THREE ESSAYS ON U.S. RENEWABLE ENERGY POLICIES

by

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(Under the Direction of Michael E. Wetzstein)

ABSTRACT

This study investigates three issues on U.S. renewable energy markets. The primary objective is to describe how U.S. renewable energy policies affect solar photovoltaic (PV) and biodiesel industries.

The first essay develops and estimates an analytical framework for assessing the optimal solar energy subsidy, which takes into account the environment, health, employment, and electricity accessibility benefits. Results indicate that an optimal subsidy is positively affected by the marginal external benefit. Calibrating the model, using published elasticities, yields estimates of the optimal solar energy subsidy equaling to approximately $0.02 per kilowatt hour when employment effects are omitted. The estimated optimal subsidy is in line with many current state feed-in-tariff rates, giving support to these initiatives aimed at fostering solar energy production.

The second essay examines price volatility spillovers among U.S. crude oil, diesel, biodiesel, and soybeans based on weekly prices from 2007 to 2014. A univariate EGARCH model along with a DCC-MGARCH model are employed. The univariate EGARCH model provides evidence of double-directional price-volatility spillovers between biodiesel and soybean markets and between crude oil and biodiesel markets. Further there exists unidirectional price-volatility spillovers from the crude oil market to the soybean market and from the diesel market to the biodiesel market. The DCC-MGARCH model indicates time-varying conditional correlations among markets and the pairwise conditional correlations fluctuated from 2008 to 2009.

The third essay investigates the effect of Poisson type policy jumps on biodiesel investment through the theory of investment under uncertainty. The analysis considers the probability of a policy being implemented if it is not in effect and the probability of it being withdrawn if it is in effect. As an application, the policy switching regime of the discontinuous federal tax credit of $1.00 per gallon on biodiesel is modeled as a Poisson jump process. Results support that time inconsistent government policies do lead to market uncertainty. The analysis reveals a pronounced negative impact on the decisions to invest in a biodiesel refinery.

INDEX WORDS: Optimal subsidy, Marginal external benefit, Solar Photovoltaic (PV), Price volatility, Biodiesel investment, Poisson policy jumps, Real options

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DEDICATION

Dedicated to my parents, Ping Liu and Zhihong Wang, for their love and support.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

This dissertation consists of five chapters. This chapter (Chapter 1) is the introduction, Chapters 2-4 are three essays, and Chapter 5 is the conclusion. Chapter 2 (Essay 1): Toward an Optimal U.S. Solar Photovoltaic Subsidy, develops an analytical framework for assessing the optimal solar energy subsidy, which takes into account the environment, health, employment, and electricity accessibility benefits. Chapter 3 (Essay 2): Price Volatilities among U.S. Biodiesel, Diesel, Crude Oil, and Soybean Markets, employs a univariate EGARCH along with a Dynamic Conditional Correlation (DCC) Multivariate GARCH model to examine the price-volatility spillovers among the markets and indicated time-varying conditional correlations among markets. Chapter 4 (Essay 3): Biodiesel Investment in a Disruptive Policy Environment, investigates the effect of Poisson type policy jumps on biodiesel investment through the theory of investment under uncertainty. Conclusions and discussions of future research are presented in Chapter 5.

1.1. Background

1.1.1. Solar Photovoltaic (PV) Industry Development and Government Policies

The solar photovoltaic (PV) device that produces a useable amount of electricity was first introduced by Bell Labs in 1954. The energy crisis of the 1970s turned attention to using solar cells to produce electricity in homes and businesses, however, prohibitive prices (nearly 30 times higher than the current price) made large-scale applications impractical (SEIA, 2014a). The development of technology resulted in a decreasing cost industry making solar PV more feasible and affordable. Figure 1.1 illustrates U.S. solar PV installations and average system price from 2000 to 2013 (SEIA, 2014a). The installation capacity in 2013 was over ten times larger than in 2009 while the average system price in 2013 was around one-third less.

In terms of residential solar PV, in the first quarter of 2014, 232 megawatts of residential solar PV was installed in the United States. This exceeded the non-residential (commercial) market's 225 megawatts for the first time in the history (SEIA, 2014b). Such growth is driven by a range of government policies. At the federal level, taxpayers may claim a 30% personal tax credit for residential systems and installation costs (DSIRE, 2012). State and municipal authorities also employ various supporting policies in the form of net metering, feed-in tariff, cash rebates, renewable-portfolio standards (RPS), solar set-asides, and solar renewable-energy credits (Burns and Kang, 2012; Timilsina et al., 2012).

Net metering is the simplest incentive for renewables (Burns and Kang, 2012). Net metering policies allow distributed generation customers to sell excess electricity to a utility at a retail rate and receive credit in their utility bill. Net metering policies have facilitated the expansion of renewable energy through on-site generation, known as distributed generation (National Conference of State Legislatures, 2014). Solar panels are one of the common distributed generation.

Feed-in tariffs (FIT) are an alternative to net metering. In general, feed-in tariff rates that lead to significant additional renewable energy investment are set above the retail cost of electricity. As of May 2013, the statewide feed-in tariff programs were implemented in seven states, California, Hawaii, Maine, Oregon, Rhode Island, Vermont, and Washington. There are more electricity provider programs in many states. Feed-in tariff policies usually specify rate and contract terms, system size and sector restrictions, and program size limitations. Most contracts are long term (10-20 years). Most FIT programs have a maximum size for individual projects and may limit participation to certain sectors, like residential customers (EIA, 2013a).

Feed-in tariff and net metering are both methods where a utility company compensates energy producers (e.g. homeowners) for the energy fed back into the grid. Simply put, net metering requires one meter while feed-in tariff requires two (Hoffmann, 2009). In net metering, the meter simply runs backwards when homeowners' solar panels are producing more electricity than the property is using. Most electricity meters are bi-directional and can measure current flowing in two directions. While feed-in tariff requires a second meter and additional wiring. The second meter allows different pricing for electricity consumption and generation. The advantage is it offers the homeowner an attractive rate of return without significantly raising the overall cost of electricity (Hoffman, 2009). Chapter 2 develops and assesses the optimal solar energy subsidy in the form of feed-in tariff.

1.1.2. Biodiesel Industry Development and Government Policies

Biodiesel is the second largest category of global biofuels, accounting for 6.9 billion gallons in 2013, which is 22.6% of total biofuel production (Rapier, 2014). Table 1.1 indicates U.S. biodiesel production in 2013 and 2014 are around four times as large as that in 2010. The U.S. consumption in 2013 and 2014 are more than five times as large as that in 2010.

The U.S. biodiesel policies along with European Union policies directly affect the U.S. biodiesel market. The two primary means by which subsidies affect the demand for U.S. biodiesel are the Renewable Fuel Standard (RFS) and the Blender Tax Credit (BTC) (Babcock, 2011). The RFS is a federal mandate requiring the blending of biofuels into U.S. transportation fuels. It originated with the Energy Policy Act of 2005 and was expanded and extended by the

Energy Independence and Security Act of 2007 (EISA) (U.S. Department of Energy, 2014a). The initial RFS (referred to as RFS1) mandated that a minimum of four billion gallons of renewable fuel be incorporated into the nation's gasoline supply in 2006, and that this minimum volume rise to 7.5 billion gallons by 2012 (Schnepf and Yacobucci, 2013). EISA was passed on December 19, 2007, and the EPA issued its final rule to implement and administer the expanded RFS (referred to as RFS2) on February 3, 2010. RFS2 subdivides the total renewable fuel requirement into four separate but nested categories (Schnepf and Yacobucci, 2013). One of the four categories is biomass-based diesel, which is a diesel fuel substitute made from renewable feedstock, including biodiesel and non-ester renewable diesel. The 2013 biodiesel mandate was revised upwards from one billion gallons to 1.28 billion gallons (Schnepf and Yacobucci, 2013). EPA proposed to maintain the same volume for biomass-based diesel for 2014 and 2015 as was adopted for 2013 (EPA, 2015a).

A biodiesel tax credit of $1.00 per gallon was established in 2005 by the American Jobs Creation Act of 2004. It was then extended by the Energy Policy Act of 2005 and amended by the Energy Improvement and Extension Act of 2008. The tax credit temporarily lapsed in 2010. It was then extended again by the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 (Yacobucci, 2012). The credit was allowed to expire at the end of 2011, with the American Taxpayer Relief Act of 2012 retroactively extending the tax credit through December 31, 2013 (U.S. Department of Energy, 2014). The credit was then allowed to expire, but could possibly be reestablished. On May 15, 2014, the U.S. Senate failed to pass the Expiring Provisions Improvement Reform and Efficiency (EXPIRE) act. The EXPIRE act included extension of biodiesel tax credit through December 31, 2015 and retroactive to January 1, 2014 (U.S. Senate Committee on Finance, 2014).

The impact of Untied States biodiesel policies also depends on their interaction with EU biodiesel policies (de Gorter et al., 2011). The European Commission (EC) initiated anti-dumping and anti-subsidy investigations into imports of biodiesel from the United States on June 13, 2008, after a complaint was lodged by the European Biodiesel Board (EBB), which represents the European biodiesel industry, in April 2008. According to the EC investigation, the U.S. tax credit of $1.00 per gallon of biodiesel caused European producers to lose market share. Meanwhile, U.S. biodiesel production and prices fell sharply in June 2008 (de Gorter et al., 2013). The EC imposed temporary anti-dumping and anti-subsidy duties on imports of biodiesel from the United States in March 13, 2009. The measures were in place for four months while the investigation continued. On July 12, 2009, the EC imposed definitive anti-dumping and anti-subsidy duties for a period of five years (EBB, 2014). The U.S. biodiesel prices stabilized after the duties were implemented in March 2009.

1.2. Problem Statement

1.2.1. Optimal Solar Photovoltaic (PV) Subsidy

In the past, qualitative research has summarized and categorized solar photovoltaic government policies. While the stimulus for government subsidies is rooted in standard economic theory of externalities, it is surprising that a simple yet critical question for determining the optimal government policy has not previously been explored. Simply put, what is the economically optimal solar subsidy? Despite the long history of subsidizing solar energy in the United States, an optimal subsidy level has not been determined. Such an optimal subsidy would consider the external benefits arising from improved environmental, health, and (potentially) employment. Empirical studies are lacking, which examine the impact of subsidies on these macroeconomic factors.

One may believe solar PV subsidy is certain to have a marked impact on the consumption of fossil energy and on the adoption of solar panels. However, the impact is uncertain and depends on household preferences. Prior to CO_2 emission concerns, fossil energies were generally thought of as normal goods. In this case, the direction of fossil-energy consumption from favorable solar PV policies is unclear. An increase in the subsidy can result in reduced, an increase, or no change in fossil-energy consumption. Given public concern with CO_2 emissions, fossil energies are becoming an inferior good where households with higher incomes will tend to spend proportionally less of their income on carbon based fuels. This leads to a proposition that an increase in the subsidy yields less fossil-energy consumption. Therefore, changing household preferences can have a marked impact on the effect a solar PV subsidy has on adoption of solar panels and on the consumption of fossil energy. Given inferior-good characteristics for fossil energies, government policies favorable to solar and alternative energies in general will result in reduced fossil-energy consumption, higher fossil prices, and reduced environmental damage.

In contrast to the popular relief, the effect of a solar subsidy on panel prices is generally uncertain. In the long run, a solar subsidy may stimulate demand for panels leading to a supply response and if the panel industry is characterized by economies to scale, then panel prices would fall. However, in the short run the sign could be reversed. In this case, the sign is similar to the share of a commodity tax being borne by both the seller and buyer. It is the result of a portion of the subsidy being received by the sellers of solar panels in the form of higher panel prices. The more elastic the panel price is to a change in the subsidy, the larger will be the response of panel price and the less effective will be the subsidy. The slippage in the effects of the subsidy yields a lower optimal subsidy. The subsidy is being absorbed into higher prices for solar panels, which mitigates its effectiveness. Depending on the magnitude of the elasticities, this slippage can affect intended policy results.

1.2.2. Biodiesel Price Volatilities and Investment Decisions

Ethanol and biodiesel are the two common types of biofuels. Most of the biofuel-related price level and volatility literature considers ethanol as the representative of biofuel, especially for the U.S. biofuel market (Saghaian, 2010; Serra et al., 2011; McPhail, 2011; Zhang et al., 2009; Trujillo-Barrera et al., 2012; Du and McPhail, 2012; Gardebroek and Hernandez, 2013). U.S. biodiesel draws much less attention than ethanol, despite the fact that the United States is the largest national producer of biodiesel (Rapier, 2014). The study provides a first attempt to investigate price volatility in the U.S. biodiesel market.

In addition to the market characteristics, government policies may also play a role in the volatility relation. The disruptive federal policies of on and off tax credit are possibly leading to the link in biodiesel/soybean price volatility.

Hence the disruptive policies may also play an impact on investment decisions. The history of government policy uncertainty coupled with annual changes in the RFS does not provide a stable policy platform for a young and maturing biodiesel industry. Theory would then hypothesize that such disruptive policies would negatively impact the biodiesel market. Instead of providing a stable price regime, it is hypothesized policies would lead to price volatility.

1) If these exists a high probability of a tax credit being implemented in the near future, then biodiesel investors will want to delay investment.

The tax credit will reduce the cost of investment and hence increase the value of waiting. An increased expectation of establishing a tax credit in the next period appears to have a marked effect on the lack of willingness to invest in the current period.

2) With a current tax credit, as the probability of the credit being withdrawn increases, biodiesel investors will want to capitalize on this tax credit before it is withdrawn.

The increasing possibility of losing the tax credit within the next year lowers the premium of the option. The prospect of losing the credit induces firms to invest more readily now.

1.3. Objectives

The overall objective of this dissertation is to describe how U.S. renewable energy policies affect solar photovoltaic (PV) and biodiesel industries. These objectives will be addressed through three essays with the following specific objectives:

1. Develop a theoretical framework for assessing the optimal solar energy subsidy and calibrate the model using published elasticities.

Detailed objectives include:

- Develop a comparative statics theoretical model on the optimal solar-energy subsidy
- Explore external benefits (environment, health, and employment) as well as electricity accessibility benefits
- Analyze welfare effects and marginal external benefits (MEB) of solar-energy generation
- Collect benchmark values and calculate parameter ranges
- Capture key factors influencing the optimal solar-energy subsidy by sensitivity analysis
- Employ Monte Carlo simulation to investigate the likelihood of a positive subsidy

2. Examine price volatilities among U.S. biodiesel, diesel, crude oil, and soybean markets by employing univariate EGARCH and DCC-MGARCH models

Detailed objectives include:

- Summarize U.S. biodiesel policies and the impact of EU biodiesel policies on U.S. biodiesel market
- Conduct descriptive statistics, augmented unit root tests, normality tests, autocorrelation tests, and arch effect on crude oil, biodiesel, and food time-series prices
- Employ univariate EGARCH model to investigate price-volatility spillovers among markets
- Apply Dynamic Conditional Correlation (DCC) MGARCH model to identify time-varying conditional correlations

3. Investigate the impact of time inconsistent government policies on market uncertainty

Detailed objectives include:

- Summarize inconsistent government biodiesel policies over the past decade
- Employ a geometric Brownian motion model on biodiesel prices
- Incorporate Poisson type policy jumps into a real options model for biodiesel investments decisions
- Estimate the threshold prices for biodiesel investments decisions

Table 1.1. U.S. Biodiesel Production, Exports, and Consumption (Million Gallons), 2005 – 2014 (U.S. Department of Energy, 2015)

U.S. Biodiesel Production, Exports, and Consumption (Million Gallons)					
Year	Production	Imports	Exports	Net Exports	Consumption
2005	91	9	9	0	91
2006	250	46	36	-10	261
2007	490	145	281	136	354
2008	678	326	700	375	304
2009	516	80	275	195	322
2010	343	24	109	85	260
2011	967	37	76	38	886
2012	991	36	128	93	899
2013	1359	342	196	-146	1429
2014	1240	212	83	-130	1402

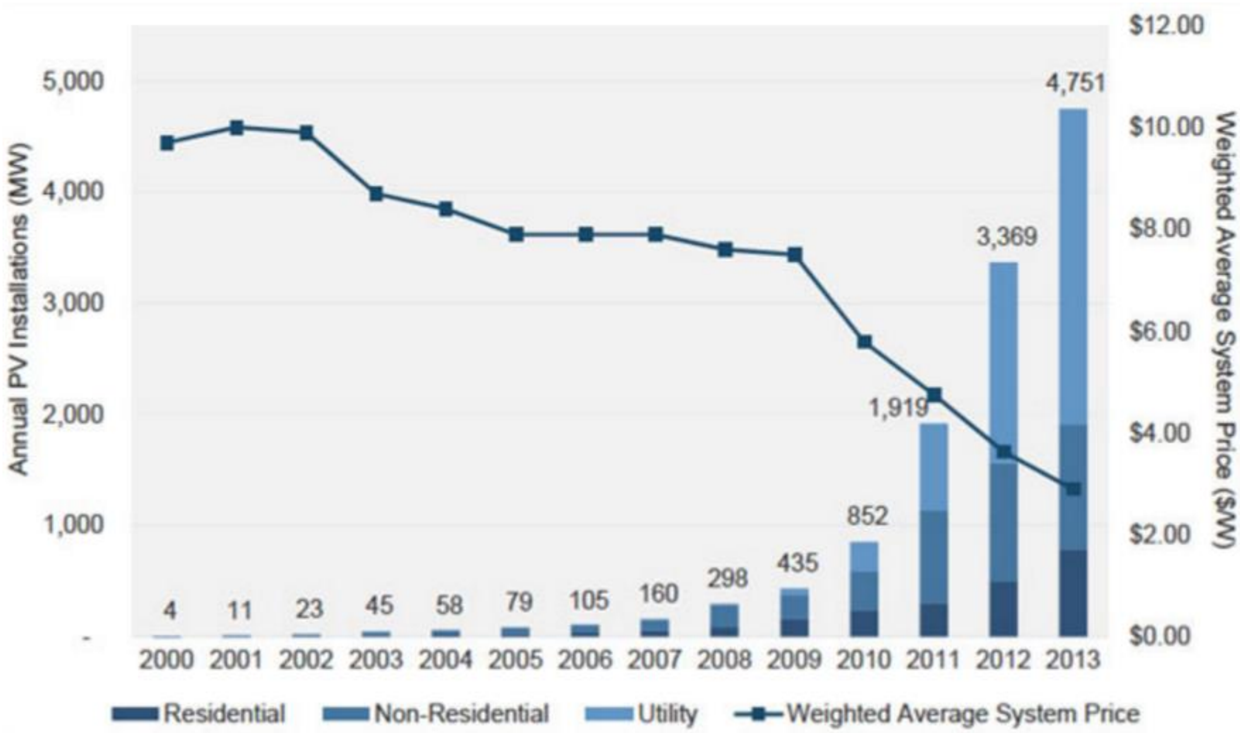


Figure 1.1. U.S. solar PV installations and average system price, 2000—2013

(Source: Solar Energy Industry Association, Photovoltaic (Solar Electric))

CHAPTER 2

TOWARD AN OPTIMAL U.S. SOLAR PHOTOVOLTAIC SUBSIDY[1]

[1] Liu, S., G. Colson, and M.E. Wetzstein. 2016. Submitted to *Resource and Energy Economics*, 04/12/2016.

Abstract

An analytical framework for assessing the optimal solar energy subsidy is developed and estimated, which takes into account the environment, health, employment, and electricity accessibility benefits. Results indicate that an optimal subsidy is positively affected by the marginal external benefit. However, this effect is mitigated by the elasticity of demand for conventional electricity and elasticity of supply for solar electricity with respect to the solar subsidy. One result indicates when the elasticity of demand is negative, the more responsive fossil energy is to a solar energy subsidy, the higher is the marginal external benefit. Calibrating the model using published elasticities yields estimates of the optimal solar energy subsidy equal to approximately $0.02 per kilowatt hour when employment effects are omitted. The estimated optimal subsidy is in line with many current state feed-in-tariff rates, giving support to these initiatives aimed at fostering solar energy production.

2.1. Introduction

Fostered by an array of government policies, programs, and financial support, solar photovoltaic (PV) was the fastest growing renewable power technology in the past decade worldwide (IEA, 2014), with generation expanding from 1.5GW in 2000 (IEA, 2014) to just over 100GW in 2012 (REN21, 2013). In the United States, the expansion of residential-renewable energy systems is driven by a range of government programs and substantial transfers of wealth via subsidies. At the federal level, taxpayers may claim a 30% personal tax credit for residential PV systems and installation costs (DSIRE, 2012). State and municipal authorities also employ various supporting policies in the form of cash rebates, net metering, renewable-portfolio standards (RPS), solar set-asides, and solar renewable-energy credits (Burns and Kang, 2012; Timilsina et al., 2012). Recently, states have enacted Feed-in-Tariff (FIT) systems (California, Hawaii, Oregon, Vermont, and Rhode Island) (REN21, 2013). In the United States, Goldberg (2000) estimates that when cumulative subsidies and electricity generation between 1947-1999 are considered, solar energy received subsidies worth $0.51/kWh (in 1999 dollars). Badcock and Lenzen (2010) estimate that in 2007 the global total subsidy for solar PV was $0.64/kWh (in 2007 dollars). More recent studies by the EIA (2007, 2010) estimate that the direct federal financial interventions and subsidies in U.S. solar energy markets grew from $179 million in 2007 to $1,134 million in 2010 (2010 dollars).

While the impetus for government subsidies of solar energy production as an alternative to traditional fossil fuels is rooted in standard economic theory of externalities, surprisingly a simple yet critical question for determining optimal government policy has not previously been explored. Simply put, what is the economically optimal solar subsidy? Despite the long history of subsidizing solar energy in the U.S., a policy with sound economic basis due to the external benefits arising from improved environmental, health, and (potentially) employment, previous research has not estimated what monetary level this subsidy should actually take. In order to foster growth in the solar industry and shift away from carbon emitting fossil fuels with the aim of maximizing social welfare and correcting the fossil fuel externality, quantifying the optimal level for solar energy subsidies is required.

As a step in quantifying this critical value, the objective of this study is to derive the socially optimal solar PV subsidy for residential energy production. Proceeding in two steps, first a model based on utility maximization is developed that incorporates environmental, health, employment, and electricity accessibility benefits affected by the level of solar subsidization. The model critically considers the influence of solar PV subsidies not only on the stimulation of the use of renewable energy, but also the income incentive for households to increase their use of electricity from fossil fuels. As is shown, the nature of demand for electricity from fossil fuels can partially or even completely swamp the benefits from solar subsidies. Second, using published elasticities and parameter values the model is calibrated to deliver a numerical estimate of the optimal residential solar PV energy subsidy. A positive result for current policymakers is found in that the estimated optimal subsidy is in line with the levels of support under some of the feed-in-tariffs employed in the U.S.

2.2. Theoretical Model

Building upon previous work in the optimal tax/subsidy literature, including gasoline taxes (Parry and Small, 2005), ethanol subsidies (Vedenov and Wetzstein, 2008), and biodiesel subsidies (Wu et al. 2012), a theoretical model for the optimal residential solar PV subsidy is developed. It is assumed solar energy, S, is determined by peak hours of sunlight per year z (hours) and quantity of solar panels purchased by the household I (watts or kW). Let h denote peak hours of sunlight per day. $z = 365h$. In general, a household receives utility from electricity consumption and from generating solar energy (personal satisfaction and independent security from generating energy) (Welsch and Biermann, 2014). A household also receives satisfaction from non-interference of electrical power, A. Within the United States most power outages are natural environmental problems effecting transmission and distribution networks. Solar PV systems are generally left untouched by such natural causes (Fthenakis, 2013). Installed rooftop solar PV can mitigate these power outages. Specifically, access to electricity, A, is assumed to depend on a household's solar energy

$$A = A(S) \text{ with } \frac{\partial A}{\partial S} > 0. \tag{1}$$

Further assume a household also receives satisfaction from a conventional utility plant (coal, natural gas, and petroleum), F, and a composite consumption good, X, with associated numeraire price $p_X = 1$. A utility function may then be represented as

$$u[X, F, S, A(S)], \tag{2}$$

where all the determinants positively influence utility.

Associated with this utility function are external environmental effects along with "green" and high-tech job opportunities effects.[1] Let the environmental effect of consuming power-plant electricity, D, be decomposed into greenhouse gas emissions, D_g, and localized air pollution, D_a. Climate change is mainly induced by emissions of greenhouse gases. Non-greenhouse gases, including SO_2, NO_X, $PM_{2.5}$, and PM_{10}, also have negative local impact on health, environment, and infrastructure. It is assumed greenhouse gas emissions and localized air pollution depend on aggregate conventional electricity, $\bar{F}$. Specifically,

$$D = D_g(\bar{F}) + D_a(\bar{F}), \tag{3}$$

$$\frac{\partial D_g}{\partial \bar{F}} > 0, \qquad \frac{\partial D_a}{\partial \bar{F}} > 0.$$

In addition to these environmental effects, there are "green" and high-tech job opportunities, *J*, effects. Employment has been argued to be a macroeconomic benefit of renewable-energy deployment (IRENA, 2014). Subsidies for renewable-electricity generation will change the composition of domestic employment. Job opportunities, *J*, then depends on aggregate solar energy, $\bar{S}$.

$$J = J(\bar{S}),$$

$$\frac{\partial J}{\partial \bar{S}} > 0. \qquad (4)$$

Additively attaching these external effects to the household utility function (2) yields

$$U = u[X, F, S, A(S)] - \delta(D) + \phi(J). \qquad (5)$$

The external effects D and J are features of the household's environment, so they are perceived by the household as exogenous. The functions *u* and ϕ are quasi-concave, whereas δ is weakly convex representing the disutility from environmental damages. The external benefits of reduced environmental damages (both greenhouse gas emissions and localized air pollution) and increased "green" and high-tech job opportunities are embedded in (5).

Given the presence of externalities, households ignore the effect of their own electricity consumption on environmental damages from consuming and generating electricity and job opportunities. A households' expenditures are on *X*, the composite good, *E*, its consumption of electricity (kWh), and $\frac{S}{z}$, the purchasing of solar panels (kW), with associated per unit prices, 1, p_E, and p_S. Income, *W*, is augmented with the sale of solar electricity, *S*, (kWh) at price $(p_E + s)$, where s is the subsidy. A household then attempts to maximize utility (2), subject to the budget constraint

$$X + p_E E + p_S \frac{S}{z} = W + (p_E + s)S,$$

$$X + p_E F + (p_z - s)S = W, \tag{6}$$

where $p_z = \frac{p_S}{z}$, and $F = E - S$ denotes household consumption of non-solar electricity.

This subsidy is a Feed-in Tariff (FIT) subsidy, which in practice differs across states and countries. If a FIT is consistently higher than the market price of electricity, it represents a continuous subsidy, as is the case in Germany (Eurelectric, 2004; Badcock and Lenzen, 2010). However, in Spain, FITs are set at a level 80% to 90% of the average market electricity price (Badcock and Lenzen, 2010), which does not provide a continuous subsidy. Only during periods of fluctuating electricity prices does the subsidy effectively exist (Hoffman, 2006; Badcock and Lenzen, 2010). But in general, FIT rates leading to significant renewable-energy investments are set above the retail cost of electricity (EIA, 2013a).

Aggregate household consumption of electricity $\bar{E}$ consists of aggregate conventional electricity from the power plant $\bar{F}$ and aggregate solar energy generated by the household, $\bar{S}$. The power plant sells $\bar{E}$ at a price p_E, and buys $\bar{S}$ at a price of $(p_E + s)$. It is assumed the power plant produces $\bar{F} = \bar{E} - \bar{S}$ at a marginal constant cost c. Electricity price p_E depends on aggregate household electricity consumption, $\bar{E}$, aggregate solar energy generation $\bar{S}$, and subsidy s.

In terms of the United States, approximately 75% of its population is served by investor-owned utilities, which are private companies but subject to state regulation (RAP, 2011). The remaining 25% of the population are served by consumer-owned utilities, which are established as nonprofit utilities. However, even the investor-owned utilities are regulated to only earn a normal return on investments with revenue equaling costs.

$$p_E \bar{E} = (p_E + s)\bar{S} + c\bar{F}.$$

Solving for p_E yields the price of electricity as a function of the subsidy and aggregate conventional and solar electricity,

$$p_E(s, \bar{F}, \bar{S}) = \frac{\bar{S}}{\bar{F}} s + c. \tag{7}$$

The utility sets the electricity price as the solar-to-fossil energy ratio times the subsidy plus the marginal cost. Given the nonprofit status of the utility, the subsidy is paid by the utility customers in the form of an increase in the price of electricity p_E.

2.2.1. Agent's choice

The optimal subsidy is determined from the indirect utility function

$$V(s, p_E, p_z, D, J, A) = \max u(X, F, S, A) - \delta(D) + \phi(J) + \lambda[W - X - p_E F - (p_z - s)S], \tag{8}$$

obtained by maximizing (5) subject to (6), where λ is the Lagrange multiplier. The terms $s, p_E, p_z, D, J,$ and A become the model's parameters.

The F.O.C.s for (8) are

$$\frac{\partial \mathcal{L}}{\partial X} = u_X - \lambda = 0,$$

$$\frac{\partial \mathcal{L}}{\partial F} = u_F - \lambda p_E = 0,$$

$$\frac{\partial \mathcal{L}}{\partial S} = u_S + u_A A_S - \lambda(p_Z - s) = 0,$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = W - X - p_E F - (p_z - s)S = 0.$$

Taking the ratio and rearranging,

$$\frac{u_F}{\lambda} = p_E, \tag{9a}$$

$$\frac{(u_S + u_A A_S)}{\lambda} = p_z - s = \frac{p_S}{z} - s. \tag{9b}$$

Equation (9a) states that the household's marginal monetary benefit of consuming an additional kWh of energy from a power plant is equal to the price of energy purchased from the electrical plant. Equation (9b) states that the agent's marginal monetary benefit of producing an additional kWh of solar energy is equal to the cost of producing an additional kWh ($\frac{p_S}{z}$) less the subsidy s. The marginal benefit is the sum of the direct benefits from using solar, u_S, plus the indirect benefit of increasing access, $u_A A_S$.

2.2.2 Welfare effects

The welfare effects of an incremental change in the solar energy subsidy may be determined by totally differentiating the indirect utility function (8) with respect to the subsidy level s. Noting that $\partial V/\partial s = \lambda S > 0$, and $\partial V/\partial p_E = -\lambda F < 0$, $\partial V/\partial p_z = -\lambda S < 0$, $\partial V/\partial D = -\delta' < 0$, $\partial V/\partial J = \phi' > 0$, $\partial V/\partial A = u_A > 0$ yields

$$\frac{dV}{ds} = \lambda S - \lambda F\frac{dp_E}{ds} - \lambda S\frac{dp_z}{ds} - \delta'\frac{dD}{ds} + \phi'\frac{dJ}{ds} + u_A\frac{dA}{ds}. \quad (10)$$

From the definition of p_E, D, J, and A in (7), (3), (4), and (1), respectively,

$$\frac{\mathrm{d}p_E}{\mathrm{ds}} = \frac{S}{F} - s\frac{S}{F^2}\frac{\partial F}{\partial s} + s\frac{1}{F}\frac{\partial S}{\partial s}, \quad (11a)$$

$$\frac{dD}{ds} = \frac{\partial D_a}{\partial F}\frac{\partial F}{\partial s} + \frac{\partial D_g}{\partial F}\frac{\partial F}{\partial s}, \quad (11b)$$

$$\frac{dJ}{ds} = \frac{\partial J}{\partial S}\frac{\partial S}{\partial s}, \quad (11c)$$

$$\frac{dA}{ds} = \frac{\partial A}{\partial S}\frac{\partial S}{\partial s}. \quad (11d)$$

In determining (11), aggregate electricity from power plant, $\bar{F}$, and aggregate solar energy generated by a household, $\bar{S}$, are no longer constant, so their partials with respect to s are partials of F and S.

Substituting (11) into (10) and dividing by λ results in the marginal monetary welfare effect of the solar energy subsidy s:

$$\frac{1}{\lambda}\frac{dV}{ds} = \mathrm{S} - F\left[\frac{S}{F} - s\frac{S}{F^2}\frac{\partial F}{\partial s} + s\frac{1}{F}\frac{\partial S}{\partial s}\right] - S\frac{dp_z}{ds} - \frac{\delta'}{\lambda}\left[\frac{\partial D_g}{\partial F}\frac{\partial F}{\partial s} + \frac{\partial D_a}{\partial F}\frac{\partial F}{\partial s}\right]$$

$$+\frac{\phi'}{\lambda}\frac{\partial J}{\partial S}\frac{\partial S}{\partial s} + \frac{u_A}{\lambda}\frac{\partial A}{\partial S}\frac{\partial S}{\partial s}$$

$$= s\frac{S}{F}\frac{\partial F}{\partial s} - s\frac{\partial S}{\partial s} - S\frac{dp_z}{ds} - \left(\frac{\delta'}{\lambda}\frac{\partial D_a}{\partial F} + \frac{\delta'}{\lambda}\frac{\partial D_g}{\partial F}\right)\frac{\partial F}{\partial s}$$

$$+\left(\frac{\phi'}{\lambda}\frac{\partial J}{\partial S} + \frac{u_A}{\lambda}\frac{\partial A}{\partial S}\right)\frac{\partial S}{\partial s}. \tag{12a}$$

Equation (12a) may be simplified by defining the externality and access effects as

$$E^{D_aF} = \frac{\delta'}{\lambda}\frac{\partial D_a}{\partial F} > 0\ ,$$

$$E^{D_gF} = \frac{\delta'}{\lambda}\frac{\partial D_g}{\partial F} > 0\ ,$$

$$E^{JS} = \frac{\phi'}{\lambda}\frac{\partial J}{\partial S} > 0,$$

$$A^{AS} = \frac{u_A}{\lambda}\frac{\partial A}{\partial S} > 0,$$

yielding

$$\frac{1}{\lambda}\frac{dV}{ds} = s\frac{S}{F}\frac{\partial F}{\partial s} - s\frac{\partial S}{\partial s} - S\frac{dp_z}{ds} - \left(E^{D_aF} + E^{D_gF}\right)\frac{\partial F}{\partial s} + \left(E^{JS} + A^{AS}\right)\frac{\partial S}{\partial s}. \tag{12b}$$

2.2.3. Marginal external effects

For further analysis and interpretation, it is convenient to express the marginal welfare effects (12b) in terms of elasticities. This is accomplished by first defining MEB as the net marginal external benefit of solar energy generation

$$MEB = E^{JS} - \left(E^{D_aF} + E^{D_gF}\right)\frac{\tau}{\alpha_{SF}}, \tag{13}$$

where the parameters τ and α_{SF} are defined as

$$\tau = \frac{\left(\frac{\partial F}{\partial s}\right) S}{\left(\frac{\partial S}{\partial s}\right) F} = \frac{\epsilon_{Fs}^{D}}{\epsilon_{Ss}^{S}},$$

$$\alpha_{SF} = \frac{S}{F},$$

where ϵ_{Fs}^{D} and ϵ_{Ss}^{S} denote elasticity of demand for conventional electricity with respect to the subsidy and elasticity of supply for solar electricity with respect to the subsidy, respectively. The ratio of solar electricity to conventional electricity is denoted by α_{SF}.

MEB is composed of the direct benefits of solar-energy generation, E^{JS}, and the indirect net external marginal benefits from a per-unit change in energy consumption. The direct marginal benefits are the effect of solar-energy generation on job opportunities, E^{JS}. The indirect marginal benefits are changes in greenhouse gas emissions from conventional electricity consumption, $-E^{D_aF}\frac{\tau}{\alpha_{SF}}$, and air quality pollution from conventional electricity consumption, $-E^{D_gF}\frac{\tau}{\alpha_{SF}}$.

The welfare effects of a change in the subsidy are summarized in the following two propositions and associated corollaries. First, given public concern with CO_2 emissions, fossil energies are becoming an inferior good where households with higher incomes will tend to spend proportionally less of their income on carbon based fuels. This leads directly to Proposition 1.

Proposition 1. If $\frac{\partial F}{\partial W} < 0$, fossil energy is an inferior good, then $\frac{\partial F}{\partial s} < 0$. An increase in the subsidy yields less fossil-energy consumption.

Proof:

The Marshallian demand function for F is $F = F(p_z - s,\ p_E, W)$, the Hicksian demand function is $F_V = F_V(p_z - s,\ p_E, V)$, and the expenditure function is $W = W(p_z - s, p_E, V)$. The consumption of fossil-energy identity is then

$$F_V(p_z - s, p_E, V) \equiv F[p_z - s,\ p_E, W(p_z - s,\ p_E, V)].$$

With two commodities, fossil energy F and solar energy S, the Slutsky equation for a change in the price of solar energy is,

$$\frac{\partial \mathrm{F}}{\partial(p_z - s)} = \frac{\partial F_V}{\partial(p_z - s)} - \frac{\partial F}{\partial W} S.$$

If S is a net substitute for F, then $\frac{\partial F_V}{\partial(p_z - s)} > 0$, and $\frac{\partial F_V}{\partial \mathrm{s}} < 0$. For a constant p_z , the Slutsky equation can then be written as

$$\frac{\partial \mathrm{F}}{\partial \mathrm{s}} = \frac{\partial F_V}{\partial s} + \frac{\partial F}{\partial W} S. \tag{14}$$

$$(-)$$

If $\frac{\partial F}{\partial W} < 0$, an inferior good, then $\frac{\partial \mathrm{F}}{\partial \mathrm{s}} < 0$. Q.E.D.

With households' preferences to reduce their proportion of income spent on fossil fuels as incomes rise, policies favoring solar PV will not only increase solar PV, but also reduce fossil-energy consumption.

Corollary 1.1. From Proposition 1, $\frac{\partial F}{\partial s} < 0$, then $\frac{\mathrm{d}p_E}{\mathrm{ds}} > 0$. An increase in the subsidy will increase the fossil-fuel price.

Proof:

From (11a)

$$\frac{\mathrm{d}p_E}{\mathrm{ds}} = \frac{S}{F} - s\frac{S}{F^2}\frac{\partial F}{\partial s} + s\frac{1}{F}\frac{\partial S}{\partial s}.$$

Given $\frac{\partial F}{\partial s} < 0$ and $\frac{\partial S}{\partial s} > 0$, then $\frac{\mathrm{d}p_E}{\mathrm{ds}} > 0$. Q.E.D.

If the utility incurs the cost of a solar PV subsidy, it will pass a portion of this cost unto consumers of fossil energy through higher fuel prices.

Corollary 1.2. From Proposition 1, $\frac{\partial F}{\partial s} < 0$, then $\frac{dD}{ds} < 0$. An increase in the subsidy will decrease environmental damage.

Proof:

From (11b)

$$\frac{dD}{ds} = \frac{\partial D_g}{\partial F}\frac{\partial F}{\partial s} + \frac{\partial D_a}{\partial F}\frac{\partial F}{\partial s},$$

and from (3)

$$\frac{\mathrm{d}D_g}{\mathrm{d}\bar{F}} > 0, \qquad \frac{dD_a}{d\bar{F}} > 0,$$

Given $\frac{\partial F}{\partial s} < 0$, then $\frac{dD}{ds} < 0$. Q.E.D.

Corollary 1.2 states if the objective of a solar PV subsidy is to reduce fossil-energy consumption, then given fossil energy is an inferior good the objective will be realized.

Corollary 1.3. From Proposition 1, $\epsilon_{\mathrm{Fs}} < 0$, then the more responsive fossil energy, F, is to a solar-energy subsidy, *s*, the higher is the MEB, $\frac{\partial MEB}{\partial \epsilon_{Fs}} < 0$.

Proof:

Taking the partial derivative of (13) with respect to the elasticity ϵ_{Fs} yields

$$\frac{\partial MEB}{\partial \epsilon_{Fs}} = -\frac{(E^{D_a F} + E^{D_g F})}{\epsilon_{Ss}\alpha_{SF}} < 0 \qquad \text{Q.E.D.}$$

From Corollary 1.3, the more responsive F is to s, the higher will be the MEB. A large reduction in F from a change in s will lead to a large impact on reducing negative externalities.

Corollary 1.4. From Proposition 1, $\epsilon_{\mathrm{Fs}} < 0$, then the more responsive solar energy, S, is to a solar-energy subsidy, *s*, the lower is the MEB, $\frac{\partial MEB}{\partial \epsilon_{Ss}} < 0$.

Proof:

Taking the partial derivative of (13) with respect to the elasticity ϵ_{Ss} yields

$$\frac{\partial MEB}{\partial \epsilon_{Ss}} = \frac{(E^{D_a F} + E^{D_g F})\epsilon_{Fs}}{{\epsilon_{Ss}}^2 \alpha_{SF}} < 0 \qquad \text{Q.E.D.}$$

Similar to Corollary 1.3, in terms of S, a large increase in S from s will lead to a large impact on reducing negative externalities.

Prior to CO_2 emission concerns, fossil energies were generally thought of as normal goods. In this case, as demonstrated in Proposition 2, the direction of fossil-energy consumption from favorable solar PV policies is unclear.

Proposition 2. If $\frac{\partial F}{\partial W} > 0$, fossil energy is a normal good, then the sign of $\frac{\partial F}{\partial s}$ is indeterminant. An increase in the subsidy can result in reduced, an increase, or no change in fossil-energy consumption.

Proof:

The proof follows directly from (14) in the proof of Proposition 1. If $\left|\frac{\partial F_V}{\partial s}\right| > \frac{\partial F}{\partial W} S$, then $\frac{\partial \mathrm{F}}{\partial \mathrm{s}} < 0$, which is consistent with Proposition 1. Instead, if $\left|\frac{\partial F_V}{\partial s}\right| < \frac{\partial F}{\partial W} S$, then $\frac{\partial F}{\partial s} > 0$. The income effect, $\frac{\partial F}{\partial W} S$, completely offsets the negative net substitution effect $\frac{\partial F_V}{\partial s}$, leading to $\frac{\partial \mathrm{F}}{\partial \mathrm{s}} > 0$. Q.E.D.

Given Proposition 2, an increase in a solar subsidy may result in more fossil energy consumption.

Corollary 2.1. From Proposition 2, $\frac{\partial F}{\partial s}$ is indeterminant, then $\frac{\mathrm{d}p_E}{\mathrm{ds}}$ is also indeterminant.

Corollary 2.2. From Proposition 2, $\frac{\partial F}{\partial s}$ is indeterminant, then $\frac{dD}{ds}$ is also indeterminant.

The proofs follow directly from the proofs of Corollaries 1.1 and 1.2.

In summary, an increase in a solar subsidy will lead to less fossil-fuel consumption, lower environmental damage, but higher cost of electricity unless the income effect completely offsets the negative substitution effect. However, as in the general case of a Giffen good, this is a paradox, which is unlikely to occur. It would require a relatively large proportion of income spent on solar PV and a small Hicksian elasticity of substitution between solar and fossil energy.

2.2.4. Optimal solar energy subsidy

Theorem 1. The optimal solar-energy subsidy is

$$s^* = \frac{(MEB + A^{AS})\epsilon_{Ss} - \epsilon_{p_z s} p_z}{(1-\tau)\epsilon_{Ss}}. \tag{15}$$

where

$$\epsilon_{p_z s} = \frac{dp_z}{ds}\frac{s}{p_z},$$

is the elasticity for the price of solar panels with respect to the subsidy.

Proof:

Setting first-order condition (12b) to zero and dividing by $\frac{\partial S}{\partial s}$ yields

$$0 = \tau s - s - \frac{\epsilon_{p_z s}}{\epsilon_{Ss}} p_z + MEB + A^{AS}.$$

Solving for s then yields the optimal solar-energy subsidy. Q.E.D.

For interpretation, (15) may be rewritten as

$$s^* = \frac{(MEB + A^{AS})}{\left(1 - \frac{\epsilon_{Fs}}{\epsilon_{Ss}}\right)} - \frac{\epsilon_{p_z s} p_z}{\epsilon_{Ss} - \epsilon_{Fs}}, \tag{16}$$

leading to Proposition 3.

Proposition 3. If $\epsilon_{Ss} > \epsilon_{Fs}$, then $\partial s^*/\partial MEB > 0$ and $\partial s^*/\partial A^{As} > 0$.

The proof follows directly from the denominators in (16). If $\epsilon_{Ss} > \epsilon_{Fs}$, then $\left(1 - \frac{\epsilon_{Fs}}{\epsilon_{Ss}}\right) > 0$ and $\epsilon_{Ss} - \epsilon_{Fs} > 0$, leading to $\partial s^*/\partial MEB > 0$ and $\partial s^*/\partial A^{As} > 0$. Q.E.D.

Proposition 1 implies Proposition 3, so if $\partial F/\partial W < 0$, fossil energy is an inferior good, then $\partial s^*/\partial MEB > 0$ and $\partial s^*/\partial A^{As} > 0$. However, even given Proposition 2, where the sign of $\partial F/\partial s$ is indeterminent, as long as solar energy is more subsidy responsive than fossil energy, the optimal subsidy is positively influenced by the marginal external benefits and accessibility and negatively by the price of solar panels.

The sign of s^* depends on the responsiveness of the solar-panel price to the subsidy as developed in Proposition 4.

Proposition 4. If $\epsilon_{p_z s} < \frac{(MEB + A^{AS})\epsilon_{Ss}}{p_z}$, then $s^* > 0$.

Proof: Given the denominator $(1 - \tau)\epsilon_{Ss} > 0$, the sign of s^* depends directly on the numerator, $(MEB + A^{AS})\epsilon_{Ss} - \epsilon_{p_z s} p_z$,. Solving for $\epsilon_{p_z s}$ yields the proposition. Q.E.D.

Proposition 4 states the benefits of solar ($MEB + A^{AS}$) per-unit price of solar panels, weighted by how responsive solar power is to the subsidy, ϵ_{Ss}, must be greater than the responsiveness of the price of solar panels to the subsidy, $\epsilon_{p_z s}$, for a positive optimal solar subsidy, $s^* > 0$. In general, the subsidy must have a larger impact on benefits than on the solar panel prices.

The effect of a solar subsidy on panel prices is generally unknown. In the long run a solar subsidy may stimulate demand for panels leading to a supply response and if the panel industry is characterized by economies to scale, then panel prices would fall. This scenario implies $\epsilon_{p_z s} < 0$, which leads to Corollary 4.1.

Corollary 4.1. If $\epsilon_{p_z s} < 0$, then $s^* > 0$.

The proof follows directly from the proof of Proposition 4.

However in the short run the sign could be reversed, $\epsilon_{p_z s} > 0$. In this case, the sign is similar to the share of a commodity tax being borne by both the seller and buyer. It is the result of a portion of the subsidy being received by the sellers of solar panels in the form higher panel prices, p_z. The numerator in (15) indicates MEB plus A^{AS} multiplied by ϵ_{Ss}, is mitigated by the any positive response of p_z to a change in the subsidy. The more elastic p_z is to a change in the subsidy, the larger will be the response of p_z and the less effective will be the subsidy. This slippage in the effects of the subsidy yields a lower optimal subsidy. The subsidy is being absorbed into higher prices for solar panels, which mitigates its effectiveness. Depending on the magnitude of the elasticities, this slippage can affect intended policy results. The denominator in (15) can be rewritten as $(\epsilon_{Ss} - \epsilon_{Fs})$, which weights the MEB mitigated by the solar panel cost effect by the responsiveness of generating solar energy and use of conventional energy by the subsidy. The greater this responsiveness, the lower will be the subsidy.

From (15) a tandem relation is revealed between subsidizing the generation of solar electricity, s, and the solar panels through a reduction in p_z. Reducing p_z through some panel subsidy will raise the optimal subsidy, s^*, for solar electricity, $\partial s^*/\partial p_z < 0$. A solar-panel subsidy reduces the slippage associated with higher panel prices. The degree of this relation depends on the strength of the elasticity of panel price to the subsidy, $\epsilon_{p_z s}$. The more responsive the panel price is to the subsidy, the larger in magnitude is this tandem relation. Policymakers should be aware of this relation and its magnitude when setting solar-energy policies and establishing programs. This is particularly true in diverse regions with solar energy bifurcation. In Arizona with abundant hours of solar energy the price of solar panels will be low, $p_z = \frac{p_S}{z}$, which will increase the elasticity $\epsilon_{p_z s}$. The price of panels will then be more responsive to the subsidy;

leading to a lower optimal subsidy. In contrast, Alaska with relatively limited solar hours, the optimal solar subsidy would be higher.

In general, if fossil energy is an inferior good, so $\partial F/\partial s < 0$, then a subsidy will both enhance solar adoption, $\epsilon_{Ss} > 0$, and retard fossil energy use, $\epsilon_{Fs} < 0$. The reduction in fossil energy from an increase in the solar-energy subsidy will reinforce the positive effect the subsidy has on solar adoption. The more responsive these elasticities are, the lower is the optimal subsidy. The magnitude of this responsiveness is an empirical question requiring the parameterization of (15).

2.3. Application

The optimal solar subsidy (15) is generally true for any region or country, although the parameters and elasticities will likely vary. As an application, parameter and elasticity values, obtained from published sources, are employed for determining the optimal U.S. solar subsidy. These values reflect just one possible scenario. Alternative subsidy levels will occur for different regions with modifications to these values. For the numerical analysis of determining the optimal solar PV subsidy (15), benchmark values and parameter ranges are summarized in Table 2.1. The appendix provides a summary outlining the determination of these estimated values. Based on Table 2.1, the optimal solar PV subsidy for median income household is $s^* = 7.69$ cents/kWh with associated $\text{MEB} = 7.87$ cents/kWh. If excluding the external effect of employment, the optimal solar PV subsidy for median income household reduces to $s^* = 2.24$ cents/kWh with associated $\text{MEB} = 2.23$ cents/kWh.

2.3.1. Sensitivity Analysis

The wide range of parameter values in Table 2.1 suggests the benchmark optimal subsidy has an associated rather large variance. In order to investigate the sensitivity of the optimal solar PV subsidy, s^*, to ranges of these parameter values, both individual parameter variation and Monte Carlo analysis were implemented.

2.3.1.1. Individual parameter variation

In terms of the individual parameter variations, results indicate the optimal solar PV subsidy is mainly influenced by the elasticity of solar-panel price with respect to the subsidy, $\epsilon_{p_z s}$, environmental effects, $E^{D_aF} + E^{D_gF}$, job opportunities effects, E^{JS}, and access to electricity effects, A^{AS}. All the other parameters have a relatively small impact on the optimal subsidy. In particular, the optimal subsidy is not sensitive to household income. This implies a supporting policy should be similar for both low-income and high-income households.

Even within the influential parameters their respective impacts vary. In terms of Corollary 4.1, Figure 2.1 illustrates the response of the optimal solar PV subsidy to a range of the elasticity of solar-panel price with respect to the subsidy. As the responsiveness of panel price to a subsidy increases, the slippage in the effects of the subsidy also increases, leading to a lower subsidy. The optimal subsidy for Arizona relative to Alaska households is lower. With a positive percentage change in the panel price larger than the subsidy percentage change the optimal subsidy is negative. The subsidy is just increasing the panel price and any subsidy benefits are evaporated.

As illustrated in Figure 2.2, the range of increase in access benefit, from zero to $0.12 \times 10^{-2}\$/\text{kWh}$) has little impact on the optimal subsidy. The subsidy only increases by 1.6%. In contrast, the external benefit of greenhouse gas emissions, D_g, and localized air pollution, D_a, have a relatively larger impact on the optimal subsidy, mainly due to their large magnitudes. For the range of the external benefit, the subsidy increased 73% (Figure 2.3). However, the major impact on the optimal subsidy is the employment parameter. As illustrated in Figure 2.4, for the range of the employment parameters, the optimal subsidy increases five times. This implies the changes in the employment parameter have a major impact on the subsidy level. As indicated in the results and discussed in the Implication section, employment is a major determinant of the subsidy and probably the most controversial with proponents and detractors of subsidy taking a markedly different line on the employment effect.

2.3.1.2. Monte-Carlo analysis

For investigating the macro effect of simultaneously changing all the parameters, Monte-Carlo analysis on the optimal subsidy is performed. In particular, 5000 random draws of parameters in Table 2.1 were generated using a uniform probability distribution over respective ranges of the parameters. The drawn parameters were then employed to calculate the optimal solar PV subsidy in (15), and to create an empirical CDF for the optimal subsidy. Table 2.2 lists the probabilities of the optimal subsidy being below specific thresholds. As indicated in the table, the probability of the optimal subsidy being non-positive is only 17.3%. Thus, the likelihood of a positive subsidy is reinforced by the Monte-Carlo analysis. There is also over an 80% probability that the optimal subsidy is less than $0.15/kWh.

2.3.2. Implications

The optimal solar PV for a median income household is $s^* = 7.69$ cents/kWh. If excluding the external effect of employment, the optimal solar PV for median income households declines to $s^* = 2.24$ cents/kWh. In the Dominion Virginia Power’s voluntary FIT program, residential participants will receive 15 cents/kWh, which is approximately one-third higher than Virginia’s average 2012 retail electricity price (EIA, 2013a). The solar PV subsidy for Virginia residential participants is approximately 3.75 cents/kWh, which is between our estimates of optimal solar

PV subsidy 2.24 cents/kWh (excluding employment effect) and 7.69 cents/kWh (including employment effect).

The externality effect of job opportunities is controversial. It is believed that the energy industry contributes to economic growth by creating jobs and commerce by extracting, transforming, and distributing energy goods and services throughout the economy. Job creation is a macroeconomic benefit from the energy industry. During the 2008 campaign, Barack Obama touted the prospect that investing in renewable energy could produce five million "green jobs" (Worstall, 2013). Some studies support renewable-energy technologies generating more job opportunities than conventional energy industries (Wei et al., 2010; Stein, 2013). Counterpoints generally involve two aspects. First, the solar-energy industry does not create as many jobs as expected. Research has indicted solar employment increased just 28% while there was a nine fold increase in solar power from 2008 to 2010 (Johnson, 2013). Second, renewable energy does not necessarily create more jobs than conventional energy. For example, technologies that require ongoing fuel production (coal and natural gas) require more labor than those that do not (wind and solar PV) in the operations phase (World Economic Forum, 2012). Moreover, one may also argue that the deployment of renewable energy may increase job opportunities within a region. However, at the national level, the large domestic market would not be significantly affected by the development of a solar industry. Considering the whole U.S. economy, Rivers (2013) estimates that reducing electricity sector emissions by 10% through renewable-electricity support policies is likely to increase unemployment approximately 0.1 to 0.3%. Our sensitivity analysis indicates the optimal solar PV subsidy is sensitive to the externality effect of job creation. If one believes employment should be a macroeconomic benefit from solar PV, results indicate the optimal solar PV subsidy would be 7.69 cents/kWh. In contrast, a belief that the employment effect should be excluded, the optimal solar PV subsidy falls to 2.24 cents/kWh.

2.4. Conclusions and Policy Implications

The theoretical results indicate that changing household preferences can have a marked impact on the effect a solar PV subsidy has on adoption of solar panels and on the consumption of fossil energy. If households have a general shift toward viewing fossil energy as an inferior good, then any policies directed at incentivizing adoption will be more effective and may not be necessary. Given inferior-good characteristics for fossil energies, the proposition and associated corollaries imply policies favorable to solar and alternative energies in general will result in reduced fossil-energy consumption, higher fossil prices, and reduced environmental damage. In particular, the higher fossil-energy prices precipitating from the policy would reduce the Pareto efficiency requirement of some cap-n-trade policy or a carbon tax. If instead fossil energy is a normal good, then these impacts from policies favoring renewable energies are not certain.

A further concern with policies favoring renewable energies is the possibility of slippage in the form of resulting higher prices for renewable-energy inputs. As the results indicate for solar energy, a solar PV subsidy may drive up the price of solar panels. If so, then the effectiveness of the subsidy is compromised. Little or no information on the degree of this possible slippage is known, which is ripe for further research.

Finally, returning to the issue of camps for and against renewable-energy subsidies, empirical results indicate the optimal level of solar PV subsidies are very much dependent on the impact such subsidies have on employment. If renewable energies have limited or no positive job impacts, then the justification for a subsidy is substantially weakened. The results highlight the importance of determining the policy impacts on macroeconomic variables like job growth.

The result also touches on the complementary aspects of providing household incentives for adoption of alternatives along with educating households on the negative external costs of using conventional fossil-based energies. Theoretical results indicate that a solar PV subsidy is likely more effective when households are educated on the external cost and shift preferences towards viewing fossil energies as being an undesirable commodity.

Footnotes

[1] There are other external effects including environmental damage from transportation and extraction of fossil fuels (oil, coal, and natural gas). Including these externalities does not enrich the theoretical model, but would positively impact the optimal subsidy. Also, it is assumed the U.S. economy is closed in terms of no leakages from the United States' attempts to reduce negative external effects, influencing another country's efforts (Elloitt and Fullerton, 2013).

Appendix I

The benchmark values and parameter ranges, listed in Table 2.1, for populating (15) are based on published values and adjusted as follows.

The ratio of solar to fossil-fuel electricity has increased over time. In 2012, the amount of solar and fossil fuel energy in the residential sector were 186 and 5137 trillion Btu, respectively (EIA, 2014b). The ratio of solar over fossil-fuel electricity, α_{SF}, is then 186/5137 = 0.036, with a range of 0.026 to 0.037 based on residential sector energy consumption data in 2011 and 2013.

Since 2008, solar PV system prices, which include installation costs have continued to decline (Chen, 2013). Based on U.S. Solar Market Insight reports (SEIA, 2011-2013) from 2011 to 2013, the installed price of solar panels, p_S, is set as the average price in 2012 of 5.39 \$/W = 5390 \$/kW with a range of 4590 to 6410. It is assumed solar panels receive 4.5 peak hours of sunlight on average each day with a range of 3.0 to 6.5 (NREL, 2012). The benchmark value of p_z is set at $\frac{p_S}{z} = \frac{5390}{4.5\times 365} = 3.282$ \$/KWh with a range of 1.935 to 5.854.

The average size of a residential PV system in the U.S. is 5 kW (SEIA, n.d.) with a range of 3 to 8 kW. Due to real world efficiency losses (irradiance, dust, temperature, and wiring), it is expected system power output (AC power) to be approximately 76.9% of the system (DC power) size, overall DC to AC derate factor is 0.769 (NREL, n.d.). The benchmark value of annual household solar electricity generation is set at $\mathrm{S} = 365\ \text{days/year} \times 4.5\ \text{hrs/day} \times 5\ \text{kW} \times 0.769 = 6315\ \text{kWh/year}$ with a range of 2526 to 14,596.

According to (6), a household's income $W_T = (p_E + s)S + W$, indicating $\frac{\partial W_T}{\partial s} = S$. The 2012 average retail price of electricity in the residential sector is 0.119 \$/kWh. The benchmark value of the retail price of electricity, p_E, is set as 0.119 \$/kWh with a range of 0.117 to 0.121 based on a residential electricity price in 2011 and 2013 (EIA, 2014a). The 2012 U.S. median household income was \$51,371 (US Census Bureau, 2013). Therefore, household income is $W_T = (p_E + s)S + W = (p_E S + W) + sS = 52{,}122 + 6315s$.

Johnson (2010 and 2014) estimated the long-run price elasticity of supply of renewable electricity generation as 2.714 and 2.67 with associated standard errors of 0.611 and 0.473, respectively. Based on this estimate, the solar-electricity elasticity of supply with respect to the subsidy, ϵ_{Ss}^{S}, is set at 2.714 with a range of 1.516 to 3.912.

Limited analysis exists in estimating the income elasticity of demand for solar panels. Algieri et al. (2011) estimated that a 1% increase in income raises exports by 2.69%. With this estimate, the income elasticity of demand for solar panels, $\epsilon_{IW}^{D} = \frac{\partial I}{\partial W_T}\frac{W_T}{I}$, is set as 2.69 with a range of 1.88 to 3.50. The ranges were determined by the 95% confidence intervals of estimated parameters.

From (14), the elasticity of demand for fossil-fuel electricity with respect to the subsidy is

$$\epsilon_{Fs}^{D} = \xi_{Fs} + \eta_F \frac{sS}{W_T}, \tag{A1}$$

where $\xi_{Fs} = \frac{\partial F_v}{\partial s}\frac{s}{F}$ is the substitution elasticity and η_F denotes income elasticity of demand for F. In terms of the income elasticity estimate, Alberini et al., (2011) determined the income elasticity of electricity consumption, η_F, is approximately 0.02. After removing specifications of the home characteristics, including size, number of floors, and presence of certain appliances, their estimate of income elasticity of electricity η_F increases to 0.05. Similarly, the elasticity of supply for solar electricity with respect to the subsidy, ϵ_{Ss}^{S}, can be written as

$$\epsilon_{Ss}^{S} = \xi_{Ss} + \eta_S \frac{sS}{W_T}, \tag{A2}$$

where $\xi_{Ss}= \frac{\partial S_v}{\partial s}\frac{s}{S}$ is the substitution elasticity and η_S denotes income elasticity of demand for S. Solar energy generation depends on the amount of solar panels purchased by the household. Thus, income elasticity of demand for *S*, $\eta_S = \epsilon_{IW}^D = 2.69$ with a range of 1.88 to 3.50.

Assuming the amount of increase in the solar electricity is equal to the amount of decrease in the conventional electricity

$$\frac{\partial F_v}{\partial s} = -\frac{\partial S_v}{\partial s}, \tag{A3}$$

the substitution elasticity of conventional electricity is then

$$\begin{aligned}\xi_{Fs} &= \frac{\partial F_v}{\partial s}\frac{s}{F}\\ &= -\frac{\partial S_v}{\partial s}\frac{s}{F}\\ &= -\xi_{Ss}\alpha_{SF}\\ &= -\left(\epsilon_{Ss}^S - \eta_S\frac{sS}{\mathrm{W}_T}\right)\alpha_{SF}. \end{aligned}\tag{A4}$$

Substituting (A4) into (A1),

$$\begin{aligned}\epsilon_{Fs}^D &= -\left(\epsilon_{Ss}^S - \eta_S\frac{sS}{\mathrm{W}_T}\right)\alpha_{SF} + \eta_F\frac{sS}{\mathrm{W}_T}\\ &= -\left(\epsilon_{Ss}^S - \epsilon_{IW}^D\frac{sS}{\mathrm{W}_T}\right)\alpha_{SF} + \eta_F\frac{sS}{\mathrm{W}_T}\\ &= -\epsilon_{Ss}^S\alpha_{SF} + (\epsilon_{IW}^D\alpha_{SF} + \eta_F)\frac{sS}{\mathrm{W}_T}. \end{aligned}\tag{A5}$$

Based on benchmark values,

$$\begin{aligned}\epsilon_{Fs}^D &= -2.714 \times 0.036 + (2.69 \times 0.036 + 0.05)\frac{6315s}{(52{,}121 + 6315s)}\\ &= -0.098 + \frac{930.751s}{(52{,}121 + 6315s)}\end{aligned}$$

Limited analysis exists in estimating the elasticity for price of solar panels with respect to the subsidy. It is reported that solar panel supply will far exceed demand beyond 2012 (Wang, 2012). Besides, price of solar panels are affected by many factors, including the type of material, its accessibility, complexity in manufacturing, and amount available and demanded (Rose, 2012). It is assumed the elasticity for price of solar panels with respect to the subsidy is very inelastic. The benchmark value of the elasticity for price of solar panels with respect to the subsidy, $\epsilon_{p_z s}$, is set at zero with a range of -0.1 to 0.1.

In calculating the effect of driving on air quality, Parry and Small (2005) assume air pollution from vehicles is proportional to miles traveled. Using their study as a guide, it is assumed both local air pollution and greenhouse gas emissions from conventional electricity are proportional to electricity consumed. In 2012, approximately 68% of the U.S. electricity generated was from fossil fuel (coal, natural gas, and petroleum) (EIA, 2014c). Coal, natural gas, and petroleum account for 37%, 30%, and 1%, respectively. Muller et al. (2011) estimate that gross external damages from the sum of local pollution and greenhouse gas emissions of the electricity produced by coal-fired facilities, natural-gas plants, and oil-fired plants are 3.59, 0.56, and 2.74 cents/kWh, respectively. For the application a weighted average $2.24 \times 10^{-2}\ \$/KWh$ as a benchmark value of $E^{D_a F} + E^{D_g F} = \frac{\delta'}{\lambda}\frac{\partial D_a}{\partial F} + \frac{\delta'}{\lambda}\frac{\partial D_g}{\partial F}$ with a range of 1.75×10^{-2} to 3.12×10^{-2}. The range was determined by the 95% confidence intervals of estimated parameters.

Wei et al. (2011) determine the average of direct employment multiplier for solar PV is 0.87 Job-Years/GWh with a range of 0.2 to 1.4. Limited analysis exists in estimating the net welfare effect of job opportunities. A common measure of the relative contribution of an industry to the overall economy is the value-added per worker. Value-added per direct worker in solar PV industry is $65,000, indicating on average direct U.S. employment in the solar PV sector contributes \$65,000 to GDP (World Economic Forum, 2012). Therefore, the externality effect of job opportunities is $E^{JS} = \frac{\phi'}{\lambda}\frac{\partial J}{\partial S} = 65{,}000 \times (0.87 \times 10^{-6}) = 0.057\ \$/\mathrm{kWh}$ with a range of $0.013\ \$/\mathrm{kWh}$ to $0.091\ \$/\mathrm{kWh}$.

For the effect of access to electricity, weather-related outages are estimated to have cost the U.S. economy an inflation-adjusted annual average of \$18 billion to \$33 billion (U.S. Department of Energy, 2013). Aggregate electricity consumption in 2012 is 95,004 trillion Btu (EIA, 2012), which is approximately 27.843 trillion kWh. Dividing the average cost \$25.5 billion by the annual electricity consumption results in external benefit of access to electricity, $\mathrm{A}^{\mathrm{AS}} = \frac{\mathrm{u_A}}{\lambda}\frac{\partial \mathrm{A}}{\partial \mathrm{S}} = \frac{25.5}{27.843 \times 10^{3}} = 0.092\ \mathrm{cents/kWh}$ with a range of 0.065 to 0.118 cents/kWh.

A summary of these estimates are provided in Table 2.1 and employ in calcuating the optimal subsidy (15). Further refining of these estimates will improve the accuracy in this calculation. The estimates are provided to outline how a benchmart optimal subsidy can be estimated with lower and upper ranges.

Table 2.1. Benchmark Values and Parameter Ranges

Parameter	Symbol	Benchmark	Range	
			Lower	Upper
Peak Hours of Sunlight per Day[a] (hr)	h	4.5	3.0	6.5
Household Solar Electricity[b] (kWh)	S	6315	2526	14,596
Retail Price of Electricity[c] ($/kWh)	p_E	0.119	0.118	0.122
Price of Solar Panels[d] ($/kWh)	p_z	3.282	1.935	5.854
Ratio				
Solar Electricity/Fossil Electricity[e]	α_{SF}	0.036	0.026	0.037
Elasticities				
Income elasticity of Demand for Conventional Electricity[f]	η_F	0.05	0.02	0.05
Solar Electricity Elasticity of Supply with respect to the Subsidy[g]	ϵ_{Ss}^S	2.714	1.516	3.912
Income Elasticity of Demand for Solar Panels[h]	ϵ_{IW}^D	2.69	1.88	3.50
Elasticity for price of solar panels with respect to the subsidy	$\epsilon_{p_z s}$	0	-0.1	0.1
Externality and Access Effects				
Environmental Costs[i]($\times 10^{-2}$\$/kWh)	$E^{D_a F} + E^{D_g F}$	2.24	1.75	3.12
Job Opportunities[j]($\times 10^{-2}$\$/kWh)	E^{JS}	5.66	1.30	9.30
Access to Electricity[k]($\times 10^{-2}$\$/kWh)	A^{AS}	0.092	0.065	0.118
Marginal External Benefits($\times 10^{-2}$\$/kWh)	MEB	7.87		
Optimal Solar PV Subsidy($\times 10^{-2}$\$/kWh)	s^*	7.69		

[a] NREL, 2012
[b] SEIA, 2012 and NREL
[c] EIA, 2012
[d] SEIA, 2011-2013
[e] EIA, 2014c
[f] Alberini et al., 2011
[g] Johnson, 2010
[h] Algieri et al., 2011
[i] Muller et al., 2011
[j] Wei et al., 2011 and World Economic Forum, 2012
[k] US DOE, 2013

Table 2.2. Monte Carlo Results for Optimal Solar PV Subsidy

Level, x (dollar/kWh)	Probability $s^* < x$
-0.05	0.059
-0.04	0.074
-0.03	0.094
-0.02	0.117
-0.01	0.146
0.00	**0.173**
0.01	0.207
0.02	0.246
0.03	0.288
0.04	0.329
0.05	0.373
0.06	0.422
0.07	0.473
0.08	0.522
0.09	0.569
0.10	0.612
0.11	0.654
0.12	0.699
0.13	0.736
0.14	0.780
0.15	0.816

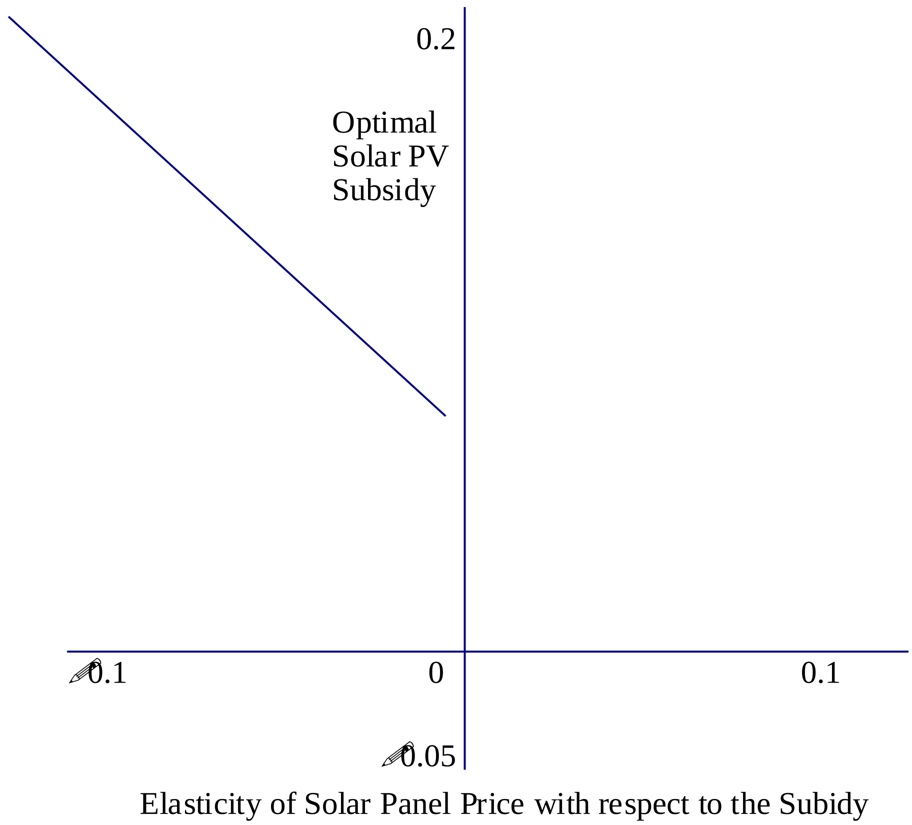


Figure 2.1. Response of the Optimal Solar PV Subsidy (dollars per kWh) to Elasticity of Solar Panel Price with respect to the Subsidy

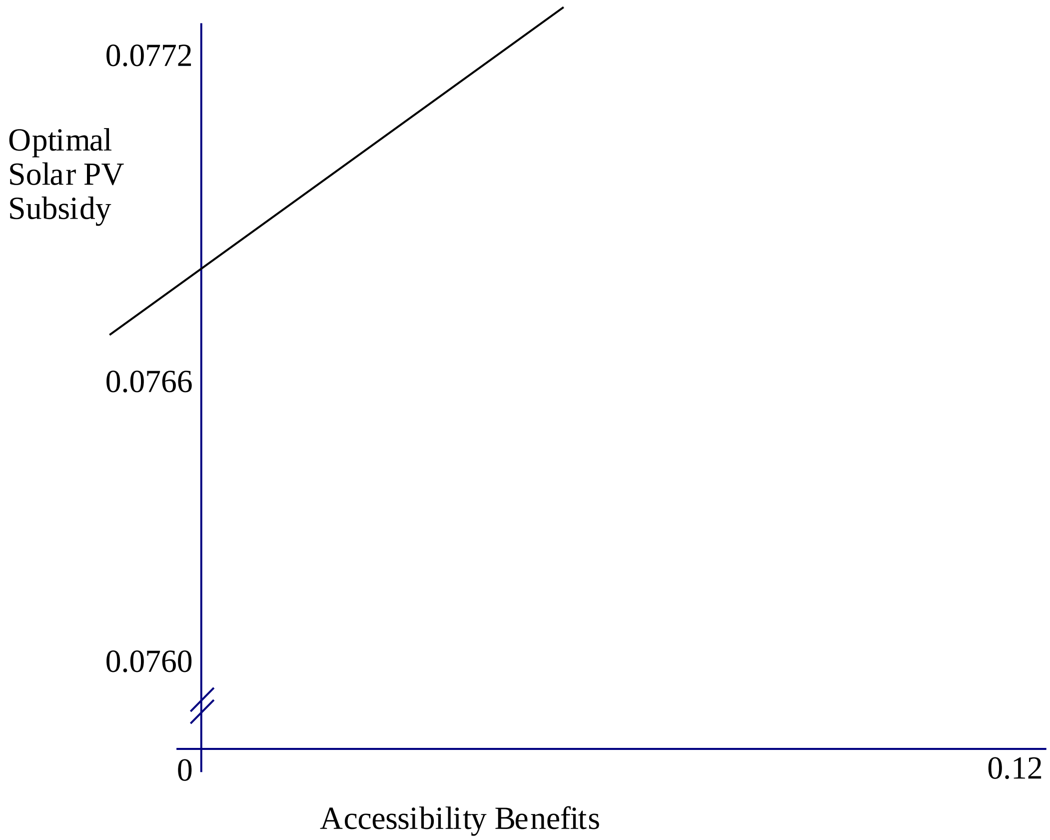


Figure 2.2. Response of the Optimal Solar PV Subsidy ($\times \mathbf{10^{-2}}\$/\mathbf{kWh}$) to Accessibility Benefits

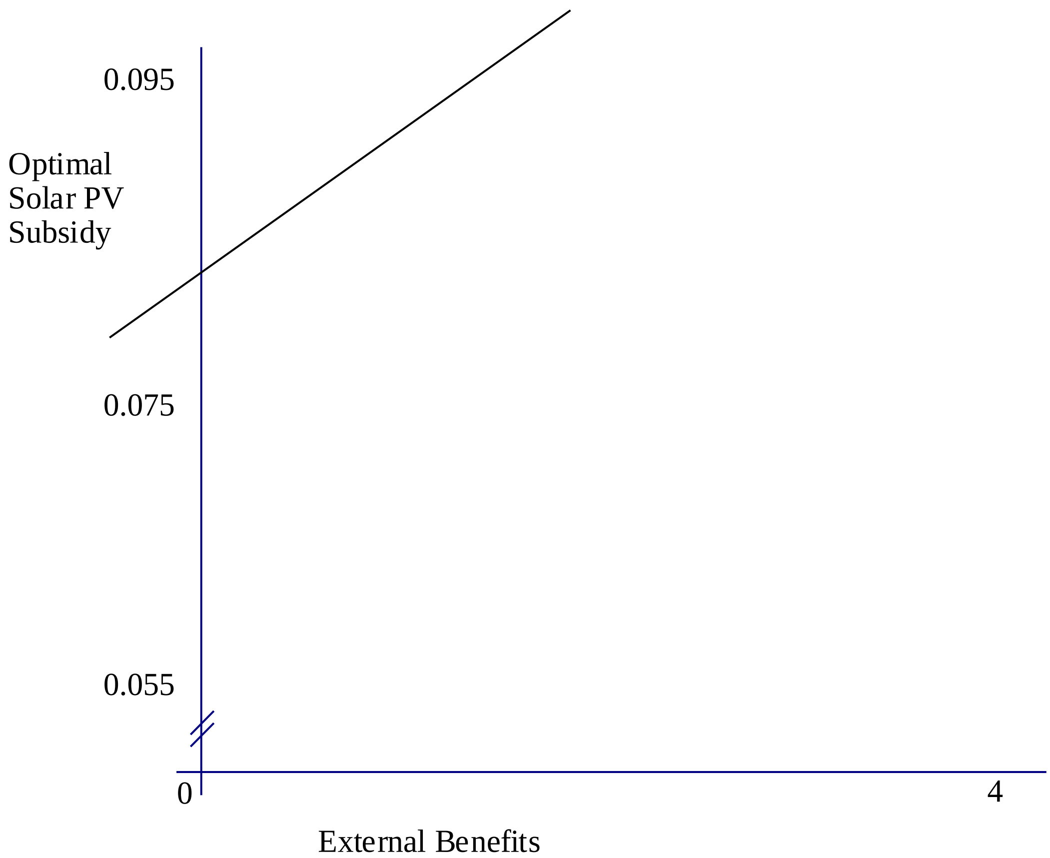


Figure 2.3. Response of the Optimal Solar PV Subsidy ($\times \mathbf{10^{-2}\$/kWh}$) to Environment Benefits

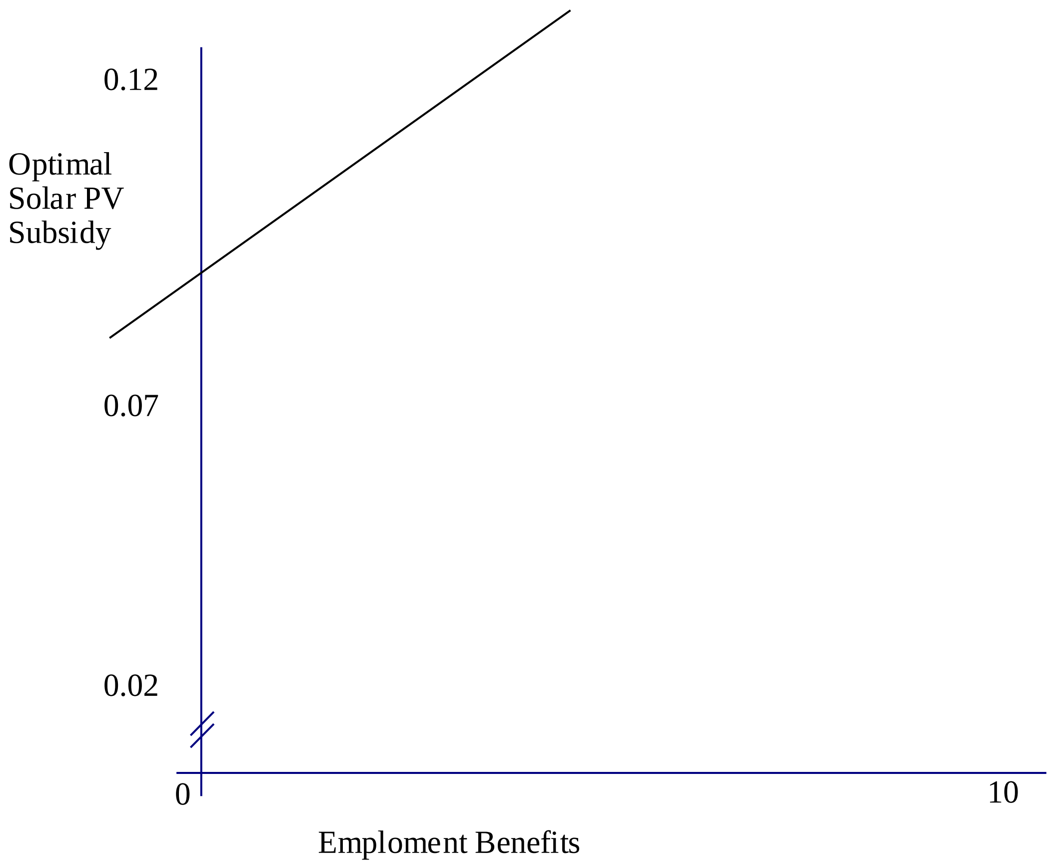


Figure 2.4. Response of the Optimal Solar PV Subsidy ($\times \mathbf{10^{-2}}\$/\mathbf{kWh}$) to Employment Benefits.

CHAPTER 3

PRICE VOLATILITIES AMONG U.S. BIODIESEL, DIESEL, CRUDE OIL, AND SOYBEAN MARKETS[2]

[2] Liu, S., G. Colson, B. Karali, and M.E. Wetzstein. To be submitted to *Energy Economics*.

Abstract

Price volatility spillovers among U.S. crude oil, diesel, biodiesel, and soybeans are examined based on weekly prices from 2007 to 2014. A univariate EGARCH model along with a DCC-MGARCH approach are employed. The results provide evidence of double-directional price-volatility spillovers between biodiesel and soybean markets and between crude oil and biodiesel markets. While unidirectional price-volatility spillovers exist from the crude oil market to the soybean market and from the diesel to the biodiesel market. The DCC-MGARCH model indicates time-varying conditional correlations among markets and the pairwise conditional correlations fluctuated from 2008 to 2009.

3.1. Introduction

The emergence of biofuel production has shaken the energy and agricultural commodity markets. Traditionally, food and conventional energy prices were mainly connected through the food-supply chain. Food prices are affected by energy prices through the use of various energy-intensive inputs including fertilizers, heating and pesticides, and motor-fuel costs. There is a general consensus among researchers that the emergence of a global biofuel industry has altered this traditional link between energy and agricultural markets (Serra, 2013). A stronger connection may now exist through output-demand channels as biofuels impact both the fossil fuel and agricultural commodities markets (Taheripour and Tyner, 2008). Increasing crude-oil prices not only affect agricultural-commodity prices through higher input costs but also stimulate policymakers to provide incentives to develop and adapt biofuels into the conventional fossil-fuel markets. This increased demand for biofuels may then put upward pressure on the demand for agricultural commodities, which are the main inputs employed for biofuel production. Underlying this biofuel/commodity market interaction is the continued dependence of these markets on crude-oil (Gilbert and Mugera, 2014).

The two common types of biofuels are ethanol and biodiesel. United States and Brazil dominate the ethanol production market, cumulatively accounting for 87% of the global total (Rapier, 2014). In 2013, the United States produced 13.2 billion gallons, which was 57% of the total global ethanol production. Brazil was second with another 6.7 billion gallons (Rapier, 2014). Biodiesel is the second largest category of global biofuels, accounting for 6.9 billion gallons globally in 2013, which is 22.6% of total biofuel production (Rapier, 2014). Biodiesel is the most commonly consumed biofuel in the European Union. The European Union produced 2.8 billion gallons of biodiesel in 2013, 40% of the global total (Rapier, 2014).

Most of the biofuel-related price level and volatility literature considers ethanol as the representative of biofuel, especially for the U.S. biofuel market (Saghaian, 2010; Serra et al., 2011; McPhail, 2011; Zhang et al., 2009; Trujillo-Barrera, Mallory, and Garcia, 2012; Du and McPhail, 2012; Gardebroek and Hernandez, 2013). U.S. biodiesel draws much less attention than ethanol, despite the fact that the United States is the largest national producer of biodiesel (Rapier, 2014). Although U.S. biodiesel production was only one tenth as much as the ethanol production in 2013, it is rising sharply. The U.S. biodiesel production in 2010 was 0.343 billion gallons (USDA, 2014). It reached 0.967 and 0.991 billion gallons in 2011 and 2012, respectively; almost three times 2010 production. In 2013, at 1.339 billion gallons it was almost four times 2010 volume (USDA, 2014). Biodiesel is an emerging major alternative fuel within the United States.

Despite this growing U.S. biodiesel market, a literature review reveals no studies conducted on the price volatility in the U.S. biodiesel market. The objection is to then fill this gap. The biodiesel market is affected by different policies relative to the ethanol market. Furthermore, price-volatility spillover effects may vary by countries due to differences in the structure and size of the biodiesel markets, as well as differences in the feedstocks employed and the agricultural sector providing these feedstocks (Hassouneh et al., 2012). For addressing price volatility, Univariate Exponential GARCH models are employed in conjunction with examining volatility interdependence across time by a Dynamic Conditional Correlation (DCC) Multivariate GARCH model.

The reminder of the introduction briefly discusses federal biodiesel policies along with European Union policies directly affecting the U.S. biodiesel market. A literature review on empirical volatility models addressing biofuels is then presented in Section 2. Section 3 outlines the univariate EGARCH and DCC-MGARCH with Section 4 describing the underlying data. Section 5 presents the empirical results and concluding remarks are presented in the final section, Section 6.

Biofuel policies have an impact on prices relations among oil, biofuel, and agricultural-commodity markets (de Gorter, Drabik, and Just, 2013). Biofuel mandates, subsidies, and the fuel-blending restrictions will affect the fossil and agricultural-commodity price relations (Gardebroek and Hernandez, 2013). The two primary means that subsidies affect the demand for U.S. biodiesel are the Renewable Fuel Standard (RFS) and the blender tax credit (Babcock, 2011). The RFS is a federal program, which requires transportation fuel sold within the United States to contain a minimum volume of renewable fuels (U.S. Department of Energy, 2014) and was created under the Energy Policy Act of 2005 (EPA, 2014). The expanded RFS (referred to as RFS2), implemented in 2010, subdivides the total renewable fuel requirement into four separate but nested categories (Schnepf and Yacobucci, 2013). One of the four categories is biomass-based diesel, which is a diesel-fuel substitute made from renewable feedstock, including biodiesel and non-ester renewable diesel. The biodiesel mandates were 1.15, 0.80, and 1.00 billions of gallons in 2010, 2011, and 2012, respectively. The 2013 biodiesel mandate was revised upwards from one billion to 1.28 billion gallons (Schnepf and Yacobucci, 2013). The biodiesel production in 2013 was beyond the mandate at 1.28 billion gallons. EPA proposed to set the renewable fuel standards for 2014 at the levels that were actually produced and used as transportation fuel, heating oil or jet fuel in the contiguous U.S. and Hawaii (EPA, 2015). EPA proposed annual increases in the required volume of biomass-based diesel for 2015, 2016, and 2017 (EPA, 2015). The blender tax credit is paid on every gallon of biodiesel that is blended in the United States with any quantity of fossil fuel. The $1.00 per gallon blender tax credit for biodiesel was established in 2005 by the American Jobs Creation Act of 2004. It was extended by several acts. The tax credit temporarily lapsed in 2010 and was then extended again by the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 (Yacobucci, 2012). The credit was allowed to expire on December 31, 2013 (U.S. Department of Energy, n.d.), but could possibly be reestablished. On May 15, 2014, the U.S. Senate failed to pass the “Expiring Provisions Improvement Reform and Efficiency (EXPIRE) Act. The EXPIRE Act includes extension of biodiesel tax credit through December 31, 2015 and retroactive to January 1, 2014 (U.S. Senate Committee on Finance, 2014). This tax credit helped raise the United States biodiesel price by making exports to the European Union more profitable, thereby possibly increasing the soybean and corn prices, as land is taken out of corn and used in soybean production (de Gorter, Drabik, and Just, 2013).

The impact of Untied States biodiesel policies also depends on their interaction with EU biodiesel policies (de Gorter, Drabik, and Just, 2011). The European Commission (EC) initiated anti-dumping and anti-subsidy investigations into imports of biodiesel from the United States on June 13, 2008, after a complaint was lodged by the European Biodiesel Board (EBB), which represents the European biodiesel industry, in April 2008. According to the EC investigation, the U.S. tax credit of $1.00 per gallon of biodiesel caused European producers to lose market share. Meanwhile, U.S. biodiesel production and prices fell sharply in June 2008 (de Gorter, Drabik, and Just, 2013). The EC imposed temporary anti-dumping and anti-subsidy duties on imports of biodiesel from the United States in March 13, 2009. The measures were in place for four months while the investigation continued. On July 12, 2009, the EC imposed definitive anti-dumping and anti-subsidy duties for a period of five years (EBB, 2014). The U.S. biodiesel prices stabilized after the duties were implemented in March 2009.

3.2. Literature Review

While most of the biofuel-related time-series literature has investigated price-level links, the literature on the price volatility interactions is relatively limited. The 2007-2008 food crisis stimulated research on the price-volatility spillover, which complements research investigating price-level impacts. With a few exceptions, the biofuel-related price volatility literature has relied on GARCH-type models (Serra, 2013).

A number of studies examine the volatility-spillover effects among fossil fuels, biofuels, and agricultural-commodity prices. Zhang et al. (2009) applied a BEKK-MGARCH model to U.S. crude oil, ethanol, and corn prices for the period 1989-2007. They found no links with ethanol volatilities influencing corn- and soybean-price volatilities. Instead, the reverse was indicated with impacts of agricultural commodity price volatility on energy price volatility. During the ethanol boom period, a shock in soybean price volatility impacts ethanol price volatility, and a shock in corn price volatility impacts oil price volatility. Serra, Zilberman, and Gil (2011) employed VECM-BEKK-MGARCH model using weekly international crude oil prices and Brazilian ethanol and sugar prices from 2000 to 2008. Their results suggest a strong link between food and energy markets in terms of both price levels and volatility. Trujillo-Barrera, Mallory, and Garcia (2012) applied univariate GJR-GARCH and BEKK-MGARCH models to weekly futures prices for crude oil, ethanol, and corn from 2006 through 2011. They found strong and varying volatility transmission from crude-oil futures market to ethanol- and corn- futures markets. Gardebroek and Hernandez (2013) employed both BEKK-MGARCH and DCC-MGARCH models using weekly prices for U.S. crude oil, ethanol, and corn from 1997 through 2011 to investigate whether price volatility in oil and ethanol markets stimulates price volatility in corn market. Their results indicate there is no volatility spillover from oil or ethanol to corn, which does not support the popular press concern of increased price volatility in agricultural markets due to biofuels.

Other studies narrowed their focus to the relationship between fossil fuels and agricultural commodity prices without incorporating biofuel prices. Du, Yu, and Hayes (2011) applied a stochastic volatility model to weekly crude oil, corn, and wheat futures prices from 1998 to 2009 and found evidence of volatility spillover among crude oil, corn, and wheat markets after the fall of 2006. Wu, Guan, and Myers (2011) estimated univariate TGARCH and asymmetric BEKK-MGARCH models using weekly crude oil and corn cash and future prices from 1992 to 2009. Their results indicate significant and positive spillover effects from crude oil prices to corn cash and future prices, and these spillover effects are time-varying. Nazlioglu, Erdem, and Soytas (2013) concluded there are volatility spillovers from the oil market to corn, wheat, and soybean markets from 2006 to 2011 and from wheat to oil market from 1986 to 2011 by employing a univariate GARCH model and causality in variance test.

Existing literature has mainly assessed the dynamic linkages of price level and volatility between food and energy markets for the ethanol market. A few studies have considered the price volatility for the biodiesel market in European countries. Schulz (2012) employed VECM and DCC-MGARCH models using weekly prices for German biodiesel, crude oil, and rapeseed from 2002 through 2012. The study indicates conditional volatilities are highly persistent and conditional correlations are mostly positive but highly fluctuating, especially since the food crisis in 2008. Emergent biodiesel market in the United States has, however, received limited if any attention.

3.3. Methodology

Two complementing methodologies are employed for investigating the volatility linkages among the crude oil, biodiesel, diesel, and soybean price series. The exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model developed by Nelson (1991) is employed to capture possible asymmetric impact of positive and negative shocks on volatilities. EGARCH also avoids imposing non-negativity restrictions on the value of the GARCH estimated parameters (Bollerslev, 1986). Complementing EGARCH is the dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model (Engel, 2002), which allows examination of possible changes in the level of price-volatility interdependence among markets through time.

3.3.1. EGARCH

Allowing asymmetric stocks, consider an EGARCH model with log difference for crude oil, biodiesel, soybean, and diesel

$$\begin{gathered} \boldsymbol{r_t} = \boldsymbol{\gamma_0} + \sum_{j=1}^{p} \boldsymbol{\gamma_j r_{t-j}} + \boldsymbol{\varepsilon_t}, \\ \varepsilon_t | \boldsymbol{I_{t-1}} \sim (0, \sigma_t^2), \end{gathered} \tag{1}$$

where $\boldsymbol{r_t}$ denotes the log-difference price vector, $\boldsymbol{\varepsilon_t}$ is the stochastic error, which is assumed to be normally distributed with a zero mean and conditional (time-varying) variance, σ_t^2, and $\boldsymbol{I_{t-1}}$ is the information set at time $\mathrm{t}-1$.

$$log(\sigma_t^2) = a_0 + \sum_{i=1}^{q} a_i g(z_{t-i}) + \sum_{j=1}^{p} b_j log(\sigma_{t-j}^2), \tag{2}$$

where

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|], \tag{3}$$

$$z_t = \frac{\varepsilon_t}{\sigma_t}.$$

Equation (2), the conditional variance equation, reflects the $\mathrm{EGARCH}(\mathrm{p}, \mathrm{q})$ representation. The left-hand side of (2) is the log of the conditional variance, which implies the leverage effect is exponential. EGARCH modeling explicitly assumes the variance is conditional on its own past values as well as a function of the standardized residuals z_t. The persistence of volatility implied by (2) is measured by $\sum_{j=1}^{p} b_j$. If the unconditional variance is finite, $\sum_{j=1}^{p} b_j$ is less than one in absolute value. The smaller the absolute value of this sum, the less persistent volatility is after a shock. In (3), $[|z_t| - E|z_t|]$ captures the ARCH effect, which is similar to the concept behind a GARCH specification. The parameter θ allows for this ARCH effect to be asymmetric. A statistically significant θ indicates an asymmetric effect exists.

Considering an EGARCH(1,1), where p = q =1, the model can test the following volatility spillovers among crude oil, biodiesel, soybeans, and diesel markets: (a) from biodiesel, soybean, and diesel prices to crude oil prices; (b) from crude oil, soybean, and diesel prices to biodiesel prices; (c) from crude oil, biodiesel, and diesel prices to soybean prices; and (d) from crude oil, biodiesel, and soybean prices to diesel prices. The modeling framework was adopted in previous studies on volatility spillovers. Hamao, Masulis, and Ng (1990) applied this approach to a GARCH-M model for detecting volatility spillover across international stock markets. Buguk, Hudson, and Hanson (2003) employed this approach in an EGRACH model examining the volatility spillover in the catfish supply chain. Wu and Li (2013) also combine this approach with an EGARCH model to analyze the volatility spillover in China’s crude oil, corn, and ethanol markets.

Allowing case (a) as an illustration, the contemporaneous squared residuals from the mean-conditional variance formulation of log difference of biodiesel, soybean, and diesel prices are exogenous variables in the conditional variance equation of log difference of crude oil prices. Thus, the conditional variance equation for log difference of crude oil prices is

$$log(\sigma_{1,t}^2) = \omega_1 + \alpha_1 \left| \frac{\varepsilon_{1,t-1}}{\sigma_{1,t-1}} - \sqrt{\frac{2}{\pi}} \right| + \beta_1 \, log(\sigma_{1,t-1}^2) + \delta_1 \frac{\varepsilon_{1,t-1}}{\sigma_{1,t-1}} + \quad (4)$$

$$c_{12} \, log(U_{2,t}) + c_{13} \, log(U_{3,t}) + c_{14} \, log(U_{4,t}),$$

where $U_{2,t}, U_{3,t}$, and $U_{4,t}$ are the contemporaneous squared residuals from the $\mathrm{EGARCH}(1,1)$ for log difference of biodiesel prices, $\mathrm{AR}(1) - \mathrm{EGARCH}(1,1)$ for log difference of soybean prices, and EGARCH(1,1) for log difference of diesel prices. Let $c_{ij}, i \neq j$, denote the spillover from market i to market j.The existence of a volatility spillover is indicated by the statistical significance of c_{12}, c_{13}, and c_{14}. Statistical inference regarding these parameters is based on robust standard errors derived by Bollerslev and Wooldridge (1992) to allow for possible violations of the assumption of normality for the conditional errors.

3.3.2. DCC-MGARCH

Multivariate GARCH models allow the conditional mean to follow a vector autoregressive (VAR) structure and allow the conditional covariance matrix of the dependent variables to follow a flexible dynamic structure. Such a DCC-MGARCH model is employed to examine the level of interdependence and the dynamics of volatility among U.S. crude oil, biodiesel, soybean, and diesel markets. Specifically, the DCC-MGARCH model by Engle (2002) approximates a dynamic conditional correlation matrix, which permits evaluation of the time-varying interdependence among markets. Employing this model, the conditional means of the log difference are modeled as a first-order vector autoregressive, VAR(1), process and the conditional covariances as a $\mathrm{DCC}(1,1)$ process where the variance of each disturbance term follows a $\mathrm{GARCH}(1,1)$ process.

Mathematically, the representation is

$$\boldsymbol{r_t} = \boldsymbol{\gamma_0} + \sum_{j=1}^{p} \boldsymbol{\gamma_j r_{t-j}} + \boldsymbol{\varepsilon_t}, \qquad (5)$$

$$\boldsymbol{\varepsilon_t}|\boldsymbol{I_{t-1}} \sim (0, \boldsymbol{H_t}),$$

where $\boldsymbol{r_t}$ is a 4×1 vector of log difference crude oil, biodiesel, soybean, and diesel prices, $\boldsymbol{\gamma_0}$ is a 4×1 vector of long-run drifts, $\boldsymbol{\gamma_j}$, with $j = 1, \dots, p$, are 4×4 matrices of parameters, and $\boldsymbol{\varepsilon_t}$ is a 4×1 vector of forecast errors for the best linear predictor of r_t, conditional on past information denoted by $\boldsymbol{I_{t-1}}$, and with corresponding variance-covariance matrix $\boldsymbol{H_t}$. As in a standard VAR representation, the elements of γ_j, $j = 1, \dots, p$, provide measures of own- and cross-mean spillovers between markets. A VAR(1) is employed to fit the conditional means of log difference. The model can then be rewritten as

$$\boldsymbol{r_t} = \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1 r_{t-1}} + \boldsymbol{\varepsilon_t}, \qquad (6)$$

$$\boldsymbol{\varepsilon_t}|\boldsymbol{I_{t-1}} \sim (0, \boldsymbol{H_t}).$$

The conditional variance-covariance matrix H_t is defined as

$$\boldsymbol{H_t} = \boldsymbol{D_t R_t D_t}, \qquad (7)$$

$$\boldsymbol{D_t} = diag(h_{11,t}^{1/2} \dots h_{44,t}^{1/2}),$$

where $h_{ii,t}^{1/2}$ is defined as a GARCH(1,1) specification

$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1}, i = 1, \dots, 4.$

The time-dependent conditional correlation matrix $R_t = (\rho_{ij,t})$, i, j $= 1, \dots, 4$ is defined as

$$\boldsymbol{R_t} = diag(q_{ii,t}^{-1/2})\boldsymbol{Q_t} diag(q_{ii,t}^{-1/2}), \qquad (8)$$

with the 4×4 symmetric positive-definite matrix $\boldsymbol{Q_t} = (q_{ij,t}), i, j = 1, \dots, 4$, given by

$$\boldsymbol{Q_t} = (1 - \alpha - \beta)\boldsymbol{\bar{Q}} + \alpha \boldsymbol{u_{t-1} u'_{t-1}} + \beta \boldsymbol{Q_{t-1}}, \qquad (9)$$

and $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$. The variable $\bar{\boldsymbol{Q}}$ is the 4×4 unconditional variance matrix of u_t, and α and β are non-negative parameters satisfying $\alpha + \beta < 1$. Equation (9) resembles an autoregressive moving average (ARMA) type process, which captures short-term deviations in the correlation around its long-run level. The variance-covariance matrix defined in (7) permits modeling the degree of volatility interdependence among markets across time.

3.4. Data

Weekly crude oil, diesel, biodiesel, and soybean price series are employed from April 13, 2007 through June 27, 2014, which results in 377 observations. Crude oil prices ($/barrel) represent the global spot price for West Texas Intermediate in Cushing, Oklahoma (EIA, 2014d). Biodiesel and diesel prices ($/gallon) are from the USDA Agricultural Marketing Service (Center for Agricultural and Rural Development, 2014) and low sulfur free diesel on board prices in New York Harbor (EIA, 2014e), respectively. Soybean spot prices ($/bushel) represent Memphis soybean prices (USDA, 2014). Nominal prices are adjusted to real by the Producer Price Index (PPI) for Crude Material (U.S. Department of Labor, 2014). Figure 3.1 illustrates the monthly coefficients of variation for crude oil, biodiesel, soybean, and diesel prices during the sample period. The coefficients of variation are unstable between mid-2008 and the end of 2009. This represents the wide price swings with the pre- and post-recession periods. Figure 3.2 illustrates the coefficients of variation for biodiesel during the sample period. The coefficient of variation for biodiesel is the largest in October 2009.

Table 3.1 provides additional insight concerning the potential interdependencies among the four markets. The table lists Pearson correlations of log differences, $r_t = \ln(P_t/P_{t-1})$, where P_t denotes the vector of real prices (crude oil, biodiesel, soybean, and diesel) at week t. This log difference is a close approximate to the percentage change of weekly real prices. All log-difference correlations are statistically significant at the 1% level, with the correlation between oil and diesel likely stronger than the correlations among the other pairs. These correlations and plots indicate U.S. energy and soybean markets appear to be interrelated. Yet, establishing the sources of these interdependences on price-volatility spillover requires further analysis.

Descriptive summary statistics for the log difference are listed in Table 3.2. Log differences of crude oil and diesel are more than twice that of biodiesel along with log difference of soybean more than three times. This indicates biodiesel prices are potentially not as volatile as the other prices. All the prices are all skewed to the left with Jarque-Bera test statistics rejecting the null hypothesis of a normal distribution at a 1% significance level. The log difference in crude oil indicates a leptokurtosis distribution compared to the other mesokurtic distributions. At least at the 10% significance level, the Ljung-Box statistics indicate all the log-difference prices exhibit autocorrelation except for biodiesel and diesel log-difference prices and the Lagrange Multiplier tests indicate all the log differences of weekly real prices have some arch effects at least at the 10% significance level.

Figures 3.3 through 3.6 illustrate the log difference of weekly prices of crude oil, biodiesel, soybeans, and diesel. There is high volatility between mid-2008 and mid-2009. The price volatility of fossil fuels, crude oil and diesel, appear to dampen through time after the volatile years 2008 and 2009. This suggests the fossil fuels possibly exhibit only a single period of volatility clustering. In contrast, the agricultural commodity prices, biodiesel and soybeans, and in particular soybean prices appear to exhibit additional volatility clustering in subsequent years. The market for the fossil fuels appears to be more intertwined and somewhat distinct from the agricultural commodities markets.

Augmented Dickey-Fuller and Phillips-Perron unit-root tests for price log-differences are listed in Table 3.3. The null hypothesis is a log-difference price series contains a unit root. Results indicate all the series of log difference of real prices are stationary at the 1% significance level.

In the mean equations of univariate models, the lag lengths are determined by the autocorrelation function (ACF) and the partial autocorrelation function (PACF) plots along with Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBIC). The ACF and PACF plots indicate there is no evidence of autocorrelation for the log differences of biodiesel and diesel prices, while the log differences of crude oil and soybean prices are related to their one lag. There is a negative lag one autocorrelation for log differences of crude oil and soybean prices. AIC and SBIC support this conclusion.

3.5. Results

3.5.1. Univariate EGARCH models and volatility spillover

The estimation results of the univariate EGARCH models are listed in Table 3.4. All models were determined to be the best fit by EGARCH(1,1) and mean equations were determined by results of serial correlation tests. Lagrange Multiplier tests indicate there are no arch effects in the standardized residuals of EGARCH (1,1). The mean equations were determined by ACF and PACF plots and AIC and SBIC.

The results in Table 3.4 indicate significant negative lag-one autocorrelation for both crude oil and soybeans at the 5% level. These negative autocorrelations imply the lack of autocorrelation persistence in the price series where prices through time remain either above or below the mean. A shock to either crude oil or soybean prices will not persist with the bracketed prices likely alternating above and below the historical mean. The ARCH effect, α_1, is significant at the 10% level for only log difference in soybean prices. This indicates volatility clustering within the soybean prices where large (small) volatility tends to be persistent. All the β_1 coefficients measuring the GARCH effect are significant at the 1% level. The news from a previous period significantly determines the current volatility. The GARCH coefficients for crude oil, biodiesel, and diesel are in the neighborhood of 0.3 to 0.4, which indicates the presence of persistence within these price series. The strongest level of persistence is associated with soybean prices with a GARCH effect of 0.597. Asymmetry in the shocks on volatility is apparent in the crude oil prices at a 5% significance level. This asymmetry indicates the crude oil market will respond to a positive price shock by increasing production and mitigating the price rise. In contrast, there is a lack of market adjustment for a negative price shock as the market attempts to maintain production. A negative shock brings about volatility more than a positive shock in the crude-oil market.

Of particular interest is the spillover effects across the fuel and agricultural markets. There are significant, at the 1% level, spillover effects from a shock in crude-oil prices to biodiesel, soybean, and diesel markets. The magnitudes of the spillover coefficients are relatively small for biodiesel and soybeans, both around 0.10 compared with a diesel coefficient, 0.269. Diesel prices appear much more elastic to a crude-oil shock than either biodiesel or soybean prices. A crude oil price shock impacts all the other markets indicating the importance of this fossil resource in economic activity. The results indicate no spillover effect of a biodiesel shock on diesel prices, but a positive spillover on crude oil and soybean prices at a 1% level. The positive influence of biodiesel prices on the soybean market at the 1% level is not surprising considering the derived demand for soybeans in biodiesel production. The underlying demand for crude oil in the fuel market may explain the biodiesel spillover, with both diesel and biodiesel price shocks spilling over into the crude-oil market. The magnitudes of these shocks are diverse with the diesel spillover over three time that of biodiesel. Relative to the double-directional volatility spillovers between crude oil and diesel, the other spillovers are low with the soybean shock on biodiesel prices being slightly higher at 0.134 (1% significance level). This indicates a soybean shock has a stronger impact on biodiesel prices than the reverse. Biodiesel is more responsive to a soybean shock, more elastic, than a soybean is to a biodiesel shock. With soybeans the major input in biodiesel refining and biodiesel not a major market for soybeans, this difference in elasticities can be explained. However, in general the elasticities of these spillovers are relatively low, highly inelastic. The results do indicate unilateral spillovers. In particular, diesel price shocks influence biodiesel but the reverse does not hold. This indicates the substitution effect of biodiesel completing with diesel as the price of diesel increases.

In summary, there are significant spillovers among the fuel and agricultural-commodity markets. In terms of fossil fuels, these spillovers appear to be larger, leading to a stronger link, between the crude oil and diesel markets relative to the other markets. A possible exception is the biodiesel/soybean market with soybeans influencing biodiesel. In tandem with these spillovers is the presence of persistence associated with price shocks. In terms of pervious literature, Serra (2013) summarized the general findings as follows: (1) Biofuel (or energy) price transmits volatility to feedstock prices; (2) Biofuel prices do not transmit volatility to fossil fuel prices; (3) Feedstock prices transmit volatility to biofuel prices. The results of the univariate EGARCH model are generally consistent with the summary of the time-series literature assessing volatility in the U.S. ethanol markets. An exception is the transmission of biofuel prices to the crude oil market; although relatively weak. However, possibly even more important for policy analysis is the magnitude of the elasticities associated with these volatility-spillover shocks.

The Ljung-Box test results are listed in Table 3.4 as a measure of overall model fit. The null hypothesis of no autocorrelation could not be rejected at the 10% level for all but the diesel price series. This indicates there may exist an improved diesel model specification if the objective is forecasting the price series.

3.5.2. DCC-MGARCH model and volatility spillover

The DCC model allows examination of whether the level of volatility interdependence among markets has changed across time. Table 3.5 lists the coefficient estimates for the conditional mean equation and conditional variance matrix of the DCC-MGARCH model. The Ljung-Box (LB) statistics indicate there is no evidence of autocorrelation in the standardized residuals at the 5% significance level. Overall, the residual diagnostic statistics support the adequacy of the model specification.

In the conditional mean equation, the γ_{1ii} coefficients, i $= 1, \dots, 4$, capture own-market dependence, the dependence of the log difference of prices in market i on its lagged value, while the γ_{1ij}, $i \neq j$, coefficients capture cross-market dependence. The dependence of the log difference of prices in market i on the lagged change in market j. Crude oil prices have no significant, at the 10% level, own-mean spillover, while biodiesel, soybean, and diesel prices at the 10%, 5%, and 1% significance level, respectively, exhibit relatively strong and negative own-mean spillovers. The latter findings can be explained by own substitution effects in demand. A shock in prices above market equilibrium will lead to a decrease in demand, with the market then adjusting prices downward in subsequent periods. This demand-substitution effect is not significant for crude oil, which may be more driven by slowly changing macro-economic conditions, income effects. In terms of the cross-market dependence, the fossil resources are negatively influencing the agricultural commodity, soybeans. Generally, a portion of a positive shock in fossil input prices would be through the supply curve in the form of higher agricultural commodity prices. However, the results do not support this theory. Instead, the negative macroeconomic effects from a positive fossil-resource shock may be dampening commodity prices. This is supported by the positive diesel shock on the crude oil price series; explained by derived demand theory.

Turning to the conditional variance-covariance equations, the parameter α_i is positive and significant at 1% in all the series, except for biodiesel, which is significant at the 5% level and positive. This implies ARCH market shocks have a positive impact on volatility, however, the persistence is relatively low. The persistence coefficients β_i are also all significant at a 1% level and relatively large, which indicates a high degree of persistency in the volatility. A persistence coefficient close to one implies a high degree of persistency in the volatility. The β_i for diesel is 0.901, indicating the diesel market has the highest persistency in the volatility. The soybean market has the lowest persistency in the volatility.

Estimates for the DCC (1, 1) model, yield α and β coefficients, which are positive and significant at the 1% and 5% levels, respectively. This indicates the presence of time-varying correlations. It also indicates that shocks in the market cause correlations to increase. The magnitudes of α and β indicate that the evolution of the conditional covariances depends more on their past values than on lagged residuals' innovations. Note that the sums of α_i and β_i are all less than one, which satisfies the restrictions.

The estimated time-varying conditional pairwise correlations of crude oil, biodiesel, soybean, and diesel prices are illustrated in Figures 3.7-3.9. The pairwise conditional correlations are generally positive. In Figure 3.7, the crude oil and diesel correlation is extremely stable at around 75% during the sample period, except from the end of 2008 to the beginning of 2009. This period of a decline in correlation toward zero represents the Great Recession where economic activity sharply declined. Other than this abnormal economic period, the time-varying correlations between conventional fuels are relatively strong and stable. Similarly, the biodiesel and diesel correlations, Figure 3.8, are also very stable at a lower correlation, around 40%, although not quite as stable as crude oil and diesel correlations.

It is not just the crude oil and diesel correlations that exhibit unstable correlations during the Great Recession; all the pairwise conditional correlations are unstable during this period. However, as indicated in Figure 3.9, biodiesel and soybean correlations also exhibit instability both before as well as after the Great Recession. This may partially be the result of intermittent policies, which disrupts the market relation between soybean inputs for biodiesel refining. On March 13, 2009, the European Commission imposed temporary anti-dumping and anti-subsidy duties on imports of biodiesel from the U.S. Subsequently, on July 12, 2009, the commission extended the duties for five years. From 2005 through 2009 the U.S. federal government provided an incentive to produce biodiesel in the form a $1.00 tax credit. This tax credit lapsed in 2010 was then renewed in 2011 and lapsed again 2014. Further the U.S. federal government established a biodiesel mandate in 2010 providing a biodiesel supply floor. These policies have disrupted the market linkages between soybean and biodiesel prices, which leads to unstable correlations relative the fossil fuel (crude oil and diesel) price correlations.

The overall soybean and biodiesel correlation, around 50%, is 33% less than the crude oil and diesel correlation. In 2011, approximately 7% of the soybean oil from the U.S. soybean crop was diverted from agricultural commodities to biodiesel production (USDA, 2014). This small percentage of soybeans flowing into biodiesel suggests soybean prices respond to other major demands for their beans. The livestock market may exert a larger effect on soybean price than the biodiesel. From Figure 3.9, there is also a slight decline in their correlations subsequent to the recession. This may partially be explained by the declining share of soybeans as an input into biodiesel refining. In 2007, U.S. soybean's share of the biodiesel biomass inputs was 80% and in 2009 it decreased to 49% before rebounding to approximately 57% in 2011 (EPA, 2010). This relative weak and slightly declining correlation between soybean and biodiesel prices does not support recent concerns of food before biodiesel.

3.6. Conclusions

As a first attempt to investigate price volatility in the U.S. biodiesel market, an investigation is presented of volatility spillovers employing Univariate EGARCH model and DCC-MGARCH model. The empirical results of the univariate EGARCH model are consistent with the general findings in the U.S. ethanol market. There exists double-directional price volatility spillovers between the biodiesel and the soybean markets and unidirectional price volatility from crude oil markets to the soybean market. Fossil fuels prices transmit volatility to biodiesel prices. The dominant impact is crude oil price spillovers into the other markets (biodiesel, soybean, and diesel). The magnitude of these spillovers is relatively strong for the fossil fuel markets (crude oil and diesel), with more inelastic spillovers between the agricultural commodities (soybeans and biodiesel) and across with the fossil fuels. An exception is the relatively more elastic impact soybean-price effect on the biodiesel market. In terms of persistence, previous volatility as measured by the GARCH effect indicates a shock will not be corrected within one time period. These results indicate there is a spillover in biodiesel shock into the soybean market. Price volatility in the biodiesel market does spillover into the soybean market and as a result of this spillover soybean prices have some persistence in deviating from market trends. However, the elasticity of this spillover is very inelastic relative to the spillovers between crude oil and diesel markets. Also, the elasticity from soybean-price volatility onto the biodiesel market is more elastic than the reverse. These results generally indicate in terms of price volatility, the food before biodiesel issue has weak empirical support. Results indicate biodiesel price volatility has about the same spillover elasticity on soybean prices as it does on crude oil prices.

The results from the EGARCH model are reinforced with estimation outcomes of the DCC-MGARCH model. DCC-MGARCH allows for time-varying conditional correlations in price volatility between markets. Removing the Great Recession, the results indicate the correlation between crude oil and diesel has not varied much over time. In contrast, the price volatility conditional correlations between biodiesel and soybeans exhibit considerable time-varying with a slight declining trend. This instability and downward trend in conditional correlations indicates the lack of strong linkages within these markets. As addressed in the results, the presence of substitutes for soybeans in biodiesel refining and the relatively small biodiesel market for soybean may explain this weak price-volatility relation. However, in addition to these market characteristics, governmental policies may also play a role in this volatility relation. The disruptive federal policies of on and off tax credits are possibly leading the weak link in biodiesel/soybean price volatility.

As the share of biodiesel in our vehicle fuel mix increases, concern arises with biodiesel’s impacts on agricultural commodity prices. This initial analysis on biodiesel-price volatility effects on soybean-price volatility indicates that, while biodiesel-price volatility does appear to influence soybean-price volatility, the relation is highly inelastic relative to the crude oil-volatility impacts on diesel-price volatility. If this degree of volatility spillover is still of concern, then U.S. agricultural policy should be directed toward mitigating such spillovers. Agricultural-commodity buffers would be one possible policy for supplementing supplies in years of insufficient harvests. Such commodity buffers could blunt food price spikes caused not only by possible biofuel shocks but also by other political, institutional, and environmental shocks. However, the cost of these policies must be weighed against the magnitude of the elasticities and possible ill effects of the spillover. Just considering existing policy impacts on price volatilities in terms of enhancing or mitigating price volatility would be a sound prescription for any policymaker.

Table 3.1. Pearson Correlation for Log Difference in Weekly Prices, 2007-2014[a]

Commodity	Crude Oil	Biodiesel	Soybean	Diesel
Oil	1.000	0.337*	0.341*	0.717*
Biodiesel		1.000	0.546*	0.437*
Soybean			1.000	0.431*
Diesel				1.000

[a] * Denotes significance at the 1% level.

Table 3.2. Summary Statistics for Log Difference of Weekly Real Prices, 2007-2014[a]

	Crude Oil	Biodiesel	Soybean	Diesel
Mean ($\times 10^{-2}$)	0.139	0.055	0.184	0.112
Median ($\times 10^{-2}$)	0.390	0.225	0.657	0.312
Minimum ($\times 10^{-2}$)	−29.592	−17.971	−16.748	−23.987
Maximum ($\times 10^{-2}$)	26.456	12.120	14.594	14.956
Standard Deviation ($\times 10^{-2}$)	5.402	3.445	4.248	4.351
Skewness	−0.706	−0.734	−0.621	−0.578
Kurtosis	6.025	3.413	1.987	3.093
Coefficent of Variation	38.863	62.691	23.087	38.848
Jarque-Bera	599.970***	216.212***	86.018***	170.791***
Ljung-Box Test for Autocorrelations				
Q(1)	6.460**	0.142	8.715***	1.099
Q(6)	10.677*	5.404	13.443**	17.548**
Lagrange Multiplier Test for ARCH Effects				
LM(1)	14.088***	3.928**	33.732***	0.665
LM(6)	147.935***	10.609	53.964***	64.468***

[a] Number of observations is 376 and *, **, and *** asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3.3. Unit Root Tests[a]

Prices	Augmented Dickey-Fuller	Phillips-Perron
Crude Oil	−22.045	−21.902
Biodiesel	−18.954	−18.958
Soybean	−22.510	−22.698
Diesel	−20.461	−20.440

[a] All the coefficients are significant at the 1% level, which indicates a stationary process.

Table 3.4. Univariate EGARCH Models of Volatility Spillover, Weekly Data, 2007-2014

Parameters	Returns of Crude Oil (j = 1)	Returns of Biodiesel (j = 2)	Returns of Soybean (j = 3)	Returns of Diesel (j = 4)
Univariate EGARCH Models				
Intercept	0.003^{*}	0.001	0.002	0.003^{**}
(Mean)	(0.001)	(0.001)	(0.002)	(0.001)
AR(1)	-0.107^{**}		-0.118^{**}	
	(0.048)		(0.058)	
Intercept	-0.719^{**}	-2.356^{***}	-1.048^{*}	-1.345^{***}
(Variance)	(0.345)	(0.657)	(0.539)	(0.354)
α_1	0.118	-0.069	0.169^{*}	0.159
	(0.130)	(0.110)	(0.091)	(0.145)
β_1	0.391^{***}	0.319^{***}	0.597^{***}	0.411^{***}
	(0.050)	(0.107)	(0.104)	(0.052)
δ_1	-0.191^{**}	0.068	-0.074	-0.032
	(0.078)	(0.081)	(0.072)	(0.094)
Spillover				
Crude oil to		0.100^{***}	0.096^{***}	0.269^{***}
c_{1j}		(0.028)	(0.020)	(0.019)
Biodiesel to	0.087^{***}		0.094^{***}	0.001
c_{2j}	(0.029)		(0.028)	(0.032)
Soybean to	0.036	0.134^{***}		0.077^{**}
c_{3j}	(0.034)	(0.029)		(0.039)
Diesel to	0.276^{***}	0.074^{**}	0.009	
c_{4j}	(0.027)	(0.031)	(0.029)	
Diagnostic test				
Ljung-Box test for autocorrelation (H_0: no autocorrelation in standardized residuals)				
LB(16)	13.499	23.288	11.857	32.980^{***}
	(0.636)	(0.106)	(0.754)	(0.007)

Note: For the EGARCH and spillover results, values in the parentheses below parameter estimates are standard errors. For the diagnostic tests, numbers in parentheses beneath diagnostic statistics are p-values. The symbol single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3.5. Estimation Results for the DCC-MGARCH Model, Weekly Data, 2007-2014

Coefficient	Crude oil (i=1)	Biodiesel (i=2)	Soybean (i=3)	Diesel (i=4)
Conditional Mean Equation				
γ_0	0.004^{*}	0.002	0.004^{*}	0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.002)
γ_{11i}	0.036	0.087	-0.111^{*}	-0.149^{*}
	(0.079)	(0.055)	(0.057)	(0.088)
γ_{12i}	0.071	-0.114^{*}	-0.001	0.082
	(0.050)	(0.061)	(0.048)	(0.056)
γ_{13i}	0.041	-0.041	-0.141^{**}	0.018
	(0.053)	(0.062)	(0.062)	(0.062)
γ_{14i}	0.160^{**}	0.038	-0.087^{*}	-0.234^{***}
	(0.062)	(0.048)	(0.048)	(0.071)
Conditional Variance-covariance Equation				
ω_i	0.000^{**}	0.000^{***}	0.000^{***}	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)
α_i	0.107^{***}	0.074^{**}	0.127^{***}	0.064^{***}
	(0.021)	(0.031)	(0.035)	(0.017)
β_i	0.834^{***}	0.837^{***}	0.786^{***}	0.901^{***}
	(0.033)	(0.052)	(0.051)	(0.024)
α				0.087^{***}
				(0.032)
β				0.465^{**}
				(0.232)
Diagnostic Tests				
Ljung-Box test for autocorrelation (H_0: no autocorrelation in standardized residuals)				
LB(16)	20.661	16.927	13.134	25.730^{*}
	(0.192)	(0.390)	(0.663)	(0.058)

Note: For the DCC-MGARCH model results, values in the parentheses below parameter estimates are standard errors. For Ljung-Box tests, numbers in parentheses beneath diagnostic statistics are p-values. The symbol single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

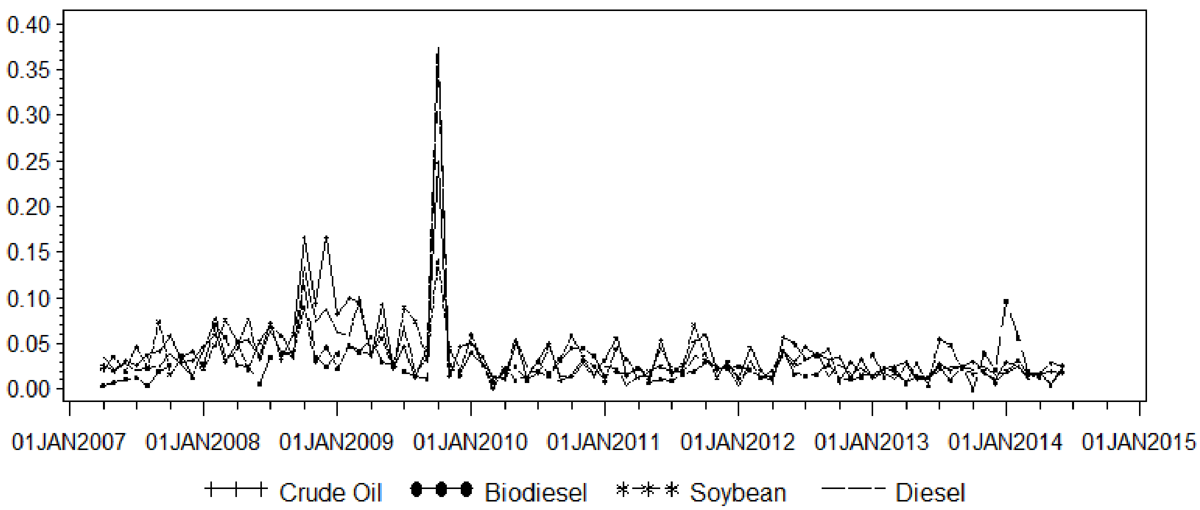


Figure 3.1. Monthly Coefficients of Variation for Crude Oil, Biodiesel, Soybean, and Diesel Prices, 2007-2014

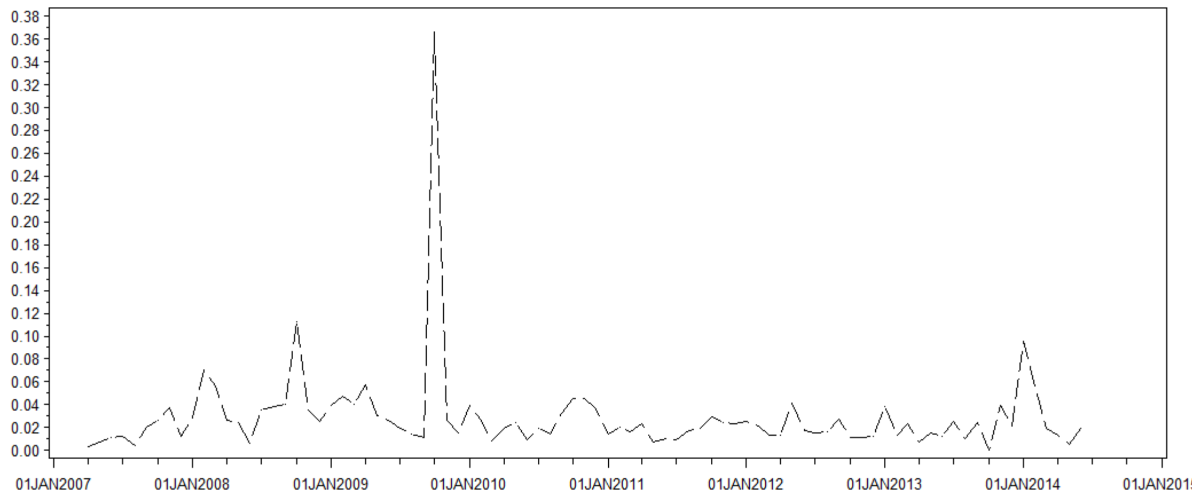


Figure 3.2. Monthly Coefficients of Variation for Biodiesel Prices, 2007-2014

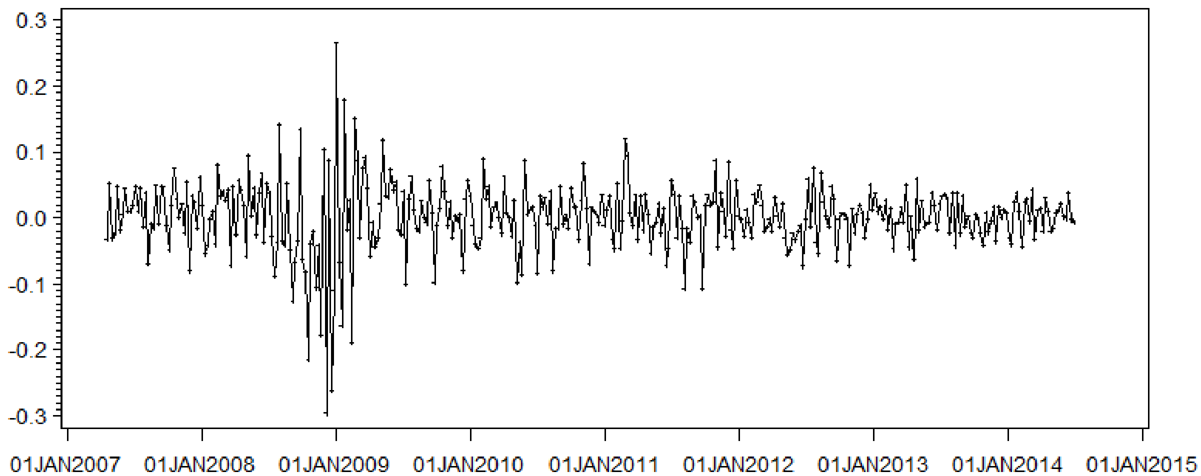


Figure 3.3. Log Difference of Crude Oil Weekly Prices, 2007-2014

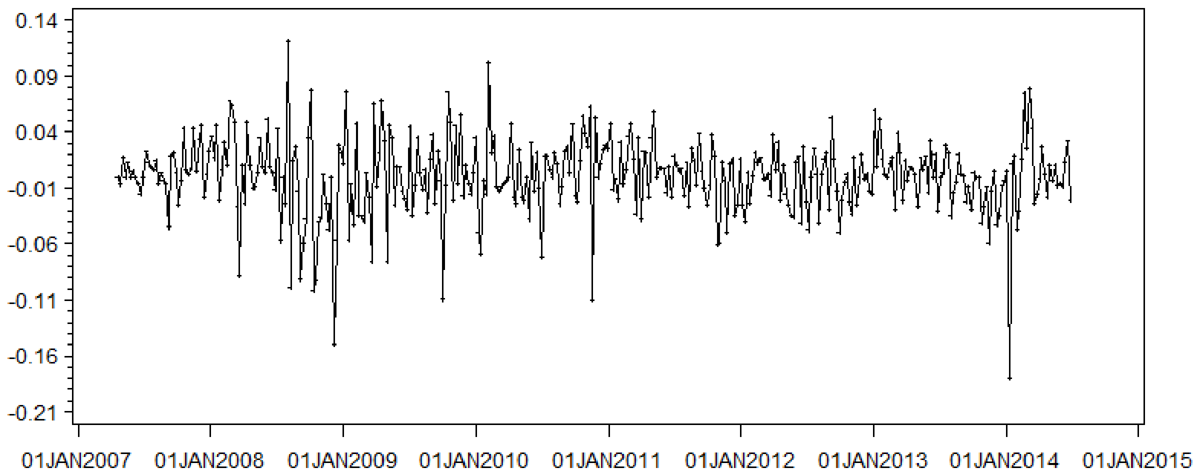


Figure 3.4. Log Difference of Biodiesel Weekly Prices, 2007-2014

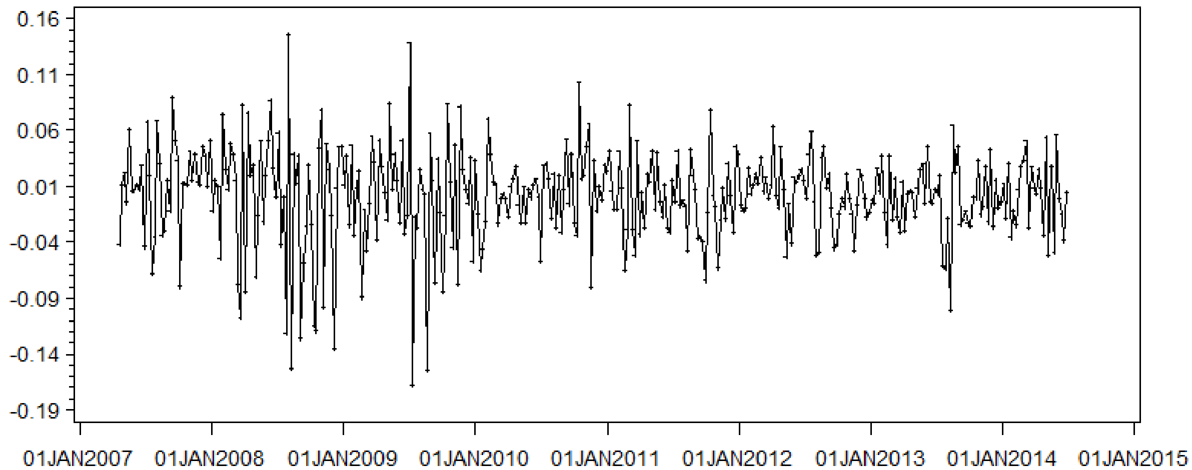


Figure 3.5. Log Difference of Soybean Weekly Prices, 2007-2014

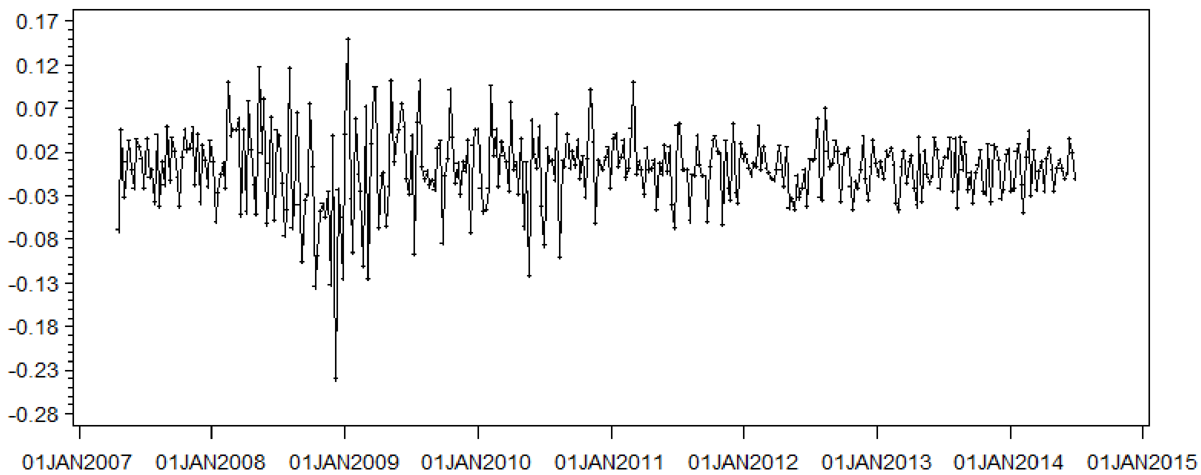


Figure 3.6. Log Difference of Diesel Weekly Prices, 2007-2014

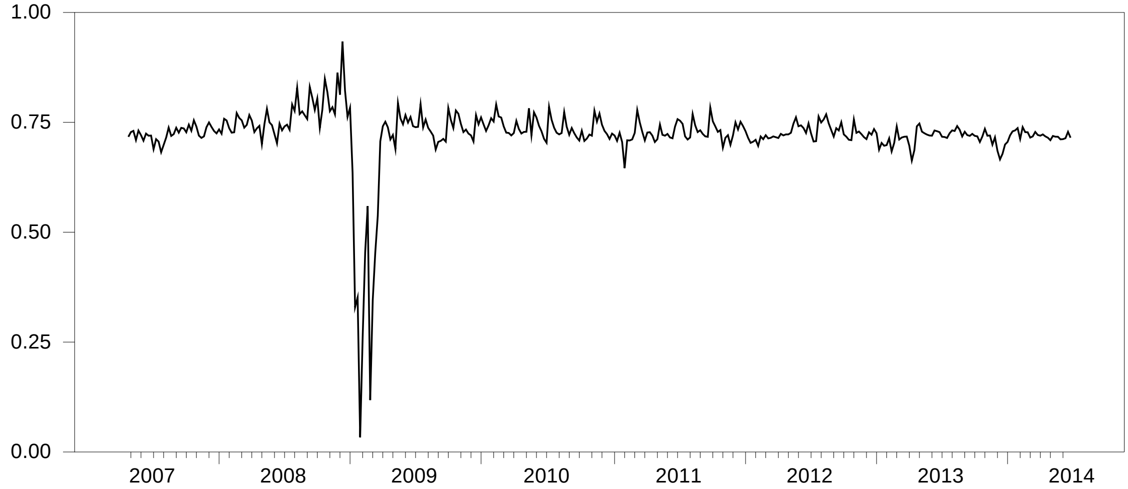


Figure 3.7. Dynamic Conditional Correlations between Crude Oil and Diesel

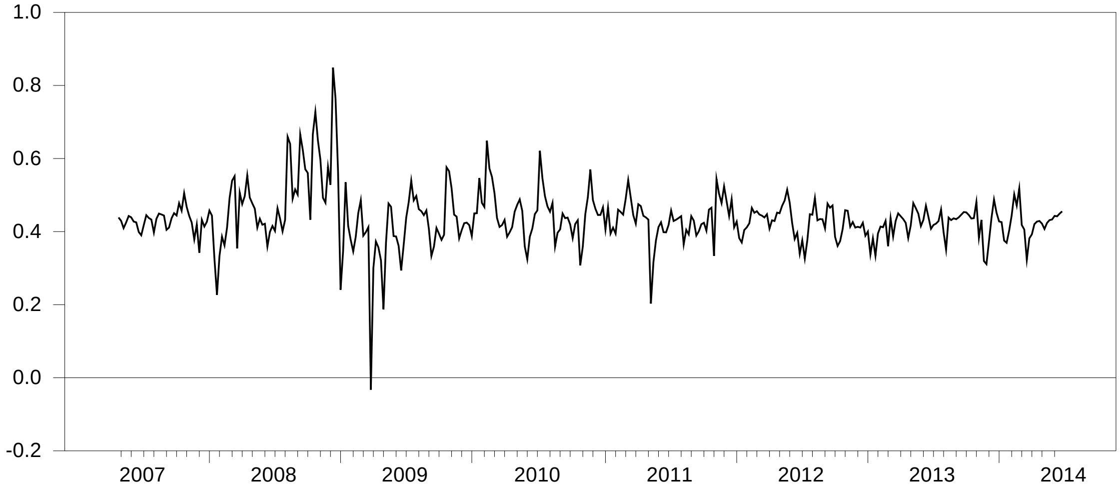


Figure 3.8. Dynamic Conditional Correlations between Biodiesel and Diesel

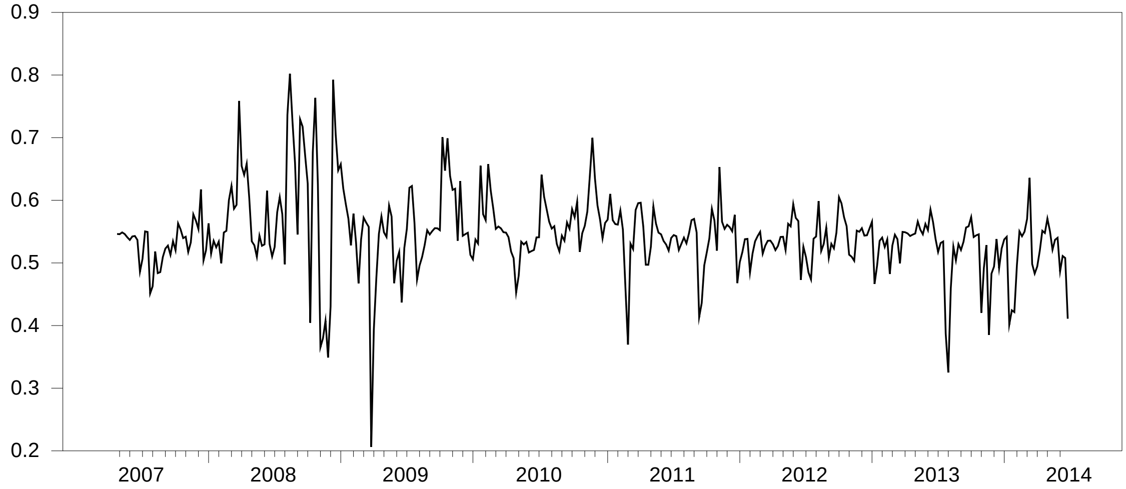


Figure 3.9. Dynamic Conditional Correlations between Biodiesel and Soybean

CHAPTER 4

BIODIESEL INVESTMENT IN A DISRUPTIVE POLICY ENVIRONMENT[3]

[3] Liu, S., G. Colson, and M.E. Wetzstein. To be submitted to *Energy Policy*.

Abstract

The effect of Poisson type policy jumps on biodiesel investment is investigated through the theory of investment under uncertainty. The analysis considers the probability of a policy being implemented if it is not in effect and the probability of it being withdrawn if it is in effect. As an application, the policy switching regime of the discontinuous federal tax credit of $1.00 per gallon on biodiesel is modeled as a Poisson jump process. Results support that time inconsistent government policies do lead to market uncertainty. The analysis reveals a pronounced negative impact on the decisions to invest in a biodiesel refinery. However, results indicate a consistent policy switching regime may not be that disruptive. It is policy uncertainty that drives the option pricing thresholds and a consistent policy switching does not increase the uncertainty.

4.1. Introduction

Economic research on alternative energy investments has generally considered the effect a particular policy type has on adoption. In 2014 alone, there were at least 11 studies addressing the impact of policy types (e.g. standards, subsidies, or taxes) on the economics of renewable energy (samples are Fera et al., 2014; del Rio, 2014; Yi and Feiock, 2014). Considerably less research has addressed the timing of when a policy should be instigated. A decade ago, Pindyck (2002) considered timing of policy adoption in environmental economics. In terms of alternative energy adoption, Xian et al. (2014) addressed the timing of a U.S. wood pellet subsidy. Type and timing are two legs in the 3-Ts of effective government policy development, with the third being transience. Transience is concerned with the length and consistency of a policy. The literature is void in presenting research directed toward the transience of energy policies. Tangential to transience is policy commitment where there are some past research efforts considering a policymaker's commitment through time to enforcing environmental regulations (Poyage-Theotoky and Teerasuwannajak, 2002). As a first attempt at filling this policy transience void in alternative energy adoption, empirical results are presented demonstrating the importance of consistent (nondisruptive) policies. Specifically, the U.S. production of biodiesel is investigated under shifting, on and off again, federal tax credits. The underlying hypothesis is these inconsistent tax credits lead to market uncertainty, which have a pronounced impact on the decisions to invest in a biodiesel refinery.

For investigating this hypothesis, a real options analysis is developed, which considers the likelihood of a tax credit policy shift. The analysis considers the probability of a policy being implemented if it is not in effect and the probability of the credit being withdrawn if it is in effect. This real options analysis follows closely Dixit and Pindyck (1994) section on policy uncertainty. Results support the hypothesis that inconsistent tax credits lead to market uncertainty, which can have a pronounced impact on the decision to invest in a biodiesel refinery. If there exists a high probability of a tax credit being implemented in the near future, then biodiesel investors will want to delay investment. Similarly, with a current tax credit, as the probability of the credit being withdrawn increases, biodiesel investors will want to capitalize on this tax credit before it is withdrawn. The results do reveal it is not a policy switching regime that affects investment. It is instead policy uncertainty. A known consistent policy switching regime does not increase investment uncertainty. For policy analysis and implementation, it is important to make a distinction between policy uncertainty and known policy switching.

4.1.1. U.S. Biodiesel Subsidies

The two primary means by which subsidies affect the demand for U.S. ethanol and biodiesel are the Renewable Fuel Standard (RFS) and the Blender Tax Credit (BTC) (Babcock, 2011). The RFS is a federal mandate requiring the blending of biofuels into U.S. transportation fuels. It originated with the Energy Policy Act of 2005 and was expanded and extended by the Energy Independence and Security Act of 2007 (EISA) (U.S. Department of Energy, 2014). The initial RFS (referred to as RFS1) mandated that a minimum of four billion gallons of renewable fuel be incorporated into the nation’s gasoline supply in 2006, and that this minimum volume rise to 7.5 billion gallons by 2012 (Schnepf and Yacobucci, 2013). EISA was passed on December 19, 2007, and the EPA issued its final rule to implement and administer the expanded RFS (referred to as RFS2) on February 3, 2010. RFS2 subdivides the total renewable fuel requirement into four separate but nested categories (Schnepf and Yacobucci, 2013). One of the four categories is biomass-based diesel, which is a diesel fuel substitute made from renewable feedstock, including biodiesel and non-ester renewable diesel. Table 4.1 lists the RFS2 biomass-based diesel mandate.

The 2013 biodiesel mandate was revised upwards from one billion gallons to 1.28 billion gallons (Schnepf and Yacobucci, 2013). EPA proposed to set the renewable fuel standards for 2014 at the levels that were actually produced and used as transportation fuel, heating oil or jet fuel in the contiguous U.S. and Hawaii (EPA, 2015). EPA proposed annual increases in the required volume of biomass-based diesel for 2015, 2016, and 2017 (EPA, 2015).

A biodiesel tax credit of $1.00 per gallon was established in 2005 by the American Jobs Creation Act of 2004. It was then extended by the Energy Policy Act of 2005 and amended by the Energy Improvement and Extension Act of 2008. The tax credit temporarily lapsed in 2010. It was then extended again by the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 (Yacobucci, 2012). The credit was allowed to expire at the end of 2011, with the American Taxpayer Relief Act of 2012 retroactively extending the tax credit through December 31, 2013 (U.S. Department of Energy, 2014). The credit was then allowed to expire, but could possibly be reestablished. On May 15, 2014, the U.S. Senate failed to pass the Expiring Provisions Improvement Reform and Efficiency (EXPIRE) act. The EXPIRE act included extension of biodiesel tax credit through December 31, 2015 and retroactive to January 1, 2014 (U.S. Senate Committee on Finance, 2014). Table 4.1 lists the on and off biodiesel tax credit from 2005 through 2014.

4.1.2. Literature Review

Markets generally do not perform well to uncertainty. This results in adverse market price swings damping investment and innovation. Policymakers can, through policy and programs, improve efficiency by reducing market uncertainty. One example is USDA’s situation and outlook reports, which provide information on current and projected future market conditions. Such information can avoid problems with information asymmetry by reducing market uncertainty. However, even well intended policies can through implementation be less effective and may actually be disruptive by aggravating the uncertainty. Policies associated with the biodiesel tax credit may be an example of such a well-intended policy not yielding its full potential of stimulating biodiesel investment.

As also indicated in Table 4.1, the history of governmental policy uncertainty coupled with annual changes in the RFS does not provide a stable policy platform for a young and maturing biodiesel industry. Theory would then hypothesize such disruptive policies would negatively impact the biodiesel market. Instead of providing a stable price regime, it is hypothesized policies would lead to price volatility.

Such inconsistent policy has the potential of disrupting investment by limiting biodiesel producers' access to financing. Specifically, Yokado Biofuels, a small biodiesel maker in California, stopped producing vehicle fuel and closed its retail outlet due to the suspension of the federal tax credit and the stagnation of the RFS in 2014 (Anderson, 2014). The inconsistent policy toward biodiesel has harmed the industry.

As described in Dixit and Pindyck (1994), firms have the flexibility to begin or defer projects given current economic and price environments. This flexibility cannot be captured by net present value or discounted cash flow analyses. The presence of real options in an industry can have important implications for public policy, particularly in capital intensive industries such as telecommunications and energy, where policy changes such as deregulation can have significant implications for market uncertainty and the potential for sunk cost investments (Mahnovski, 2006).

Real options theory is widely employed for deriving the optimal investment and operative decisions under uncertain policy conditions. Studies have aimed at correctly modeling the market-driven sources of uncertainty under specific policy schemes (Laurikka, 2006; Linnerud et al., 2014). These studies present models were investment is regarded as a single-firm problem in an operating environment with multiple exogenous and stochastic prices. They explore the impact of the European Union Emissions Trading Scheme (EU ETS). Wang et al. (2014) developed a policy benefit real options model to identify the optimal investment strategy with/without the consideration of revenue from a certified emission reduction. Other studies acknowledge that policy uncertainty should be explicitly considered. They include stochastic jumps in the prices of policy instruments reflecting sudden changes in the policy target. Fuss et al. (2008) and Yang et al. (2008) create a stochastic volume of jumps to simulate a carbon price shocks under a particular climate policy event.

With regard to the literature on tax policy uncertainty, the literature indicates how the prospect of introducing tax incentives to invest raises the threshold revenue at which a firm invests and thereby delays investments. Rodrik (1991) notes that policy reform in developing countries can result in the private investors withholding investment until much of the residual uncertainty regarding the eventual success of reform is eliminated. In his paper, policy uncertainty is modeled in the form of a probability that the reform will be reversed. Mauer and Ott (1995) apply the method proposed by Dixit and Pindyck (1994) to analyze the effect of tax policy uncertainty on replacement investment decisions and allow for uncertainty in the entire arsenal of government tax policy instruments.

The general conclusion based on geometric Brownian motion processes is policy uncertainty should delay firm-level investment and lead to lower levels of investment. The literature on the effect tax-policy uncertainty has on investment had received little attention until the work by Hassett and Metcalf (1993). They indicate policy uncertainty is not likely to be well captured by a Brownian motion process; it is instead likely to follow a Poisson jump process. A few recent studies incorporate the Poisson jump process into a real options model for decision making. Handley and Limao (2012) model trade policy shocks as a Poisson process. Lin and Huang (2010, 2011) present decision models based on the real options approach for firms that have not yet established the energy-saving equipment with entry and exit strategies. They determine the optimal timing to adopt an energy-saving investment project and the optimal timing to terminate it. Their study takes account of the occurrence of unexpected events under a Poisson jump process.

The literature is void in estimating the effect policy shifts (the third leg) have on biodiesel investments. The objective is to fill this gap by incorporating a Poisson process into a real options model. The policy of the discontinuous federal tax credit of $1.00 per gallon of biodiesel is then modeled as a Poisson jump process.

4.2. Methodology and Data

4.2.1. Model

The effect of these Poisson type policy jumps on biodiesel investment can be investigated through the theory of investment under uncertainty. Let θ represent the federal income tax credit with $\lambda_1 dt$ denoting the probability it will be implemented in the next interval of time, dt and $\lambda_0 dt$ the probability it will be withdrawn.

It is assumed that biofuel plants are price takers as long as biofuel production remains a small fraction of total petroleum fuel production (ESMAP, 2006; Maung and Gustafson, 2011). Following closely Dixit and Pindyck (1994) along with Lin and Huang (2010, 2011), the theory assumes a firm is considering becoming an entrant into the biodiesel market by producing biodiesel with sunk cost of I and an operating cost of v per gallon of biodiesel produced.

Assume the price per gallon of biodiesel, p, follows the geometric Brownian motion

$dp = \alpha p dt + \sigma p dz,$ (1)

where α is the drift, σ is the variance parameter, and dz is the increment of a Wiener process.

It is further assumed over an interval of low prices say $(0, p_1)$, a biodiesel refinery will not be initiated regardless if the tax credit is allowed. Over the interval (p_1, p_0) the refinery will be built if the tax credit is allowed, but will wait if the credit is not allowed with the hope of it possibly being allowed at some future time. Beyond p_0 regardless of the tax policy the biodiesel refinery will be built. As illustrated in Figure 4.1, interest is in determining the trigger prices p_1 and p_0 where within this price interval the tax credit is effective in stimulating investments in biodiesel refineries.

Over the range (p_0, ∞), the dominant strategy is to always establish a biodiesel refinery regardless if there is tax credit or not. The investment opportunity is then

$$V_0(p) = \frac{P}{\delta} - \frac{v}{r} - I, \quad (2a)$$

in the absence of a tax credit and

$$V_1(p) = \frac{P}{\delta} - \frac{v-\theta}{r} - I, \quad (2b)$$

with a credit. The prices p and v per period are divided by δ and the discount rate r, respectively for determining the present value of the perpetuity, with $r - \alpha = \delta$.

In contrast, over the range (p_1, p_0), with a tax credit the refinery is established and without it is not. The investment opportunity with a credit is the same as (2b) and without, $V_0(p)$ is determined as follows. In the next time interval, dt, the tax credit will be implemented with probability $\lambda_1 dt$ and the refinery established with value $V_1(p + dp)$. Without the credit, it will not be established yielding a value of $V_0(p + dp)$. This yields

$$V_0(p) = e^{-rdt}\{\lambda_1 dt\, E[V_1(p + dp)] + (1 - \lambda_1 dt)\, E[V_0(p + dp)]\},$$

where E is the expectation operator.

The Bellman equation yielding the optimal timing for establishing a biodiesel refinery in the absence of a tax credit (waiting to invest) is

$$E[dV_0(p)] = \{rV_0(p) - \lambda_1[V_1(p) - V_0(p)]\}dt\,, \qquad (3)$$

where over the time interval dt the expected rate of capital appreciation, $dV_0(p)$, is equal to the total expected return, $rV_0(p) - \lambda_1[V_1(p) - V_0(p)]$. This total expected return is the discount rate r times the investment opportunity absence the tax credit mitigated by the expected capital gain from institution of the credit in the immediate future, $\lambda_1[V_1(p) - V_0(p)]$.

Expanding the left-hand-side of (3) by employing Ito's Lemma results in

$$dV_0(p) = V_0'(p)dp + \tfrac{1}{2}V_0''(p)(dp)^2, \qquad (4)$$

where $V_0' = dV/dp$ and $V_0'' = d^2V/dp^2$. Substituting (1) into (4) and realizing $E(dz) = 0$, yields

$$E[dV_0(p)] = \alpha p V_0'(p)dt + \tfrac{1}{2}\sigma^2 p^2 V_0''(p)dt.$$

The Bellman equation (3) is then

$$\tfrac{1}{2}\sigma^2 p^2 V_0''(p) + (r - \delta)pV_0'(p) - rV_0(p) + \lambda_1[V_1(p) - V_0(p)] = 0, \qquad (5a)$$

which is a second-order nonhomogeneous differential equation for determining when to establish a biodiesel refinery. The last term captures the expected capital gain from an effective tax credit in the immediate future. Solving (5a) yields

$$V_0(p) = A_1 p^{\beta_1} + A_2 p^{\beta_2} + \frac{\lambda_1 p}{\delta(\delta+\lambda_1)} + \frac{\lambda_1(\frac{\theta-v}{r} - I)}{r+\lambda_1},$$

where A_1 and A_2 are constants and β_1 and β_2 are the positive and negative characteristic roots of the quadratic equation

$$\tfrac{1}{2}\sigma^2 \beta(\beta - 1) + (r - \delta)\beta - (r + \lambda_1) = 0,$$

determined by noting $V_0 = Ap^{\beta}$, $V_0' = \beta A p^{\beta-1}$, and $V_0'' = \beta(\beta - 1)Ap^{\beta-2}$.

In the final range $(0, p_1)$ the decision to invest in a biodiesel refinery is postponed regardless of if there is tax credit program or not. Over this range, the differential equation for determining when to enter the biodiesel industry with no tax credit is (5a). Similarly, given a credit, the differential equation for determining when to enter the biodiesel industry is

$$\tfrac{1}{2}\sigma^2 p^2 V_1''(p) + (r - \delta)pV_1'(p) - rV_1(p) + \lambda_0[V_0(p) - V_1(p)] = 0. \tag{5b}$$

As demonstrated by Dixit and Pindyck (1994), (5) yields solutions to the differential equations for the range $(0, p_1)$

$$V_0(p) = (\lambda_0\lambda_1 C p^{\beta_a} - \lambda_1 D p^{\beta_s})/(\lambda_0 + \lambda_1), \tag{6a}$$

$$V_1(p) = (\lambda_0\lambda_1 C p^{\beta_a} + \lambda_0 D p^{\beta_s})/(\lambda_0 + \lambda_1), \tag{6b}$$

where β_a and β_s are roots of quadratic equations (see Appendix) with C and D parameters.

At the trigger p_1 there will be biodiesel entry if a tax policy exists, which leads to the following value-matching and smooth-pasting conditions

$$(\lambda_0\lambda_1 C p^{\beta_a} + \lambda_0 D p^{\beta_s})/(\lambda_0 + \lambda_1) = \frac{\mathrm{P}}{\delta} - \frac{v-\theta}{r} - \mathrm{I}, \text{ value matching,} \tag{7a}$$

$$(\lambda_0\lambda_1\beta_a C p^{\beta_a - 1} + \lambda_0\beta_s D p^{\beta_s - 1})/(\lambda_0 + \lambda_1) = 1/\delta, \text{ smooth pasting.} \tag{7b}$$

For the p_0 trigger the conditions are

$$A_1 p^{\beta_1} + A_2 p^{\beta_2} + \frac{\lambda_1 p}{\delta(\delta+\lambda_1)} + \frac{\lambda_1(\frac{\theta-v}{r} - I)}{r+\lambda_1} = \frac{\mathrm{P}}{\delta} - \frac{v}{r} - \mathrm{I}, \text{ value matching,} \tag{7c}$$

$$A_1\beta_1 p^{\beta_1 - 1} + A_2\beta_2 p^{\beta_2 - 1} + \frac{\lambda_1}{\delta(\delta+\lambda_1)} = 1/\delta, \text{ smooth pasting.} \tag{7d}$$

Following Dixit and Pindyck (1994), the last conditions are

$$(\lambda_0\lambda_1 C p^{\beta_a} - \lambda_1 D p^{\beta_s})/(\lambda_0 + \lambda_1) = A_1 p^{\beta_1} + A_2 p^{\beta_2} + \frac{\lambda_1 p}{\delta(\delta+\lambda_1)} + \frac{\lambda_1(\frac{\theta-v}{r} - I)}{r+\lambda_1}, \tag{7e}$$

$$(\lambda_0\lambda_1\beta_a C p^{\beta_a - 1} - \lambda_1\beta_s D p^{\beta_s - 1})/(\lambda_0 + \lambda_1) = A_1\beta_1 p^{\beta_1 - 1} + A_2\beta_2 p^{\beta_2 - 1} + \frac{\lambda_1}{\delta(\delta+\lambda_1)}. \tag{7f}$$

The six equations in (7) are solved numerically for the two triggers, p_0 and p_1, and the four parameters A_1, A_2, C, and D.

4.2.2. Data

Weekly biodiesel price series are employed from January 4, 2008 through June 27, 2014, which results in 339 observations. Biodiesel prices ($/gallon) are from the USDA Agricultural Marketing Service (CARD, 2014). Nominal prices are adjusted to real by the Producer Price Index (PPI) for crude material (U.S. Department of Labor, 2014).

4.2.2.1. Unit-root analysis

Following Pindyck's work studying long-run energy price evolution (Pindyck, 1999), unit root tests for biodiesel price series are employed prior to estimating the geometric Brownian motion parameters. Augmented Dickey-Fuller (ADF) tests with and without a time trend are performed for the logarithm of biodiesel price series

$$\Delta \ln p_t = \alpha + \beta ln p_{t-1} + \sum_{i=1}^{k} \zeta_i \, \Delta ln p_{t-i} + \epsilon_t,$$

$$\Delta \ln p_t = \alpha + \beta ln p_{t-1} + \delta t + \sum_{i=1}^{k} \zeta_i \, \Delta ln p_{t-i} + \epsilon_t,$$

where Δ is the first-difference operator and k is the number of lags. AIC and SBIC suggest lag one. In the ADF test, the null hypothesis is $\beta = 0$. If it is rejected, then there is no unit root. Results, presented in Table 4.2, indicate with and without a time trend, at a 5% significance level the ADF tests cannot reject the presence of a unit toot for the logarithm of biodiesel prices. The presence of a unit root suggest it is reasonable to model the biodiesel price series as a geometric Brownian motion.

4.2.3. Estimation procedure

From Ito's Lemma, if the biodiesel price follows a geometric Brownian motion (1), then its logarithm follows a simple Brownian motion

$$d(lnp) = \left(\alpha - \frac{1}{2}\sigma^2\right)dt + \sigma dz = \mu dt + \sigma dz, \qquad (8)$$

where $d(lnp)$ follows a normal distribution with mean μdt and variance $\sigma^2 dt$, so over a finite time interval τ, the change in logarithm of p is normally distributed with mean $\mu\tau$ and variance $\sigma^2\tau$. Given weekly price series, τ is $1/52$ of a year, set $\gamma_t = \Delta p_t / p_t$.

Applying the maximum likelihood method to (8), the estimates for drift and volatility can be determined separately. Thus, for the first difference of the logarithm of biodiesel prices, the weekly drift ($\mu\tau$) and weekly volatility ($\sqrt{\sigma^2\tau}$) are estimated as

$$\hat{\mu}\tau = \bar{\gamma} = \frac{1}{n}\sum_{t=1}^{n}\gamma_t,$$

$$\sqrt{\sigma^2\tau} = std(\gamma_t) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\gamma_t - \hat{\mu}\tau)^2},$$

where n is the number of observations. The drift estimate of the weekly stochastic prices are then

$$\hat{\alpha}_{week} = \hat{\alpha}\tau = \hat{\mu}\tau + \frac{1}{2}\widehat{\sigma^2}\tau.$$

While the volatility estimate for biodiesel prices are the same as

$$\widehat{\sigma^2}_{week} = \widehat{\sigma^2}\tau.$$

In (1), the optimal threshold price is in terms of annual drift, α, volatility, σ, and discount rate, r, thus, the drift and volatility estimates are adjusted as

$$\hat{\alpha} = \hat{\alpha}_{week}/\tau,$$

$$\hat{\sigma} = \hat{\sigma}_{week}/\sqrt{\tau}.$$

The drift and volatility estimates of the weekly stochastic prices are $\hat{\alpha}_{week} = 5.80 \times 10^{-4}$ and $\hat{\sigma}_{week} = 3.57 \times 10^{-2}$. The corresponding estimates of annual drift and volatility are $\hat{\alpha} = 0.030$ and $\hat{\sigma} = 0.257$.

A 5% risk-free interest rate is assumed with sunk cost I and operating cost v obtained from the Agricultural Marketing Resource Center (Hofstrand and Johanns, 2015). They calculated total construction costs at $47 million for a 30 million gallon biodiesel refinery. Sunk cost per unit is then determined by dividing total construction cost by capacity, $1.57 per gallon. Operating cost per unit is the sum of variable costs and fixed costs. Variable costs include soybean oil, natural gas, methanol, chemical, and other direct costs. Fixed costs consist of depreciation, interest, labor and management, marketing and procurement, and tax and insurance. Current, 2015, operating costs are employed, which is $3.16 per gallon. All of these benchmark values are listed in Table 4.3.

4.3. Results and Discussion

Considering first a no tax credit policy scenario over the 2005 to 2015 period, the optimal investment threshold is $p^* = 5.976$, which is calculated by

$$p^* = \frac{\beta_a}{\beta_a - 1}(\frac{v}{r} + I)\delta,$$

where β_a is the positive root of

$$\frac{1}{2}\sigma^2\beta(\beta - 1) + (r - \delta)\beta - r = 0.$$

The Marshallian investment threshold is $\left(\frac{v}{r} + I\right)\delta = 1.294$. The normal options value premium over the Marshallian threshold is 4.683. When the biodiesel tax credit of $1.00 per gallon is in effect, the threshold would be

$$p_1 = \frac{\beta_a}{\beta_a - 1}\left(\frac{v - \theta}{r} + I\right)\delta = 4.131, \tag{9}$$

which is $\frac{\beta_a}{\beta_a - 1}\frac{\theta}{r}\delta = 1.845$ lower than 5.976. However, when the two regimes can switch back and forth in a Poisson process, both thresholds are affected. The effects on the two thresholds are examined for p_0, when the tax credit is not currently in effect, and p_1 when it is currently in effect. The probability rates of enactment λ_1 and removal λ_0 are varied over a range 0 to 1, with results listed in Tables 4.4 and 4.5, and Figures 4.2 and 4.3.

Table 4.4 indicates that the threshold p_0 increases as the probability of enactment λ_1 within the next year increases. The tax credit will reduce the cost of investment and hence increase the value of waiting. The magnitude of this effect is relatively large. An increased expectation of establishing a tax credit in the next period appears to have a marked effect on the lack of willingness to invest in the current period. Just the hint of a possible future tax credit can reduce current biodiesel investment. A 10% probability of a tax in the next period will increase the price threshold from 5.976 to 7.963, a 33% increase. There appears to be a large option value in delaying investment.

Even when the tax credit is not in place, the threshold p_0 is affected by the probability of its removal, λ_0. There is a trivial decreasing trend in p_0 as the probability of removal λ_0 increases. For example, when $\lambda_1 = 0.2$, p_0 drops less than 1% (from \$10.015 to \$9.987 per gallon) as λ_0 increases from 0 to 1. At some future time when the tax credit is enacted, it might be removed before it was feasible to invest. This reduces the value of waiting now. However, the effect is quantitatively negligible. As the probability of enactment λ_1 goes up, this negligible effect approaches zero. Firms tend to ignore the possibility of removal at a future time when there is a great chance that the tax credit will be implemented within the next year.

Table 4.5 indicates that the threshold p_1 decreases as the probability of removal, λ_0, within the next year increases. The increasing possibility of losing the tax credit within the next year lowers the premium of the option. The prospect of losing the credit induces firms to invest more readily now. This effect is quantitatively not as strong as the delaying effect of λ_1 on p_0, Table 4.4.

Even when the tax credit is in effect, the threshold p_1 is affected by the probability of its enactment λ_1. There is a marked increase in p_1 as the probability of implemented λ_1 increases. A current tax credit that is subsequently removed has the possibility of being restored, so the incentive to invest immediately declines.

The results in Tables 4.4 and 4.5 indicate that a disruptive policy can have a major impact on biodiesel adoption. This supports the hypothesis that inconsistent tax credits lead to market uncertainty, which can have a pronounced impact on the decision to invest in a biodiesel refinery. If there exists a high probability of a tax credit being implemented in the near future, high λ_1, then the threshold price p_o will increase up to more than five times from not considering this possible implementation. Similarly, with a current tax credit, as the probability of the tax being withdrawn increases, high λ_0, then the threshold price p_1 will decline. Biodiesel investors will want to capitalize on this tax credit before it is likely to be withdrawn.

With the results indicating the potential exists for inconsistent tax credit policy impacting biodiesel adoption, the natural question is if it actually has had an impact. Considering the ten-year 2005-2014 period, the tax credit was implemented for five consecutive years from 2005 to 2009. After that, there are three transitions from having a tax credit to not having a tax credit, which are from 2009 to 2010, 2011 to 2012, and 2013 to 2014 (Table 4.1). As a measure of this disruption, let

$$\hat{\lambda}_0 = Pr(No\ tax\ credit\ at\ Year = t+1 | Tax\ credit\ at\ Year = t) = \frac{3}{7},$$

There are two transitions from not having a tax credit to having a tax credit, which are from 2010 to 2011 and 2012 to 2013. During the ten-year period, the tax credit would be implemented within the next year when the tax credit was not in effect this year. Therefore,

$$\hat{\lambda}_1 = Pr(Tax\ credit\ at\ Year = t+1 | No\ tax\ credit\ at\ Year = t) = 1.$$

When $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$, the threshold prices are $p_0 = 27.400$ and $p_1 = 3.997$. As indicated in Table 4.4, the investment threshold p_0 when the tax credit is not in effect is markedly higher than the biodiesel real prices in all the years, so no investment would occur without a tax credit. This is also the result when considering a no tax credit policy scenario over 2005 to 2015, where the threshold is $p^* = 5.976$. Although it is considerably lower than p_o, it is still not feasible to invest without a tax credit. However, the likelihood of the tax credit being established in the following year, will discourage current investment. The investment in biodiesel was always questionable without a tax credit, but the likelihood of the implementation of a credit in the near future markedly increases the barrier to current investment.

When the tax credit scenario over the 2005 to 2015 period is considered the threshold is $p_1 = 4.131$, which is very close to the $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$ threshold of $p_1 = 3.997$. With a close to 50% probability the tax credit will be withdrawn, this does not greatly increase the likelihood of currently adopting. Thus, the disruptive policy does not appear to have a large impact on adoption of biodiesel. Future discontinuance of a policy with the hope of stimulating current biodiesel investment is not likely to produce much of an effect. With a 100% probability of the tax credit being restored if it is withdrawn, current investment decisions in biodiesel are only partially affected. Investors are believing the loss in credits is only transitory, so the threshold price, p_1, does not raise appreciably. In both cases, biodiesel real prices in 2008, 2011, and 2013 are greater than the investment threshold p_1 when tax credit is in effect, thus producers would choose to invest in these years. While biodiesel refineries would not invest in 2007 and 2009.

If interest is in jump starting the biodiesel industry, any hint of a future tax credit can markedly reduce current adoption, so a policymaker should consider immediately implementing a credit. However, in establishing such a credit policy, a set short expiration time versus no set expiration does not appear to make a large difference. Thus, at least for biodiesel adoption, the on and then off tax credit policy does not indicate a large impact on investment as opposed to a consistent policy of maintaining tax credits. Currently, with the tax credit not in effect, the uncertainty of it being restored does increase the investment threshold p_0, more than five times, which further dampens interest in investment. The policy uncertainty markedly increases the value of waiting. However, with a history of reestablishing pasted tax-credit expirations, the possibility of a current tax credit being withdrawn does not markedly increase the option value of waiting. The frequency of the on and off policy may explain this result. As in the case of the biodiesel tax credit, since 2009 the annual switch in policy has actually established a consistent policy. Biodiesel investors will respond to this expectation of a continued annual policy switch and not markedly increase their option value. The result is just a lower effective tax credit, if the volume of biodiesel production is fairly constant across years. In fact, with an annual on and off tax credit, biodiesel producers will attempt to increase production in years with the credit and reduce production in the credit expiration years. Such a production response to policy shifts is, however, inefficient. It prevents the refinery from continuously operating at or near full capacity (minimum point of average cost) and limits the ability to establish long-run contracts providing a consistent flow of variable inputs (soybeans). On the spectrum, as the time interval of policy switching shortens, the disruptive policy approaches a continuous policy. In the case of biodiesel, the annual shift, indicated in Table 4.1, appears from the results not to have much of an impact on investment during an active tax credit phase. If, as it may appear in the future, this annual switch in policy is disrupted, then a marked change in the price thresholds may occur. If the tax credit is not renewed in 2015, then an annual policy switch is disrupted and the impact on investment during an active tax credit phase may well be affected by the future discontinuous. Again, it is the uncertainty in policy that effects investment.

On the surface, these results may indicate an annual switching of policy is does not have much of an impact on investment. However, in an infant industry such as biodiesel refining, it will tend to retard a smooth trajectory of investment. A continuous tax credit will yield a continuous stream of biodiesel investment. In contrast, a discontinuous tax credit will result in a burst of investment then a tax credit is established and then an investment moratorium once removed. Such a disjoint investment trajectory may not be efficient with any entry and exit costs in firms' construction of biodiesel facilities and supplying any unique equipment for biodiesel refining. The shorter the interval of no tax credit the less of a disruption in investment. However, then a tax credit has expired, an extended legislative process required for reestablishing the credit, will tend to place any biodiesel investment on hold until the credit is reestablished. Particularly in terms of investments with large sunk costs, such delays in establishing or just reestablishing a policy can have a major impact on investments.

4.3.1. Sensitivity Analysis

For further understanding into the direction and magnitude of the results, sensitivity to the changes in the parameters is investigated. First, the threshold price response to a biodiesel tax credit with policy certainty yields a linear negative relationship. From (9), the slope of the threshold price to credit is $\frac{\mathrm{dp}}{\mathrm{d\theta}} = -\frac{\beta_a}{\beta_a - 1}\frac{\delta}{r} = -1.844$ in Figure 4.4a. Figures 4.4b and 4.4c illustrate the response of threshold prices p_1 and p_0 to the credit when $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$. With policy uncertainty, both prices are sensitive to the tax credit, which also yields linear relationships. Threshold price p_0 increases while p_1 decreases as the tax credit increases. Even when the tax credit is not in place, the threshold p_0 is affected by the tax credit. A biodiesel refinery calculates that at a random future time when the tax credit is enacted, greater tax credit yields enhanced benefits. This increases the value of waiting. When the tax credit is in effect, a larger tax credit would accelerate investment, so p_1 declines as the tax credit increases. The slope in Figure 4.4b is approximately -1.788 while in Figure 4.4c it is approximately 23.552. The threshold p_0 is markedly more responsive to a change in the tax credit than p_1.

The response of the thresholds to a change in operating cost, *v*, and sunk cost, *I*, are similar. Costs have positive and linear effects on both thresholds. The effect of costs on p_1 is greater than the effect on p_0. From (9), $\frac{\mathrm{dp}}{\mathrm{dv}} = \frac{\beta_a}{\beta_a - 1}\frac{\delta}{r} = 1.844$ and $\frac{\mathrm{dp}}{\mathrm{dI}} = \frac{\beta_a}{\beta_a - 1}\delta = 0.092$ without policy uncertainty.

Figure 4.5 illustrates the response of threshold prices to the risk-free interest rate. When there is no policy uncertainty, Figure 4.5a, a negative relationship exists between the risk-free interest rate and the threshold price. From Figure 4.5a, the slope of threshold price to interest rate is negative; an increase in the interest rate will decrease the incentive for postponing investment. The threshold price decreases at a decreasing rate. Figures 4.5b and 4.5c illustrate the response of threshold prices p_1 and p_0 to risk-free interest rate when $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$. With policy uncertainty, both threshold prices also decline at a decreasing rate as interest rate increases. At a high interest rate, there is a large discount in future values. Biodiesel refineries would then invest now rather than in the future. With an interest rate close to zero, future values are close to current, so there is limited urgently for biodiesel investment. Threshold p_0 is more sensitive to the interest rate than p_1. As the risk-free interest rate increases from 0.05 to 0.10, p_0 and p_1 decline by 42.9% and 10.6%, respectively.

Figure 4.6a illustrates the response of the threshold prices to the drift without policy uncertainty. The threshold price declines at a decreasing rate as the drift rate of biodiesel prices increases. The expected biodiesel prices grow at an increasing rate as the drift increases. Biodiesel firms tend to accelerate investment given this expected price increase. Figures 4.6b and

4.6c illustrate the response of threshold prices p_1 and p_0 to the drift when $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$. As the drift rate increases, threshold price p_1 decrease at a decreasing rate while drift rate has a negligibly negative effect on p_0. Figure 4.7a illustrates the response of the threshold price to volatility rate of biodiesel prices without policy uncertainty. Figures 4.7b and 4.7c illustrate the response of threshold prices p_1 and p_0 to the volatility rate when $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$. Threshold prices increase at an increasing rate as volatility rate increases. As the volatility increases, the biodiesel prices process more uncertainty. Biodiesel refineries would then postpone the time of investment.

4.4. Conclusion and Policy Implications

Effective government policy development should consider the 3-Ts: type, timing, and transience. For alternative energy policy, type has generally received extensive investigation while timing only a limited extent. However, transience consideration has receive no consideration. The research results addressing this transience consideration support the hypothesis of time inconsistent government policies (tax credits) do lead to market uncertainty. This does appear to have a pronounced negative impact on the decisions to invest in a biodiesel refinery. However, results indicate a consistent policy switching regime may not be that disruptive. It is policy uncertainty that drives the option pricing thresholds and a consistent policy switching does not increase the uncertainty. However, even a consistent policy switching regime is likely to result in economic inefficiencies. These inefficiencies take the form of both scale and investment inefficiencies. Scale inefficiency are in terms of determining production level in response to changing policies and investment inefficiency is in terms of annual disjoint biodiesel investment levels. If there exists a high probability of a tax credit being implemented in the near future, then biodiesel investors will want to delay investment. Similarly, with a current tax credit, as the probability of the credit being withdrawn increases, biodiesel investors will want to capitalize on this tax credit before it is withdrawn.

The empirical results provide evidence that government policymakers involved with alternative energy legislative should consider the listens learned by macroeconomic policymakers. Based on macroeconomic theory, monetary policy is aimed at taking a long-run perspective in targeting inflation and unemployment levels. The idea is a stable long-run policy perspective will translate into a stable macroeconomic economy. Such a policy perspective may also hold well for alternative energy policies. Markets generally do not respond well to uncertainty not only in terms of price shocks but also government policy shocks. As the results indicate, for biodiesel investments, a time-inconsistent tax credit will markedly raise the price thresholds for investment. Just the hint of enacting a tax credit will dampen current investment and once established a burst of investment will then likely occur. With the results indicating a stop and go investment response from time-inconsistent policies, this will not likely lead to efficient market investments. Instead, taking a long-run perspective leading to a smooth developing infant biodiesel industry is consistent with the 3-Ts for efficient policy. Such a perspective would suggest a minimum delay in establishing a tax credit and maintaining it for a set number of years, rather than requiring an annual renewal.

Appendix II

The quadratic equation associated with range (p_1, p_0) is

$$\tfrac{1}{2}\sigma^2 \beta(\beta - 1) + (r - \delta)\beta - (r + \lambda_1) = 0.$$

The corresponding characteristic roots, β_1 and β_2, are

$$\beta_1 = \frac{1}{2} - \frac{r-\delta}{\sigma^2} + \sqrt{\left(\frac{r-\delta}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r+\lambda_1)}{\sigma^2}} > 1,$$

$$\beta_2 = \frac{1}{2} - \frac{r-\delta}{\sigma^2} - \sqrt{\left(\frac{r-\delta}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r+\lambda_1)}{\sigma^2}} < 0.$$

The quadratic equations associated with range $(0, p_1)$ are

$$\tfrac{1}{2}\sigma^2 \beta(\beta - 1) + (r - \delta)\beta - r = 0$$

$$\tfrac{1}{2}\sigma^2 \beta(\beta - 1) + (r - \delta)\beta - (r + \lambda_0 + \lambda_1) = 0$$

The corresponding positive characteristic roots, β_a and β_s, are

$$\beta_1 > \beta_a = \frac{1}{2} - \frac{r-\delta}{\sigma^2} + \sqrt{\left(\frac{r-\delta}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2r}{\sigma^2}} > 1,$$

$$\beta_s = \frac{1}{2} - \frac{r-\delta}{\sigma^2} + \sqrt{\left(\frac{r-\delta}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r+\lambda_0+\lambda_1)}{\sigma^2}} > \beta_1.$$

Table 4.1. Energy Independence and Security Act of 2007 (EISA) Expansion of Biomass-based Diesel Mandate and U.S. Biodiesel Tax Credit

Year	Biodiesel Mandate (billion gallons)	Tax Credit Existence ($1.00 per gallon)
2005	–	Yes
2006	–	Yes
2007	–	Yes
2008	–	Yes
2009	–	Yes
2010	1.15	No
2011	0.80	Yes
2012	1.00	No
2013	1.28	Yes
2014	1.63	No
2015	1.70	?
2016	1.80	?
2017	1.90	?

Table 4.2. Augmented Dickey-Fuller Unit-root Test Results

	Test statistics	Mackinnon approximate p-value
With trend	-1.568	0.8046
Without trend	-1.567	0.5001

Table 4.3. Parameters and Benchmark Values

Parameter	Symbol	Benchmark value
Annual biodiesel price drift	α	0.030
Annual biodiesel price volatility	σ	0.257
Risk-free interest rate	r	0.050
Sunk cost ($/gallon)	I	1.570
Operating cost ($/gallon)	v	3.160
Biodiesel tax credit ($/gallon)	θ	1

Table 4.4. Investment Threshold When Tax Credit is not in Effect ($\boldsymbol{P_0}$)
(Parameters: $\alpha = 0.030$, $\sigma = 0.257$, $r = 0.050$, $I = 1.57$, $v = 3.16$, $\theta = 1$)

	λ_1[a]										
λ_0[b]	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.0	5.976	7.963	10.015	12.159	14.340	16.529	18.716	20.897	23.071	25.239	27.400
0.1	5.976	7.934	10.005	12.156	14.339	16.529	18.716	20.897	23.071	25.239	27.400
0.2	5.976	7.922	9.999	12.154	14.338	16.529	18.716	20.897	23.071	25.239	27.400
0.3	5.976	7.915	9.995	12.152	14.338	16.529	18.716	20.897	23.071	25.239	27.400
0.4	5.976	7.911	9.993	12.151	14.337	16.529	18.716	20.897	23.071	25.239	27.400
0.5	5.976	7.908	9.991	12.151	14.337	16.529	18.716	20.897	23.071	25.239	27.400
0.6	5.976	7.906	9.990	12.150	14.337	16.528	18.716	20.897	23.071	25.239	27.400
0.7	5.976	7.904	9.989	12.149	14.337	16.528	18.716	20.897	23.071	25.239	27.400
0.8	5.976	7.903	9.988	12.149	14.337	16.528	18.716	20.897	23.071	25.239	27.400
0.9	5.976	7.901	9.987	12.149	14.337	16.528	18.716	20.897	23.071	25.239	27.400
1.0	5.976	7.901	9.987	12.149	14.336	16.528	18.716	20.897	23.071	25.239	27.400

[a] $\lambda_1 dt$ denotes the probability a tax credit will be implemented in the next interval of time, *dt.*
[b] $\lambda_0 dt$ denotes the probability a tax credit will be withdrawn in the next interval of time, *dt*.

Table 4.5. Investment Threshold When Tax Credit is in Effect ($\boldsymbol{P_1}$)
(Parameters: $\alpha = 0.030$, $\sigma = 0.257$, $r = 0.050$, $I = 1.57$, $v = 3.16$, $\theta = 1$)

	λ_1[a]										
λ_0[b]	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.0	4.131	4.131	4.131	4.131	4.131	4.131	4.131	4.131	4.131	4.131	4.131
0.1	3.396	3.692	3.852	3.942	3.996	4.029	4.051	4.067	4.078	4.086	4.092
0.2	3.123	3.472	3.685	3.816	3.898	3.952	3.989	4.014	4.033	4.048	4.059
0.3	2.974	3.336	3.573	3.725	3.824	3.891	3.937	3.971	3.996	4.015	4.030
0.4	2.877	3.243	3.491	3.655	3.766	3.841	3.895	3.934	3.963	3.986	4.004
0.5	2.809	3.174	3.428	3.600	3.718	3.800	3.858	3.902	3.935	3.961	3.981
0.6	2.758	3.120	3.377	3.555	3.678	3.764	3.827	3.874	3.910	3.938	3.961
0.7	2.717	3.077	3.336	3.517	3.644	3.734	3.800	3.849	3.887	3.918	3.942
0.8	2.684	3.042	3.302	3.485	3.614	3.707	3.775	3.827	3.867	3.899	3.925
0.9	2.657	3.012	3.272	3.457	3.589	3.684	3.754	3.807	3.849	3.882	3.910
1.0	2.634	2.986	3.247	3.433	3.566	3.663	3.734	3.789	3.833	3.867	3.895

[a] $\lambda_1 dt$ denotes the probability a tax credit will be implemented in the next interval of time, *dt.*
[b] $\lambda_0 dt$ denotes the probability a tax credit will be withdrawn in the next interval of time, *dt*.

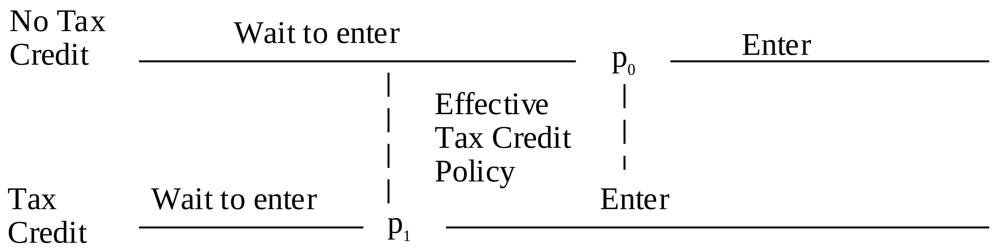


Figure 4.1. Price Triggers for Effective Tax Credit Policy

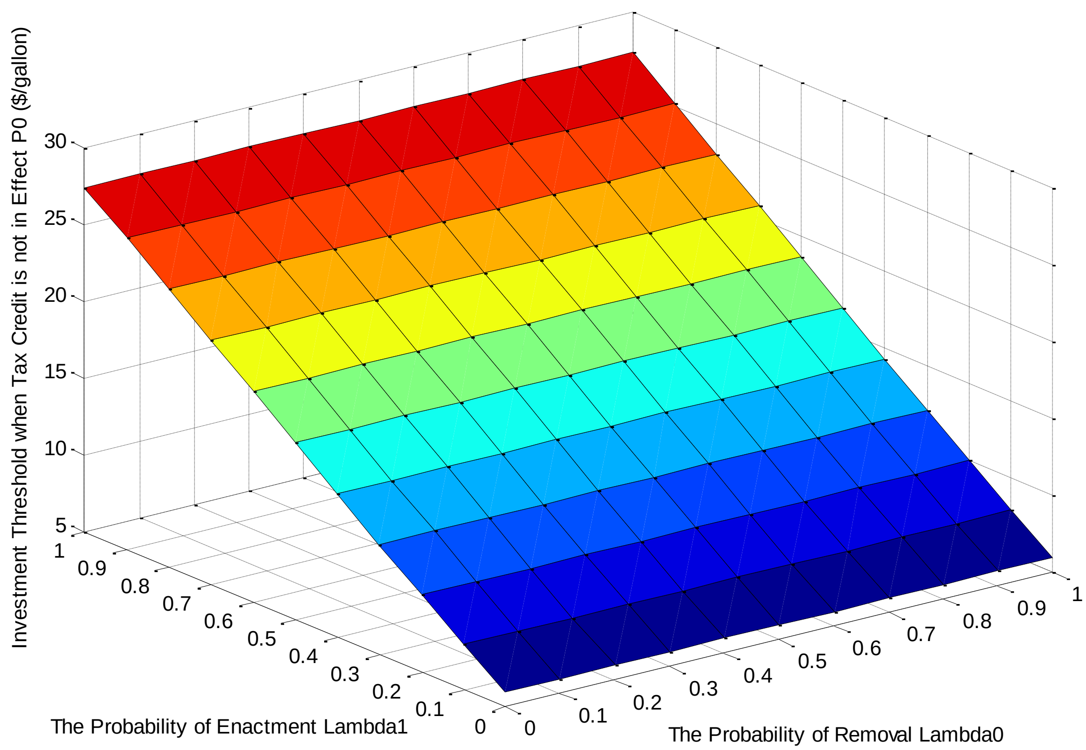


Figure 4.2. Investment Threshold When Tax Credit is not in Effect (P_0)

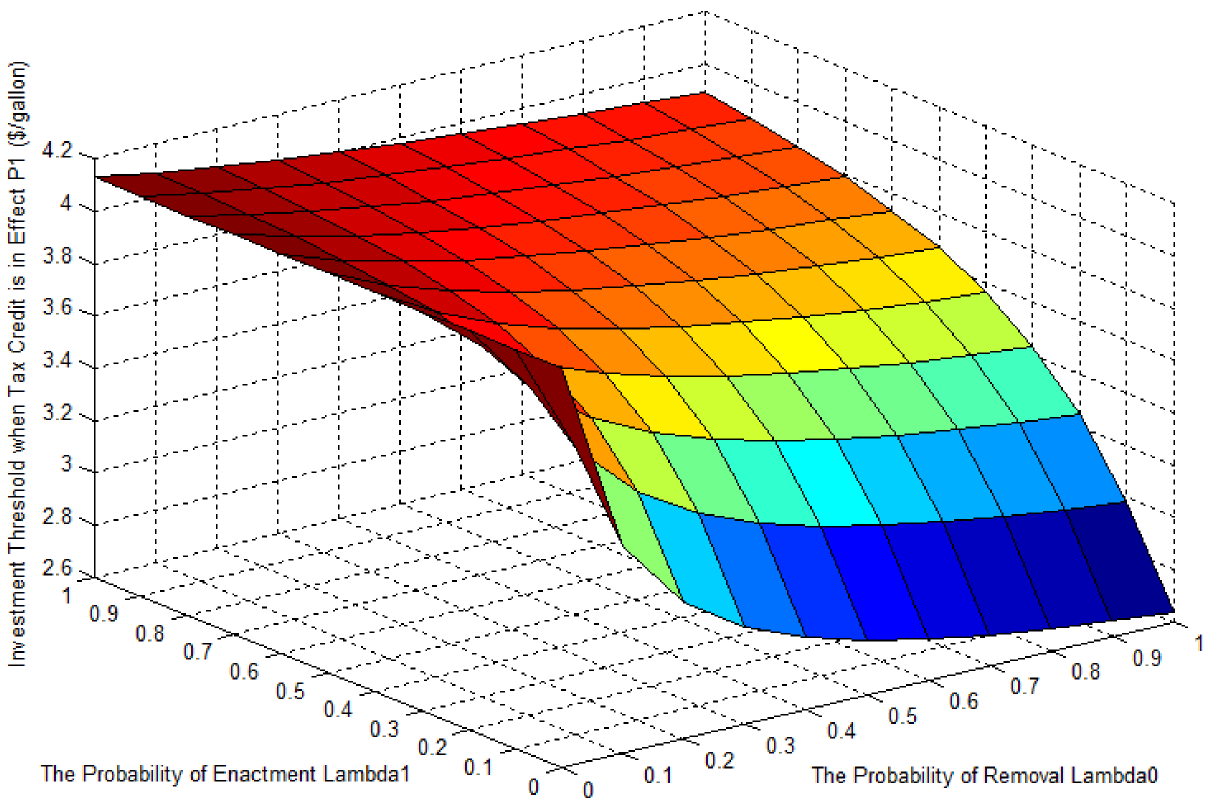
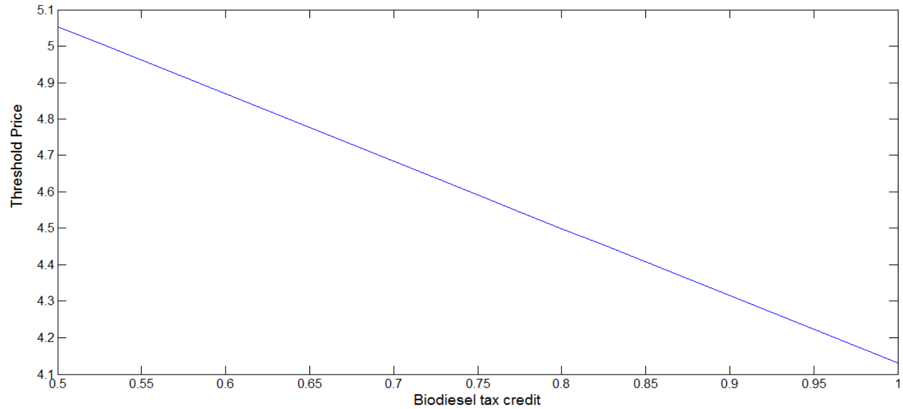
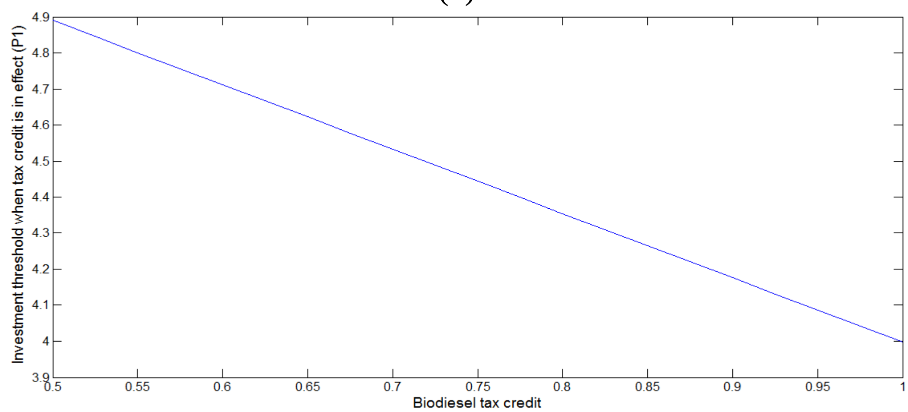


Figure 4.3. Investment Threshold When Tax Credit is in Effect (P_1)

(a)



(b)



(c)

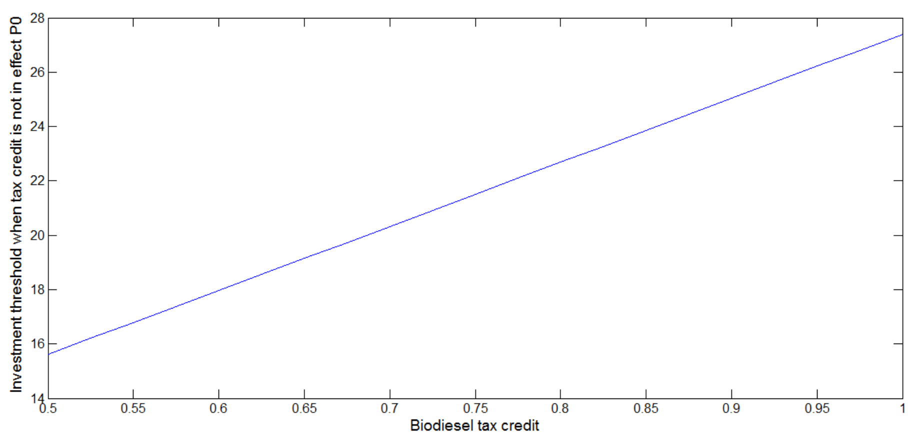


Figure 4.4. Responses of the Investment Threshold to a Biodiesel Tax Credit Policy Certainty (a) and Thresholds P_1 (b) and P_0 (c) with Policy Uncertainty When $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$

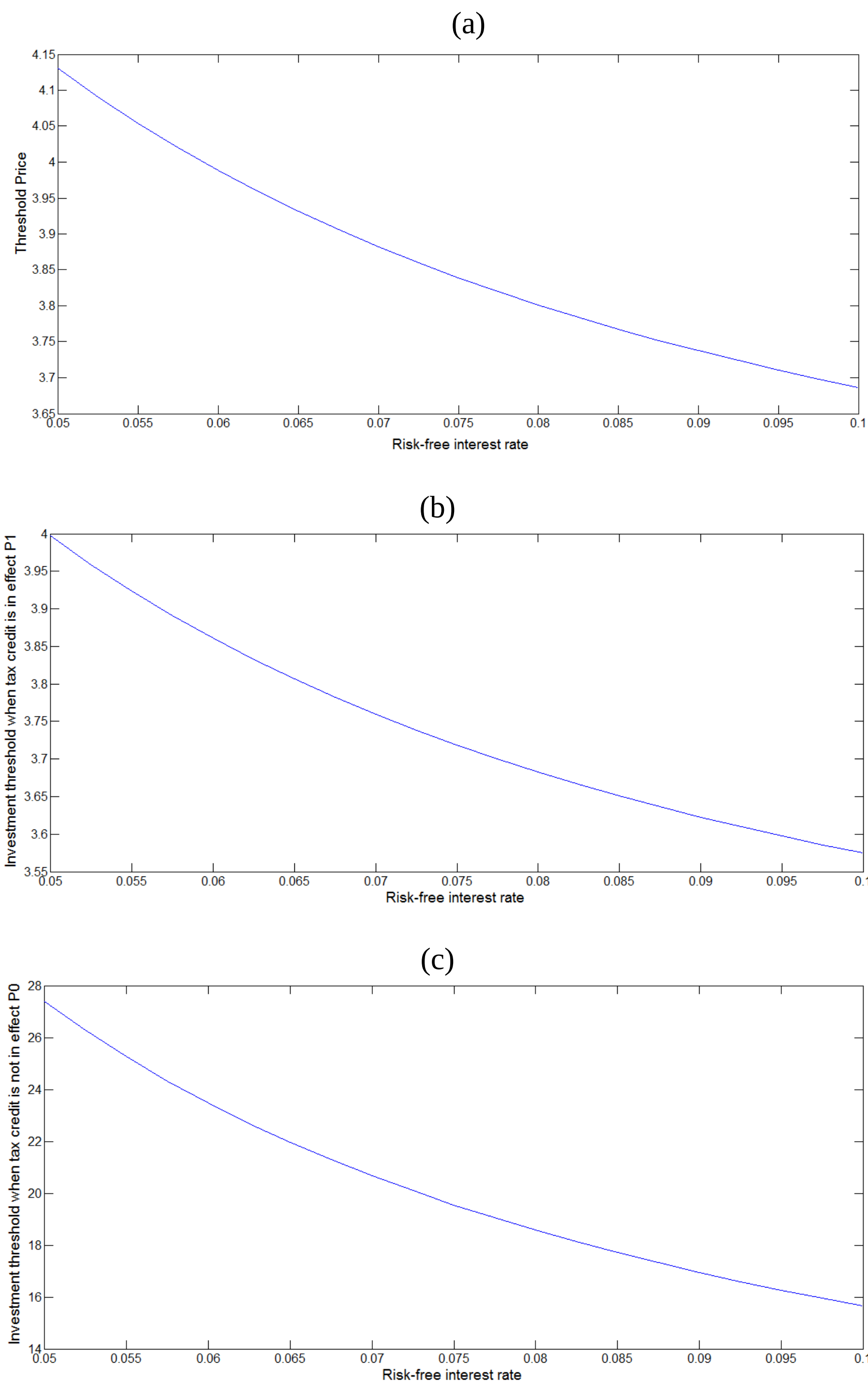


Figure 4.5. Responses of Investment Threshold to a Risk-free Interest Rate Policy Certainty (a) and Thresholds P_1 (b) and P_0 (c) with Policy Uncertainty When $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$

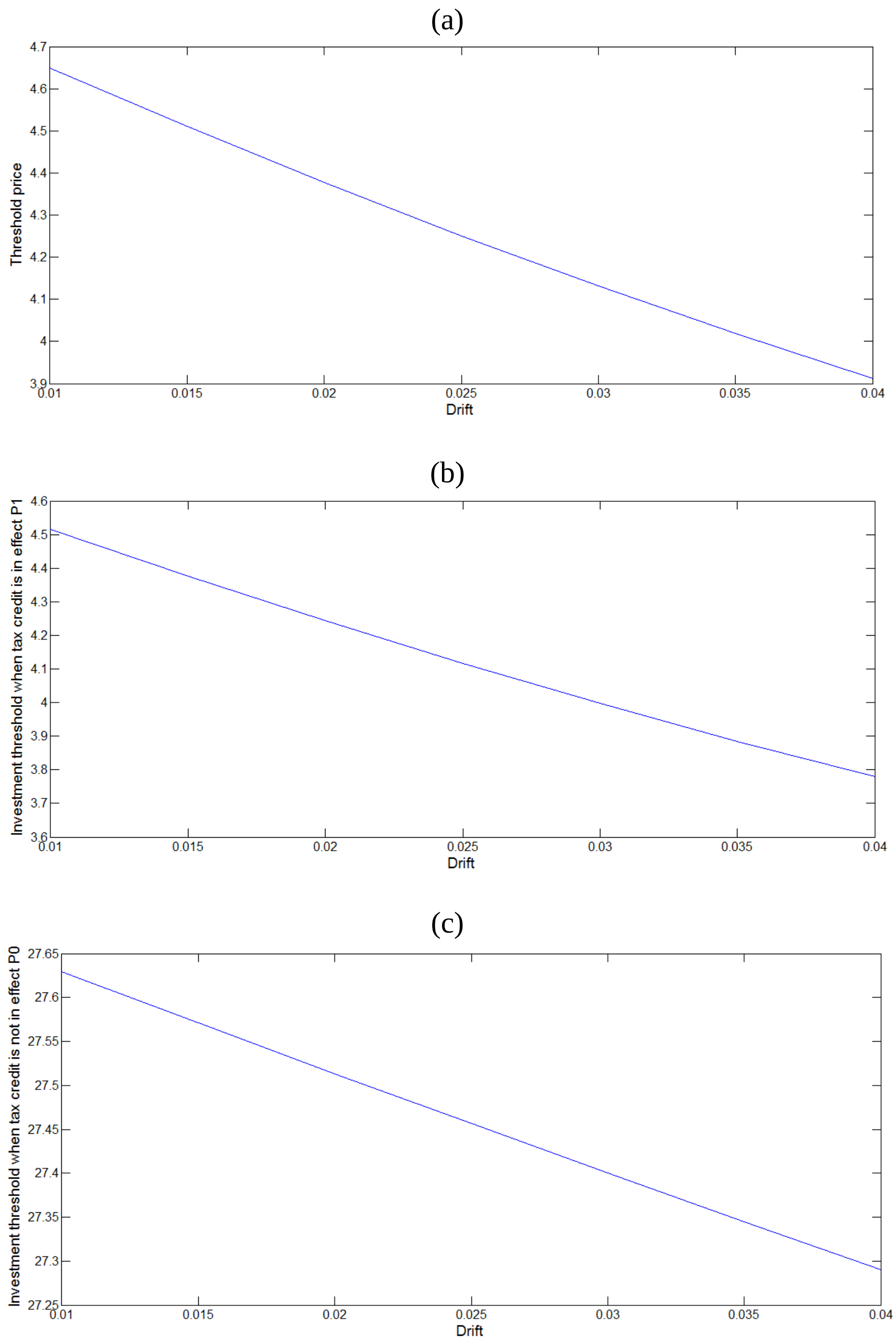
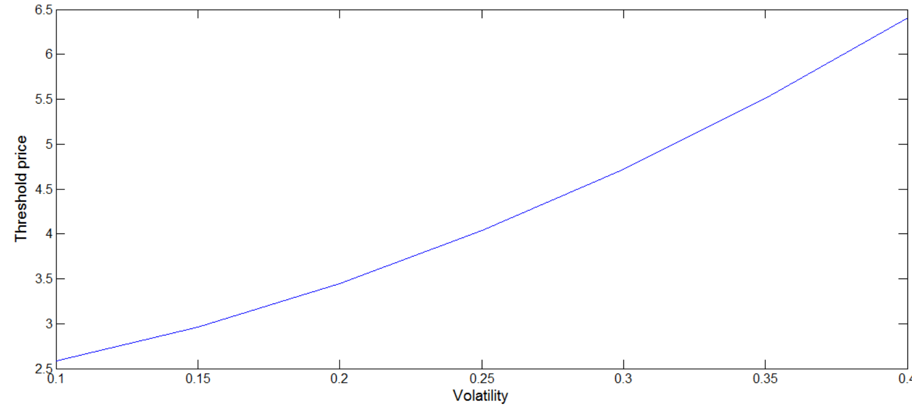
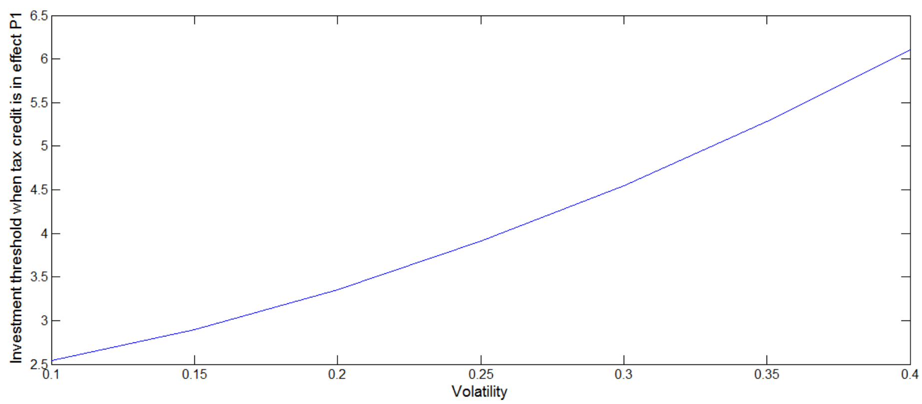


Figure 4.6. Responses of Investment Threshold to Drift Policy Certainty (a) and Thresholds P_1 (b) and P_0 (c) with Policy Uncertainty When $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$

(a)



(b)



(c)

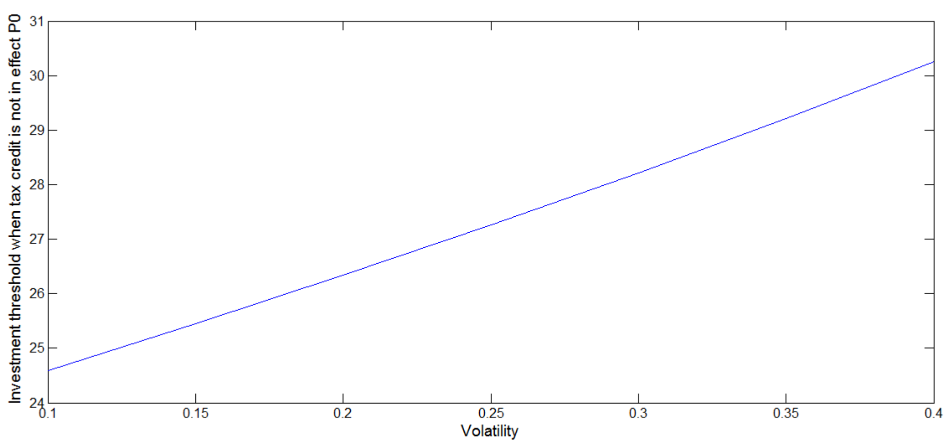


Figure 4.7. Responses of Investment Threshold to Volatility Policy Certainty (a) and Thresholds P_1 (b) and P_0 (c) with Policy Uncertainty When $\hat{\lambda}_0 = \frac{3}{7}$ and $\hat{\lambda}_1 = 1$

CHAPTER 5

SUMMARY AND CONCLUSIONS

5.1. Summary of Conclusions

This dissertation investigates three issues on U.S. renewable energy markets; specifically, solar photovoltaic (PV) and biodiesel markets. The primary objectives involve developing an analytical framework for assessing the optimal solar energy subsidy, examining price volatility spillovers among U.S. biodiesel, crude oil, diesel, and soybean markets, and investigating the effect of Poisson type policy impacts on biodiesel investment through the theory of investment under uncertainty.

Globally, solar photovoltaic (PV) was the fastest growing renewable power technology in the past decade (IEA, 2014). As one essay in the dissertation, the socially optimal solar PV subsidy is derived and quantified for U.S. residential energy production. The essay develops a model based on utility maximization that incorporates environment, health, employment, and electricity accessibility benefits affected by the level of solar subsidization. Empirical results indicate the optimal level of solar PV subsidies are very much dependent on the impact such subsidies have on employment. If one believes employment should be a macroeconomic benefit from solar PV, results indicate the optimal solar PV subsidy would be 7.69 cents/kWh. In contrast, a belief that the employment effect should be excluded, the optimal solar PV subsidy falls to 2.24 cents/kWh.

The model critically considers the influence of solar PV subsidies not only on the stimulation of the use of renewable energy, but also the income incentive for households to increase their use of electricity from fossil fuels. Given public concern with CO_2 emissions, fossil energies are becoming an inferior good where households with higher incomes will tend to spend proportionally less of their income on carbon based fuels. With household's preferences to reduce their proportion of income spent on fossil fuels as incomes rise, policies favoring solar PV will not only increase solar PV, but also reduce fossil-energy consumption. However, prior to CO_2 emission concerns, fossil energies were generally thought of as normal goods. In this case the impact of favorable solar PV policies on fossil-energy consumption is unclear.

Biodiesel is an emerging major alternative fuel within the United States. The U.S. biodiesel production in 2010 was 0.343 billion gallons (U.S. Department of Agriculture, 2014b). It reached 0.967 and 0.991 billion gallons in 2011 and 2012, respectively; almost three times 2010 production. In 2013, at 1.339 billion gallons it was almost four times 2010 volume (U.S. Department of Agriculture, 2014b).

The empirical results of the univariate EGARCH model indicate there are double-directional price-volatility spillovers between biodiesel and soybean markets and between crude oil and biodiesel markets. The dominant impact is crude oil price spillovers into the other markets (biodiesel, soybean, and diesel). The magnitudes of these spillovers are relatively strong for the fossil fuel markets (crude oil and diesel), with more inelastic spillovers between the agricultural commodities (soybeans and biodiesel). There is a relatively more elastic impact soybean-price effect on the biodiesel market. Price volatility in the biodiesel market does spillover into the soybean market and as a result of this spillover soybean prices have some persistence in deviating from market trends. However, the elasticity of this spillover is very inelastic relative to the spillovers between crude oil and diesel markets. Also, the elasticity from soybean-price volatility onto the biodiesel market is more elasticity than the reverse. These results generally indicate in terms of price volatility, the food before biodiesel issue has weak empirical support.

The results from the EGARCH model are reinforced with estimation outcomes of the DCC-MGARCH model. The price volatility conditional correlations between biodiesel and soybeans exhibit considerable time-varying with a slight declining trend. This instability and downward trend in conditional correlations indicate the lack of strong linkages within these markets. As addressed in the essay, the presence of substitutes for soybeans in biodiesel refining and a relatively small biodiesel market for soybean may explain this weak price-volatility relation. However, in addition to these market characteristics, government policies may also play a role in this volatility relation. The disruptive policies of on and off tax credits are possibly leading to the weak link in biodiesel/soybean price volatility.

The two primary means by which subsidies affect the demand for U.S. biodiesel are the Renewable Fuel Standard (RFS) and the Blender Tax Credit (BTC). The RFS is a federal mandate requiring the blending of biofuels into U.S. transportation fuels. The biodiesel tax credit of $1.00 per gallon was established in 2005 by the American Jobs Creation Act of 2004. It was then extended by the Energy Policy Act of 2005, the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010, and the American Taxpayer Relief Act of 2012 (Yacobucci, 2012; U.S. Department of Energy, 2014). During the ten-year period from 2005 to 2014, the biodiesel tax credit lapsed three times, in 2010, 2012, and 2014, respectively. The history of government policy uncertainty along with annual changes in the RFS does not provide a stable policy platform for a young and maturing biodiesel industry. The underlying hypothesis is these inconsistent tax credits lead to market uncertainty, which have a pronounced impact on the decisions to invest in a biodiesel refinery. For investigating this hypothesis, a real options analysis is developed, which considers the likelihood of a tax credit policy shift.

Results support the hypothesis that inconsistent biodiesel policy leads to market uncertainty. If there exists a high probability of a tax credit being implemented in the near future, then biodiesel investors will want to delay investment. The tax credit will reduce the cost of investment and hence increase the value of waiting. Empirical results indicate the magnitude of this effect is relatively large. An increased expectation of establishing a tax credit in the next period appears to have a marked effect on the lack of willingness to invest in the current period. With a current tax credit, as the probability of the credit being withdrawn increases, biodiesel investors will want to capitalize on this tax credit before it is withdrawn. The increasing possibility of losing the tax credit within the next year lowers the premium of the option. The prospect of losing the credit induces firms to invest more readily now.

During the ten-year 2005-2014 period, empirical results indicate that the investment in biodiesel was always questionable without a tax credit, but the likelihood of the implementation of a credit in the near future increases the barrier to current investment. On the other hand, with a close to 50% probability the tax credit will be withdrawn, this does not greatly increase the likelihood of currently adopting. The disruptive policy does not appear to have a large impact on adoption of biodiesel. Future discontinuance of a policy with the hope of stimulating current biodiesel investment is not likely to produce much of an effect. Biodiesel real prices in 2008, 2011, and 2013 are greater than the investment threshold when tax credit is in effect, thus producers would choose to invest in these years while biodiesel refineries would not invest in 2007 and 2009.

In summary, this dissertation makes three primary contributions to the energy economics research:

First, it provides both a theoretical framework and empirical analysis for assessing the optimal solar energy subsidy. This study fills a gap in quantifying the optimal level for solar energy subsidies. It takes into account external benefits from environment, health, and employment as well as electricity accessibility benefits. Theoretical results indicate that a solar PV subsidy is likely more effective when households are educated on the external cost and shift preferences towards viewing fossil energies as being an undesirable commodity. Empirical results reveal that the optimal level of solar PV subsidies are very much dependent on the impact such subsidies have on employment.

Second, the study extends multiple time series models to the price volatility for the biodiesel market in the U.S. market. The adjusted univariate EGARCH model provides evidence of double-directional price-volatility spillovers between crude oil and biodiesel markets and between biodiesel and soybean markets. Further there exists unidirectional price-volatility spillovers from the diesel market to the biodiesel market. The DCC-MGARCH model indicates time-varying conditional correlations among markets and the pairwise conditional correlations fluctuated from 2008 to 2009.

Third, the real options analysis on biodiesel investment addressing the transience in government policy supports the hypothesis of time inconsistent government policies do lead to market uncertainty. If there exists a high probability of a tax credit being implemented in the near future, then biodiesel investors will want to delay investment. Similarly, with a current tax credit, as the probability of the credit being withdrawn increases, biodiesel investors will want to capitalize on this tax credit before it is withdrawn.

5.2. Policy Implications

Based on the results of the analyses from these three papers, there are multiple implications that government policy makers may want to consider. In the optimal solar subsidy study, theoretical results indicate that changing household preferences can have a marked impact on the effect a solar PV subsidy has on the consumption of fossil energy. If households have a general shift toward viewing fossil energy as an inferior good, then any policies directed at incentivizing adoption will be more effective. Given inferior-good characteristics for fossil energies, government policies favorable to solar and alternative renewable energies in general will result in reduced fossil-energy consumption, higher fossil prices, and reduced environmental damage. If instead fossil energy is considered as a normal good, then these impacts from policies favoring renewable energies are not certain. Therefore, a solar PV subsidy is likely more effective when households are educated on the external cost and shift preferences towards viewing fossil energies as being an undesirable commodity. Another concern with policies favoring renewable energies is the possibility of slippage in the form of resulting higher prices for renewable-energy inputs. Results indicate that a solar PV subsidy may drive up the price of solar panels. If so, then effectiveness of the subsidy is compromised.

As the share of biodiesel in our vehicle fuel mix increases, concern arises with biodiesel's impacts on agricultural commodity prices. The initial study on biodiesel-price volatility effects on soybean-price volatility indicates that, while biodiesel-price volatility does appear to influence soybean-price volatility, relation is highly inelastic relative to the crude oil-price volatility impacts on diesel-price volatility. If this degree of volatility spillover is still of concern, then U.S. agricultural policy should be directed toward mitigating such spillovers. Agricultural-commodity buffers could be one possible policy for supplementing supplies in years of insufficient harvests. Such commodity buffers could stabilize food price spikes caused not only by possible biofuel shocks but also by other political, institutional, and environmental shocks. However, the cost of these policies must be weighed against the magnitude of the elasticities and possible ill effects of the spillover. Just considering existing policy impacts on price volatilities in terms of enhancing or mitigating price volatility would be sound prescription for any policymaker.

Markets generally do not respond well to uncertainty not only in terms of price shocks but also government policy shocks. Effective government policy development should consider the 3-Ts: type, timing, and transience. Results of the biodiesel investment study indicate that a time-inconsistent tax credit will markedly raise the price thresholds for investment. If interest is in jump starting the biodiesel industry, any hint of a future tax credit can markedly reduce current adoption, so a policymaker should consider immediately implementing a credit. However, in establishing such a credit policy, a set short expiration time versus no set expiration does not appear to make a large difference. Taking a long-run perspective leading to a smooth developing infant biodiesel industry is consistent with the 3-Ts for efficient policy. Such a perspective would suggest a minimum delay in establishing a tax credit and maintaining it for a set number of years, rather than requiring an annual renewal.

5.3. Suggestions for Future Research

More work could be extended in several directions.

First, empirical results indicate the optimal level of solar PV subsidies are very much dependent on the impact such subsidies have on employment. If renewable energies have limited or no positive job impacts, then the justification for a subsidy is substantially weakened. The results highlight the importance of determining the policy impacts on macroeconomic variables like job growth in renewable energy industry. Further research should be directed toward the renewable policy impacts on macroeconomic variables.

Second, limited analyses exist in estimating the elasticities and externalities in the solar PV subsidy research. The study derived and estimated most parameters based on previous literature. The estimates are provided to outline how a benchmark optimal subsidy can be estimated with lower and upper ranges. For more accurate empirical result, further refining of these estimates are desirable and necessary.

Third, the price volatility spillover study is an initial analysis on biodiesel and related agricultural commodity markets. Further analysis may be conducted by introducing macro-economic factors into time series models.

Fourth, the biodiesel investment study employs the history of disruptive policy from 2005 to 2014 to estimate the probability rates of removal and enactment. Due to the short time period, the estimates of probabilities are relatively rough. Robust estimation method or a longer time period would yield more accurate estimates of threshold prices.

REFERENCES

Alberini, A., Gans, W., and Velez-Lopez, D. (2011). Residential consumption of gas and electricity in the U.S.: The role of prices and income. *Energy Economics, 33,* 870-881. doi:10.1016/j.eneco.2011.01.015

Algieri, B., Aquino, A., and Succurro, M. (2011). Going "green": trade specialization dynamics in the solar photovoltaic sector. *Energy Policy, 39,* 7275-7283. doi:10.1016/j.enpol.2011.08.049

Ambec, S. and Crampes, C. (2012). Electricity Provision with Intermittent Sources of Energy. *Resource and Energy Economics, 34,* 319-336. doi: 10.1016/j.reseneeco.2012.01.001

Anderson, G. (2014, July 16). Ukiah biofuel company to close. The Press Democrat. Retrieved from http:// http://www.pressdemocrat.com/

Babcock, B. (2011). *The Impact of US Biofuel Policies on Agricultural Price Levels and Volatility.* Retrieved from http://www.ictsd.org/downloads/2011/12/the-impact-of-us-biofuel-policies-on-agricultural-price-levels-and-volatility.pdf

Badcock, J., and Lenzen, M. (2010). Subsidies for electricity-generating technologies: A review. *Energy Policy, 38,* 5038-5047. doi:10.1016/j.enpol.2010.04.031

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal Econometrics, 31,* 307-327. Retrieved from http://www.journals.elsevier.com/journal-of-econometrics/

Bollerslev, T., & Wooldridge, J. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Rev, 11*, 143-172. Retrieved from http://www.tandfonline.com/loi/lecr20#.VHp_5OOSy54

Buguk, C., Hudson, D., & Hanson, T. (2003). Price Volatility Spillover in Agricultural Markets: An Examination of U.S. Catfish Markets. *Journal of Agrilcultural and Resource Economics,* 28, 86-99. Retrieved from http://www.waeaonline.org/publications/jare

Burns, J. and Kang, J. (2012). Comparative Economic Analysis of Supporting Policies for Residential Solar PV in the United States: Solar Renewable Energy Credit (SREC) Potential. *Energy Policy, 44*, 217-225. doi:10.1016/j.enpol.2012.01.045

CARD. (2014). Historical Biodiesel Operating Margins. Retrieved October 27, 2014, from http://www.card.iastate.edu/research/bio/tools/hist_bio_gm.aspx

Chen, A. (2013). Installed Price of Solar Photovoltaic Systems in the U.S. Continues to Decline at a Rapid Pace. Retrieved June 16, 2014, from http://newscenter.lbl.gov/2013/08/12/installed-price-of-solar-photovoltaic-systems-in-the-u-s-continues-to-decline-at-a-rapid-pace/

Cucchiella, F., and D'Adamo, I. (2012). Estimation of the energetic and environmental impacts of a roof-mounted building-integrated photovoltaic systems. Renewable and Sustainable Energy Reviews, 16, 5245-5259. doi:10.1016/j.rser.2012.04.034

de Gorter, H., Drabik, D., & Just, D.R. (2011). The economics of a blender’s tax credit versus a tax exemption: The case of US “splash and dash” biodiesel exports to the European Union. *Applied Economic Perspectives and Policy, 33*(4), 510-527. Retrieved from http://aepp.oxfordjournals.org/

de Gorter, H., Drabik, D., & Just, D.R. (2013). Biofuel Policies and Food Grain Commodity Prices 2006-2012: All Boom and No Bust? *AgBioForum*, *16*(1): 1-13. Retrieved from http://www.agbioforum.org/

del Rio, P. (2014). On Evaluating Success in Complex Policy Mixes: The Case of Renewable Energy Support Schemes. *Policy Sciences, 47*(3), 267-287. doi: 10.1007/s11077-013-9189-7

DSIRE. (2012). Residential Renewable Energy Tax Credit. Retrieved April 16, 2014, from http://www.dsireusa.org/library/includes/incentive2.cfm?Incentive_Code=US37F&State=federal%C2%A4tpageid=1&ee=1&re=1

Du, X., & McPhail, L. L. (2012). Inside the Black Box: the Price Linkage and Transmission between Energy and Agricultural Markets. *Energy Journal*, *33*(2), 171-194. Retrieved from http://www.iaee.org/en/publications/journal.aspx

Du, X., Yu, C. L., & Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics*, *33*, 497-503. doi:10.1016/j.eneco.2010.12.015

Dixit, A. K., & Pindyck, R. S. (1994). Investment under uncertainty. Princeton, N.J: Princeton University Press.

EBB. (2014). EBB Official Press Release. Retrieved October 18, 2014, from http://www.ebb-eu.org/EBBpress.php

EIA. (2007). Federal Financial Interventions and Subsidies in Energy Markets 2007. Retrieved June 16, 2014, from http://www.eia.gov/oiaf/servicerpt/subsidy2/

EIA. (2010). Direct Federal Financial Interventions and Subsidies in Energy in Fiscal Year 2010. Retrieved from http://www.eia.gov/analysis/requests/subsidy/pdf/subsidy.pdf

EIA. (2012). Energy Consumption by Sector. Retrieved from http://www.eia.gov/totalenergy/data/monthly/pdf/sec2_3.pdf

EIA. (2013a). Feed-in tariff: A policy tool encouraging deployment of renewable electricity technologies. Retrieved June 16, 2014, from http://www.eia.gov/todayinenergy/detail.cfm?id=11471

EIA. (2013b). *Monthly Biodiesel Production Report*. Retrieved from http://www.eia.gov/biofuels/biodiesel/production/biodiesel.pdf

EIA. (2014a). Electricity Power Monthly. Retrieved September 22, 2014, from http://www.eia.gov/electricity/monthly/

EIA. (2014b). Residential Sector Energy Consumption. Retrieved from http://www.eia.gov/totalenergy/data/monthly/pdf/sec2_5.pdf

EIA. (2014c). What is U.S. electricity generation by energy source? Retrieved April 16, 2014, from http://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3

EIA. (2014d). Cushing, OK WTI Spot Price FOB. Retrieved October 27, 2014, from http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RWTC&f=D

EIA. (2014e). New York Harbor Ultra-Low Sulfur No 2 Diesel Spot Price. Retrieved October 27, 2014, from http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EER_EPD2DXL0_PF4_Y35NY_DPG&f=D

Elliott, J., & Fullerton, D. (2014). Can a unilateral carbon tax reduce emissions elsewhere? Resource and Energy Economics, 36, 6-21. doi:10.1016/j.reseneeco.2013.11.003

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business &*

Economic Statistics, *20*, 339-350. Retrieved from http://amstat.tandfonline.com/loi/jbes#.VHp4nOOSy54

EPA. (2010). *Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis.* Retrieved from http://www3.epa.gov/otaq/renewablefuels/420r10006.pdf

EPA. (2013). *EPA Proposed 2014 Renewable Fuel Standard, 2015 Biomass-Based Diesel Volume*. Retrieved from http://www.epa.gov/otaq/fuels/renewablefuels/documents/420f13048.pdf

EPA. (2014). Renewable Fuel Standard (RFS). Retrieved October 18, 2014, from http://www.epa.gov/otaq/fuels/renewablefuels/

EPA. (2015). EPA Proposed Renewable Fuel Standards for 2014, 2015, and 2016, and the Biomass-Based Diesel Volume for 2017. Retrieved from http://www.epa.gov/otaq/fuels/renewablefuels/documents/420f15028.pdf

ESMAP. (2006). Potential for Biofuels for Transport in Developing Countries. Retrieved February 12, 2015 from https://openknowledge.worldbank.org/bitstream/handle/10986/17958/374860KE40Biof1also0ESM31201PUBLIC1.pdf?sequence=1

Eurelectric. (2004). A Quantitative Assessment of Direct Support Schemes for Renewables. Retrieved from http://gasunie.eldoc.ub.rug.nl/FILES/root/2004/2913948/2913948.pdf

Fera, M., Iannone, R., Macchiaroli, R., Miranda, S., & Schiraldi, M. M. (2014). Project Appraisal for Small and Medium Size Wind Energy Installation: The Italian Wind Energy Policy Effects. *Energy Policy, 74,* 621-631. doi: 10.1016/j.enpol.2014.07.012

FRED. (2015). Effective Federal Funds Rate. Retrieved March 12, 2015 from http://research.stlouisfed.org/fred2/series/FEDFUNDS#

Fthenakis, V., and Kim, H. (2010). Life Cycle Assessment of Amonix 7700 HCPV Systems. *AIP Conference Proceedings, 1277*, 260-263. doi:10.1063/1.3509206

Fthenakis, V. (2013). The resilience of PV during natural disasters: The Hurricane Sandy case. 2013 IEEE 39Th Photovoltaic Specialists Conference (PVSC), 2364. doi:10.1109/PVSC.2013.6744949

Fuss, S., Szolgayova, J., Obersteiner, M., & Gusti, M. (2008). Investment under market and climate policy uncertainty. *Applied Energy*, *85*, 708-721. doi:10.1016/j.apenergy.2008.01.005

Gardebroek, C., & Hernandez, M. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics, 40*, 119-129. doi: 10.1016/j.eneco.2013.06.013

Gilbert, C.L. and Mugera, H.K. (2014) Food Commodity Prices Volatility: The Role of Biofuels. *Natural Resources*, *5*, 200-212. doi: 10.4236/nr.2014.55019

Goldberg, M. (2000). Federal energy subsidies: not all technologies are created equal. Retrieved from http://www.earthtrack.net/files/repp-subsidies.pdf

Gunther, M. (2013, September 3). With Rooftop Solar on Rise, U.S. Utilities Are Striking Back. Yale Environment 360. Retrieved from http://e360.yale.edu/

Hamao, Y., Masulis, R.W., & Ng, V. (1990). Correlations in Price Changes and Volatility across International Stock Markets. *The Review of Financial Studies*, 3, 281-307. Retrieved from http://rfs.oxfordjournals.org/

Handley, K., & Limao, N. (2012). Trade and Investment under Policy Uncertainty: Theory and Firm Evidence. Retrieved from http://web.stanford.edu/group/SITE/archive/SITE_2010/segment_4/segment_4_papers/limao.pdf

Hassouneh, I., Serra, T., Goodwin, B. K., & Gil, J. M. (2012). Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships. *Energy Economics, 34*(5), 1507-1513. doi:10.1016/j.eneco.2012.06.027

Hassett, K.A., & Metcalf, G.E. (1999). Investment with Uncertain Tax Policy: Does random Tax Policy Discourage Investment? *The Economic Journal, 109*: 372-393. Retrieved from http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1468-0297

Hemplings, S., Elefant, C., Cory, K., and Porter, K. (2010). Renewable Energy Prices in State-Level Feed-in Tariffs: Federal Law Constraints and Possible Solutions. doi:10.2172/971096

Hoffman, W. (2006). PV solar electricity industry: market growth and perspective. *Solar Energy Materials and Solar Cells, 90*, 3285-3311. doi:10.1016/j.solmat.2005.09.022

Hofstrand, D., & Johanns, A. (2015). Tracking the profitability of biodiesel production. Retrieved March 12, 2015 from http://www.agmrc.org/renewable_energy/biodiesel/tracking-the-profitability-of-biodiesel-production/

IEA. (2012). CO2 Emissions from Fuel Combustion Highlights. Retrieved from http://www.iea.org/co2highlights/co2highlights.pdf

IEA. (2014). Solar (PV and CSP). Retrieved June 16, 2014, from http://www.iea.org/topics/solarpvandcsp/

IRENA. (2014). The Socio-economic Benefits of Solar and Wind Energy. Retrieved from http://www.irena.org/DocumentDownloads/Publications/Socioeconomic_benefits_solar_wind.pdf

Johnson, E. (2010). The Price Elasticity of Supply of Renewable Electricity Generation: Evidence from State Renewable Portfolio. Retrieved from https://smartech.gatech.edu/bitstream/handle/1853/44246/WP2011-001EJohnson.pdf?sequence=1

Johnson, E. (2014). The cost of carbon dioxide abatement from state renewable portfolio standards. *Resource and Energy Economics, 36*, 332-350. doi:10.1016/j.reseneeco.2014.01.001

Johnson, K. (2013, September 22). Six Myths about Renewable Energy. The Wall Street Journal. Retrieved from http://online.wsj.com/home-page

Kalkuhl, M., Edenbofer, O., and Lessmann, K. (2013). Renewable energy subsidies: Second-best policy or fatal aberration for mitigation? *Resource and Energy Economics, 35*, 217-234. doi:10.1016/j.reseneeco.2013.01.002

Laurikka, H. (2006). Option value of gasification technology within an emissions trading scheme. *Energy Policy, 34,* 3916-3928. doi:10.1016/j.enpol.2005.09.002

Let the sun shine: The future is bright for solar power, even as subsidies are withdrawn. (2014, March 8). The Economist. Retrieved from http://www.economist.com/

Lin, T. T., & Huang, S. (2010). An entry and exit model on the energy-saving investment strategy with real options. *Energy Policy, 38*(2), 794-802. doi:10.1016/j.enpol.2009.10.024

Lin, T. T., & Huang, S. (2011). Application of the modified Tobin's q to an uncertain energy-saving project with the real options concept. *Energy Policy, 39*(1), 408-420. doi:10.1016/j.enpol.2010.10.018

Linnerud, K., Andersson, A. M., & Fleten, S. (2014). Investment timing under uncertain renewable energy policy: An empirical study of small hydropower projects. *Energy, 78*,154-164. doi:10.1016/j.energy.2014.09.081

Mahnovski, S. (2006). Robust decisions and deep uncertainty. Pardee RAND Graduate School. California. Retrieved from http://www.rand.org/content/dam/rand/pubs/rgs_dissertations/2007/RAND_RGSD210.pdf

Mauer, D. C., & Ott, S. H. (1995). Investment under Uncertainty: The Case of Replacement Investment Decisions. *Journal of Financial & Quantitative Analysis, 30*(4), 581-605.

Maung, T.A., & Gustafson, C.R. (2011). The economic feasibility of sugar beet biofuel production in central North Dakota. *Biomass and Bioenergy, 35*, 3737-3747. doi:10.1016/j.biombioe.2011.05.022

McPhail, L. L. (2011). Assessing the impact of US ethanol on fossil fuel markets: A structural VAR approach. *Energy Economics, 33*(6), 1177-1185. doi:10.1016/j.eneco.2011.04.012

Muller, N. Z., Mendelsohn, R., and Nordhaus, W. (2011). Environmental Accounting for Pollution in the United States Economy. *American Economic Review, 101*, 1649-1675. doi:10.1257/aer.101.5.1649

Myers, T. (2013, September 23). Stop subsidizing solar power. The Wall Street Journal. Retrieved from http://online.wsj.com/home-page

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics, 36*, 658-665. doi:10.1016/j.eneco.2012.11.009

Nelson, D.B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59*(2), 347-370. Retrieved from http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1468-0262

NREL. (2012). Solar Maps. Retrieved June 16, 2014, from http://www.nrel.gov/gis/solar.html

NREL. (n.d.) PV Watts. Retrieved June 16, 2014, from http://rredc.nrel.gov/solar/calculators/pvwatts/version1/derate.cgi

Olivia, H., S., MacGill, I., and Passey, R. (2014). Estimating the net societal value of distributed household PV systems. *Solar Energy, 100*, 9-22. doi:10.1016/j.solener.2013.11.027

Parry, I. H., and Small, K. A. (2005). Does Britain or the United States Have the Right Gasoline Tax? *American Economic Review, 95*, 1276-1289. doi: 10.1257/0002828054825510

Perez, R., Zweibel, K. and Hoff, T.E. (2011). Solar Power Generation in the US: Too expensive, or a Bargain? *Energy Policy, 39*, 7290-7297. doi: 10.1016/j.enpol.2011.08.052

Pindyck, R.S. (1999). The Long-Run Evolution of Energy Prices. *Energy Journal*, 1-27.

Pindyck, R. S. (2002). Optimal timing problems in environmental economics. *Journal of Economic Dynamics and Control*, *26*, 1677-1697. doi:10.1016/S0165-1889(01)00090-2

Poyago-Theotoky, J., & Teerasuwannajak, K. (2002). The Timing of Environmental Policy: A Note on the Role of Product Differentiation. *Journal of Regulatory Economics, 21*(3), 305-316.

RAP. (2011). Electricity Regulation in the U.S.: A Guide. Retrieved from http://www.raponline.org/document/download/id/645

Rapier, R. (2014, August 29). U.S. Dominates Globe in Biofuel Production. *Financial Sense*. Retrieved from http:// http://www.financialsense.com/

REN21. (2013). Renewables 2013 Global Status Report. Retrieved from http://www.ren21.net/portals/0/documents/resources/gsr/2013/gsr2013_lowres.pdf

Rivers, N. (2013). Renewable Energy and Unemployment: A General Equilibrium Analysis. *Resource and Energy Economics, 35*, 467-485. doi: 10.1016/j.reseneeco.2013.04.004

Rodrik, D. (1991). Policy uncertainty and private investment in developing countries. *Journal of Development Economics, 36*(2), 229.

Rose. (2012, January 14). What Affects the Price of Solar Panels? [Blog post]. Retrieved from http://www.thesolarco.com/what-affects-the-price-of-solar-panels/

Saghaian, S. H. (2010). The Impact of the Oil Sector on Commodity Prices: Correlation or Causation? *Journal of Agricultural And Applied Economics, 42*(3), 477-485. Retrieved from http://www.saea.org/currentback-issues-indexes/

Schnepf, R., & Yacobucci, B. (2013). *Renewable Fuel Standard (RFS): Overview and Issues.* Retrieved from http://fas.org/sgp/crs/misc/R40155.pdf

Schulz, F. (2012). *Volatility linkages between German biofuel prices and agricultural commodity prices.* Retrieved from http://edoc.hu-berlin.de/master/schulz-franziska-2012-10-29/PDF/schulz.pdf

SEIA. (2011-2013). U.S. Solar Market Insight. Retrieved June 17, 2014, from http://www.seia.org/research-resources/us-solar-market-insight

SEIA. (2014a). Photovoltaic (Solar Electric). Retrieved January 3, 2016, from http://www.seia.org/research-resources/us-solar-market-insight

SEIA. (2014b). U.S. Residential Solar PV Installations Exceeded Commercial Installations for the First Time in Q1 2014. Retrieved January 3, 2016, from http://www.seia.org/news/us-residential-solar-pv-installations-exceeded-commercial-installations-first-time-q1-2014

SEIA. (n.d.). Solar Photovoltaic Technology. Retrieved April 16, 2014, from http://www.seia.org/research-resources/solar-photovoltaic-technology

Sener, C., and Fthenakis, V. (2014). Energy policy and financing options to achieve solar energy grid penetration targets: Accounting for external costs. Renewable and Sustainable Energy Reviews, 32, 854-868. doi:10.1016/j.rser.2014.01.030

Serra, T. (2013). Time-Series econometric analyses of biofuel-related price volatility. *Agricultural Economics, 44*, 53-62. doi:10.1111/agec.12050

Serra, T., Zilberman, D., & Gil, J. (2011a). Price volatility in ethanol markets. *European Review of Agricultural Economics*, *38*(2), 259-280. Retrieved from http://erae.oxfordjournals.org/

Serra, T., Zilberman, D., Gil, J. M., & Goodwin, B. K. (2011b). Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. *Agricultural Economics*, *42*(1), 35-45. doi:10.1111/j.1574-0862.2010.00464.x

Stein E.W. (2013). A comprehensive multi-criteria model to rank electric energy production technologies. Renewable and Sustainable Energy Reviews, 22, 640-654. doi: 10.1016/j.rser.2013.02.001

Taheripour, F., & Tyner, W. E. (2008). Ethanol Policy Analysis--What Have We Learned So Far?. *Choices*, *23*(3), 6-11. Retrieved from http://www.choicesmagazine.org

The energy subsidy tally. (2012, August 17). The Wall Street Journal. Retrieved from http://online.wsj.com/home-page

Timilsina, G. R., Kurdgelashvili, L., and Narbel, P. A. (2012). Solar energy: Markets, economics and policies. *Renewable and Sustainable Energy Reviews, 16*, 449-465. doi:10.1016/j.rser.2011.08.009

Trujillo-Barrera, A., Mallory, M., & Garcia, P. (2012). Volatility Spillovers in U.S. Crude Oil, Ethanol, and Corn Futures Markets. *Journal of Agricultural and Resource Economics, 37*, 247-262. Retrieved from http://www.waeaonline.org/publications/jare

U.S. Census Bureau. (2013). Household Income 2012. Retrieved from http://www.census.gov/prod/2013pubs/acsbr12-02.pdf

U.S. Department of Agriculture. (2013). Oil Crops Yearbook, USDA, Economic Research Service, 2013. Retrieved November 20, 2014, from http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1290

U.S. Department of Agriculture. (2014a). Soybean Program. Retrieved October 20, 2014, from http://www.ams.usda.gov/AMSv1.0/ams.fetchTemplateData.do?template=TemplateA&navID=SoybeanProgram&rightNav1=SoybeanProgram&topNav=&leftNav=IndustryMarketingandPromotion&page=SoybeanPage&resultType=&acct=lspromores

U.S. Department of Agriculture. (2014b). U.S. Bioenergy Statistics. Retrieved October 20, 2014, from http://www.ers.usda.gov/data-products/us-bioenergy-statistics.aspx#.VEWbQfnF98E

U.S. Department of Energy. (2013). White House Council of Economic Advisors and Energy Department Release New Report on Resiliency of Electric Grid During Natural

Disasters. Retrieved June 17, 2014, from http://energy.gov/articles/white-house-council-economic-advisers-and-energy-department-release-new-report-resiliency

U.S. Department of Energy. (2014). Renewable Fuel Standard. Retrieved October 18, 2014, from http://www.afdc.energy.gov/laws/RFS

U.S. Department of Energy. (n.d.). Residential Energy Efficiency Tax Credit. Retrieved October 18, 2014, from http://energy.gov/savings/residential-energy-efficiency-tax-credit

U.S. Department of Labor. (2014). Producer Price Index-Commodities. Retrieved October 27, 2014, from http://data.bls.gov/timeseries/WPSSOP1000?output_view=pct_1mth

U.S. Senate Committee on Finance. (2014). Provisions in the Chairman’s Mark: Expiring Provisions Improvement Reform and Efficiency (EXPIRE) Act. Retrieved October 18, 2014, from http://www.finance.senate.gov/legislation/details/?id=67094f10-5056-a032-52ff-257830e0a938

Vedenov, D., and Wetzstein, M. (2008). Toward an optimal U.S. ethanol fuel subsidy. *Energy Economics, 30*, 2073-2090. doi:10.1016/j.eneco.2007.02.004

Wang, U. (2012, June 27). Report: Solar Panel Supply Will Far Exceed Demand Beyond 2012. Forbes. Retrieved from http://www.forbes.com/

Wang, X., Cai, Y., & Dai, C. (2014). Evaluating China's biomass power production investment based on a policy benefit real options model. *Energy, 73*, 751-761. doi:10.1016/j.energy.2014.06.080

Wei, M., Patadia, S., and Kammen, D. M. (2010). Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? *Energy Policy, 38*, 919-931. doi:10.1016/j.enpol.2009.10.044

Welsch, H., and Biermann, P. (2014). Electricity supply preferences in Europe: Evidence from subjective well-being data. *Resource and Energy Economics, 38*, 38-60. doi: 10.1016/j.reseneeco.2014.05.003

World Economic Forum. (2012). Energy for Economic Growth Energy Vision Update 2012.Retrieved from http://www3.weforum.org/docs/WEF_EN_EnergyEconomicGrowth_IndustryAgenda_2012.pdf

Worstall, T. (2013, September 30). It's Excellent That Renewable Energy Doesn't Create Many Green Jobs For Jobs Are A Cost Not A Benefit. Forbes. Retrieved from http://www.forbes.com/

Wu, F., Guan, Z., & Myers, R. J. (2011). Volatility Spillover Effects and Cross Hedging in Corn and Crude oil futures. *Journal of Futures Markets, 31*(11), 1052-1075. doi:10.1002/fut.20499

Wu, H., Colson, G., Escalante, C., & Wetzstein, M. (2012). An optimal U.S. biodiesel fuel subsidy. *Energy Policy, 48*, 601-610. doi:10.1016/j.enpol.2012.05.063

Wu, H. & Li, S. (2013). Volatility spillovers in China's crude oil, corn and fuel ethanol markets. *Energy Policy*, *62*, 878-886. doi: 10.1016/j.enpol.2013.07.026

Xian, H., Colson, G., Mei, B., & Wetzstein, M. (2015) “Co-Firing coal with wood pellets for U.S. electricity generation: A real options analysis,” *Energy Policy, 81*, 106-116.

Yacobucci, B. (2012). Biofuels Incentives: A Summary of Federal Programs. Retrieved from http://fas.org/sgp/crs/misc/R40110.pdf

Yang, M., Blyth, W., Bradley, R., Bunn, D., Clarke, C., and Wilson, T. (2008). Evaluating the power investment options with uncertainty in climate policy. *Energy Economics*, *30*, 1933-1950. doi:10.1016/j.eneco.2007.06.004

Yi, H., and Feiock, R. C. (2014). Renewable Energy Politics: Policy Typologies, Policy Tools, and State Deployment of Renewables. *Policy Studies Journal*, *42*(3), 391-415. doi:10.1111/psj.12066

Zhang, Z., Lohr, L., Escalante, C., and Wetzstein, M. (2009). Ethanol, corn, and soybean price relations in a volatile vehicle-fuels market. *Energies*, *2*, 320-339. doi:10.3390/en20200320