effectiveness of futures contract versus ETF in hedging gasoline price movements and finds that the ETF is a superior hedging instrument relative to the futures contract during a high-volatility period. Maples et al., (2016) investigate the use of several commodity ETFs (including corn, soybeans, and heating oil ETFs as well as live cattle Exchange Traded Note) as hedging tools for southeastern agribusiness producers. Their analysis results suggest that the ETFs are effective in hedging commodity price risks. However, none of these studies considers the potential of energy commodity ETFs from the tail risk perspective[2]. Accordingly, the primary purpose of this paper is to examine the effectiveness of ETF as an alternative hedging tool for both energy commodity users and producers in a tail-risk hedging context[3].

[2] Even though Sukcharoen et al., (2015) also consider the ability of gasoline ETF in reducing tail risk of movements in gasoline spot price, the optimal ETF hedge ratios are calculated under a minimum-variance framework (not a minimum-tail risk framework).

[3] Note that previous studies, including Alizadeh et al. (2008); Liu et al. (2017); and Sukcharoen and Leatham, (2017), have already considered the effectiveness of energy commodity futures in dealing with tail risk. Also, Cotter and Hanly, (2006) have previously addressed the problem of differential hedging performance for long and short hedgers for various objective functions. Therefore, the novelty of this paper is to examine whether ETFs might be a better instrument than futures contracts for hedging tail risk in the energy commodity markets.

As the goal of most hedgers is to avoid unfavorable extreme-tail outcomes or tail risk (Stulz, 1996; Unser, 2000; Veld and Veld-Merkoulova, 2008), we apply a minimum-tail risk framework to estimate optimal hedge ratios. Specifically, this study considers both the minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) objectives. To determine the minimum-VaR and minimum-ES hedge ratios, the distribution of hedged portfolio returns needs to be estimated. The standard practice is to use an empirical distribution method (see, for example, Demirer and Lien, 2003; Harris and Shen, 2006; Lien and Tse, 2000, 2001). This is considered an indirect method as the distribution of hedged portfolio returns is not directly derived from the joint distributions of spot and futures (or ETF) returns. This study adopts a direct approach and estimates the joint distributions of relevant returns using a kernel copula method. Similar to the empirical distribution method, the kernel copula approach is a nonparametric method and therefore does not require any prior assumptions regarding the shape of the returns distributions.

3.2 Objectives of the Study

This paper aims to contribute to the literature in several aspects:

1) It adds to the rare literature on ETF hedging by examining the usefulness of ETFs in dealing with tail risk in the energy commodity markets. In particular, both average and dynamic out-of-sample hedging effectiveness of ETFs are analyzed and compared with those of futures contracts.

2) Unlike previous studies on ETF hedging, the paper investigates hedging performance of ETFs for more than one energy commodities. Specifically, four energy commodities are considered including crude oil, gasoline, heating oil, and

natural gas. This allows us to inspect whether the hedging results are sensitive to the underlying energy commodities.

3) The kernel copula approach is applied to determine minimum-VaR and minimum-ES hedge ratios. To confirm the robustness of the results, we also conduct an analysis using the empirical distribution method.

4) Given that long and short hedgers are concerned with opposite tails of the distribution of portfolio returns, we calculate the optimal hedge ratios for both long hedgers (energy commodity users) and short hedgers (energy commodity producers). This allows us to evaluate the sensitivity of the hedging performance vis-à-vis the hedge positions. Our findings would benefit both energy commodity users and producers who seek out the best hedging instrument for reducing the risks of adverse price movements in energy commodity markets.

The remainder of this paper is organized as follows. Section 3.3 describes the characteristics of energy commodity ETFs. Section 3.4 outlines the minimum tail-risk hedging problem, methods for estimating the optimal hedge ratios, and hedging effectiveness measures. Section 3.5 presents the data and preliminary analysis results. Section 3.6 reports and discusses the empirical results on the optimal ETF and futures hedge ratios and their out-of-sample hedging effectiveness. Finally, Section 3.7 provides the conclusions drawn from this study

3.3 Characteristics of Energy Commodity ETFs

An exchange-traded fund or ETF was first introduced in 1989 on the Toronto Stock Exchange and has matured substantially over the last few decades as an investment product. By construction, the ETF is designed to track the performance of an underlying asset or a basket of underlying assets (including stocks, bonds, commodities, and/or derivative products). The ownership of those underlying assets is then allocated into individual shares, which are traded like stocks on a real-time intraday basis. This is one of the most desirable characteristics of the ETF because it has provided all types of investors (including small and mid-sized investors) with an inexpensive way to gain exposure to a particular market. For example, an investor may purchase only five shares of the United States Oil (USO) Fund that would give him exposure to roughly 5 barrels of crude oil, as opposed to purchasing one crude oil futures contract that covers 1,000 barrels of crude oil. In this section, we first discuss the construction of ETFs (including the practical differences between ETFs and futures contracts), and then outline the trading of the four energy commodity ETFs considered in this study.

3.3.1 ETF Construction

The supply of ETF shares is generated through a creation/redemption mechanism. The mechanism involves large specialized investors, known as authorized participants. The authorized participants can increase the supply of shares (i.e., create the ETF shares) by exchanging the underlying assets required to create a fund with ETF providers/issuers. On the other hand, they can reduce the supply of shares (i.e., redeem the ETF shares) by accumulating a sufficient number of the ETF shares and then exchanging them with the ETF providers for the underlying assets of equivalent value. The number of ETF shares created and redeemed mainly depends on the market demand for ETF shares. For example, if the market demand for ETF shares is high, the authorized participants will exchange the underlying assets with the ETF providers in an exchange for additional ETF shares. The ETF shares created are then traded by individual investors on a stock exchange.

It should be noted that the authorized participants bear the transaction costs associated with the creation and redemption of the ETF shares. Therefore, the ETFs offer market participants a more cost-effective way of gaining exposure to a specific market than the traditional futures contracts. Table 3.1 summarizes practical differences between ETF and futures trading. As mentioned earlier, the ETF market provides small investors and hedgers with more trading flexibility than the futures market as the ETF market allows investors to trade as little as a single share. In addition, unlike futures investors, ETF investors are not required to meet any initial or maintenance margin requirements. Regarding transaction costs, ETF investors have to pay an annual management fee of 0.45-0.60 percent (depending on the funds). The commission fee on an ETF trade is \$0-\$4.95 per trade (depending on the brokerage firms), whereas the commission fee on a futures trade is \$1.45 per futures contract. Nevertheless, despite these transaction costs, the ETF market is still an appealing avenue for smaller investors who have no or limited access to futures hedging due to the large margin requirements and large contract size. In terms of accessibility, ETF investors can conveniently trade ETF shares during regular trading hours (as well as during extended trading hours, depending on the brokerage firms), whereas the futures contracts are traded six days a week (nearly 24 hours a day) on the Chicago Mercantile Exchange (CME) Globex system.

Table 3.1. Practical differences between ETF and futures trading

Issue	ETF Trading	Futures Trading
Accessibility	Trades executed throughout the trading day and during extended hours trading	Nearly 24 hours, six days a week
Investment Minimum	1 share	1 contract
Brokerage/Commission Fee	$0 - $4.95 per trade	$1.45 per contract
Management Fee	0.45%-0.60% per year (for energy commodity ETFs)	None
Initial Margin	None	Required
Maintenance Margin	None	Required
Leverage	Lower Leverage	Higher Leverage
Short Selling	Allowed	Allowed
Liquidity	Good but Lower Liquidity	Higher Liquidity
Transparency	High Degree of Transparency	High Degree of Transparency

Table 3.2 reports average daily dollar volume of ETF and futures markets for crude oil, gasoline, heating oil, and natural gas. As can be seen from Table 3.2, both ETF and futures markets are liquid. Thus, investors in both markets should be able to quickly get in and out of the markets. However, the futures market is more liquid than the ETF market. When it comes to leverage, futures investors are able to utilize more leverage than are ETF investors. For example, investors who wish to trade ETF shares on margin may borrow only up to 50% of the transaction price. On the other hand, futures investors only need to deposit 5% to 15% of the total contract value (that is, they can borrow more than 50% of the transaction price). Short selling is possible for both ETF and futures investors. Nevertheless, while the margin requirements remain the same for the long and short positions in the futures market, short selling an ETF share involves an interest charged on the loaned ETF shares as well as a fee that needs to be paid to the lender for the right to borrow the share. To avoid these extra costs related to short selling, short hedgers in crude oil and natural gas markets may instead purchase “inverse ETFs” or “short ETFs” offered

Table 3.2. Average daily dollar volume of ETF and futures markets for crude oil, gasoline, heating oil, and natural gas (from the ETF launch date to August 31, 2017)

ETF/Futures	ETF Average Daily Dollar Volume	Futures Average Daily Dollar Volume
United States Oil (USO) Fund/ West Texas Intermediate (WTI) crude oil	$381.94 million (14.32 million shares)	$21,851.24 million (0.31 million contracts)
United States Gasoline (UGA) Fund/ New York Harbor Regular gasoline	$2.44 million (63,274 shares)	$4,013.60 million (42,962 contracts)
United States Diesel-Heating Oil (UHN) Fund/ New York Harbor No. 2 heating oil	$0.16 million (5,644 shares)	$4,069.29 million (41,926 contracts)
United States Natural Gas (UNG) Fund/ Henry Hub natural gas	$148.81 million (1.42 million shares)	$4,424.58 million (0.11 million contracts)

by ProShares, which are designed to return the inverse of the performance of a certain benchmark. With respect to transparency, both markets are very transparent, given that both ETF shares and futures contracts are traded on regulated exchanges. In addition, most ETFs publicly disclose their complete portfolios every day.

3.3.2 Energy Commodity ETFs

During the last decade, numerous energy commodity ETFs have been introduced. The four energy commodity ETFs considered in this study are the United States Oil (USO) Fund, the United States Gasoline (UGA) Fund, the United States Diesel-Heating Oil (UHN) Fund, and the United States Natural Gas (UNG) Fund. These energy commodity ETFs operate under investment objectives that are defined relative to the daily returns on the underlying futures contracts.

The USO Fund (ticker symbol: USO) tracks in percentage terms the daily changes of West Texas Intermediate (WTI) crude oil futures prices. The USO Fund's launch (inception) date is April 10, 2006. The USO Fund's top portfolio holdings include near-month crude oil futures contracts and other oil-related futures contracts. In 2019, the USO

Fund has approximately $1.58 billion in assets and 133.6 million shares outstanding. Since its inception date, the average daily dollar volume of the USO shares is $381.94 million, whereas that of the West Texas Intermediate (WTI) crude oil futures contracts is $21,851.24 million (see Table 3.2). In terms of physical volume, the average daily trading volumes of the USO shares and crude oil futures contracts (with each contract equal to 1,000 barrels) are 14.32 million shares and 0.31 million contracts, respectively.

The UGA Fund (ticker symbol: UGA) tracks in percentage terms the daily changes of New York Harbor RBOB gasoline futures prices. The launch date of the UGA is February 27, 2008. It holds mainly near-month RBOB futures contracts and other gasoline-related futures contracts. As of March 2019, the UGA Fund has about $45.4 million in assets under management and 1.6 million shares outstanding. Since the UGA's launch date, the average daily dollar volume of the UGA shares is $2.44 million (or 63,274 shares), whereas that of the New York Harbor Regular gasoline futures contracts (with each contract equal to 42,000 gallons) is approximately $4,013.60 million (or 42,962 contracts).

The UHN Fund (ticker symbol: UHN) tracks in percentage terms the daily changes of New York Harbor No. 2 heating oil futures prices. The UHN Fund's launch date is April 9, 2008. Its top portfolio holdings are near-month heating oil futures contracts and other heating oil-related futures contracts. As of June 2018, the UHN Fund has approximately $7.3 million in assets and 350,000 shares outstanding. Since the UHN's inception date, the average daily dollar volume of the UHN shares is $0.16 million (or 5,644 shares), whereas that of the New York Harbor No. 2 heating oil futures contracts (with each contract equal to 42,000 gallons) is approximately $4,069.29 million (or 41,926 contracts).

Lastly, the UNG Fund (ticker symbol: UNG) tracks in percentage terms the daily changes of Henry Hub natural gas futures prices. Its launch date is April 18, 2007. The UNG Fund holds mainly near-month natural gas futures contracts and other natural gas-related futures contracts. In 2019, the UNG Fund has about $263.6 million in assets under management and 10.8 million shares outstanding. Since its launch date, the average daily dollar volume of the UNG shares is $148.81 million, whereas that of the Henry Hub natural gas futures contracts is $4,424.58 million. In terms of physical volume, the average daily trading volumes of the UNG shares and natural gas futures contracts (with each contract equal to 10,000 mmBtu) are 1.42 million shares and 0.11 million contracts, respectively. Note that these funds roll over their near-month futures contracts to the next-month contracts as soon as the near-month futures contracts are within two weeks of expiration.

3.3.3 Hedging with Energy Commodity ETFs

The concept behind the use of energy commodity ETFs in hedging price risks in the energy commodity markets is straightforward. Take, for example, the USO Fund that is designed to match the change of WTI crude oil futures price on a daily basis. More specifically, if WTI crude oil futures prices increases by one percent on a given day, the USO Fund is designed to rise by one percent that day. Therefore, cash flows emanating from an energy commodity ETF investment would theoretically provide protection for a hedger in a similar way as would cash flows from futures trading.

Nonetheless, a hedger should keep in mind that the mechanics of ETF hedging is somehow different from futures hedging. Specifically, an energy commodity ETF is a cash product whereas a futures contract is a derivative product. As the derivative product has a fixed maturity date, the hedger knows that the no arbitrage condition helps ensure that the futures price and the spot price of the underlying commodity equate on a specified future date. This is no such condition for an ETF. In effect, there may be a perpetual basis risk with ETF.

Furthermore, the ETF is not marked-to-market. In other words, ETF investors would not realize a gain or loss until they sell or buy back the ETF, potentially leaving a naked position if the maturities do not match (especially if the ETF holders are forced to sell their ETF shares due to liquidity issues). In addition, as energy commodity ETF managers strive to match the percentage change of the target futures contract on a day-to-day basis, the compounding of the gross return of the ETF may differ from the total return received from holding the respective futures contract over a specified period of time (Burney, 2012; Cheng and Madhavan, 2009). Due to the single-day objective of the energy commodity ETF, a constant rebalancing of the hedge is required and this involves transaction costs (Burney, 2012; Hill and Teller, 2010). Depending on the hedge period, a futures hedger might also need to rebalance the futures position periodically to ensure the effectiveness of the hedge. These are important factors that all hedgers should consider before selecting a hedging instrument.

3.4 Methodology

The determination of the optimal hedge ratio depends on the underlying asset position to which a particular hedger is exposed (i.e., whether a long or short position should be taken to manage risk) and his/her risk management objective (hedging objective). In this section, we first outline the hedging problem facing two types of tail-risk hedgers: long and short tail-risk hedgers, and then present the kernel copula approach for estimating the optimal hedge ratios. We also discuss how hedging effectiveness is analyzed in this section.

3.4.1 Minimum-tail Risk Hedging Problem

The two hedging instruments considered in this study are energy commodity futures and ETFs. This paper takes the point of view of both energy commodity users (long hedgers) and producers (short hedgers). In general, an energy commodity user (typically either an end consumer or energy commodity processor) that wishes to lock the price of an energy commodity to be purchased at some time in the near future is engaged in a long hedge. At time t, such a long hedger expects to purchase (or process) a known quantity, Q_t, of a particular energy commodity at time $t+1$. The spot price at time t, denoted by S_t, is known, whereas the spot price at time $t+1$, denoted by S_{t+1}, is unknown. To hedge the change in spot price, the long hedger would take a long position of X_t units of the energy commodity in either the futures or ETF market at time t. The long hedger's per-period return on the hedged portfolio (i.e., from time t to time $t+1$) for the case of futures hedging is therefore given by:

$$R_{t+1}^{h,long} = -R_{t+1}^{S} + h_t R_{t+1}^{F} \tag{3.1}$$

where $R_{t+1}^{S} = \ln(S_{t+1}/S_t)$ is the per-period return on the spot position at time $t+1$, $R_{t+1}^{F} = \ln(F_{t+1}/F_t)$ is the per-period return on the futures position at time $t+1$, and $h_t = X_t/Q_t$ is the hedge ratio to be determined at time t.

On the other hand, an energy commodity producer that commits to selling an energy commodity at some time in the future typically wishes to protect against the risk of declining commodity price and hence engages in a short hedge. To hedge the change in spot price, the short hedger (that expects to sell a known quantity, Q_t, of a specific energy commodity at time $t+1$) would take a short position of X_t units of the energy commodity in either the futures or ETF market at time t. The short hedger's per-period return on the hedged portfolio for the case of futures hedging is thus given by:

$$R_{t+1}^{h,short} = R_{t+1}^{S} - h_t R_{t+1}^{F} \tag{3.2}$$

For the case of ETF hedging, the per-period ETF return at time $t+1$, $R_{t+1}^{ETF} = \ln(ETF_{t+1}/ETF_t)$, is used in place of R_t^F.

As mentioned previously, the determination of the optimal hedge ratio, h_t, depends not only on whether a short or long hedge position is to be taken but also on the hedger's risk management objective. In practice, most hedgers are only concerned with dangerous "lower-tail outcomes" or "tail risk" (Stulz, 1996; Unser, 2000; Veld and Veld-Merkoulova, 2008). Accordingly, this paper assumes that the hedger's objective is to minimize the tail risk of the hedge portfolio returns. Thus, the hedger's problem at time t is then to select the optimal hedge ratio, h_t^* that minimizes the tail risk of the hedged portfolio. The following equation formally presents the hedger's problem:

$$h_t^* = \arg\min_{h_t} RM(R_{t+1}^{h,type}) \tag{3.3}$$

where $R_{t+1}^{h,type}$ is the hedger's per-period return on the hedged portfolio, $type = long$ for long hedgers and $type = short$ for short hedgers, and $RM(\cdot)$ denotes the risk measure. The construction of $R_{t+1}^{h,long}$ and $R_{t+1}^{h,short}$are described in Eq. (3.1) and Eq. (3.2), respectively. This paper considers the two most popular tail risk measures: Value at Risk (VaR) and Expected Shortfall (ES).

For a given confidence level, $(1-\alpha)100\%$, VaR is defined as the largest potential loss on a hedged portfolio over a given time horizon (i.e., from time t to time $t+1$) and given by:

$$VaR_{(1-\alpha)100\%}\left(R_{t+1}^{h,type}\right) = -G^{-1}(\alpha) \tag{3.4}$$

where G is the cumulative distribution function (CDF) of $R_{t+1}^{h,type}$. On the other hand, the ES at the is defined as the expected loss on a hedge portfolio conditional on the amount of losses exceeding the VaR of the portfolio. More specifically, the ES at the $(1-\alpha)100\%$ confidence level over a given time horizon is given by:

$$ES_{(1-\alpha)100\%}\left(R_{t+1}^{h,type}\right) = -E\left[R_{t+1}^{h,type} | R_{t+1}^{h,type} \leq -VaR_{(1-\alpha)100\%}\left(R_{t+1}^{h,type}\right)\right] \tag{3.5}$$

In this study, VaR and ES are calculated for three confidence levels: $(1-\alpha)100\% = 90\%, 95\%$, and 99%.

3.4.2 Estimation of the Optimal Hedge Ratios

Since there is no explicit analytical solution for the minimization problem in Eq. (3.3), the minimum-VaR and minimum-ES hedge ratios need to be solved numerically. To calculate the VaR and ES values, we need to first estimate the CDF of hedger's per-

period return on the hedged portfolio, $G(R_{t+1}^{h,type})$. In this study, the kernel copula method is adopted to estimate the CDF of hedged portfolio returns. The kernel copula approach is based on the Sklar's theorem (Sklar et al., 1959). For the case of two random variables, the Sklar's theorem states that any bivariate distribution can be decomposed into two parts: two individual marginal distributions and a copula that describes their dependence structure. More formally,

$$G(x_1, x_2) = C\big(G_1(x_1), G_2(x_2)\big) \tag{3.6}$$

where $G_1(x_1)$ and $G_2(x_2)$ are marginal distributions of random variables x_1 and x_2, respectively, and $C: [0,1]^2 \longrightarrow [0,1]$ is a copula function. If $G_1(x_1)$ and $G_2(x_2)$ are differentiable, the joint density function, $g(x_1, x_2)$, can be expressed as:

$$g(x_1, x_2) = g_1(x_1) \cdot g_2(x_2) \cdot c\big(G_1(x_1), G_2(x_2)\big) \tag{3.7}$$

where $g_1(x_1)$ and $g_2(x_2)$ are the density of $G_1(x_1)$ and $G_2(x_2)$, and $c(\cdot)$ is the density of the copula function. This decomposition implies that the modeling of the two marginal distributions can be separated from the modeling of the dependence structure.

Accordingly, the procedure for constructing the joints distribution of R_{t+1}^{S} and R_{t+1}^{F} (or R_{t+1}^{S} and R_{t+1}^{ETF}) using the kernel copula approach can be briefly summarized in four steps. First, we estimate the marginal distribution for each return series using an empirical distribution function, and then transform the return series into a standard uniform variable (also known as copula data)[4]. Second, the copula density,

[4] To avoid the possible misspecification of parametric distributions, the marginal distributions of spot, futures, and ETF returns are estimated nonparametrically instead of parametrically. Similar to Barbi and Romagnoli, (2014); Bouyé and Salmon, (2009); Power and Vedenov, (2010); and Sukcharoen and Leatham, (2017), the marginal distributions are estimated using the unfiltered return data instead of using the GARCH filtered return data to avoid the first stage estimation and specification errors.

$c(G_1(x_1), G_2(x_2))$, is estimated nonparametrically using a kernel-type copula density estimator of (Geenens et al., 2017). Third, we generate $m = 10{,}000$ Monte Carlo draws of the two standard uniform variables from the estimated copula density.

Finally, the draws from the copula are converted to spot and futures (or ETF) return series by applying the inverse of the corresponding marginal distribution function of each return series. For any given h, we use the simulated R_{t+1}^S and R_{t+1}^F (or R_{t+1}^S and R_{t+1}^{ETF}) series to generate the distribution of $R_{t+1}^{h,type}$. For a given hedge ratio h, let $\{R_1^{h,type}, R_2^{h,type}, \dots, R_m^{h,type}\}$ be a series of hedged portfolio returns constructed from the data series of spot and futures (or ETF) returns. The kernel copula method suggests estimating $VaR_{(1-\alpha)100\%}(R_{t+1}^{h,type})$ as:

$$VaR_{(1-\alpha)100\%}(R_{t+1}^{h,type}) = -percentile\left(\{R_\tau^{h,type}\}_{\tau=1}^{m}, (\alpha \cdot 100\%)\right) \tag{3.8}$$

The minimum-VaR hedge ratio is then determined as the value of h that minimizes the VaR of hedged portfolio returns. On the other hand, for a given hedge ratio h, $ES_{(1-\alpha)100\%}(R_{t+1}^{h,type})$ can be calculated as:

$$ES_{(1-\alpha)100\%}(R_{t+1}^{h,type}) = -\frac{1}{\lfloor \alpha m \rfloor}\sum_{i=1}^{\lfloor \alpha m \rfloor} R_{(i)}^{h,type} \tag{3.9}$$

where $\lfloor \alpha m \rfloor$ denotes the largest integer not greater than αm, and $R_{(1)}^{h,type} \le R_{(2)}^{h,type} \le \cdots \le R_{(m)}^{h,type}$ are the order statistics in ascending order corresponding to the simulated hedged portfolio returns $R_1^{h,type}, R_2^{h,type}, \ldots, R_m^{h,type}$. The minimum-ES hedge ratio is then determined as the value of h that minimizes the ES of hedged portfolio returns[5].

3.4.3 Hedging Effectiveness

To analyze hedging effectiveness of two alternative hedging instruments, we apply a rolling window analysis similar to Barbi and Romagnoli (2014); Conlon and Cotter (2013); and Sukcharoen and Leatham (2017). Due to daily mark-to-market practices, the appropriate hedge horizon – the time frame for measuring price changes – is one day (Demirer et al., 2005). Therefore, this paper focuses on a daily hedge horizon[6]. Specifically, we compute the minimum-VaR and minimum-ES hedge ratios for both short and long hedgers using the first 250 daily return observations (i.e., a rolling window of 250 trading days)[7]. To capture the out-of-sample hedging performance, the next 250 daily observations are used to measure the hedging effectiveness. Following Ederington, (1979), hedging effectiveness is measured as a percentage reduction in the risk of

[5] To check the robustness of the hedging results, we also conduct an analysis using the empirical distribution method (also known as the historical simulation method). It should be noted that both the empirical distribution and kernel copula approaches are nonparametric methods. However, unlike the kernel copula method, the empirical method is considered as an indirect approach because the VaR and ES values are calculated from the probability distribution of the hedged portfolio returns, not from the joint distributions of spot and futures (or ETF) returns.

[6] Note that a similar analysis can be applied to different hedge horizons such as weekly, monthly and quarterly.

[7] To check the robustness of the results, an additional analysis is also conducted using a rolling window of 500 trading days. We find that the main conclusion regarding the relative hedging performance of ETFs and futures remains unchanged. Moreover, we also find that using the 500-day rolling window leads to poorer hedging outcomes (in terms of percentage of risk reduction) than using the 250-day rolling window for most cases (especially for the gasoline and heating oil markets). Nevertheless, studies on the optimal size of the rolling windows for calculating optimal hedge ratios based on empirical distribution and kernel copula methods are still needed.

unhedged (spot) position relative to the risk of hedged position. That is, hedging effectiveness (in percentage) is defined as:

$$HE = \left(1 - \frac{RM(R^{h^*,type})}{RM(R^{0,type})}\right) \times 100 \tag{3.10}$$

where $R^{h^*,type}$ is the return on optimal hedged portfolio, $R^{0^*,type}$ is the return on unhedged portfolio, and $RM(\cdot)$ is the risk measure. In this study, two tail-risk measures are considered in evaluating the hedging effectiveness: VaR (90%, 95%, and 99%) and ES (90%, 95%, and 99%). We then move the rolling window by one day and recalculate the optimal hedge ratios as well as the out-of-sample effectiveness. Finally, the average hedging effectiveness is calculated across all rolling windows for each hedging instrument, hedging objective and types of hedger.

3.5 Data and Preliminary Analysis

The empirical analysis is based on daily spot, futures, and ETF prices for four different energy commodities: crude oil, gasoline, heating oil, and natural gas. The spot and futures price data used include daily spot and futures prices for West Texas Intermediate (WTI) crude oil (trading location: Cushing, Oklahoma), New York Harbor Regular gasoline (trading location: New York Harbor), New York Harbor No. 2 heating oil (trading location: New York Harbor), and Henry Hub natural gas (trading location: Louisiana Gulf coast). These spot and futures price data are drawn from the U.S. Energy Information Administration (EIA) [8]. With respect to the ETF price data, we employ daily

[8] Here, the spot price is defined as “the price for a one-time open market transaction for immediate delivery of a specific quantity of a production at a specific location where the commodity is purchased ‘on the spot’

ETF prices for the United States Oil (USO) Fund, United States Gasoline (UGA) Fund, United States Diesel-Heating Oil (UHN) Fund, and United States Natural Gas (UNG) Fund. The ETF price data are obtained from Thomson Reuters Datastream.

For each energy commodity, we use the ETF launch date (see Section 3.3.2) as the first date of the spot, futures and ETF time series. Accordingly, daily log returns are calculated using the price data from April 10, 2006 to August 31, 2017 for crude oil, from February 27, 2008 to August 31, 2017 for gasoline, from April 9, 2008 to August 31, 2017 for heating oil, and from April 18, 2007 to August 31, 2017 for natural gas. To construct each continuous series of futures returns, we use the nearby futures contract and switch to the next contract month two weeks before expiration[9]. Care has been taken to ensure that the log returns of futures prices are calculated using the same futures contract. Altogether, we have a total of 2,862 observations for crude oil, 2,389 observations for gasoline, 2,360 observations for heating oil, and 2,606 observations for natural gas. Accordingly, our rolling window analysis discussed in Section 3.3 would result in 2,363 (out-of-sample) test windows for crude oil, 1,890 test windows for gasoline, 1,861 test windows for heating oil, and 2,107 test windows for natural gas.

Table 3.3 reports summary statistics for daily spot, futures, and ETF log returns for crude oil, gasoline, heating oil, and natural gas. Over the time period studied, the means

at current market rates" (U.S. Energy Information Administration, 2019). All futures contracts settle in the same locations as the spot market counterparts.

[9] It should be noted that all the energy commodity ETFs considered periodically roll over their futures contracts as soon as the near-month futures contracts are within two weeks of expiration. Therefore, a two-week rollover strategy is adopted in this study. As part of the robustness analysis, we also consider a rollover strategy where contracts are held until expiration and a one-week rollover strategy. We find that the rollover strategy does not affect the main findings of the study. This is consistent with Carchano and Pardo, (2009) who show that the choice of rollover date to construct the futures return series is irrelevant.

of all return series are negative but close to zero. The spot returns are found to be more volatile than the futures and ETF returns for all four commodities, with the natural gas market being the most volatile. All return series are slightly skewed and display high excess kurtosis (especially the gasoline and natural gas spot returns). This implies that all return series are not normally distributed.

The Augmented Dicky-Fuller (ADF) test results indicate that each return series is stationary[10]. For crude oil and heating oil markets, there is a stronger correlation and tail dependence (both upper and lower) between the spot and futures returns than between the spot and ETF returns, but the opposite is observed for gasoline and natural gas markets (except for the upper tail dependence in the gasoline market)[11]. The lowest correlation and tail dependence are observed between the natural gas spot and futures returns. The highest correlation and tail dependence are found between the crude oil spot and futures returns.

3.6 Empirical Results

In this section, we present our empirical findings for optimal hedge ratios and out-of-sample hedging effectiveness determined for both long and short hedgers in four energy commodity markets: crude oil, gasoline, heating oil, and natural gas markets. Comparisons

[10] A Seasonal Autoregressive Integrated Moving Average (ARIMA) model and an Exponential Smoothing State Space (ETS) model with seasonality were estimated to check the existence of seasonality in each return series. Both the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicate that the inclusion of a seasonal component does not help improve forecast accuracy. The finding is consistent with Liu et al., (2017) who find that there is insufficient evidence to support the existence of seasonality in returns series of energy commodities.

[11] In this study, the pair-wise tail dependence coefficients are estimated non-parametrically using an empirical copula. A threshold used in the estimation of tail dependence coefficients is 0.05. In other words, 5% of the most extreme data are used in the calculation of tail dependence coefficients.

Table 3.3. Summary statistics of daily spot, futures, and ETF log returns for crude oil, gasoline, heating oil, and natural gas

	Spot	Futures	ETF
Crude Oil			
Mean (%)	-0.013	-0.023	-0.068
Standard Deviation (%)	2.441	2.337	2.181
Minimum (%)	-12.827	-12.595	-11.300
Maximum (%)	16.414	16.410	9.169
Skewness	0.141	0.063	-0.146
Excess Kurtosis	4.458	4.020	2.272
ADF	-38.841*	-39.813*	-38.427*
Correlation (with Spot)		0.923	0.903
Lower Tail Dependence ($k = 0.05$)		0.846	0.741
Upper Tail Dependence ($k = 0.05$)		0.846	0.734
Gasoline			
Mean (%)	-0.006	-0.030	-0.020
Standard Deviation (%)	3.651	2.439	2.175
Minimum (%)	-19.327	-16.109	-12.331
Maximum (%)	48.380	21.665	10.572
Skewness	1.156	-0.025	-0.299
Excess Kurtosis	17.396	6.567	2.624
ADF	-33.237*	-35.123*	-34.918*
Correlation (with Spot)		0.524	0.601
Lower Tail Dependence ($k = 0.05$)		0.353	0.403
Upper Tail Dependence ($k = 0.05$)		0.328	0.319
Heating Oil			
Mean (%)	-0.029	-0.033	-0.049
Standard Deviation (%)	2.194	2.075	1.985
Minimum (%)	-12.708	-19.749	-10.130
Maximum (%)	14.862	10.118	9.549
Skewness	0.047	-0.365	0.001
Excess Kurtosis	4.339	5.876	2.360
ADF	-35.448*	-34.207*	-34.301*
Correlation (with Spot)		0.888	0.845
Lower Tail Dependence ($k = 0.05$)		0.712	0.678
Upper Tail Dependence ($k = 0.05$)		0.797	0.746
Natural Gas			
Mean (%)	-0.036	-0.043	-0.157
Standard Deviation (%)	3.904	2.941	2.649
Minimum (%)	-27.844	-13.797	-13.198
Maximum (%)	39.007	26.874	13.952
Skewness	0.912	0.637	0.087
Excess Kurtosis	15.677	4.735	1.370
ADF	-41.819*	-36.276*	-35.613*
Correlation (with Spot)		0.163	0.198
Lower Tail Dependence ($k = 0.05$)		0.169	0.169
Upper Tail Dependence ($k = 0.05$)		0.200	0.215

Note: ADF is the Augmented Dickey-Fuller test statistic, where * denotes the rejection of the null hypothesis of a unit root (non-stationarity). For lower and upper tail dependence, k is the threshold number, meaning k% of most extreme return data are used in the calculation.

of out-of-sample hedging effectiveness also are made between the two hedging instruments: futures and ETFs. The kernel copula methods is applied to estimate the VaR and ES values at the 90%, 95%, and 99% confidence levels[12].

3.6.1 Optimal Hedge Ratios

Average ETF and futures hedge ratios calculated using the kernel copula approach are shown for different hedging objectives and for both long and short hedgers in Table 3.4. Examining first the impact of hedge positions, we find that of the 48 hedge-ratio pairs the optimal hedge ratios for short hedgers are larger than those for long hedgers in about 60 percent of the cases. In keeping with previous findings (Demirer et al., 2005; Demirer and Lien, 2003), the overall results indicate no discernible pattern in the relative sizes of optimal hedge ratios for long and short hedgers. However, few distinct patterns are found when considering each energy commodity market and each hedging instrument individually. In the crude oil market, regardless of the hedging instruments, long hedgers are almost always hedge more than short hedgers (except for the minimum-VaR (90% and 95%) objectives). In the gasoline market, long hedgers almost always hedge more than short hedgers when an ETF is used as a hedging instrument. The only exception is for the minimum-VaR (90%) objective. In contrast, for all hedging objectives (except for the minimum-ES (99%) objective), the size of the futures position for long hedgers is smaller than that for short hedgers. In the heating oil market, long hedgers consistently hedge less

[12] We also estimate the VaR and ES using the empirical distribution method. Both the empirical distribution and kernel copula methods generate qualitatively similar empirical results. The results from the empirical distribution method are available from the authors upon request.

Table 3.4. Average minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) hedge ratios for the case of ETF (futures) hedging

Hedging Objectives	Crude Oil	Gasoline	Heating Oil	Natural Gas
Panel A: Long Hedgers				
min-VaR (90%)	0.969	0.934	0.894	0.179
	(0.989)	(0.784)	(0.959)	(0.197)
min-VaR (95%)	0.995	1.029	0.901	0.253
	(0.998)	(0.764)	(0.967)	(0.257)
min-VaR (99%)	1.062	1.373	0.979	0.491
	(1.020)	(0.893)	(0.936)	(0.413)
min-ES (90%)	1.028	1.115	0.932	0.251
	(1.008)	(0.791)	(0.936)	(0.254)
min-ES (95%)	1.053	1.254	0.959	0.319
	(1.016)	(0.821)	(0.913)	(0.295)
min-ES (99%)	1.124	1.512	1.017	0.456
	(1.014)	(0.97)	(0.917)	(0.381)
Panel B: Short Hedgers				
min-VaR (90%)	0.999	0.939	0.928	0.302
	(1.000)	(0.881)	(0.978)	(0.257)
min-VaR (95%)	1.015	1.017	0.948	0.281
	(1.002)	(0.853)	(0.989)	(0.216)
min-VaR (99%)	1.043	1.304	1.042	0.547
	(0.997)	(0.928)	(1.018)	(0.355)
min-ES (90%)	1.028	1.093	0.982	0.335
	(0.995)	(0.864)	(1.002)	(0.249)
min-ES (95%)	1.038	1.194	1.016	0.361
	(0.992)	(0.876)	(1.012)	(0.268)
min-ES (99%)	1.064	1.376	1.121	0.496
	(0.940)	(0.962)	(1.067)	(0.271)

Notes: The optimal hedge ratios for both short and long hedgers are estimated using a rolling window approach with a rolling window of 250 trading days. The total number of rolling windows is 2,363 windows for crude oil, 1,890 windows for gasoline, 1,861 windows for heating oil, and 2,107 windows for natural gas.

than short hedgers, regardless of the hedging objectives and hedging instruments. In the natural gas market, ETF hedge ratios for long hedgers are steadily smaller than ETF hedge ratios for short hedgers. Conversely, except for the minimum-VaR (90%) objective, the size of the futures position for long hedgers is larger than that for short hedgers.

Considering next the size of ETF position versus futures position, we find that ETF hedge ratios are always larger than futures hedge ratios in the gasoline market. In addition, the difference in the relative magnitudes of ETF and futures hedge ratios in the gasoline market is found to increase monotonically with the confidence levels. In the crude oil, heating oil and natural gas markets, we find no systematic pattern in the relative sizes of ETF and future hedge ratio[13]. The only exception is for the short hedgers in the natural gas market, where the ETF hedge ratios are always larger than the futures hedge ratios. We also find that, for the minimum-ES objective, the difference in the relative size of the ETF and futures hedge ratios in these three markets increases monotonically with the confidence levels. Examining the impact of hedging objectives (tail risk measures), the most prominent pattern observed is that the minimum-VaR hedge ratios are smaller than the minimum-ES hedge ratios for most cases (specifically, for 35 out of 48 hedge-ratio pairs). This suggests that the minimum-ES hedging strategy almost always requires that the long (short) hedgers purchase (sell) more units of relevant futures or ETF than the minimum-VaR strategy.

Finally, considering the relationship between confidence levels and optimal hedge ratios, we get varied results across the four energy commodity markets. In the crude oil market, we find that, regardless of hedge positions, the optimal ETF hedge ratios increase monotonically with confidence levels. On the other hand, the optimal futures hedge ratios decrease monotonically with confidence levels for short hedgers with the minimum-ES objective, but the reverse relationship is observed for long hedgers with the minimum-

[13] According to Liu et al., (2017), the dependence measures (including the correlation coefficient and Kendall's tau) are the key determinants of the optimal hedge ratios. Thus, the differences in futures and ETF hedge ratios (across different commodity markets) are likely explained by the differences in the upper and lower tail dependence coefficients (see
Table ***3.3*** for the information on the upper and lower tail dependence coefficients).

VaR objective. For the long hedgers with the minimum-ES objective and the short hedgers with the minimum-VaR objective, we find no systematic relationship between optimal futures hedge ratios and confidence levels. In the gasoline market, the optimal hedge ratios are found to have larger magnitude at higher confidence levels for almost all cases. The only exception is for the minimum-VaR futures hedge ratios. In the heating oil market, we observe a monotonic positive relationship between optimal hedge ratios and confidence levels for most cases (except for the case of long futures hedgers). In the natural gas market, excluding the case of short hedgers with the minimum-VaR objective where no systematic relationship is observed, we find that the optimal hedge ratios increase monotonically with confidence interval. Overall, these findings indicate the importance of considering hedger's preferences on hedge position, tail risk measure, and confidence level in computing both futures and ETF hedge ratios.

3.6.2 Out-of-sample Hedging Effectiveness

To analyze the usefulness of ETFs in dealing with risk in energy commodity markets, we examine the out-of-sample hedging effectiveness of energy commodity ETFs and compare their hedging performance with energy commodity futures. For each hedge position and hedging objective, we measure the hedging effectiveness by computing a percentage reduction in VaR (90%, 95%, 99%) and ES (90%, 95%, 99%) of the unhedged portfolio relative to the hedged position. In this section, we report the average out-of-sample hedging effectiveness of ETF and futures hedge ratios in reducing tail risk in crude oil, heating oil, and natural gas markets, respectively. The best performing hedging instrument for each hedging objective and each hedging effectiveness measure is highlighted in bold type. To test whether the best performing hedging instrument performs statistically significantly better than the alternative hedging instrument, a paired t-test (based on a heteroscedasticity and autocorrelation (HAC) standard error) is conducted. The test results (with * and ** respectively denoting the rejection of the null hypothesis of equal out-of-sample hedging effectiveness between the two hedging instruments at the 5% and 1% significance levels) are also reported in this section.

For each hedging objective, we also provide plots of percentage reduction in the respective tail risk – the specific tail risk in which the hedgers attempt to minimize – across all out-of-sample test windows. These plots provide a detailed illustration of dynamic hedging performance of ETFs and futures in crude oil, gasoline heating oil, and natural gas markets. Overall, our findings suggest that the hedging performance of ETF and futures contract depends greatly on the underlying energy commodity and partly on the confidence level and hedge position. In what follows, we discuss the out-of-sample results obtained for each energy commodity under consideration.

3.6.2.1 Crude oil

We first consider the crude oil market. The results reported in Table 3.5 indicate that, on average, both ETF and futures hedge ratios produce positive tail-risk reduction, regardless of the tail-risk measures used to compute the hedging effectiveness. Depending on the hedging objective and risk measure considered, the average hedging effectiveness ranges from 46.80% to 74.38% for ETF hedging and from 51.80% to 88.80%% for futures hedging. In general, the average hedging effectiveness is found to be smallest at the largest confidence level (99%) and largest at the lowest confidence level (90%). We also find that

Table 3.5. Average out-of-sample hedging effectiveness (in percentage) of crude oil ETF (futures)

Hedging Objectives	Hedging Effectiveness, Measured as a Percentage Reduction in					
	VaR (90%)	VaR (95%)	VaR (99%)	ES (90%)	ES (95%)	ES (99%)
Panel A: Long Hedgers						
min-VaR (90%)	70.335	68.694	52.153	62.451	58.365	48.207
	(87.640)**	**(82.780**)**	**(66.937**)**	**(76.777**)**	**(71.635**)**	**(59.585**)**
min-VaR (95%)	70.147	68.576	52.037	62.386	58.400	48.341
	(87.621)**	**(82.895**)**	**(66.864**)**	**(76.751**)**	**(71.582**)**	**(59.631**)**
min-VaR (99%)	67.904	67.051	50.943	61.068	57.505	47.778
	(84.804)**	**(80.649**)**	**(65.419**)**	**(74.783**)**	**(69.999**)**	**(58.659**)**
min-ES (90%)	69.650	68.571	52.111	62.398	58.608	48.558
	(87.341)**	**(82.681**)**	**(66.730**)**	**(76.613**)**	**(71.492**)**	**(59.631**)**
min-ES (95%)	68.643	67.789	51.698	61.758	58.146	48.389
	(86.619)**	**(82.233**)**	**(66.439**)**	**(76.235**)**	**(71.253**)**	**(59.541**)**
min-ES (99%)	65.328	64.659	49.070	58.883	55.372	46.804
	(76.101)**	**(72.710**)**	**(58.505**)**	**(66.936**)**	**(62.339**)**	**(51.797**)**
Panel B: Short Hedgers						
min-VaR (90%)	74.278	71.119	61.574	66.979	63.491	53.373
	(88.725)**	**(84.007**)**	**(70.763**)**	**(77.824**)**	**(72.393**)**	**(56.700**)**
min-VaR (95%)	74.345	71.081	61.449	66.978	63.421	53.235
	(88.799)**	**(84.091**)**	**(70.870**)**	**(77.887**)**	**(72.441**)**	**(56.690**)**
min-VaR (99%)	73.896	70.604	60.854	66.444	62.813	52.641
	(87.691)**	**(83.055**)**	**(70.363**)**	**(77.060**)**	**(71.781**)**	**(56.523**)**
min-ES (90%)	74.383	70.860	61.442	66.904	63.268	53.049
	(88.458)**	**(83.659**)**	**(70.733**)**	**(77.582**)**	**(72.178**)**	**(56.688**)**
min-ES (95%)	74.229	70.621	61.154	66.679	63.029	52.843
	(87.982)**	**(83.293**)**	**(70.455**)**	**(77.265**)**	**(71.936**)**	**(56.649**)**
min-ES (99%)	72.864	69.507	60.113	65.590	62.025	51.916
	(81.451)**	**(77.402**)**	**(65.260**)**	**(71.649**)**	**(66.814**)**	**(52.106)**

Notes: The table reports the average out-of-sample hedging effectiveness for both long and short hedgers. The average hedging effectiveness is calculated across 2,363 test windows. The best performing hedging instrument for each hedging objective and each hedging effectiveness measure is highlighted in bold type. A pair t-test is performed to test the null hypothesis of equal hedging effectiveness between the two hedging instruments. * and ** denote the rejection of the null hypothesis at the 5% and 1% significance levels, respectively.

the minimum-VaR objective almost always leads to greater risk reduction than the minimum-ES objective with the same confidence level. In addition, comparing the two hedge positions with the same hedging objective, we find that short hedgers achieve greater risk reduction from hedging than long hedgers for almost all cases.

Comparing the two hedging instruments, except for one case (out of 72), the crude oil futures contract has the ability to significantly reduce a larger amount of risk than the crude oil ETF (see Table 3.5). Examining the dynamic hedging performance across 2,363 out-of-sample test windows, it is apparent that the futures contract is almost always a better instrument for hedging tail risk in crude oil market than the ETF. For long hedgers, futures hedging results in greater risk reductions than ETF hedging in all test windows for the minimum-VaR (90% and 99%) and minimum-ES (90%) objectives. For other long-hedging cases, the futures contract produces greater tail-risk reductions than the ETF for at least 92% of all test windows, except for the minimum-ES (99%) objectives. These results are illustrated in Figure 3.1 and Figure 3.2. For short hedgers, the futures contract yields better hedging performance than the ETF at least 88% of all test windows, except for the minimum-ES (99%) objectives[14]. We therefore conclude that while both ETF and futures contract are effective in reducing tail risk in the crude oil market, the futures contract is a better hedging instrument than the ETF.

3.6.2.2 Gasoline

We next consider the gasoline market. We find that both ETF and futures hedging on average help reduce VaR, and ES of the unhedged position. The average hedging effectiveness varies from 8.30% to 30.01% for ETF hedging and from 0.49% to 25.93% for futures hedging, depending on the hedging objective and risk measure used to calculate hedging effectiveness. Similar to the crude oil market, we find that the average hedging

[14] For the minimum-ES (99%) objective, futures hedging yields better hedging effectiveness than ETF hedging about 74.35% and 64.45% of all test windows for long hedgers and short hedgers, respectively.

Figure 3.1. Crude oil: Percentage reductions in VaR for long hedgers (left panels) and short hedgers (right panels) with a minimum-VaR objective

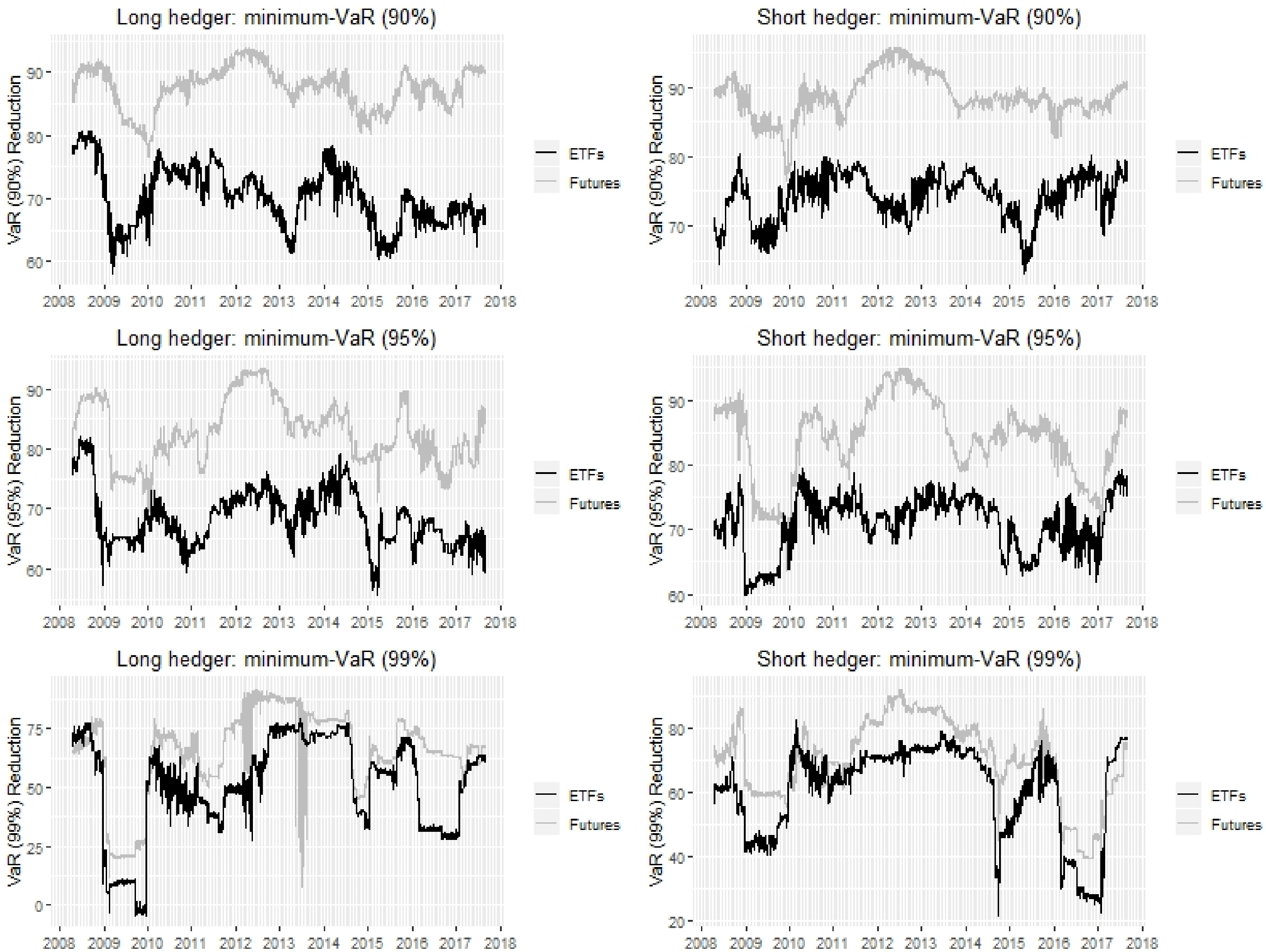
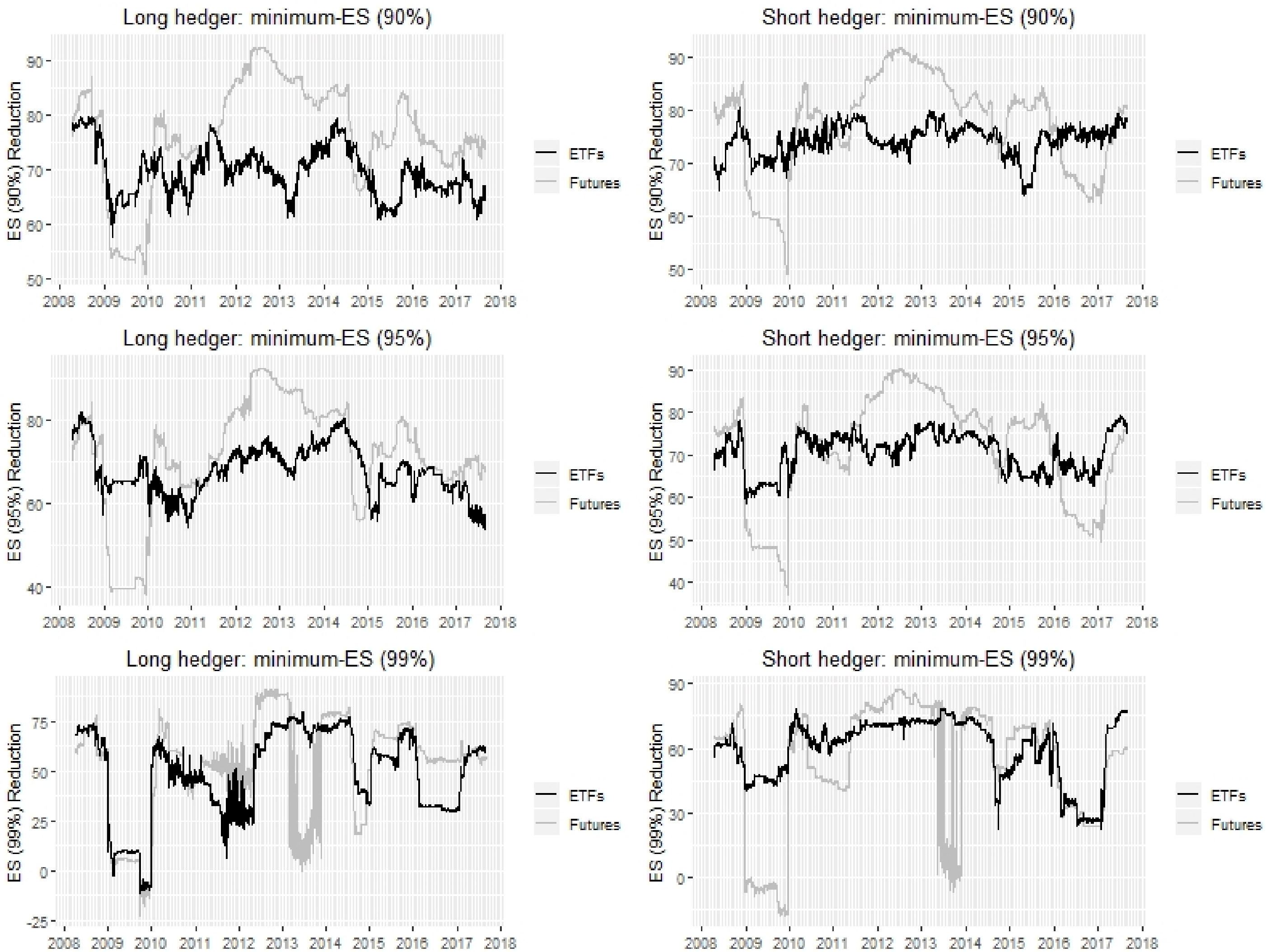


Figure 3.2. Crude oil: Percentage reductions in ES long hedgers (left panels) and short hedgers (right panels) with a minimum-ES objective



effectiveness tends to be smallest at the highest confidence level and that the minimum-VaR objective generally produces better hedging performance than the minimum-ES objective with the same confidence level as shown in Table 3.6.

Table 3.6. Average out-of-sample hedging effectiveness (in percentage) of gasoline ETF (futures)

	Hedging Effectiveness, Measured as a Percentage Reduction in					
Hedging Objectives	VaR (90%)	VaR (95%)	VaR (99%)	ES (90%)	ES (95%)	ES (99%)
Panel A: Long Hedgers						
min-VaR (90%)	**29.826****	**24.886****	**9.639****	**19.410****	**15.212****	**9.311****
	(23.598)	(16.202)	(4.372)	(12.647)	(8.413)	(4.726)
min-VaR (95%)	**29.880****	**24.741****	**10.141****	**19.523****	**15.253****	**9.175****
	(23.104)	(15.699)	(4.390)	(12.364)	(8.267)	(4.540)
min-VaR (99%)	**23.525****	**19.711****	**10.298****	**16.858****	**13.717****	**9.247****
	(21.446)	(14.383)	(4.719)	(10.839)	(6.884)	(2.411)
min-ES (90%)	**30.012****	**24.738****	**10.154****	**19.636****	**15.304****	**9.393****
	(22.719)	(15.702)	(4.650)	(12.348)	(8.297)	(4.373)
min-ES (95%)	**27.409****	**22.849****	**10.375****	**18.763****	**14.749****	**9.254****
	(22.292)	(15.166)	(4.619)	(11.926)	(8.005)	(3.865)
min-ES (99%)	18.677	**16.335****	**9.476****	**14.230****	**12.120****	**8.734****
	(20.690)**	(14.012)	(4.510)	(10.249)	(6.285)	(1.788)
Panel B: Short Hedgers						
min-VaR (90%)	**26.588***	**23.392****	**15.694****	**20.443****	**18.089****	**11.344****
	(25.934)	(19.130)	(10.727)	(15.763)	(11.708)	(4.780)
min-VaR (95%)	**26.626****	**23.509****	**15.819****	**20.581****	**18.087****	**11.282****
	(25.458)	(19.255)	(10.482)	(15.709)	(11.964)	(5.620)
min-VaR (99%)	23.760	**20.389****	**14.155****	**18.373****	**15.968****	**9.234****
	(24.355)	(19.386)	(8.408)	(14.254)	(10.205)	(1.636)
min-ES (90%)	**26.840****	**23.291****	**15.599****	**20.548****	**17.946****	**11.056****
	(25.614)	(20.025)	(10.184)	(15.779)	(11.885)	(4.910)
min-ES (95%)	**25.791**	**22.227****	**15.022****	**19.749****	**17.192****	**10.312****
	(25.341)	(20.201)	(9.755)	(15.549)	(11.678)	(4.330)
min-ES (99%)	21.748	18.935	**13.523****	**16.992****	**14.820****	**8.302****
	(24.449)**	**(19.697)**	(8.099)	(14.099)	(9.839)	(0.491)

Notes: The table reports the average out-of-sample hedging effectiveness for both long and short hedgers. The average hedging effectiveness is calculated across 1,890 test windows. The best performing hedging instrument for each hedging objective and each hedging effectiveness measure is highlighted in bold type. A pair t-test is performed to test the null hypothesis of equal hedging effectiveness between the two hedging instruments. * and ** denote the rejection of the null hypothesis at the 5% and 1% significance levels, respectively.

When comparing long and short hedgers with the same hedging objective, we find that short hedgers tend to achieve greater risk reduction from both ETF and futures hedging than long hedgers. This result is consistent with that obtained from the crude oil market.

Comparing the average hedging performance of the two hedging instruments, the ETF outperforms the futures contracts in 68 out of 72 cases (see Table 3.6). In addition, the superior performance of ETF hedging is statistically significant at 1% significance level for 71 out of 72 cases.

In contrast to the results obtained from the crude oil market, it is evident from the figures that the gasoline ETF is a superior hedging instrument than the gasoline futures contract. Figure 3.3 and Figure 3.4 illustrate their dynamic hedging effectiveness across 1,890 out-of-sample test windows. More specifically, for the long (short) hedgers with the minimum-VaR objective, ETF hedging outperforms futures hedging about 86.03% (59.05%), 92.16% (81.90%), and 78.94% (86.30%) of all test windows for the 90%, 95%, and 99% confidence levels, respectively. Similarly, for the long (short) hedgers with the minimum-ES objective, ETF hedging leads to greater tail risk reduction than futures hedging 100.00% (99.58%), 85.97% (91.32%), 81.01% (80.79%) of all test windows for the 90%, 95%, and 99% confidence levels, respectively. Hence, it can be concluded that, when hedging tail risk in the gasoline market, the ETF is a better hedging vehicle than the futures contract.

Figure 3.3. Gasoline: Percentage reductions in VaR for long hedgers (left panels) and short hedgers (right panels) with a minimum-VaR objective

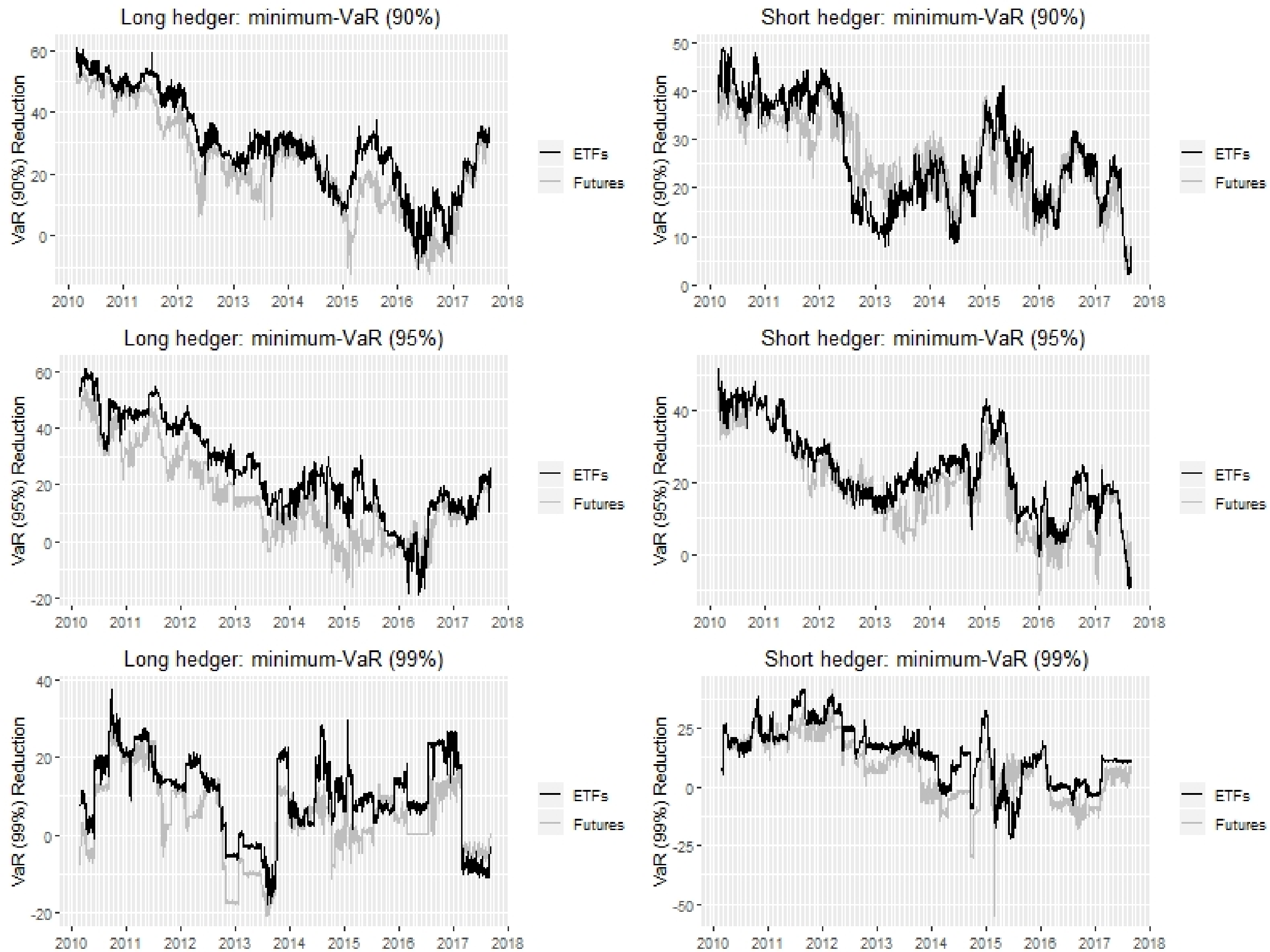
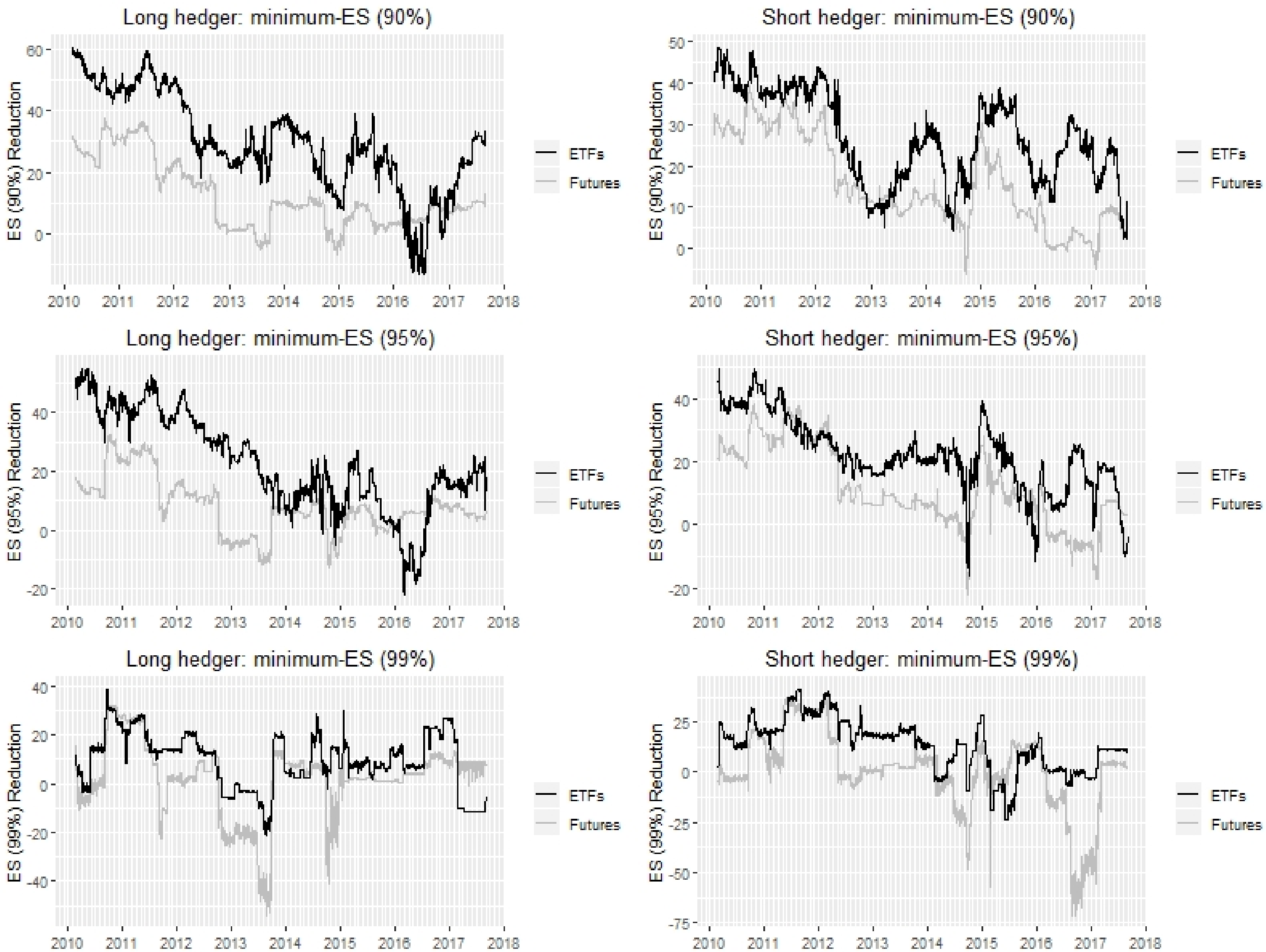


Figure 3.4. Gasoline: Percentage reductions in ES for long hedgers (left panels) and short hedgers (right panels) with a minimum-ES objective



3.6.2.3 Heating oil

We now consider the heating oil market. The findings in Table 3.7 indicate that the average hedging effectiveness for both hedging instruments are positive. Thus, regardless of the hedging objective and hedge position, the ETF and futures contract are effective in VaR, and ES of the unhedged position. The magnitude of average hedging effectiveness again varies with the hedging objective and tail-risk measure considered. The average hedging effectiveness ranges from 33.15% to 58.16% for ETF hedging and from 35.97% to 67.14% for futures hedging.

Similar to the crude oil and gasoline markets, we observe an inverse relationship between the size of average hedging effectiveness and confidence level in most cases. In accordance with the results obtained from the crude oil and gasoline markets, we find that the minimum-VaR objective generally produces greater risk reduction than the minimum-ES objective.

We also find that short hedgers almost always achieve greater tail-risk reduction from both ETF and futures hedging than long hedgers. Comparing the average hedging effectiveness of the two hedging instruments, the futures contract unanimously leads to greater risk reduction than the ETF (Table 3.7).

The results are statistically significant at the 5% level for 95 out of 96 cases. It is fairly clear that, regardless of hedging objectives and positions, the futures contract is almost always a better vehicle for hedging tail risk of in the heating oil market.

Table 3.7. Average out-of-sample hedging effectiveness (in percentage) of heating oil ETF (futures)

Hedging Objectives	Hedging Effectiveness, Measured as a Percentage Reduction in					
	VaR (90%)	VaR (95%)	VaR (99%)	ES (90%)	ES (95%)	ES (99%)
Panel A: Long Hedgers						
min-VaR (90%)	56.661	52.283	36.881	46.478	41.715	34.377
	(66.403)**	**(62.350**)**	**(46.381**)**	**(55.262**)**	**(49.932**)**	**(37.108*)**
min-VaR (95%)	56.522	52.069	36.409	46.384	41.675	34.439
	(66.418)**	**(62.318**)**	**(46.405**)**	**(55.315**)**	**(50.002**)**	**(37.240*)**
min-VaR (99%)	56.522	52.069	36.409	46.384	41.675	34.439
	(63.027)**	**(60.267**)**	**(45.387**)**	**(53.419**)**	**(48.624**)**	**(35.968)**
min-ES (90%)	56.328	51.796	36.086	46.266	41.510	34.406
	(65.545)**	**(62.055**)**	**(46.748**)**	**(55.204**)**	**(50.147**)**	**(38.018**)**
min-ES (95%)	55.368	51.240	35.403	45.800	41.113	34.210
	(64.031)**	**(61.071**)**	**(46.693**)**	**(54.588**)**	**(49.956**)**	**(38.841**)**
min-ES (99%)	52.199	49.145	33.587	44.019	39.737	33.152
	(60.848)**	**(58.800**)**	**(46.589**)**	**(52.759**)**	**(48.584**)**	**(37.153**)**
Panel B: Short Hedgers						
min-VaR (90%)	58.120	52.906	41.503	49.014	45.317	34.670
	(67.103)**	**(65.022**)**	**(51.327**)**	**(59.859**)**	**(56.450**)**	**(42.910**)**
min-VaR (95%)	58.044	52.939	41.532	49.006	45.318	34.613
	(67.125)**	**(65.140**)**	**(51.500**)**	**(59.874**)**	**(56.453**)**	**(42.956**)**
min-VaR (99%)	58.044	52.939	41.532	49.006	45.318	34.613
	(66.609)**	**(64.206**)**	**(51.032**)**	**(59.220**)**	**(55.855**)**	**(42.793**)**
min-ES (90%)	58.155	52.640	42.049	48.941	45.208	34.594
	(67.135)**	**(64.873**)**	**(51.569**)**	**(59.778**)**	**(56.375**)**	**(43.044**)**
min-ES (95%)	57.411	52.159	42.103	48.525	44.907	34.502
	(67.007)**	**(64.592**)**	**(51.545**)**	**(59.615**)**	**(56.212**)**	**(43.035**)**
min-ES (99%)	52.652	48.625	40.681	45.453	42.746	33.622
	(64.667)**	**(62.841**)**	**(49.508**)**	**(57.963**)**	**(54.812**)**	**(42.585**)**

Notes: The table reports the average out-of-sample hedging effectiveness for both long and short hedgers. The average hedging effectiveness is calculated across 1,861 test windows. The best performing hedging instrument for each hedging objective and each hedging effectiveness measure is highlighted in bold type. A pair t-test is performed to test the null hypothesis of equal hedging effectiveness between the two hedging instruments. * and ** denote the rejection of the null hypothesis at the 5% and 1% significance levels, respectively.

Figure 3.5 and Figure 3.6 illustrate the dynamic hedging effectiveness across 1,861 out-of-sample test windows. Specifically, for long (short) hedgers with the minimum-VaR objective, futures hedging is found to beat ETF hedging about 83.50% (70.88%), 90.44% (87.96%), and 77.38% (82.16%) of all test windows for the 90%, 95%, and 99% confidence levels, respectively. For long (short) hedgers with the minimum-ES objective,

Figure 3.5. Heating oil: Percentage reductions in VaR for long hedgers (left panels) and short hedgers (right panels) with a minimum-VaR objective

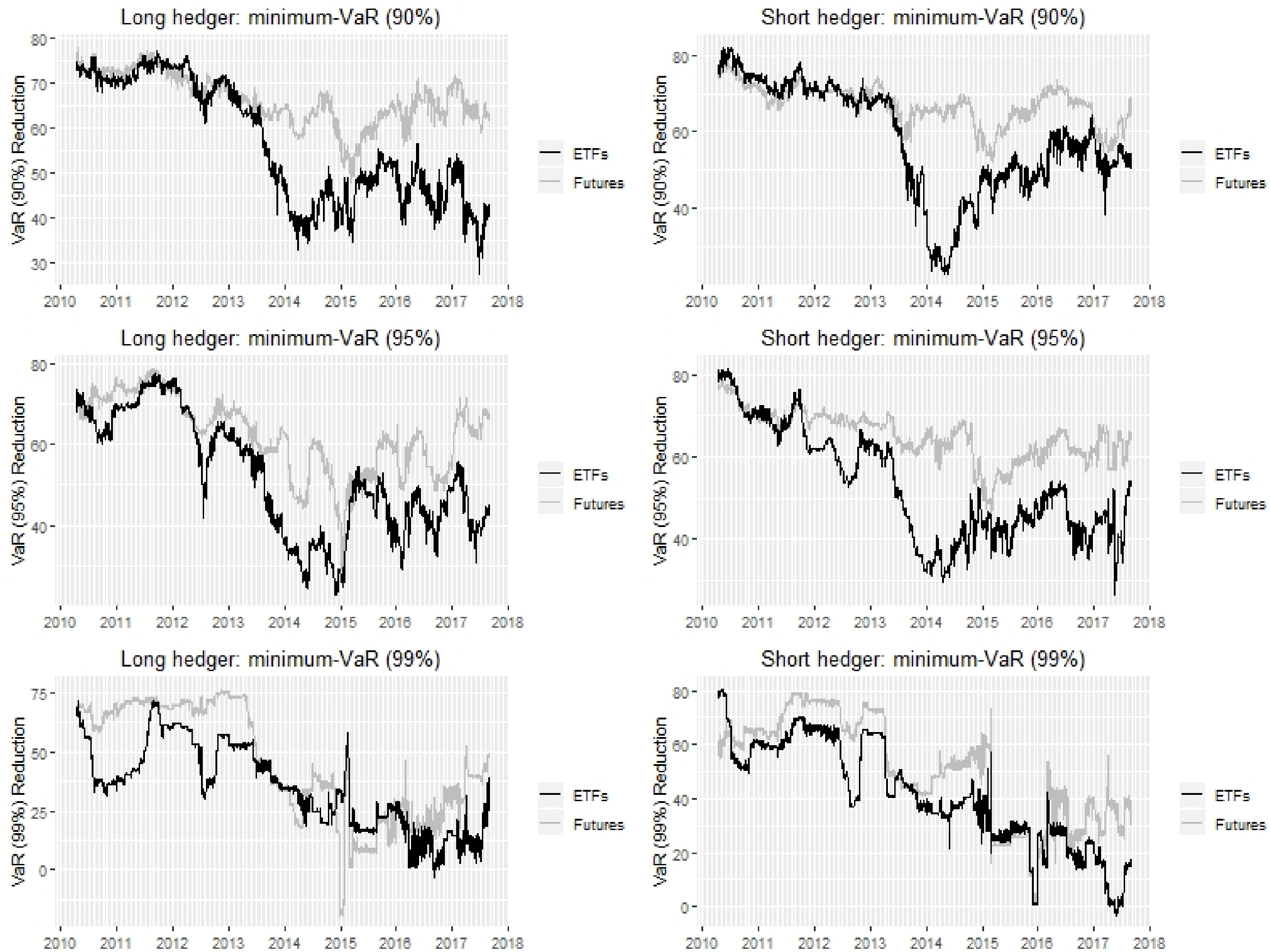
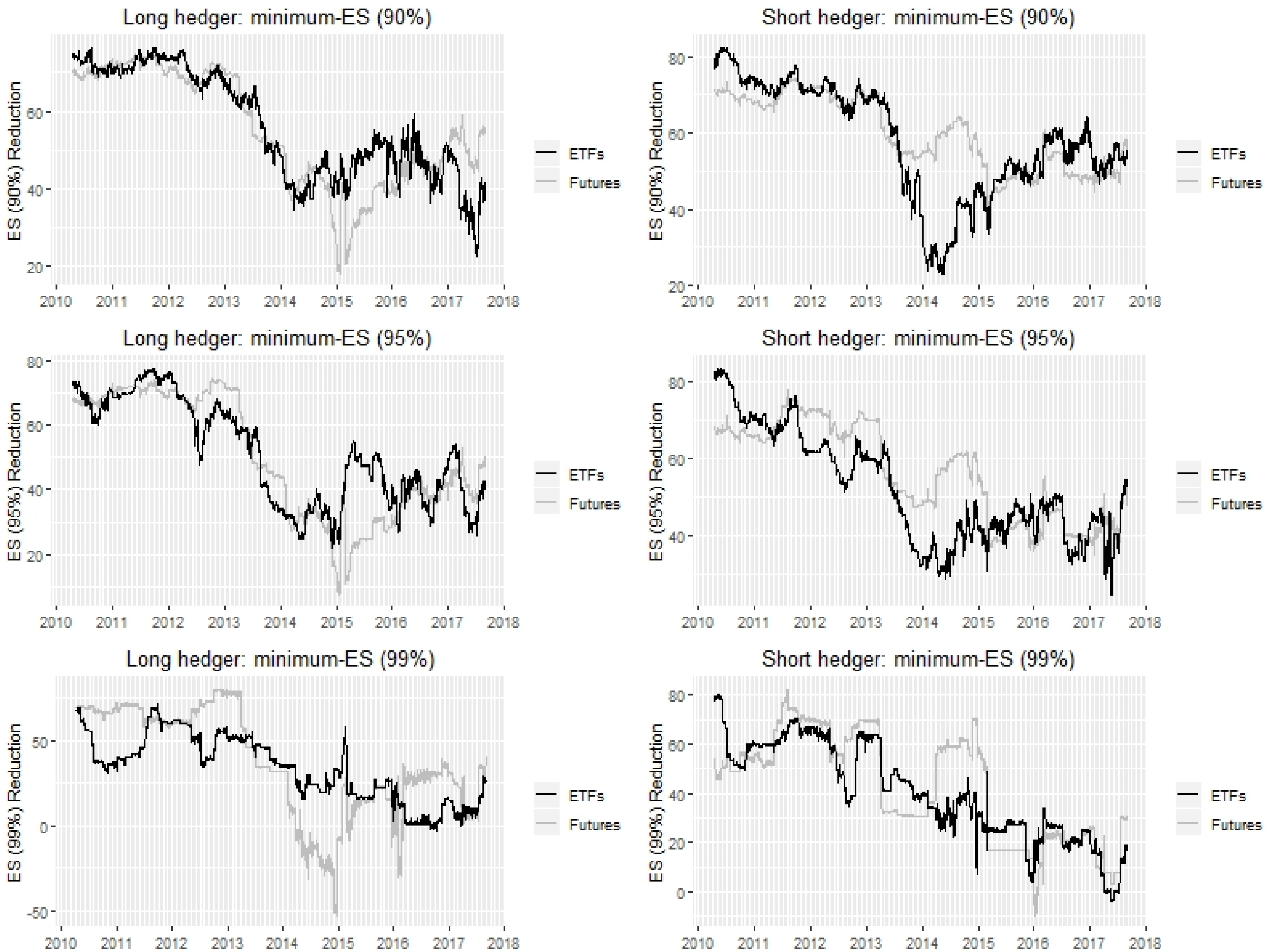


Figure 3.6. Heating oil: Percentage reductions in ES for long hedgers (left panels) and short hedgers (right panels) with a minimum-ES objective



the futures contract produces a better hedging performance than the ETF about 90.76% (94.47%), 83.61% (96.78%), and 70.12% (54.16%) of all test windows for the 90%, 95%, and 99% confidence levels, respectively. Therefore, we can conclude that the futures contract provides better tail risk protection in the heating oil market than the ETF.

3.6.2.4 Natural gas

Lastly, we consider the natural gas market. Unlike the other three markets, the results reported in Table 3.8 indicate that the average hedging effectiveness of both ETF and futures contract are not always positive. More specifically, the ETF leads to a negative average hedging effectiveness in 14 out of 72 cases whereas the futures contract produces a negative outcome in 25 out of 72 cases. Examining the hedging performance across different hedging objectives, we also find that both minimum-VaR (99%) and minimum-ES (99%) futures hedge ratios almost always yield negative average hedging effectiveness.

Depending on the hedging objective and type of tail-risk measure considered, the average hedging effectiveness ranges from -16.78% to 7.47% for ETF hedging and from -16.12% to 5.34% for futures hedging. In the natural gas market, we find an inverse relationship between the magnitude of average hedging effectiveness and confidence level for both minimum-VaR and minimum-ES objectives. Opposite to the other three markets, the minimum-ES objective tends to produce better hedging performance than the minimum-VaR objective with the same confidence level. In addition, we find no distinct pattern between the hedge position and the size of average hedging effectiveness.

Table 3.8. Average out-of-sample hedging effectiveness (in percentage) of natural gas ETF (futures)

Hedging Objectives	Hedging Effectiveness, Measured as a Percentage Reduction in VaR (90%)	VaR (95%)	VaR (99%)	ES (90%)	ES (95%)	ES (99%)
Panel A: Long Hedgers						
min-VaR (90%)	2.575	2.873	**1.433**	2.279	2.131	**1.657****
	(3.119)**	**(2.873)**	(1.248)	**(2.605**)**	**(2.229)**	(1.469)
min-VaR (95%)	2.797	2.651	2.593	2.815	3.206	**2.508**
	(3.834)**	**(2.294*)**	**(2.970*)**	**(3.232**)**	**(3.263)**	(2.414)
min-VaR (99%)	-16.780	**-9.210**	**-9.416**	**-9.667**	**-7.713****	**-7.533****
	(-16.123)	(-9.331)	(-10.112)	(-10.025)	(-8.858)	(-10.371)
min-ES (90%)	3.144	**3.312**	**2.136**	3.093	**3.206****	**2.515****
	(3.268)	(3.011)	(2.036)	**(3.244*)**	(2.990)	(2.141)
min-ES (95%)	1.954	**2.868****	2.404	**2.796**	**3.202****	**2.613****
	(2.198)	(2.249)	**(2.613)**	(2.790)	(2.817)	(1.840)
min-ES (99%)	-7.860	-3.323	-2.321	-2.603	-0.963	**0.156***
	(-4.792)**	**(-2.793)**	**(-0.923**)**	**(-1.593**)**	**(-0.602)**	(-0.283)
Panel B: Short Hedgers						
min-VaR (90%)	**6.812****	**4.859****	**2.494****	**3.691****	**2.260****	**2.355****
	(5.338)	(2.835)	(-0.947)	(1.756)	(0.199)	(1.087)
min-VaR (95%)	**5.618****	**3.852****	**2.391****	**3.197****	**1.822****	**1.633****
	(4.241)	(1.987)	(-0.331)	(1.375)	(0.036)	(0.416)
min-VaR (99%)	**0.117****	**-1.286****	**0.479****	**-0.106****	**-0.290****	**1.205****
	(-3.243)	(-3.637)	(-2.145)	(-2.833)	(-3.09)	(-0.330)
min-ES (90%)	**7.466****	**4.997****	**3.095****	**4.030****	**2.470****	**2.553****
	(5.064)	(2.612)	(0.283)	(1.878)	(0.414)	(1.242)
min-ES (95%)	**7.408****	**4.588****	**3.131****	**3.795****	**2.276****	**2.614****
	(5.030)	(2.005)	(0.687)	(1.888)	(0.475)	(1.551)
min-ES (99%)	**3.476****	**1.988****	**1.919****	**1.891****	**1.133****	**1.953****
	(1.323)	(-0.292)	(-1.857)	(-0.629)	(-1.571)	(-0.050)

Notes: The table reports the average out-of-sample hedging effectiveness for both long and short hedgers. The average hedging effectiveness is calculated across 2,107 test windows. The best performing hedging instrument for each hedging objective and each hedging effectiveness measure is highlighted in bold type. A pair t-test is performed to test the null hypothesis of equal hedging effectiveness between the two hedging instruments. * and ** denote the rejection of the null hypothesis at the 5% and 1% significance levels, respectively.

As can be seen from Table 3.8, ETF hedging clearly outperforms futures hedging for short hedgers. The pair t-tests confirm that the findings are statistically significant at the 1% significance level for all cases. However, based on the average hedging effectiveness alone, it is not apparent which instrument is better for long hedgers. Inspecting the dynamic hedging effectiveness illustrated in Figure 3.7 and Figure 3.8, we find that, except for minimum-VaR (90%) long hedgers, the natural gas ETF outperforms the futures counterpart in more than half of the 2,107 out-of-sample test windows. Figure 3.7 and Figure 3.8 also reveal that both ETF and futures hedging yield negative hedging performance in many out-of-sample test windows.

Depending on the hedge position and hedging objective, the ETF hedge ratios produce poor hedging performance between 4.79% and 51.87% of the time, whereas the futures hedge ratios result in negative hedging effectiveness between 21.55% and 49.36% of the time. The poor hedging performance of both instruments is likely explained by the low correlation and tail dependence of log returns of spot and hedging instrument prices (Brinkmann and Rabinovitch, 1995; Moosa, 2003).

It is also well known that the natural gas market can suffer extreme backwardation or contango (especially during extreme weather events). This likely leads to an occasional dislocation between spot and futures prices, resulting in distinct periods where poor hedging performance occurs.

Nevertheless, despite its repeated poor hedging performance, ETF hedging seems to be a better and safer choice in dealing with tail risk in the natural gas market (especially for short hedgers)[15].

[15] We also examine the possibility of using crude oil, gasoline, and heating oil ETFs and futures contracts to cross hedge downside risk in the heating oil market. However, these hedging instruments provide worse performance than the natural gas ETF and futures contract. The results on cross hedging are available from the authors upon request. It should also be pointed out that while a comprehensive search for effective instruments for hedging tail risk in the natural gas market is essential, it is beyond the scope of this paper and is a subject of future work.

Figure 3.7. Natural gas: Percentage reductions in VaR for long hedgers (left panels) and short hedgers (right panels) with a minimum-VaR objective

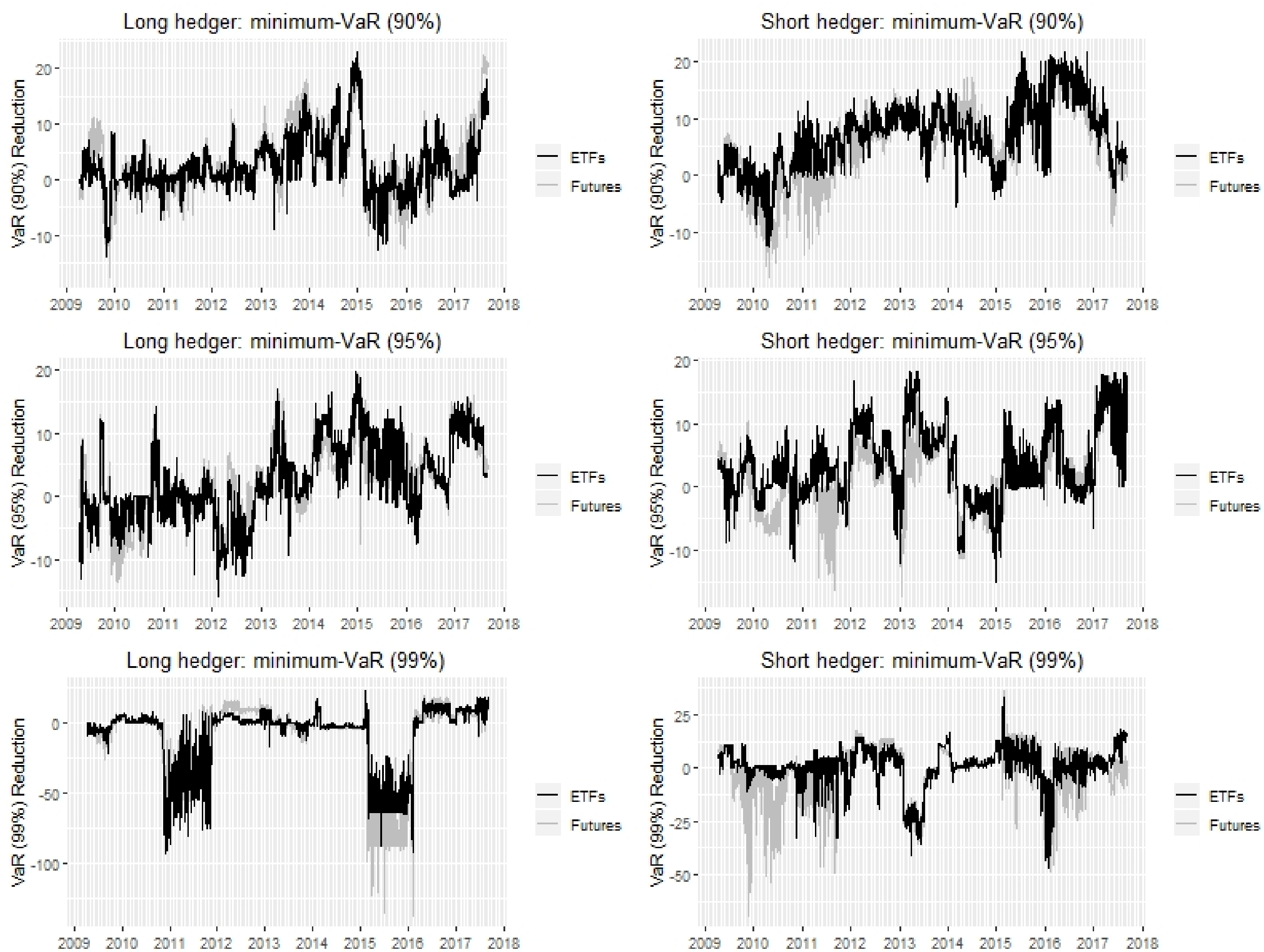
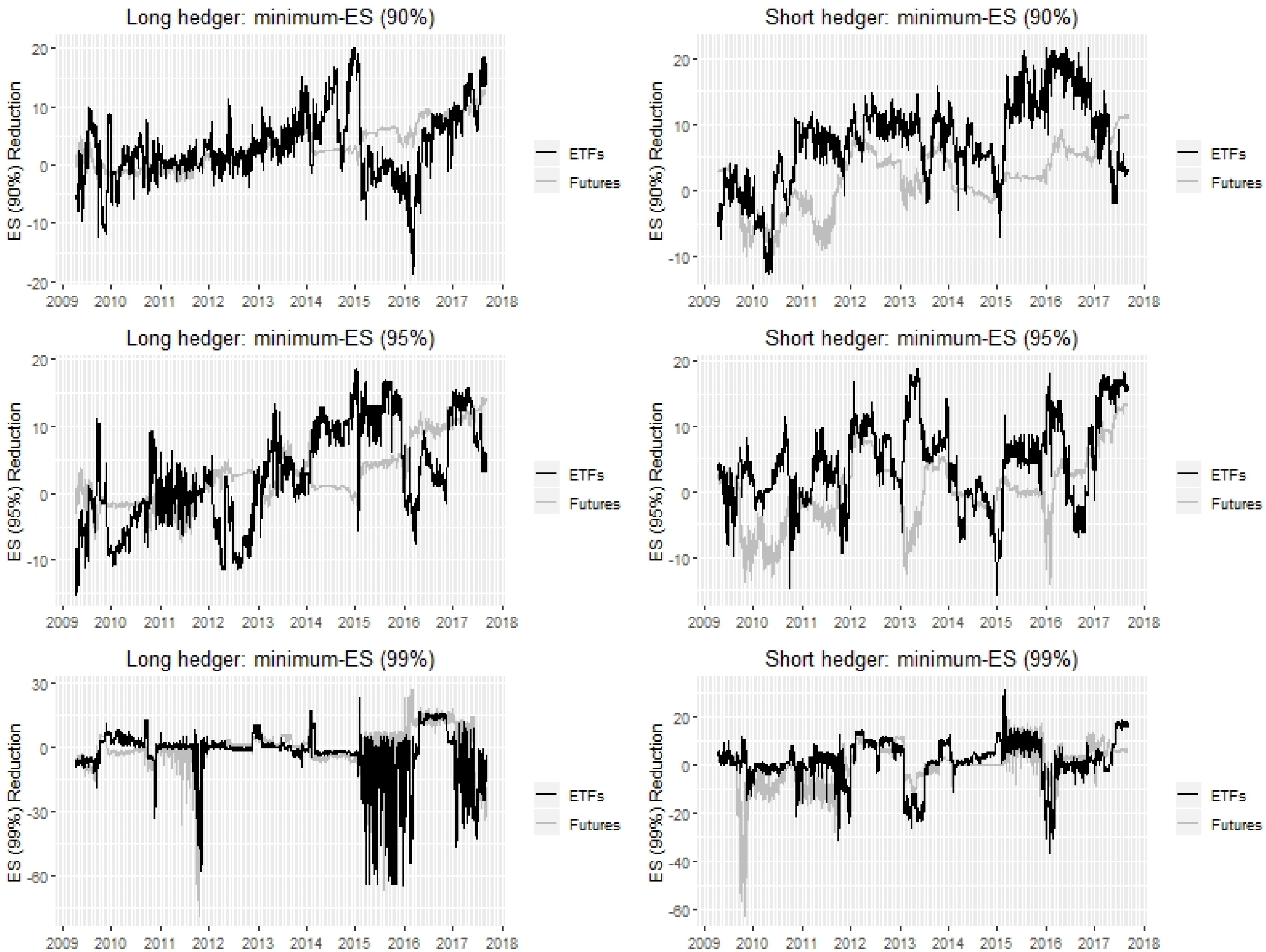


Figure 3.8. Natural gas: Percentage reductions in ES for long hedgers (left panels) and short hedgers (right panels) with a minimum-ES objective



3.6.3 Differential Hedging Abilities

As an energy commodity ETF aims to track daily price movements in a benchmark futures market, one may expect the two hedging instruments to offer the same hedging performance. However, the out-of-sample hedging effectiveness results indicate differences in hedging abilities between ETFs and futures contracts. This result seems to suggest that there is a discrepancy between ETF and futures returns, known as “tracking error”. According to Pope and Yadav (1994), tracking error can be measured as an absolute difference between ETF and benchmark (i.e., futures) returns. More specifically, it can be calculated as:

$$TE_t = \frac{\sum_{t=1}^{T} |R_t^{ETF} - R_t^{F}|}{T} \tag{3.11}$$

where R_t^{ETF} is the return of the ETF at time t, R_t^{F} is the return of the benchmark futures contract, and T is the number of observations.

The descriptive statistics of tracking errors of crude oil, gasoline, heating oil, and natural gas ETFs are summarized in Table 3.9. The daily tracking error ranges from an average of 0.443% to 0.619% across the four ETFs. In addition, the means of tracking errors are found to be statistically significant for all ETFs considered.

These results indicate that all ETFs fall well short of perfectly tracking the return of the underlying futures contracts. This evidence supports our conjecture that tracking error is an underlying reason behind the differential hedging abilities.

Table 3.9. Tracking error of ETFs

	Crude Oil	Gasoline	Heating Oil	Natural Gas
Mean (%)	0.443**	0.478**	0.558**	0.619**
Standard Deviation (%)	0.764	0.962	0.770	1.077
Minimum (%)	0.001	0.000	0.000	0.000
Maximum (%)	24.044	22.881	15.919	27.043
Number of Observations	2862	2389	2360	2606

** denotes the rejection of the null hypothesis that the mean is equal to zero at the 1% significance level.

3.7 Conclusions

Energy commodity exchange-traded funds (ETFs) provide an alternative vehicle for both commodity users (long hedgers) and producers (short hedgers) to hedge their exposure to unfavorable energy price movements. Here we analyzed the usefulness of ETFs in dealing with energy market tail risk. To do this we examine out-of-sample hedging effectiveness of ETFs and compare their hedging performance with those of the futures counterparts. The empirical application focuses on four different energy commodities: crude oil, gasoline, heating oil, and natural gas. The kernel copula method is applied to estimate the minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) hedge ratios for both long and short hedgers.

Our findings suggest that the optimal sizes of ETF and futures positions are dependent upon hedger's preferences on hedge position, the tail risk measure, and desired confidence level. We find that out of sample hedging performance depends on energy commodity. Both ETF and futures contract usage are effective in reducing crude oil, gasoline, and heating oil tail risk. However, both hedging instruments perform poorly in the natural gas market due to the low correlation and tail dependence between log returns of spot and hedging instrument prices.

In all energy commodity markets considered, average hedging effectiveness of both ETF and futures are typically found to be smallest at the largest confidence level (99%) and largest at the smallest confidence level (90%). In addition, we find that the minimum-VaR objective almost always leads to greater tail risk reduction in the crude oil, gasoline, and heating oil markets relative to the minimum-ES objective. However, the opposite is observed in the natural gas market. Also excepting in the natural gas market, short hedging is generally able to achieve greater risk reduction than long hedging. Average and dynamic out-of-sample analyses indicate that the futures contract is a better hedging instrument for crude oil and heating oil than the ETF. However, the ETF provides better tail risk protection than the futures contract in the gasoline and natural gas markets. These findings are especially useful for both energy commodity users and producers who seek out the best hedging instrument for reducing the risks of adverse price movements in energy commodity markets.

This research can be extended in several directions. First, a similar research problem can be studied in other commodity and asset markets. Second, the analysis can also be extended to the multi-commodity hedging case. Finally, the impact of hedge horizons and transaction costs on the relative hedging performance of the ETF and futures contracts should also be examined.

CHAPTER IV

ANALYSIS OF THAI CROP - ZONING POLICY

4.1 Introduction

The agricultural sector has played a critical role in driving economies of many developing countries, including Thailand. According to the Thai National Economic and Social Development Council, the sector contributes approximately 10 percent of Thailand's gross domestic production (GDP). Furthermore, in 2017, about 11.7 million people (or 30.7 percent of the labor force) were employed in agriculture, with approximately 5.9 million households involved as reported by National Statistical Office of Thailand.

Agricultural productivity is directly linked with the match between crop nutrient demands and the supply of soil and chemical based nutrients. However, crops are frequently planted under less than ideal soil conditions. Thailand's Land Development Department, estimate approximately 39.17 percent of the rice planted (specifically, about 27.41 out of 69.86 million rai or 10.84 out of 27.62 million acres) occurs on lands that have a low level of soil suitability for rice (National Committee to Develop Organic Agriculture, 2017). Mesgaran et al. (2017) asserts that productivity could be enhanced by better matching lands. In addition, production on unsuitable lands exacerbates land degradation, ecosystem damage, and water scarcity (Mauser, et al., 2015). Nevertheless, there are currently no guidelines nor restrictions on crop production on low quality lands in Thailand.

In 2017, the Thai government initiated a zoning program that was intended to discontinue planting of secondary rice on unsuitable lands by replacing them with more suitable crops. The zoning program utilizes support for converting rice production on unsuitable soils with other crops. In 2017, the program caused 6 million unsuitable rai (2.4 million acres) to be shifted to more suitable crops (National Committee to Develop Organic Agriculture, 2017). This shift covered 4.8 million rai of rice, which accounts for 40% of the converted area. However, there has not been a study quantifying the economic market and welfare impacts of the program nor have estimates been developed of its longer term impact on crop mix.

This study aims to analyze the welfare and land use questions associated with the zoning policy. To do this a Thai agricultural sector model was developed based on the type of optimization model discussed in McCarl and Spreen (1980). That model is then employed to evaluate the economic costs and benefits arising from the zoning program. Furthermore, we also take into account the existence of an on-going rice price-support program into the study. The results from this study can aid policy makers in identifying crops that are most suitable for replacing crops being grown on unsuitable lands.

The reminder of this chapter is structured as follows. Section 4.2 provides the background of Thailand’s rice price-support program and agro-economic zoning initiative. Section 4.3 describes specific objectives of this study. Section 4.4 describes our study justification. Section 4.5 provides the background on methods used in this study. Section 4.6 presents the data and empirical analysis. Section 4.7 provides the empirical results, and Section 4.8 concludes the chapter.

4.2 Background

4.2.1 Rice Price-support Program

Before analyzing the crop-zoning program, it is noteworthy to discuss an ongoing price-support program, which significantly affects the rice market in Thailand. The Thai rice price-support was first used in 2001. The main purpose of the program was to raise farmers' incomes. Under this price support program, farmers are allowed to sell their rice to the government at the support price of THB 15 per kilogram, when the market price falls below the specified price. Afterward, in an attempt to recover the government spending incurred from the program, the government would sell the purchased rice to foreign governments through the Government-to-Government (G-to-G) rice sale, which is handled by the Thai Rice Exporter Association (TREA) (Poapongsakorn et al., 2014). As a result, this program created incentives for rice producers to grow more rice instead of other crops that may be more suitable with the land they have. In addition, critics of the program argue that the government not only has to bear the high costs running the program, but also creates market distortions.

4.2.2 Crop-Zoning Policy

Thailand introduced the agro-economic zone in 1979. In the Thai Agricultural Economics Act 1979, agro-zoning is defined as "an area of agricultural production established according to the soil type, rainfall, temperature, economic crop, and farm type by using the boundary line of the province as border zone". The main objective of zoning is to encourage farmers to grow crops on suitable lands and to enhance a long-term development in Thai agriculture. Later in 2013, the definition of agricultural zoning was changed to “an area of agricultural production, including animal husbandry, and reforestation to be established according to the market conditions by taking into consideration conditions similar to the main factors such as climate, water resources, crop area, animal feed, types of farming and income of farmers” (National Committee to Develop Organic Agriculture, 2013). That change was intended to support land use that matches with soil suitability while also ensuring that crop production would meet market demand. In addition, the agricultural zoning program is expected to increase crop productivity as the crops selected for replacing those grown on unsuitable soils are expected to perform better.

Crop switching is, however, costly from the point of view of farmers. Knowledge on how to grow the crops, available marketing channels, machinery needed, altered transport needs, storage requirements, perishability, alternative pest issues and many other factors come into play. To provide farmers with incentives to participate in the program, the government has provided training for farmers on the production of the new crops. Moreover, the government has also guaranteed a minimum commodity sale price to help farmers who participated in the program and overcome any difficulties with reaching the marketplace. The training and price supports are expected to make it both possible and beneficial for farmers to comply with the zonal desires of the government. Nevertheless, since the first implementation of the program in 1979, the zoning program has turned out to have limited effect. As a result, the Ministry of Agriculture and Cooperatives (MOAC) has scheduled a road map to speed up the development of the zoning. In addition, the

MOAC has created the country’s soil-suitability map that aims to provide farmers with more reliable information.

Several factors have contributed to the low rate of success of the agro-zoning program. Boonyanam (2018) pointed out that the agricultural zones in Thailand were designed based solely on physical characteristics and failed to take into account economic and marketplace factors, mainly crop prices and input prices. These economic factors are key determinants of farmers’ crop choice and land allocation decisions, and should not be ignored when designing policy. Furthermore, the government failed to adequately consider the underlying interaction of supply and demand at the province level.

4.3 Objectives of the Study

Two main objectives of this study are:

1) To examine the effects of the agricultural land use zoning policy for rice planted areas on market outcomes and welfare of Thai consumers, and producers
2) To develop a Thai agricultural sector model (THAI-ASM) using mathematical programing that is both useful in this analysis and potentially useful in analyzing the potential implications of other Thai agricultural policies

4.4 Study Justification

Understanding the true impacts of the agricultural zoning program would provide policy makers with information on program net benefits and performance of possible policy instruments or incentive designs. Moreover, the results from this study will provide projections on market and land use implications of zoning, which farmers and policy makers might use in their planting and planning decisions. Finally yet importantly, outcomes of the agricultural land use zoning program in Thailand could provide information valuable in other countries regarding zoning like policies.

4.5 Methods Employed

To properly take into account the aforementioned economic factors, a price-endogenous, price endogenous spatial production and commodity sale model is constructed for the agricultural sector in Thailand. The model is built based on the theory in McCarl and Spreen (1980) following practices used in the agricultural portion of the Forest and Agricultural Sector Optimization Model—Green House Gas version (FASOMGHG), and it's agriculture only predecessor (ASM) which is a nonlinear programming model of the forest and agricultural sectors in the United States developed by McCarl et al. (e.g., Baumes, 1978; Burton and Martin, 1987; Adams et al., 1986; Adams et al., 1990; Adams et al., 1996; Chang et al., 1992; McCarl, 2001; Schneider et al., 2007; Adams et al., 2005; Schneider et al., 2007; Beach et al., 2009; Beach et al., 2010). Conceptually, the model is developed to evaluate the welfare and market impacts of public policies, such as zoning policy, that inevitably lead to crop mix or land use changes.

To properly address the physical characteristics of agricultural land in Thailand, crop-budgeting and satellite data were incorporated in the model. These data were obtained from the Ministry of Agriculture and Cooperatives (MOAC) and the Land Development Department (LDD) of the Thai Ministry of National Development. The satellite data contain the spatial locations of land and ratings regarding land suitability for select crops. The main results simulated by the model include: (i) the allocation of land use over time to various agricultural activities at the province level, (ii) water use for each activity with different irrigation status at the province level, and (iii) national crop prices over time.

4.6 Model Development and Specification

This section describes how the Thai agricultural sector model was constructed and describes the data used in the model. The model incorporates information from the soil suitability map for Thailand's five primary crops (namely, primary rice, secondary rice, maize, cassava, and sugarcane). Measurement units for all these crops are reported in Table 4.1.

Table 4.1. Agricultural crops

Crop Items	Units
Primary Rice (Kaojao Napee)	Kilograms of raw rice
Secondary Rice (Kaojao Naprung)	Kilograms of raw rice
Maize	Kilograms of shelled maize
Cassava	Kilograms
Sugarcane	Kilograms of harvested cane

The key endogenous variables determined in the model are crop consumption, provincial land allocation across the crops, water use, fertilizer use, and crop prices. As explained in McCarl and Spreen (1980) market equilibrium is determined by maximizing the sum of consumers' and producers' surpluses in the agricultural sector, subject to market clearing conditions, resource constraints, and crop-mix constraints. It is assumed that the agricultural markets for those crops in Thailand are perfectly competitive.

4.6.1 *Algebraic Illustration of the Agricultural Sector Model*

THAI-ASM is constructed using a price-endogenous mathematical programming method proposed by Enke (1951), Samuelson (1952), Beckmann (1973), and McCarl and Spreen (1980). In the standard price-endogenous mathematical programming model, an optimization problem is formulated with equations balancing supply and demand and in turn equilibrium prices are obtained from the shadow prices or Lagrangian multipliers on the supply demand balance rows.

THAI-ASM consists of about 6,974 constraints and 8,020 variables. The main objective of the model is to maximize total welfare of Thailand subject to all the market equilibrium constraints. The total welfare is defined as the sum of the areas under the demand curves corresponding to all the crops minus the sum of the costs incurred in producing those crops. That is, the model is structured such that the sum of consumers' and producers' surpluses in the agricultural sector is maximized subject to a set of resource constraints along with regional and national supply-demand balances ensuring that the Pareto Optimal condition is satisfied. Specifically, the objective function can be expressed as:

$$W = \sum_i \int_0^{Q_i^D} P_i^Q(Q_i)dQ_i - \sum_n \int_0^{Z_n} P_n^Z(Q_i)dQ_i \tag{4.1}$$

where

W	:	Total Welfare of Thailand;
Q_i	:	The amount of crop i consumed;
Z_n	:	The amount of factor n supplied;

$P_i^Q(Q_i)$: The inverse demand function for the crop i;

$P_n^Z(Z_n)$: The inverse supply function for the purchased factor n;

The first integral term of the objective function (4.1) denotes the sum of the areas under the demand functions for all crops with Q_i as integration variables. The second integral term represents the sum of the areas under the supply functions of all inputs with Z_n as integration variables. For simplicity, we do not consider transportation of crops to consumers. As a result, the resulting crop prices determined by the model represent producer prices at the farm-gate.

The objective function above is maximized subject to the following resource constraints:

$$Q_i^D \leq \sum_r \sum_w \gamma_{i,r,w} RAI_{i,r,w} \qquad \text{for all } i \tag{4.2}$$

$$\sum_r \sum_w \sum_i RAI_{i,r,w} \leq \ Total\ Land \tag{4.3}$$

$$\sum_i \sum_w RAI_{i,r,w} \leq L_r \qquad \text{for all } r \tag{4.4}$$

$$\sum_w RAI_{i,r,w} \leq LDD_{i,r} \qquad \text{for all } i,r \tag{4.5}$$

$$\sum_i \sum_r \omega_{i,r} RAI_{i,r,w} \leq Water\ Available \qquad \text{for } w = \text{irrigated land} \tag{4.6}$$

$$Q_i^D\ , RAI_{i,r}, P_i^Q \geq 0 \tag{4.7}$$

Eq. (4.2) represents the supply demand balance constraints for each of the crops, it balances production of the crops from allocated land with consumption. Here $\gamma_{i,r,w}$

denotes the yield of crop i per unit land (rai) for production with a specific irrigation status w in province r and $RAI_{i,r,w}$ denotes the amount of land used for growing crop i with a specific irrigation status w in province r. These constraints restrict that the domestic demand for each crop i must not exceed the sum of total supply added across all of the provinces of each crop i.

Eq. (4.3) imposes constraints on land availability at the national level. These constraints indicate that the sum of land allocated to different crops in the country, $\sum_r \sum_w \sum_i RAI_{i,r,w}$, cannot be greater than total land availability in the country, which is denoted by $Total\, Land$. Eq. (4.4), on the other hand, imposes constraints on land availability at the province level. These constraints require that the sum of land with a specific irrigation status w allocated to different crops in province r, $\sum_i \sum_w RAI_{i,r,w}$, cannot exceed total land availability in province r at time t, L_r.

Eq. (4.5) characterizes the crop-zoning constraints. In THAI-ASM, the crop-zoning program is introduced into the model by limiting the amount of land with a specific irrigation status w in province r that can be allocated to crop i, $RAI_{i,r,w}$, to be under the amount of suitable land for that crop specified by Land Development Department of Thailand, $LDD_{i,r}$. Eq. (4.6) imposes constraints on water availability for all crop production. These constraints indicate that the sum of water used for different crops on irrigated land in the country, $\sum_i \sum_r \omega_{i,r} RAI_{i,r,w}$, cannot be greater than total water availability in the country, which is denoted by $Water\ Available$. $\omega_{i,r}$ denotes water used rate of crop i in province r. Finally, Eq. (4.7) represents the non-negativity constraints on all endogenous variables.

In addition, following Chen and Önal (2012) and McCarl (1982), historical crop mix constraints were also imposed in order to prevent the model from extreme specialization in regional land use and crop production.

Demand and supply functions for all five crops are estimated using historical data on crop prices, consumption, and elasticities in 2014. The data on crop prices, p_i, consumption, q_i, and elasticities, ε_i, were obtained from three main sources: OAE, the Food and Agricultural Policy Research Institute at University of Missouri (FAPRI-MU), and Isvilanonda and Kongrith (2008). To include the demand functions in the model we linearized them. In particular, assume we add in an inverse linear demand function for each crop i of the form $p_i = \alpha_i + \beta_i q_i$. To specify this curve we use historical data and compute the intercept (α_i) and slope (β_i) as follows. First, by definition, demand elasticity for crop i is defined as:

$$\varepsilon_i = \frac{\Delta q_i}{q_i} / \frac{\Delta p_i}{p_i} \tag{4.8}$$

where Δq_i denotes the change in crop i's consumption due to a change in its market price, denoted by Δp_i. Eq. (4.8) can then be rewritten as:

$$\varepsilon_i = \frac{\frac{\Delta q_i}{q_i}}{\frac{\Delta p_i}{p_i}} = \frac{\Delta q_i}{\Delta p_i} \cdot \frac{p_i}{q_i} = \frac{p_i}{\beta_i q_i} \tag{4.9}$$

Solving for β_i, the demand curve slope is:

$$\beta_i = \frac{p_i}{\varepsilon_i q_i} \tag{4.10}$$

Given the downward sloping demand function, ε_i is negative. As p_i and q_i are both positive, we have that $\beta_i < 0$. After obtaining the value of β_i, the intercept, α_i, then can be calculated by substituting the estimated value of β_i into the inverse demand function. More specifically, we have that:

$$\alpha_i = p_i\left(1 - \frac{1}{\varepsilon_i}\right) \tag{4.11}$$

4.6.2 Graphical Analysis of Price Support Program

In this section, we illustrates the welfare and production implications of implementing the rice price support program with and without the crop-zoning policy. For simplicity, we assume that the demand curve remains unchanged under all scenarios. In this section, D is the domestic demand curve for the commodity, and S is the aggregate supply curve. Under the base scenario, P_0 and Q_0 are the competitive equilibrium price and quantity.

Figure 4.1 illustrates the welfare and production with the rice price support program. In Table 4.2, under the base scenario, producers' surplus equals area $d + g$ and consumers' surplus equals area $a + b + c + e + f$. Once the rice price support program is implemented, producers receive the fixed price $P_{PriceSupport}$ corresponding to the production of Q_c. The government agrees to purchase the excess supply of $Q_c - Q_a$ at the price $P_{PriceSupport}$. Then the government sells a portion of that amount, $Q_b - Q_a$, to governments of foreign country at the world price P_{World}. Thus, with the price support program, producers' surplus expands to $b + c + d + e + f + g + i + j + k + l + o$,

Figure 4.1. Welfare analysis of price support program

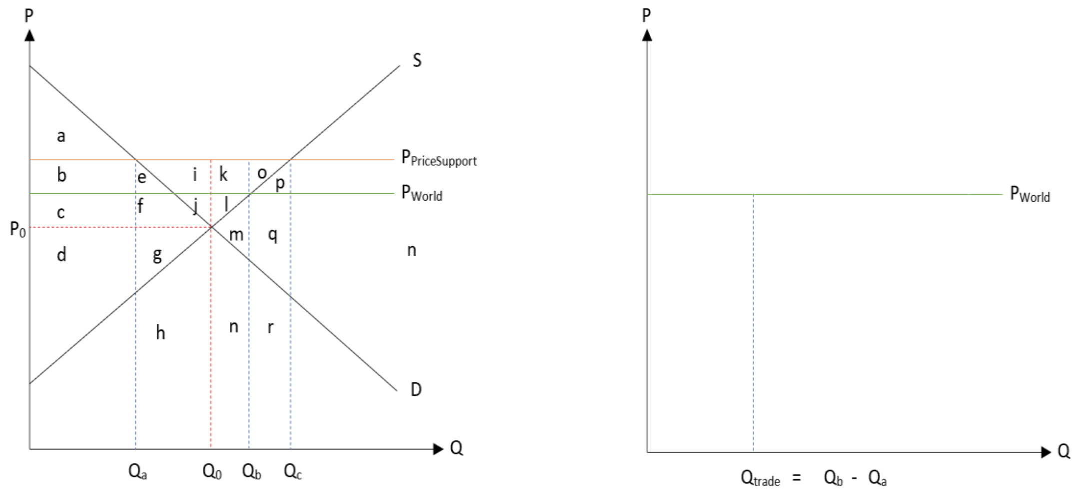


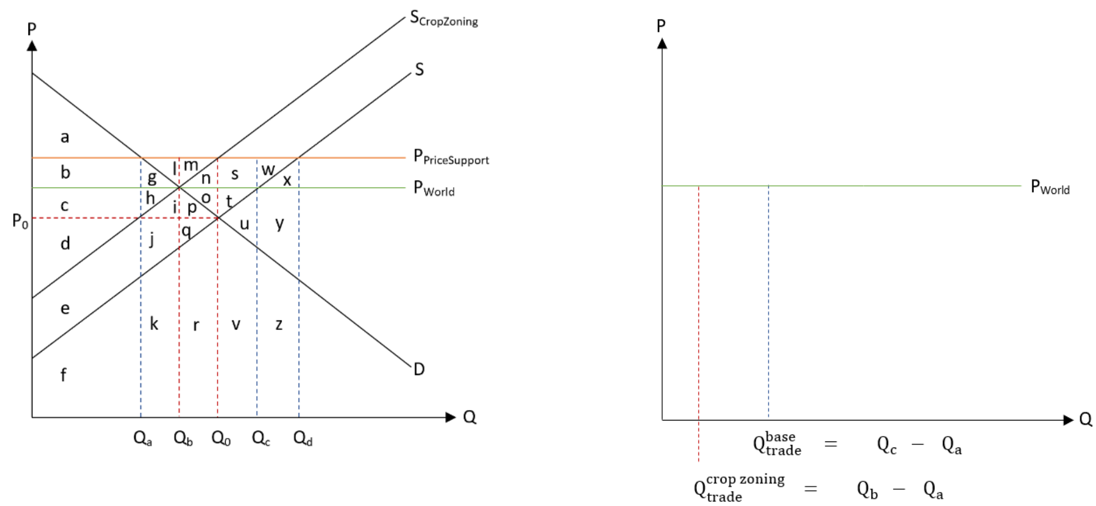
Table 4.2. Welfare components of price support program

	Without Price Support	With Price Support
Consumer Surplus	a+b+c+e+f	a
Producer Surplus	d+g	b+c+d+e+f+g+i+j+k+l+o
Government Spending	-	e+f+g+h+i+j+k+l+m+n+o+p+q+r
Trade Revenue	-	f+g+h+j+l+m+n
Total Welfare	a+b+c+d+e+f+g	a+b+c+d+f+g+j+l-p-q-r

while consumers' surplus reduces to a. The expenditure falls to the government amounts to $e+f+g+h+i+j+k+l+m+n+o+p+q+r$. However, under this program, the portion of the commodity purchased by the government is sold to foreign countries and generates the trade revenue of $f+g+h+j+l+m+n$. As a result, the total social welfare becomes $a+b+c+d+f+g+j+l-p-q-r$. The deadweight loss of $e+p+q+r-j-l$ is created by the price support program as the program increases production but at the same time increases the government program cost, which is larger than the revenue generated from trade. Note that these results are based on the assumption that there is no shift in demand curve.

In Figure 4.2 we extends our analysis by introducing the crop-zoning policy into the economy. Under the crop-zoning policy scheme, producers are restricted in terms of the areas where they can grow the crop.

Figure 4.2. Welfare analysis of price support program under crop-zoning policy



Hence, the supply curve is shifted to the left as the production is reduced. Thus, under the crop-zoning policy without the price support program, producers' surplus amounts to the area $c + h + d$ and consumers' surplus equals are $a + b + g$. Once the price support program is implemented with the crop-zoning policy, the government purchases the excess supply of $Q_0 - Q_a$ at the price $P_{PriceSupport}$ and sells a portion of that amount, $Q_b - Q_a$, to governments of foreign country at the world price P_{World}. In Table 4.3, under the crop-zoning scenario with the price support program, producers' surplus expands to $b + c + d + g + h + l + m$, while consumers' surplus reduces to a. However, the expenditure incurs to the government amounts to $g + h + i + j + k + l + m + n + o + p + q + r$ and the revenue generated from trading a portion of the excess

Table 4.3. Welfare components of price support program under crop-zoning policy

	Base		Crop-Zoning	
	Without Price Support	With Price Support	Without Price Support	With Price Support
Consumer Surplus	a+b+c+g+h+i+p	a	a+b+g	a
Producer Surplus	d+j+q+e	b+c+d+e+g+h+i+j+l +m+n+o+p+q+s+t+ w	c+h+d	b+c+d+g+h+l+ m
Government Spending	-	g+h+i+j+k+l+m+n+ o+p+q+r+s+t+u+v+ w+x+y+z	-	g+h+i+j+k+l+m +n+o+p+q+r
Trade Revenue	-	h+i+j+k+o+p+q+r+t +u+v	-	h+i+j+k
Total Welfare	a+b+c+d+e+g+h+i+j +p+q	a+b+c+d+e+h+i+j+ k+o+p+q+r+t-x-y-z	a+b+c+d+g+h	a+b+c+d+h-n-o- p-q-r

	Base	Crop-Zoning
Deadweight Loss	g+x+y+z-k-o-r-t	g+n+o+p+q+r

supply equals to $h + i + j + k$. As a result, the total social welfare becomes $a + b + c + d + h - n - o - p - q - r$. With the price support program, the crop-zoning policy leads to the reduction of the government spending by $s + t + u + v + w + x + y + z$. Furthermore, the deadweight loss changes from $g + x + y + z - k - o - r - t$ to $g + n + o + p + q + r$. This graphical visualization shows that the crop-zoning policy has the potential to reduce the cost to the government and may lead to a lower deadweight loss.

4.6.3 Data

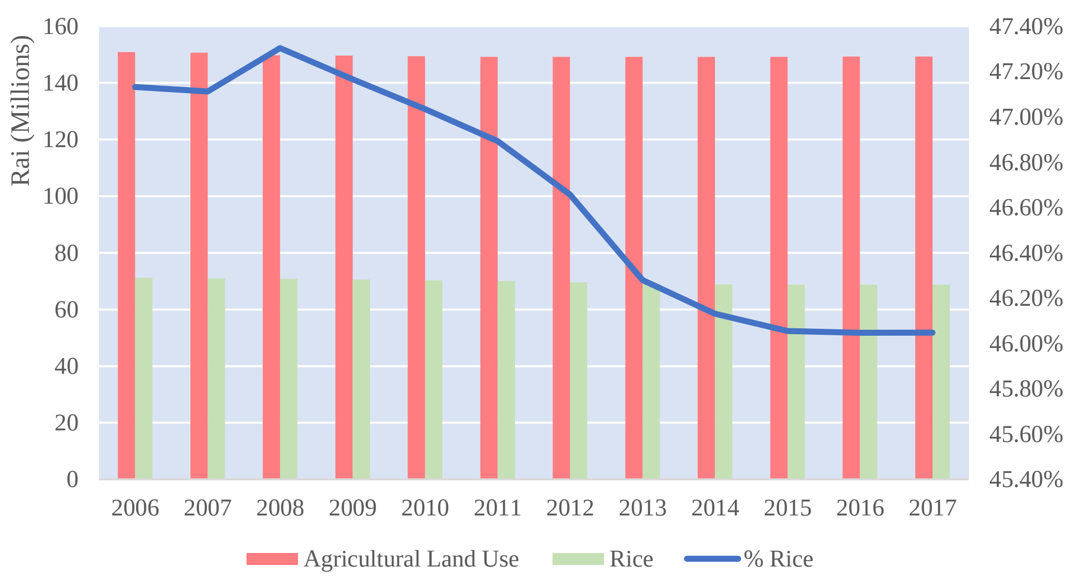
THAI-ASM allows land allocation decisions to be determined endogenously within the model. Cropland in THAI-ASM is defined as land suitable for crop production. The data on land availability was obtained from the OAE. In addition, land is classified by irrigation status (irrigated or non-irrigated), which allows us to incorporate water management into the model simulation.

Province-specific total crop production and historical planted rai of all five crops from 2006 through 2015 were collected from the OAE. We also collected the crop budgeting data for all 77 provinces in Thailand from the OAE. Data on crop production costs include the costs of inputs such as seeds, fertilizers, and chemicals; the costs of irrigation, machinery, fuels, and repairs; interest payments for loans; and labor costs. Water supply data were collected from the Royal Irrigation Department, whereas geospatial data on soil conditions for different land parcels were collected from LDD.

To assist the government in determining the crop zone, the LDD has completed the country soil survey and matched the land quality with growth requirement for each crop. Land suitability is divided into four categories: highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable (N). It should be noted that crop budgeting data vary with land suitability categories. More specifically, crops that are grown in the area with highly suitable category are expected to have the highest crop yield, followed by crops that are grown in the moderately suitable area, marginally suitable area, and unsuitable area, respectively. These land suitability data were prepared through survey and then mapped to satellite data by the LDD. Combining the LDD geospatial data with the agricultural land use data obtained from OAE, we can determine the location, size, and zone of each crop acreage in each province. By doing so, we can determine the type of land being used for the current crop production as well. Historical water use and fertilizer use associated with all crops were also obtained from the OAE.

Figure 4.3 shows the proportion of land use for rice production to total agricultural land use over the years 2006 to 2017. On average, rice production uses up to about 47% of the agricultural land use in Thailand. Although the proportion of land planted to rice has declined over time due to technological advance, it is still very large and consistent with the concern that agricultural land in Thailand might not be used efficiently. For the model to properly reflect this reality, changes in market and production conditions over

Figure 4.3. Proportion of rice land use to total agricultural land use over 2006 to 2017 (million rais)



time are incorporated into THAI-ASM. Crop yields and costs associated with crop production are continuously updated with the assumption that technology gradually has improved over time. Hence, we have that over time crop yields increase while production costs decrease. In addition, demand is assumed to increase over time as population grows.

Furthermore, the multi-period nature of the economic problem requires converting future revenues and future costs into their present values using a real (inflation-adjusted) annual discount rate. The default discount rate used in THAI-ASM is four percent, which is broadly consistent with opportunity costs of capital in Thai agriculture. It should be noted that as discount rates increase this reduces the attention paid to future revenues and costs.

Different discount rates should also be considered in order to test for the sensitivity of model results to alternative discount rates. More specifically, it is crucial for policy makers to pay attention to the sensitivity of model results with respect to the value of discount rates because it can significantly affect the timing of land use, investment, production decisions of the producers in the model.

In terms of geographical coverage, THAI-ASM covers agricultural activities at the province-scale across Thailand. In the model, all 77 provinces across the country are represented as production regions and then their production flows into 4 market regions: Northern, Northeastern, Central, and Southern regions. Each of the 77 sub-regions can be mapped into the overall 4 market regions as shown in Table 4.4.

To analyze the effect of the crop-zoning program, two scenarios are considered: (1) a base scenario; (2) a forced crop-zoning scenario. Under both scenarios, the rice price-

Table 4.4. THAI-ASM market regions/ agricultural regions

Market Regions	Provinces
Northern	Chiang Rai, Phayao, Lampang, Lamphun, Chiang Mai, Mae Hongson, Tak, Kamphaeng Phet, Sukhothai, Phrae, Nan, Uttaradit, Phitsanulok, Phichit, Nakhon Sawan, Uthai Thani, Phetchabun
Northeastern	Loei, Nong Bua Lam Phu, Udon Thani, Nong Khai, Bueng Kan, Sakon Nakhon, Nakhon Phanom, Mukdahan, Yasothon, Amnat Charoen, Ubon Ratchathani, Si Sa Ket, Surin, Buri Ram, Maha Sarakham, Roi Et, Kalasin, Khon Kaen, Chaiyaphum, Nakhon Ratchasima
Central	Saraburi, Lop Buri, Sing Buri, Chai Nat, Suphan Buri, Ang Thong, Ayutthaya, Nonthaburi, Bangkok, Pathum Thani, Nakhon Nayok, Prachin Buri, Chachoengsao, Sa Kaeo, Chanthaburi, Trat, Rayong, Chon Buri, Samut Prakan, Samut Sakhon, Nakhon Pathom, Kanchanaburi, Ratchaburi, Samut Songkhram, Phetchaburi, Prachuap Khiri Khan, Chumphon
Southern	Ranong, Surat Thani, Phangnga, Phuket, Krabi, Trang, Nakhon Si Thammarat, Phatthalung, Songkhla, Satun, Pattani, Yala, Narathiwat

support program is implemented. The base scenario represents a business-as-usual situation, where the crop-zoning program is not implemented. Under the crop-zoning scenario, crops are limited to the acreage of "suitable" land by province. Therein the suitable land is that determined via satellite data that capture the spatial characteristics of agricultural land where crops should be relocated. According to the LDD, these land can be classified into four different types according to soil suitability: highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and unsuitable (N). Once crops are restricted in terms of the areas where they can be planted, we let the model endogenously solve for the optimal choices of crops as well as the locations that are the most suitable.

By comparing the results from the two scenarios, we can then evaluate the economic effects of the crop-zoning policy in terms of changes in land use, input uses, crop prices, and welfare.

4.7 Empirical Results

To ensure the reliability of the mathematical programming model, the model is first validated by comparing estimated values of land allocated to the major crops in Thailand under the base scenario with observed values in 2015. Table 4.5 presents the observed and projected land use obtained from the model for all five major crops. Overall, the model is able to accurately predict agricultural land use. Table 4.5 also reports percentage differences between estimated and observed land use. On average, we find that the percentage differences are less than 15%. Overall, the model seems to fit the data well for most major crops.

Table 4.5. Observed and projected land uses in 2015 (million rai)

	Observed	Projected	% Change
Crop			
Primary Rice	55.10	54.94	-0.29%
Secondary Rice	8.46	8.30	-1.89%
Sugarcane	8.46	7.20	-14.89%
Cassava	9.32	10.05	7.83%
Maize	6.22	6.89	10.77%

We then estimated the supply of all five crops under the two different scenarios: the base scenario and the crop-zoning scenario. In the base scenario, we consider a business-as-usual case with no restriction on location where the crops can be produced. In the crop-zoning scenario, we incorporate the restriction on lands for crop production in all 77 provinces. Specifically, we include land constraints for the major crops in different provinces using the satellite data obtained from the LDD. In addition, under this scenario, each crop has four different yield outcomes depending on soil suitability of the available land.

We first consider the impact of crop-zoning on land uses. Table 4.6 shows land used for production of all five major crops under the base and the crop-zoning scenarios. For primary rice, maize, and cassava, we find that land use is projected to increase as a result of the crop-zoning program. More specifically, it is projected that land use for primary rice, maize, and cassava will increase approximately 9.19%, 46.84%, and 12.49%, respectively. On the other hand, the secondary rice and sugarcane acreages are projected to decrease if the crop-zoning policy is enforced. In particular, the model indicates that the number of rai planted to secondary rice and sugarcane is expected to decrease by about 17.39% and 21.10%, respectively.

Table 4.6. Projected land uses (million rais)

	Base	Crop-Zoning	% Change
Crop			
Primary Rice	48.19	52.62	9.19%
Secondary Rice	10.64	8.79	-17.39%
Maize	5.53	8.12	46.84%
Sugarcane	9.10	7.18	-21.10%
Cassava	9.61	10.81	12.49%

We next consider the impact of crop-zoning restrictions on the amount of crops produced. Table 4.7 reports projected production for all five crops. As can be seen from Table 4.7, the results are consistent with the impact of crop-zoning on land uses. More

Table 4.7. Projected crop production (million tons)

	Base	Crop-Zoning	% Change
Crop			
Primary Rice	22.83	24.38	6.79%
Secondary Rice	6.75	5.90	-12.59%
Maize	3.93	5.78	47.07%
Sugarcane	111.51	100.48	-9.89%
Cassava	33.79	34.83	3.08%

specifically, we find that crop production for primary rice, maize, and cassava is projected to increase by roughly 6.79%, 47.07%, and 3.08%, respectively.

For secondary rice and sugarcane, the amount of crops produced are projected to be about 12.59% and 9.89% lower under the base scenario than under the crop-zoning scenario, respectively. The results indicate that, by restricting land uses to the most suitable crops based on soil suitability, the crop-zoning policy as simulated causes reductions in production of secondary rice and increases in maize production.

As crop production changes as a result of implementing the crop-zoning policy, we also consider the impact of crop-zoning on crop prices. Table 4.8 presents projected prices of all five crops. The model properly captures the inverse relationship between quantities demanded and prices. The table shows that maize prices drop sharply (approximately a 37.14% decrease) under crop-zoning as compared to the base scenario. On the other hand, we find that the primary rice and secondary prices increase by 35.50% and 45.59% respectively as a result of the price support policy. Both primary and secondary rice prices are set to THB 15 per kilogram as the price support policy is implemented. On the other hand, the sugarcane price increases by 22.52% under the crop-zoning scenario. This suggests that although the crop-zoning policy shows the potential to

Table 4.8. Projected crop prices (Thai baht per kg)

	Base	Crop-Zoning	% Change
Crop			
Primary Rice	11.07	15.00	35.50%
Secondary Rice	10.31	15.00	45.49%
Maize	7.89	4.96	-37.14%
Sugarcane	1.11	1.36	22.52%
Cassava	2.29	2.27	-0.87%

deviate the land for more suitable crop production, it could lead to a higher price for some crops. This implies that the policy may positively affect sugarcane producers but negatively reduce the profit of cassava producers as the cassava price drops.

To examine the effect of the crop-zoning policy on the land rental rate, we calculate the Fisher price index, which is the geometric average of the Laspeyres and Paasche price indices (Siegel, 1941). By taking the geometric average of the two indices, the Fisher price index takes into account the upward bias of the Laspeyres price index and the downward bias of the Paasche price index. The formula of the index is:

$$\begin{aligned} \text{Fisher Price Index} &= \sqrt{\text{Laspreyre Price Index} \times \text{Paasche Price Index}} \\ &= \sqrt{\frac{\sum_i \sum_c p_{ic1} q_{ic0}}{\sum_i \sum_c p_{ic0} q_{ic0}} \times \frac{\sum_i \sum_c p_{ic1} q_{ic1}}{\sum_i \sum_c p_{ic0} q_{ic1}}} \end{aligned} \tag{4.12}$$

where p_{ic0} is the land rental rate in province i for crop c under the base scenario; q_{ic0} is amount of land used in province i for crop c under the base scenario; p_{ic1} is the land rental rate in province i for crop c under the crop-zoning scenario; and q_{ic1} is amount of land used in province i for crop c under the crop-zoning scenario.

From Table 4.9, on average, the results suggest that land rental rates under the crop-zoning scenario would be approximately 5.92% higher than those under the base

Table 4.9. Land price indices

Price Index	Land Type				All
	S1	S2	S3	N	
Laspreyre	105.29	102.11	101.38	101.41	104.00
Paasche	105.54	136.52	107.65	105.00	107.86
Fisher	105.42	118.07	104.47	103.19	105.92

scenario. Furthermore, with the crop-zoning policy, the results show that the land rental rates across all land types would be higher than those under the base scenario. Specifically, the land rental rate would be 5.42%, 18.07%, 4.47%, and 3.19% for highly suitable (type S1), moderately suitable (type S2), marginally suitable (type S3), and unsuitable (type N) lands, respectively.

Given the importance of irrigation in Thailand, we also examine how producers' irrigation decisions change as a result of implementing the crop-zoning policy. Table 4.10 reports the projected water use (in 1,000 million cubic meters) under the two scenarios. Our model results indicate an increase in total water use because of the crop-zoning policy. More specifically, total water uses under the crop-zoning scenario is approximately 6,070 million cubic meters more than under the base scenario. The increase in total water use

Table 4.10. Projected water uses (1,000 million m^3)

	Base	Crop-Zoning	% Change
Crop			
Primary Rice	33.13	38.39	15.88%
Secondary Rice	23.20	18.11	-21.94%
Maize	3.01	4.48	48.84%
Sugarcane	3.09	6.22	101.29%
Cassava	9.33	10.63	13.93%
Total	71.76	77.83	8.46%

could be explained by the fact that the majority of the highly water consuming crops are reallocated to irrigated land.

Table 4.11 reports overall crop land allocations across the four different land types under the two scenarios as well as the percentage change in land allocations from the base scenario. Overall, the model results suggest that the enforcement of the crop-zoning policy will help reduce the production of secondary rice on highly suitable (type S1) land.

In particular, it is expected that production of secondary rice will be largely relocated to moderately suitable (type S2). In addition, the crop-zoning policy will also result in a decrease in the production of primary rice and maize on marginally suitable and unsuitable (type S3 and N) land, but a drastic increase in the production of both crops on highly suitable (type S1) land. On the other hand, the policy will lead to increases in

Table 4.11. Present value of projected land uses (million rai) for all land types under base and crop-zoning scenarios

		Base	Crop-Zoning	% Change
Crop	**Land Type**			
Primary Rice	S1	9.66	26.54	174.74%
	S2	17.82	23.61	32.49%
	S3	8.52	1.87	-78.05%
	N	12.19	0.60	-95.08%
Secondary Rice	S1	6.55	3.15	-51.91%
	S2	0.64	2.73	326.56%
	S3	1.71	1.59	-7.02%
	N	1.74	1.31	-24.71%
Maize	S1	0.77	5.02	551.95%
	S2	3.51	2.92	-16.81%
	S3	1.24	0.18	-85.48%
	N	0.00	0.00	NA
Sugarcane	S1	2.88	6.56	127.78%
	S2	0.00	0.00	NA
	S3	5.80	0.02	-99.66%
	N	0.42	0.60	42.86%
Cassava	S1	4.78	10.72	124.27%
	S2	0.00	0.03	NA
	S3	0.00	0.00	NA
	N	4.83	0.05	-98.96%

production of sugarcane and cassava on highly suitable (type S1) land.

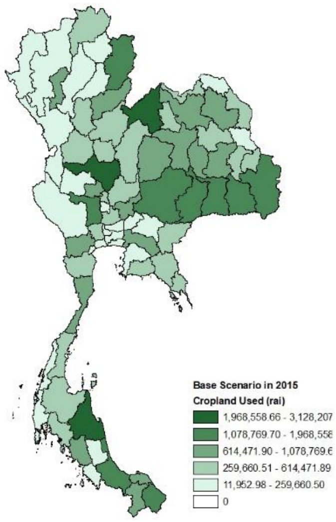
According to the LDD satellite data, there is excessive production of secondary rice and too little maize. The major problem is lands that are unsuitable for growing the secondary rice are being used to grow it. The model results also show that the crop-zoning policy has the potential to free up lands in the central and the northeastern parts of the country for primary rice and maize production. Note that land types for different crops are overlapping. That is, land that is highly suitable for one crop is not necessary highly suitable for other crops. Specifically, the areas that are categorized as highly suitable (type S1) for secondary rice are categorized as moderately suitable (type S2) for primary rice. From the results, we can see a significant decrease in highly suitable (type S1) land use for the secondary rice production with it being reallocated to primary rice and sugarcane. Moreover, in order to meet the national demand for secondary rice, the model suggests that marginally suitable (type S3) land use is expected to increase significantly for growing the rice. Compared to the base scenario, we find that secondary rice land use decreases in highly suitable (type S1) by 51.91%, in marginally suitable (type S3) by 7.02%, and in unsuitable (type N) by 24.71%, and increases significantly in moderately suitable (type S2) by 326.56% (see Table 4.11).

In addition, most of the highly suitable (type S1) land for growing cassava is located in the northern and northeastern parts of Thailand. The model results suggest that the implementation of the crop-zoning policy will lead to a significant decrease in cassava grown on unsuitable (type N) lands. The major production is then relocated from the southern and central parts to the northern and northeastern parts. This helps free up suitable land for primary rice and secondary rice production. In particular, as reported in Table 4.11, cassava use of highly suitable (type S1) increases by 124.27%, while use of unsuitable (N) decreases by 98.96%. There is no significant changes in moderately and marginally suitable land use for cassava (type S2 and S3). Consequently, primary rice use of highly suitable (type S1) increases drastically by 174.74% relative to the base scenario. Likewise, maize land use also increases significantly in highly suitable (type S1) by 551.95%. On the other hand, sugarcane land use increases on highly suitable (type S1) land by 127.78%. In this section, we also presents spatial distribution of crop production across the country in more details.

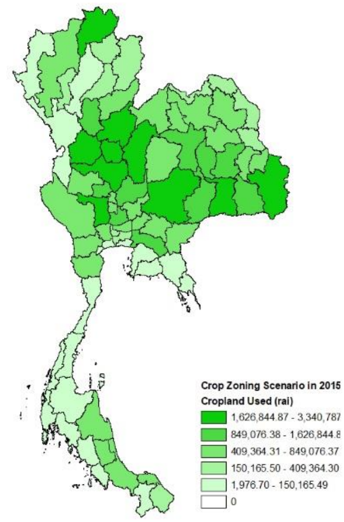
Figure 4.4 maps the spatial distribution of primary rice production under both scenarios. In the base scenario (Figure 4.4 (a)) we see the southern, central, and northeastern parts of Thailand are the main areas for primary rice production. Under the zoning program where farmers are better informed of the more suitable land and are restricted, the majority of primary rice production is shifted to the central region and total production increases significantly (as illustrated in Figure 4.4 (b)).

Figure 4.5 maps the spatial distribution of secondary rice production under the two scenarios. Under the base scenario the northern, central, and southern regions are the main areas for secondary rice production. Under the crop-zoning scenario the production of secondary rice shifts to the northeastern and eastern regions. Moreover, overall secondary rice production across the country also decreases under the crop-zoning scenario.

Figure 4.4. Spatial distribution of primary rice under the base and crop-zoning scenarios in 2015 (rai)

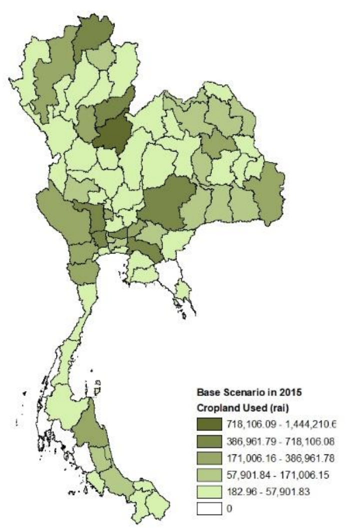


(a) Base Scenario – Primary Rice

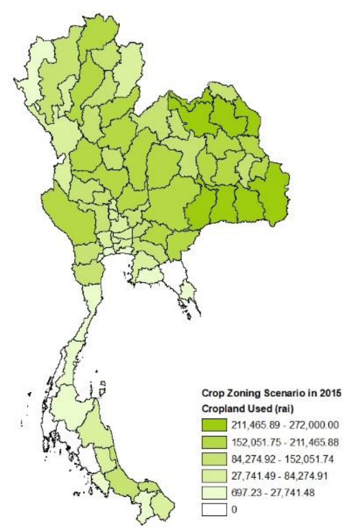


(b) Crop-Zoning Scenario – Primary Rice

Figure 4.5. Spatial distribution of secondary rice under the base and crop-zoning scenarios in 2015 (rai)



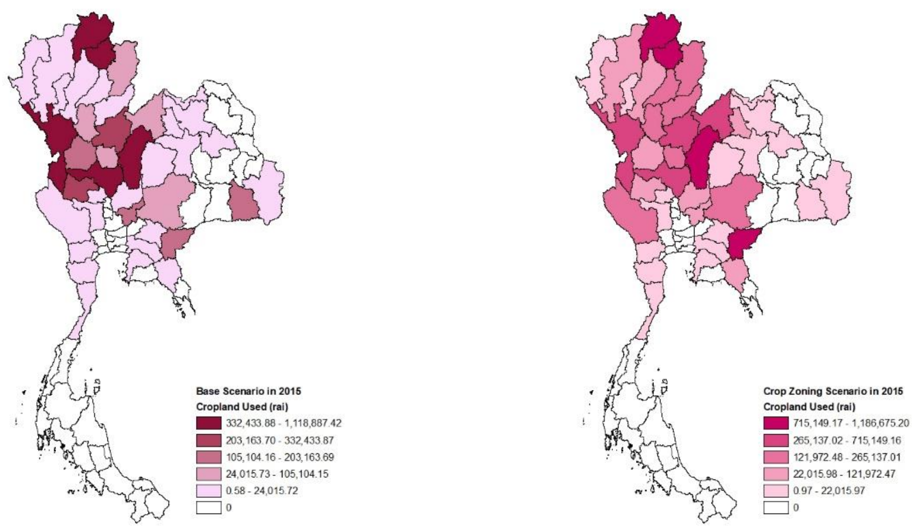
(a) Base Scenario – Secondary Rice



(b) Crop-Zoning Scenario – Secondary Rice

Figure 4.6 shows the spatial distribution of maize production under the scenarios. Under the base scenario maize is heavily grown in the eastern and northern regions. Once the crop-zoning policy is implemented, maize production is more spread out across the two regions. In total, the production of maize is expected to increase significantly under the crop-zoning scenario.

Figure 4.6. Spatial distribution of maize under the base and crop-zoning scenarios in 2015 (rai)

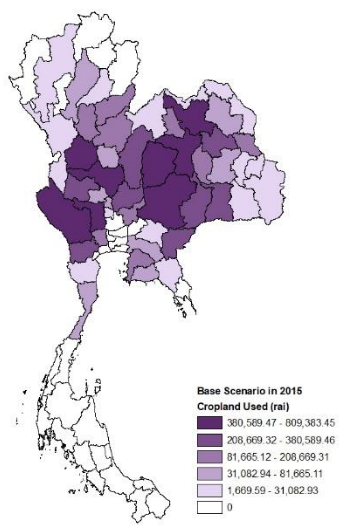


(a) Base Scenario – Maize

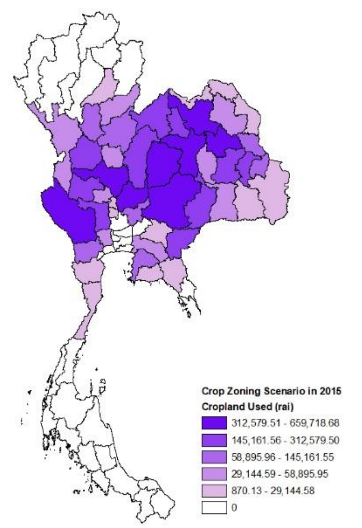
(b) Crop-Zoning Scenario – Maize

Figure 4.7 maps the spatial distribution of sugarcane production under both scenarios. In the base scenario sugarcane is grown in almost all regions except the southern region of Thailand. Under the crop-zoning scenario, there is less production in the northern region and more in the central region. Overall, sugarcane production is projected to decline under the crop-zoning policy.

Figure 4.7. Spatial distribution of sugarcane under the base and crop-zoning scenarios in 2015 (rai)



(a) Base Scenario – Sugarcane

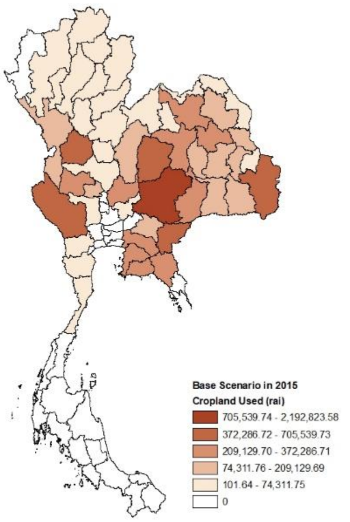


(b) Crop-Zoning Scenario – Sugarcane

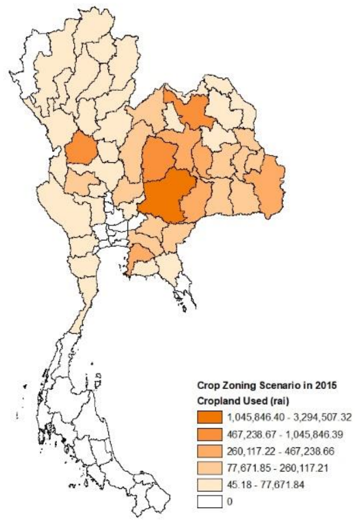
Figure 4.8 shows the distributions of cassava production by scenario. Under the base scenario, cassava is grown in almost all regions except the southern region of Thailand. Under the crop-zoning scenario, Figure 4.8 (b) shows that production across the country increases slightly.

In terms of welfare, under crop-zoning with the price support policy, the THAI-ASM model shows zoning decreases overall welfare by approximately 2.84% or 268 million Thai baht.

Figure 4.8. Spatial distribution of cassava under the base and crop-zoning scenarios in 2015 (rai)



(a) Base Scenario – Cassava



(b) Crop-Zoning Scenario – Cassava

These results are shown in Table 4.12. However, the government spending on the rice price support program also decreases from THB 16.33×10^8 to THB 12.25×10^8, which is approximately 24.97% reduction. To further see how the crop-zoning policy may help alleviate the negative effect of the price support policy, we estimate the outcomes under the base and crop-zoning scenarios without the price support program.

Table 4.13 shows implementing the rice price-support program under the crop-zoning scenario generates a smaller deadweight loss than under the base scenario. From Table 4.13, the deadweight loss reduces from THB 4.69×10^8 to THB 4.02×10^8, which is about 14.40% once the crop-zoning policy is put into action. In other words, the crop-zoning policy can alleviate the negative impact from the price support program. In effect, the policy helps reduce the amount of commodities the government has to purchase from farmers under the price support program at THB 15 per kilogram.

Table 4.12 Components of welfare by scenario (THB 100 million)

	Base	Crop-Zoning
Consumer Surplus	5,617.99	5,576.02
Producer Surplus	3,821.52	3,591.79
Government Spending	16.33	12.25
Total Welfare	9,423.17	9,155.56

Table 4.13. Welfare by scenario (THB 100 million)

	Without Price Support	With Price Support	Deadweight Loss
Base	9,427.87	9,423.17	4.69
Crop-Zoning	9,159.58	9,155.56	4.02
Deadweight Loss	268.29	267.62	

4.8 Conclusions

This study evaluated the effect of a crop-zoning policy in conjunction with rice price supports in Thailand. To do this, we developed a Thai agricultural sector model. In this framework, we take into account the interaction of supply and demand of crops in addition to physical characteristics of land. Our results indicate that the crop-zoning policy has the potential to reduce government price support spending and to increase production of primary rice, maize, and cassava. Simultaneously, the policy would reduce secondary rice and sugarcane production for, which coincides with the government's aim to discourage farmers from growing too much rice. However, total irrigation water usage also increases significantly, although it is still under the total water available, under the crop-zoning scenario. The increase is approximately 5,000 million cubic meters. In terms of environmental impacts, increases in land uses for primary rice and maize production might also lead to increases in fertilizer uses. Our spatial analysis also helps identify beneficial crop regional relocations.

These findings are useful for both agricultural producers and policy makers who seek to evaluate benefits and costs of implementing the crop-zoning policy.

This study can be extended in several directions. First, the model can be extended to cover international trade, especially in Southeast Asia. Second, the analysis can be extended to incorporate processed goods and livestock. Due to available data limitations, we were unable to expand the model to cover those items. Finally, the modeling and results analysis could be extended and coupled with other modeling efforts to account for physical environmental impacts of the policy, such as GHG emissions, water quality, nutrient runoff, and so on.

CHAPTER V

SUMMARY

This dissertation consists of three stand-alone studies: two concerning applications of optimization modeling in agricultural policy evaluation and one on the applications of copula in dealing with tail risk in energy commodity markets. The first study (Chapter II) extends a mathematical optimization model, FASOMGHG to evaluate economic and environmental effects from using marginal land in fulfilling the renewable fuel standard (RFS). The second study (Chapter III) examines the usefulness of Exchange-Traded Funds (ETFs) in dealing with tail risk in the energy commodity markets. The third study (Chapter IV) analyzes the welfare and land uses associated with an implementation of a Thai crop-zoning policy in conjunction with price supports. To do this, a Thai agricultural sector model is constructed.

The first essay (Chapter II), "Analysis of Switchgrass Production on Marginal Land in the United States", analyzes the economic and environmental effects of using marginal land in fulfilling the cellulosic ethanol part of the renewable fuel standard (RFS). In particular, the 2007 RFS mandates that US fuels must ultimately contain at least 36 billion gallons of renewable fuels with a cap of 15 billion gallons on corn-based ethanol. To achieve the goal, the remaining balance of the RFS-qualified ethanol will have to be produced from other cellulosic feedstocks. However, growing energy crops for cellulosic feedstocks will unavoidably lead to cropland competition between food and energy crops, which in turns will cause food crop prices to increase. Marginal land has been proposed as a solution to alleviate such pressure on cropland use and in turn on crop prices. However, production on marginal land may be harmful to the environment. This study examines both economic and environmental impacts of growing energy crops, specifically switchgrass, on marginal land at the national level. Overall, the analysis results suggest that growing energy crops on marginal land could help alleviate some of the pressure on land competition between traditional and energy crops, but would lead to higher GHG emission, soil erosion, and nutrient runoffs.

The second essay (Chapter III), “Dealing with Tail Risks in Energy Commodity Markets: Futures Contracts vs Exchange-Traded Funds”, examines the usefulness of Exchange-Traded Funds (ETFs) in dealing with tail risk in energy commodity markets. Four energy commodities are considered including crude oil, gasoline, heating oil, and natural gas. The kernel copula method is applied to estimate the minimum-Value at Risk (VaR) and minimum-Expected Shortfall (ES) hedge ratios for both long and short hedges. When examining the out-of-sample hedging effectiveness, we find that hedging performance of ETF and futures contract depends greatly on the underlying energy commodity and partly on the confidence level and hedge position. Overall, our empirical results indicate that both ETF and futures contract are effective in reducing tail risk in the crude oil, gasoline, and heating oil markets. However, both hedging instruments perform poorly in reducing risk in the natural gas market due to the low correlation and tail dependence between log returns of spot and hedging instrument prices.

The third essay (Chapter IV) “Analysis of Thai Crop-Zoning Policy” analyzes the welfare and land uses associated with the Thai crop-zoning policy in conjunction with rice price support policy. To do this a Thai agricultural sector model was developed based on the optimization model discussed in McCarl and Spreen (1980). Our results indicate that the crop-zoning policy has the potential to reduce the government spending incurred from the ongoing price-support program along with increasing production for primary rice, maize, and cassava. Furthermore, our results suggest that the policy would reduce secondary rice and sugarcane production. This coincides with the government's aim to discourage farmers from growing too much rice that was the result of the government's price-support program.

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