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Interdependencies Between Energy, the Environment, and Stakeholder Choices

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INTERDEPENDENCIES BETWEEN ENERGY, THE ENVIRONMENT, AND STAKEHOLDER CHOICES

by

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DISSERTATION

Submitted in Partial Fulfillment of the
Requirements for the Degree of

**Doctor of Philosophy
Economics**

The University of New Mexico
Albuquerque, New Mexico

July 2019

DEDICATION

My loving parents

AND

Suborna and the little monster, Scion

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ABSTRACT

This dissertation contributes to the field of energy economics by expanding the knowledge of energy stakeholders' decisions amid the interdependence of energy and environmental policies. I analyze three specific energy development decisions from multiple stakeholders' perspectives. Chapter 2 introduces a broader state-level policymakers' decision on renewable portfolio standards (RPS). The renewable portfolio standards is a state-mandated obligation that requires electric load-serving entities to distribute a certain percentage of electricity generated from renewable sources. I investigate the public preferences of RPS for residents in New Mexico in 2017. I find that households are willing to pay for an increase in RPS requirements. Pro-ecological and pro-environmental households tended to prefer an increase in the RPS requirement. Households in oil- and gas-rich areas tended to have lower marginal willingness to pay (MWTP) for share of renewable electricity and households in areas with extensive renewable power plants in place have higher MWTP for share of renewable electricity.

This study will help policymakers to make an informed decision when updating the RPS policy.

Chapter 3 analyzes the decision of an oil and gas well manager in the presence of an externality. The increased use of natural gas in the United States can be attributed, in part to technical development in extraction and exploration technology, which resulted in lower prices for natural gas. This makes natural gas more competitive with coal for electricity generation. There is, however, a growing literature concerning the negative externalities of natural gas production. This chapter modeled the joint production of natural gas and oil in the presence of externalities. The model shows that gross production is lower in the presence of externalities. The price and discount rate sensitivity analysis shows that the firm's Net Present Value will be higher with a higher price and lower discount rate.

Chapter 4 investigates how the decision on improved supply chain reduces the risk for cellulosic biorefinery. Variability in feedstock characteristics, feedstock supply, and selling prices are major sources of risk facing a cellulosic biorefinery. I evaluate supply-, operational- and market-risk reduction opportunities if a biorefinery adapts a supply chain design based on a distributed depot concept. In contrast to the conventional feedstock-supply system, a supply-chain design based on a network of depots providing feedstock to a biorefinery employs geographically distributed depots where the feedstock is preprocessed into densified pellets, allowing feedstock to be transported a greater distance. Results show that combining the effects of contract management and feedstock supply configuration create alternative market opportunities, which can lead to a reduction of supply, operational, and market risk, thus improving the role of cellulosic

biofuels in sustainable production. The positive return on investment for a cellulosic

biorefinery largely depends on commoditization and creation of intermediate markets for

alternative merchandisable products.

The dissertation provides information and implications of stakeholders' decision

in the light of energy and environmental policies aimed to achieve energy security and

sustainability.

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The Interdependence of Energy and Environmental Policy

▉▉ Introduction

There is a direct long-term relationship between energy consumption and emissions (Soytas, Sari, & Ewing, 2007). Energy production and use is the largest source of greenhouse gas emissions in many economies. For example, the energy sector contributed 84% of total greenhouse gas emissions in 2017 in the United States (U.S. Energy Information Administration, 2019b). Energy stakeholders are concerned about sustainable energy production and use because the energy sector is responsible for a major share of greenhouse gas emissions. A balanced 'energy triangle' that ensures energy access and security, environmental sustainability, and economic development must be adopted to tackle energy-related crises during a transitionary energy development period. In this sense, the dual objective of energy policy is to provide energy access and security and to meet environmental sustainability.

Energy and environmental policies play an important role in shaping energy markets. Many policies within the 'Energy Independence and Security Act of 2007'

address energy security that has a high impact on environmental quality. For reference, Title II, section A of the EISA, 2007 is dedicated to the renewable fuel standard policy. This policy aims to strengthen US energy independence and competitiveness by developing renewable energy. The development of renewable energy in turn, can contribute to environmental quality improvements, such as clean air and clean water. At the same time, environmental policies such as the Clean Air Act of 1963, the Clean Water Act of 1972, and the Oil Pollution Act of 1990 provide guidelines how clean air and water can be achieved through careful implementation of energy development programs. Thus, energy and environmental policies are intertwined. Stakeholders at different levels have to make decisions considering this interdependence of policy domain.

This dissertation investigates the formulation and outcome of three energy development and policy form stakeholders' perspectives. Table 1-1 lists relevant policy, stakeholders, and chapter contributions. Chapter 2 investigates households' preferences towards renewable portfolio standards, a state level energy policy. Renewable portfolio standards policy requires electric load bearing companies to distribute a certain percentage of electricity generated from renewable sources. In this chapter, I adopt a consumer-centric non-market valuation approach that asks three central questions: (1) Do consumers want an increase in mandatory renewable share? The answer of this question can help policymaker to take a decision on mandating appropriate share of renewable electricity; (2) Are consumers willing to pay for renewable electricity given that the cost of renewable electricity is higher than that of conventional electricity? The result can set a benchmark for policymaker in formulating cost threshold of renewable electricity; (3)

Are there any heterogeneity of preferences for renewable electricity? The utility companies can benefit from using information about spatial and taste heterogeneity of consumers. Chapter 3 explores the production decision of an oil and gas well manager in the presence of externalities. On a broader scale, the results can help oil and gas field leasing agencies to formulate leasing and extraction policy. Chapter 4 examines risk reduction opportunities of cellulosic biorefinery. The Renewable Fuel Standards policy encourages development of cellulosic biofuels. The U.S. Department of Energy (2016) estimated abundance of biomass in the United States. Yet, the cellulosic biofuel industry is lagging to reach the production target partly due to the inability to match the risk and return of cellulosic biorefinery. Contract management and distributed depot-based feedstock supply chain design has the potential to mitigate risk and to provide higher returns. The results can promote cellulosic biorefinery industry by attracting investors and financiers.

Table 1-1: Relevant Policy, stakeholders and contribution of each chapter of this dissertation

Chapter	Relevant policy	Stakeholder/decision maker	Contributions
Chapter 2	Renewable Portfolio Standards (Example, Renewable Energy Act, 62-16-1, New Mexico)	• State legislators • Utility companies	• First discrete choice experiment in RPS • Explain sources of heterogeneity
Chapter 3	Protect Public Welfare Oil and Gas Operations (Example, SB19-181, Colorado)	• Regulatory bodies • Well managers	Modeled oil and gas extraction: • Joint production • Externalities • Raw and final product
Chapter 4	Renewable Fuel Standards (Title II, subtitle A of the Energy Independence and Security Act of 2007)	• Investors and financiers • Biorefinery managers	• Identify risk reduction opportunities in a cellulosic biorefinery. • Quantify supply-, operational- and market risk.

This dissertation contributes to the energy economics literature by extending the knowledge of stakeholders' decision mechanism amid interdependence of energy and environmental policies. Chapter 2 is one of the few studies that employed a discrete choice experiment of mandatory renewable portfolio standards policy to obtain household preferences. In Chapter 3, I extend the literature by modeling the joint production of oil and gas considering externalities. Chapter 4 is the first study that identifies how managers decision on farmers contract and distributed supply chain management can provide operational- and market risk reduction opportunities.

The rest of Chapter 1 is organized as follows: Sections 1.2-1.4 provide a summary of the research in each chapter with motivation, methods, results, and contribution.

■ Renewable Portfolio Standards

The share of electricity generation from renewable sources is increasing over time. In 2017, renewable electricity generation was 18% of the total and was projected to increase to 40% in 2050 (Blomberg New Energy Finance, 2018). The annual projected growth is 2.1% (U.S. Energy Information Administration, 2018a). Two main driving forces behind this growth are renewable portfolio standards (RPS) and renewable tax credits (Barbose, 2017). Investors and operators in renewable electricity receive an investment tax credit when they invest and a production tax credit when they produce renewable electricity. The tax policies are aimed to encourage investors and producers towards renewable electricity. On the other hand, RPS is a state-level mandated policy enforced to electric load-serving entities. An RPS requires electric load-serving utilities to distribute a minimum portion of electricity from renewable sources. As of April 2019, 29 states and District of Columbia have mandated RPS. The combined results of the RPS

policy is to distribute 56% of total US retail electricity sales from renewable energy (Barbose, 2017). Most of the States have a percentage-based requirement, but some of them have a lump-sum amount. Three states adopted 100% clean energy requirements by 2045.

Many states are planning to update on their RPS policies as the target time of the policy is approaching. Some states proposed an increase in RPS requirement while some other proposed to decrease, repeal, or freeze existing RPS policies (Barbose et al., 2016). The social welfare of the policy can be a good measure for a policymaker to take an informed decision. The social welfare can be measured through social cost-benefit studies or mapping the public preferences towards the policy in question. The literature concentrates on conducting cost-benefit analyses.

RPS compliance may increase retail electricity prices as the cost of renewable electricity is higher than that of conventional sources according to Lazard's levelized cost of electricity. There can be a 3% to 11% increase in retail prices of electricity (Greenstone & Nath, 2019; Morey & Kirsch, 2013; Tra, 2016; Upton Jr & Snyder, 2017; H. Wang, 2016). The potential benefits of RPS policies are carbon emission reduction (Barbose et al., 2016; Greenstone & Nath, 2019; Heeter et al., 2014; J. X. Johnson & Novacheck, 2015), air quality improvement (Barbose et al., 2016), water withdrawal reduction (Barbose et al., 2016), and job creation (Barbose et al., 2016). The cost-benefit studies provide mixed results. A major part of cost-benefit studies suggests that RPS policies generate net social benefit. Recently, Upton Jr and Snyder (2017) has not found a significant benefit of RPS policies in terms of CO_2 abatement. The RPS policies does not provide net social benefit if the secondary effect to the economy through higher

electricity prices is considered (Considine, 2016). In addition to mixed results, cost-benefit studies generate several complexities: (1) comparability of states that mandated RPS policies with states that have not mandated RPS policies might not meet ceteris paribus condition (Upton Jr & Snyder, 2017); (2) cost-benefit studies are comparing direct cost (such as purchasing renewable energy contracts (REC)) with indirect benefits (in terms of environmental benefits); (3) RPS policies are not likely the most cost effective to get the intended environmental and economic benefits (Bird, Chapman, Logan, Sumner, & Short, 2011; Fischer & Newell, 2008; E. P. Johnson, 2014; Palmer & Burtraw, 2005; Rausch & Mowers, 2014; Wiser et al., 2017). In this backdrop, public preferences and underlying sources of preference heterogeneity can be used to facilitate communication among stakeholders. In this chapter, I have presented the results of a discrete choice experiment (DCE) to analyze the public preference towards RPS.

I have conducted a DCE in New Mexico, where the legislators proposed a bill in the New Mexico Senate to increase the RPS requirements. I have used a set of econometric models, including flexible generalized multinomial logistic (GMNL), proposed by Fiebig, Keane, Louviere, & Wasi (2010) to account for individual and scale heterogeneity in preferences. Along with advanced DCE method, I have also used attribute non-attendance (ANA) and incorporated stated attribute importance ranking (AIR) data to tackle reliability and validity aspect of the DCE method. I constructed a latent class model (LCM) for better interpretations and communication of the results to stakeholders. It might be the case that there are some geographic pockets where the preferences of household are significantly different from the rest. I have employed

Hotspot analysis to estimate the presence of any geographic pockets of heterogeneity and relate those to underlying geographic and demographic characteristics of households.

Results show that the mixed logit model is consistent and best-fit to the data. Incorporation of attribute non-attendance and importance ranking information increases the precision of the models. The result of the survey shows that New Mexico residents prefer an average of 36.15% by 2040 when asked about the preferred level of RPS. This result can be a benchmark for policymaker when considering an update to RPS in New Mexico. Households are willing to pay $3.1/household monthly for a 10% increase in RPS requirement, which translates to a 4.23% increase in retail prices of electricity. The willingness to pay estimate is within the boundary of previous cost estimates for mandatory RPS implementation studies. This result can help the New Mexico Public Regulatory Commission to set up important policies related to the cost of renewables. Households are willing to pay for an increase in employment and a decrease in water usage by electricity generation. Policymakers can consider renewable technologies that have a higher impact on employment and lower water usage. Household also has disutility associated with nuclear electricity generation as nuclear electricity in New Mexico is exported from another state and household has a concern regarding nuclear waste disposal. The results show considerable taste and geospatial heterogeneity of preferences. Pro-ecological, pro-environmental, and younger respondents show favorable preferences for an increase in RPS.

This chapter contributes to energy literature by applying discrete choice experiment on mandatory renewable energy policy for the first time. This study also extends the existing literature by using attribute non-attendance and attribute importance

ranking information to examine public preferences of RPS. This chapter can guide

policymakers in deciding the optimal level of renewable shares in total electricity

generation, cost threshold of renewable electricity.

■ Oil and Gas Extraction

Hydraulic fracturing and horizontal drilling is a reason for increasing production

of natural gas (Gregory, Vidic, & Dzombak, 2011). The U.S. Energy Information

Administration (2019c) estimates that nearly 57% of the U.S. natural gas production can

be attributed to shale fracturing. Global natural gas use will grow to become the second

largest fuel by 2040 worldwide (International Energy Agency, 2014). The high potential

of natural gas and oil, particularly from shale, in meeting global energy needs caught the

attention of academicians and researchers to find optimal way to use the resources. The

optimal production, transport, and market is key to balancing high demand and supply.

Zheng *et al.* (2010) provide a recent survey on production-, transportation-, and market

optimization models in the natural gas industry. Optimization in upstream (e.g.,

production), midstream (e.g., transportation) and downstream (e.g., processing and

distribution) activities primarily focus on the engineering aspect, often disregarding

economics aspects. For example, Wong and Larson (1968) and Borraz-Sánchez and Ríos-

Mercado (2005) proposed an optimized pipeline network. While some natural gas activity

optimization considers techno-economic assessments, the externality of the process is

rarely internalized.

There is a growing literature focusing on the externalities associated with shale

development. Included are positive externalities such as job creation (Weber, 2012) and

economics boom (Kinnaman, 2011) as well as negative externalities, such as impacts on

water quality (Darrah, Vengosh, Jackson, Warner, & Poreda, 2014; Entrekin, Evans-White, Johnson, & Hagenbuch, 2011; Nicot & Scanlon, 2012), air quality (Litovitz, Curtright, Abramzon, Burger, & Samaras, 2013), health (McKenzie et al., 2015) or wildlife (Bernknopf et al., 2019). Shale development often faces restriction from various stakeholders on the grounds of not considering external impacts. For example, Colorado recently passed a bill (SB19-181) mandating oil and gas companies evaluate health and environmental externalities into production. This chapter develops a model that compares how a well manager takes decision with or without internalizing the externalities into the production cost.

This chapter introduces a theoretical model for joint production of natural gas and oil from shale while considering externalities. I use simplified externality cost by assuming that externalities are additively separable. The goal of a well manager is to maximize profit by controlling extraction while taking externalities into account. As the number of control variable and stock variable does not match, this optimization problem does not have a closed form solution. Assuming functional forms and drawing parameter values from existing literature, I present a numerical simulation.

Results from the model show that gross production decreases over time. Gross production path is lower if I consider external costs. Consideration of joint production reduces the hyperbolic curvature of shale extraction as oil production, which is produced later stage, is more profitable than the natural gas production. The net present value of the firm is sensitive to change in prices of natural gas and oil and discount factor. Findings have implications for well managers and leasing agencies.

Chapter 3 proposes the aspect of incorporating social costs in optimizing natural gas extraction. I summarize positive and negative externalities and stakeholders' perception of shale development. Chapter 3 extends the literature by incorporating externalities, considering the joint production of natural gas and oil from shale, and explicitly modeling the raw and final product.

■■ Risk Management in Biorefinery

Biomass resources can be in sufficient abundance for cellulosic biofuels to be an important, sustainable and environmentally friendly component of the cellulosic industry (U.S. Department of Energy, 2005, 2011, 2016). Moreover, the Renewable Fuels Standard (RFS) capped annual corn grain ethanol at 15 billion gallons. Because corn grain ethanol is at a "blend wall", cellulosic fuels are an important part of renewable fuels strategy in the United States.[1] The RFS gap can be filled with cellulosic biofuels. The annual production of advanced biofuels needs to reach 16 billion gallons by 2022 to fill the gap (Schnepf & Yacobucci, 2010). While a high target set by the policy, the cellulosic biofuel industry could not meet the production target. The annualized production reached 10.05 million gallons in 2017 (U.S. Environmental Protection Agency, 2018), which is much lower compared to the target of 16 billion gallons by 2022. 8 of the 16 facilities registered with the U.S. Environmental Protection Agency is producing commercially as of April 2018, where two of the facilities are permanently idle (Lane, 2017; Schill, 2018; Voegele, 2015).

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[1] Blend wall refers to the upper limit of ethanol that can be blended to the gasoline. For more information about blend wall, read Yacobucci (2010).

Industry deployment hinges on the ability to quantify, mitigate, and manage risk at the biorefinery (Searcy et al., 2015). To date, much of the financial analysis on the cellulosic feedstock supply chain has addressed reducing delivered feedstock cost (Argo et al., 2018; Muth et al., 2014). Decision making at the biorefinery, therefore, lacks full information to accurately assess supply chain designs. This paper addresses two risk mitigation options for biorefinery managers. The biorefinery manager can manage farmers contract aiming to reduces risk. In terms of contract management, the biorefinery manager can use average contracting or over-contracting of feedstock. They also have the option to employ alternative feedstock configuration, distributed depot-based feedstock supply system. This feedstock supply system modifies biomass into densified pellets of feedstock that can potentially be sold in the alternative markets as merchandisable product intermediate.

In this chapter, I employed a risk simulation technique. The sources of variability in cellulosic biorefinery are identified based on current scientific literature. The variability arises from grower participation, characteristics of biomass, biorefinery configuration, and market condition. The underlying parameter data is collected from various government and laboratory sources. The average yield, farm size, and ethanol prices data are collected from the United States Department of Agriculture. The yield is allowed to vary based on drought condition. The drought data is collected from the National Oceanic and Atmospheric Administration. Biomass characteristics and market prices are collected from the Idaho National Laboratory and online sources, respectively. I model the parameter uncertainty by best fitting the data with a series of known distributions. I iterate the model 10,000 times using the software @Risk, published by the

Palisade Corporation. The equations, data, and simulation let me quantify operational and market risk.

I construct eight scenarios based on two decision parameters of the manager of cellulosic biorefinery: contract management and availability of alternative markets. In the first set of results, I add the restriction that there be no MPI market possibilities. In the second set of results, I relax the restriction and extend market possibilities by allowing excess biomass that remains under contract after the supply requirement is met to be sold in alternative MPI markets. Each market opportunity has two possibilities for excess feedstock based on the contracting assumption. Excess biomass can be sold in the animal-feed market and absorbent market. I also simulate the case for selling either of the animal feed market or absorbent market where the greater price obtains. Altogether, we have two scenarios in which the simulation assumes restricted access to alternative MPI markets and six scenarios allowing different alternative MPI-market and contract-management strategies.

The results show that distributed depot-based design along with over contracting reduce supply risk significantly for two reasons. The manager is over contracting feedstock than that is necessary to reduce the probability of supply shortage. The biorefinery can also draw feedstock from a larger distance that makes biorefinery to be operable in resource scares areas. The feedstock supply risk reduction translates into a reduction in operational risk for the biorefinery. The manager can also reduce significant market risk as the densified pellets can be sold in alternative markets. The expected return on investment increases compared to the baseline scenario, thus balancing risk and return, which is essential for sustainable cellulosic biorefinery industry. However, this

scenario is highly dependent on successful creation of merchandisable product

intermediate markets.

This chapter has two primary contributions. It is the first study that identifies

operational- and market-risk reduction opportunities if a biorefinery adopts the supply-

chain design based on a distributed depot. Second, this paper articulates the sources of

risk in a stylized cellulosic biorefinery and potential risk-mitigation techniques available.

The results from this chapter will inform a biorefinery manager on how he/she can

mitigate risk employing contract management and feedstock configuration. This result

will also help investors and financiers to make informed decisions as they seek to invest

in a cellulosic biorefinery, considering risk, potential risk-management strategies, and

expected ROI.

Discrete Choice Experiment on Renewable Portfolio Standards to Map

Household Preferences

Abstract

Renewable portfolio standards (RPS) are state-mandated requirements that require
electric load-serving entities to distribute a certain percentage of electricity generated
from renewable sources. Some states are currently re-evaluating their policies to assess
the appropriateness of the current policy. This paper employs a discrete choice
experiment (DCE) technique to map public preferences for RPS. The DCE was
administered to residents in New Mexico in 2017. Using attribute non-attendance (ANA)
and attribute importance ranking (AIR) increases the precision of the models. Households
are willing to pay $3.1/household monthly for a 10% increase in RPS requirements.
Latent class models show that pro-ecological and pro-environmental households tended
to prefer an increase in RPS requirement. Hotspot analysis shows pockets of homogenous
responses indicating households in oil- and gas-rich areas tended to have lower marginal
willingness to pay (MWTP) for share of renewable electricity and households in areas

with extensive renewable power plants in place have higher MWTP for share of renewable electricity. This study will help policymakers to make an informed decision when updating the RPS policy.

◼ Introduction

The share of electricity generation from renewable sources is increasing over time partly due to the retirement of fossil fuel power plants, especially coal-based power plants. Renewable sources are replacing retiring plants and meeting the increased demand for electricity. Renewable sources contributed 18% of the total US electricity generation in 2017 and with a projected increase to 40% by 2050 (Blomberg New Energy Finance, 2018) or an annual growth of 2.1% (U.S. Energy Information Administration, 2018a). Despite having lower oil prices and the turmoil regarding federal level policies, such as the clean power plan (CPP), the growth in renewable electricity (RE) continued due to market forces as anticipated by Obama (2017). The two most important driving forces of the RE market growth are tax credits and renewable portfolio standards (RPS) (Barbose, 2017). The tax credit, in the form of renewable investment tax credit and renewable production tax credit, aims to encourage individuals and companies to invest and produce RE whereas RPS is state-mandated policy enforced to electric load-serving entities. RPS requires that electric load-serving entities meet a minimum portion of their load with eligible forms of renewable electricity. As of April 2019, 29 states and the District of Columbia have mandated RPS. RPS applies to 56% of total US retail electricity sales in 2016 (Barbose, 2017). The requirements of RPS varies over the states, while most of the states have a percentage-based requirement. Three states (Hawaii, California, and New Mexico) have mandated 100% RPS by 2045.

Figure 2-1 shows the US states and territories that have mandated RPS and the key RPS requirement. RPS requirements are time bound and some states are planning to review their RPS as the target time is approaching. In recent times, many states' legislators propose to increase the requirements or extend the target time, while some states are seeking to decrease, repeal, or freeze existing RPS policies (Barbose et al., 2016). For example, New Jersey and Illinois are proposing 100% clean energy while the Arizona Senate is discussing a bill to move from 15% mandatory renewable portfolio standards to voluntary renewable portfolio goals. With this backdrop, it is imperative to know the social welfare of the policy in question. One way to obtain social welfare is to conduct a cost-benefit analysis (CBA) of the RPS policy. Another way is to obtain the public preferences towards the RPS policy. The literature primarily concentrates on the cost-benefit analyses of various RPS.

Figure 2-1: Renewable portfolio standards in the United States
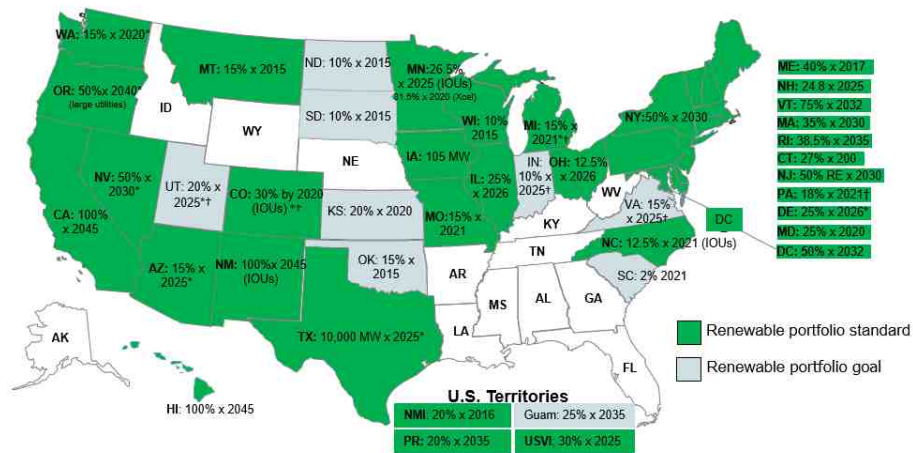
Source: updated from base map of Database of State Incentives for Renewables & Efficiency (DSIRE), 2018

RPS compliance increases retail electricity prices as the cost of renewable electricity is higher than that of conventional sources based on Lazard's levelized cost of

electricity. The cost of RPS compliance has a wide range of 3% to 11% increase in retail electricity prices (Greenstone & Nath, 2019; Morey & Kirsch, 2013; Tra, 2016; Upton Jr & Snyder, 2017; H. Wang, 2016). The benefits from RPS policy also has multi-faceted effect such as carbon emission reduction (Barbose et al., 2016; Greenstone & Nath, 2019; Heeter et al., 2014; J. X. Johnson & Novacheck, 2015), air quality improvement (Barbose et al., 2016), water withdrawal reduction (Barbose et al., 2016), and job creation (Barbose et al., 2016). Most recently, Wiser et al. (2017) conducted an extensive, national level, integrated assessment of RPS policy costs and environmental benefits. The cost-benefit studies suggest that RPS policies generate net social benefit. However, there are several issues associated with advocating RPS policies based on cost-benefit studies in this domain. First, it is debatable whether the states that mandated RPS can be compared with states that do not (Upton Jr & Snyder, 2017). Second, the compliance cost is a direct cost (such as purchasing renewable energy contracts (REC)) whereas the benefits are indirect. Third, RPS policies are not likely the most cost-effective policy to get the intended environmental and economic benefits (Bird et al., 2011; Fischer & Newell, 2008; E. P. Johnson, 2014; Palmer & Burtraw, 2005; Rausch & Mowers, 2014; Wiser et al., 2017). In addition to this complexity of cost-benefit studies, most recently, Upton Jr and Snyder (2017) have not found a significant benefit of RPS policies in terms of CO_2 abatement. Moreover, Considine (2016) argued that the RPS policies does not provide a net social benefit if the secondary economic effect to the economy through higher electricity prices is considered. In this backdrop, public preferences and underlying sources of preference heterogeneity can be used to facilitate communication among stakeholders, in the context of mandating binding RPS policies using a bottom-up approach so that the overall social

welfare can be maximized. In this paper, I present the results of a discrete choice experiment (DCE) to analyze public preference towards RPS.

The discrete choice experiment (DCE) is conducted in New Mexico, where the legislators recently passed a 100% RPS. DCE is a widely used technique to obtain consumers' preference towards a good, especially non-market goods (J. J. Louviere, Flynn, & Carson, 2010). There is a growing body of literature employing DCE to analyze consumer preferences of renewable energy (Bigerna & Polinori, 2014; Borchers, Duke, & Parsons, 2007; Ma et al., 2015; Menegaki, 2008; Mozumder, Vásquez, & Marathe, 2011; Rommel & Sagebiel, 2017; Soon & Ahmad, 2015; Sundt & Rehdanz, 2015; Zorić & Hrovatin, 2012), but none of the studies focused on mandatory renewable energy in the form of an RPS. I have used a flexible generalized multinomial logistic (GMNL), proposed by Fiebig et al. (2010) to account for individual and scale heterogeneity in preferences. Along with advanced econometric methods, I have also used attribute non-attendance (ANA) and incorporated stated attribute importance ranking (AIR) data to tackle reliability and validity aspect of the DCE method. Chalak, Abiad and Balcombe (2016) is the only study that incorporated ANA and AIR together in random parameter logistic model (RPL). This chapter extends the existing literature by examining the public preferences towards RPS policy using ANA and AIR information.

The rest of this chapter is organized as follows. I begin section 2.2 by providing an overview of RPS policies in New Mexico and then detail the survey design. The econometric models for analyzing DCE data is discussed in Section 2.3. Section 2.4 presents results and discussions. Finally, Section 2.5 summarizes the key findings of this study.

■ RPS DCE: Survey Design

2.2.1 Renewable Portfolio Standards in New Mexico

In 2004, the RPS policy of New Mexico was enacted under the Renewable

Energy Act (S.B. 43). The law requires investor-owned electricity companies of New

Mexico to distribute 20% of renewable energy by 2020. Small rural electric cooperatives

are 10% renewables distribution by 2020. In 2007, several 'carve-outs'[2] (e.g., minimum

of 30% of the RPS requirement is met using wind energy) were also incorporated in the

policy to ensure 'fully diversified renewable energy portfolio'. Figure 2-2 shows the RPS

requirement of New Mexico and compliance over time. The RPS requirement of New

Mexico in 2015 is 1.89 TWh and the compliance rate is 100% (Barbose (2017) –

supplementary information). Note that, in several years, the compliance rates were

below100%, which is due to the reasonable cost threshold policy set by the New Mexico

Public Regulation Commission (NMPRC). The NMPRC states that if the cost of

procuring renewable energy is more than 3% of the total revenue of the utility company,

then they will not be required to comply with the RPS requirement for that year.

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[2] RPS curve-outs: 30% from wind, 20% solar, 5% from other renewable sources. At least 3% of solar
requirement must be fulfilled from distributed solar.

Figure 2-2: Total RPS Obligation and Achievement in New Mexico
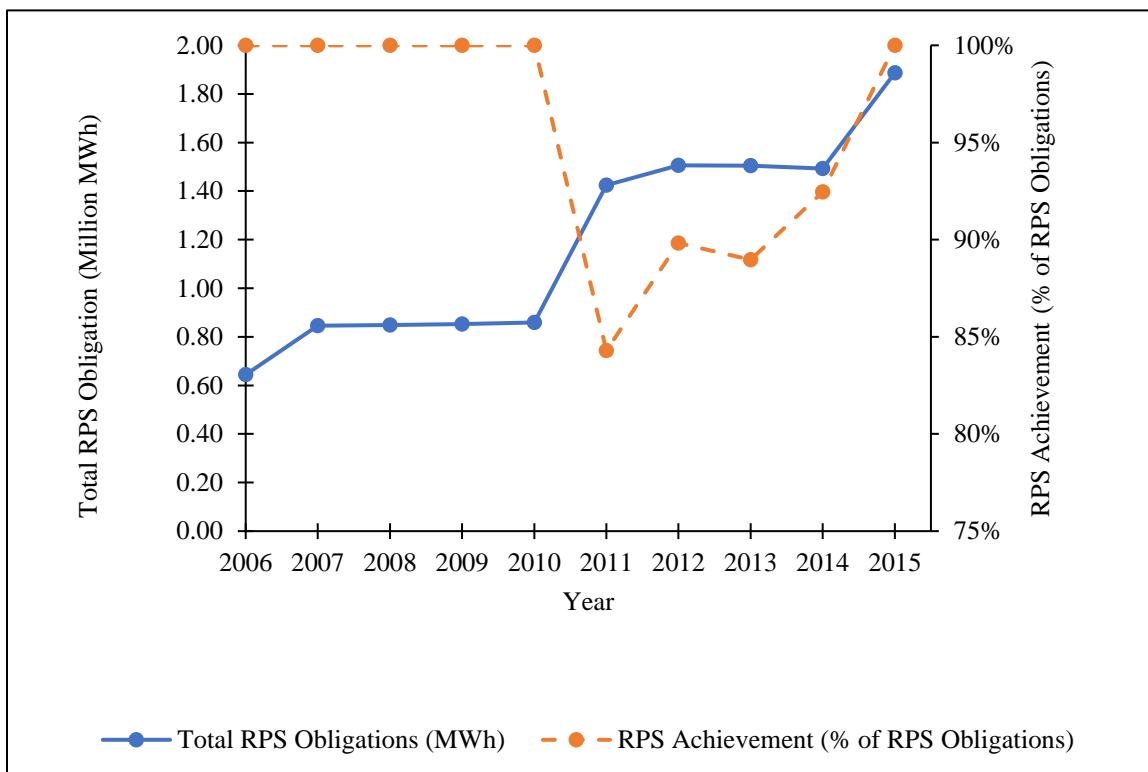
Source: Figure created from supplementary data of Barbose (2017)

In 2017, New Mexico legislators proposed a bill stating to review the RPS requirements. In the proposed bill, Investor-owned utilities would have to increase their RE distribution from 20% by 2020 to 80% of RE by 2040 with several five yearly increments. The rural electric co-operatives have 10% fewer requirements, that is 70% of RE by 2040. The bill was not approved. Subsequently, in 2019, New Mexico legislators enacted a 100% RPS bill. The current form of the policy as part of the Energy Transition Act of 2019 requires that 100% of the distributed electricity of Investor-owned utilities will come from clean sources by 2045. The requirement is the same for rural electric cooperatives, but the timeline is 2050.

Note that, the RPS requirement does not restrict load providers to distribute renewable electricity, rather it provides the flexibility of supplying nuclear electricity as it produces zero emissions. Renewable electricity is intermittent. Wind and solar electricity will not work when there is no wind and sun, respectively. This intermittency problem can be solved using two options. First, electricity generation plants can be geographically diverse such that it can produce round the clock and supply to other regions. This has a problem as electricity transmission loss increases with transmission distance increases. Second, there can be a storage system that can store electricity for intermittent use. However, current battery technology is not sophisticated enough to make this into reality. A completely alternative approach could be 100% clean electricity instead of 100% renewable electricity where clean electricity such as nuclear can provide the base load to solve the intermittency problem of renewable electricity. Thus, the Energy Transition Act of 2019 in New Mexico opens up the possibility of incorporating nuclear in New Mexico's 100% clean electricity mix.

Also, note that, the survey was conducted in the fourth quarter of 2017 when the RPS requirement of New Mexico was 20% renewable electricity by 2020. The survey design is based on 20% RPS requirement and I discuss the implication of survey results due to newly passed (April 2019) RPS policies.

2.2.2 Survey Instruments

The DCE is a widely used tool in the stated preference (SP) family of non-market valuation methods. I chose the DCE approach as policymakers are interested in the preferences of individual components of the RPS policy. I developed a questionnaire based on expert opinion and careful examination of the literature. Individual post-survey

interviews with New Mexico residents (recruited through the sites Nextdoor, and Craigslist) were used to help design the questionnaire. The choice experiment consists of five attributes with 3, 3, 3, 3, and six levels. The full factorial design needs altogether 486 profiles or alternatives, which is very high. I have employed a D-efficient orthogonal factorial design based on SAS® macro (%ChoiceEff) (Kuhfeld, 2010) that resulted in 36 profiles. I created 18 choice sets with two alternatives and one status quo each. The block design is employed to make six versions, where each respondent answers only three choice sets.

For sampling purposes, I purchased a sample from a third party who ensured a stratified random sample of 1,400 contacts.[3] The survey area and location of households shown in Figure 2-3 confirms that the survey is well dispersed within the geographic boundary of New Mexico. I conducted a short pilot study (3 communications: pre-notice letter, survey questionnaire, and postcard) for 100 samples chosen randomly from 1,400 contacts. I chose to use a mail survey because it is more convenient than a face-to-face survey in the developed world. Moreover, research shows that face-to-face, mail, telephone, and online survey provide similar results (Berrens, Bohara, Jenkins-Smith, Silva, & Weimer, 2003; Fleming & Bowden, 2009; Krysan, Schuman, Scott, & Beatty, 1994; Szolnoki & Hoffmann, 2013). Based on the results of the pilot study, I adjusted choice attribute levels.

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[3] The sample list is purchased from Research Now SSI (Currently Dynata). The third party collected the address and information of the household from multiple sources.

Figure 2-3: Survey area and location of the respondents
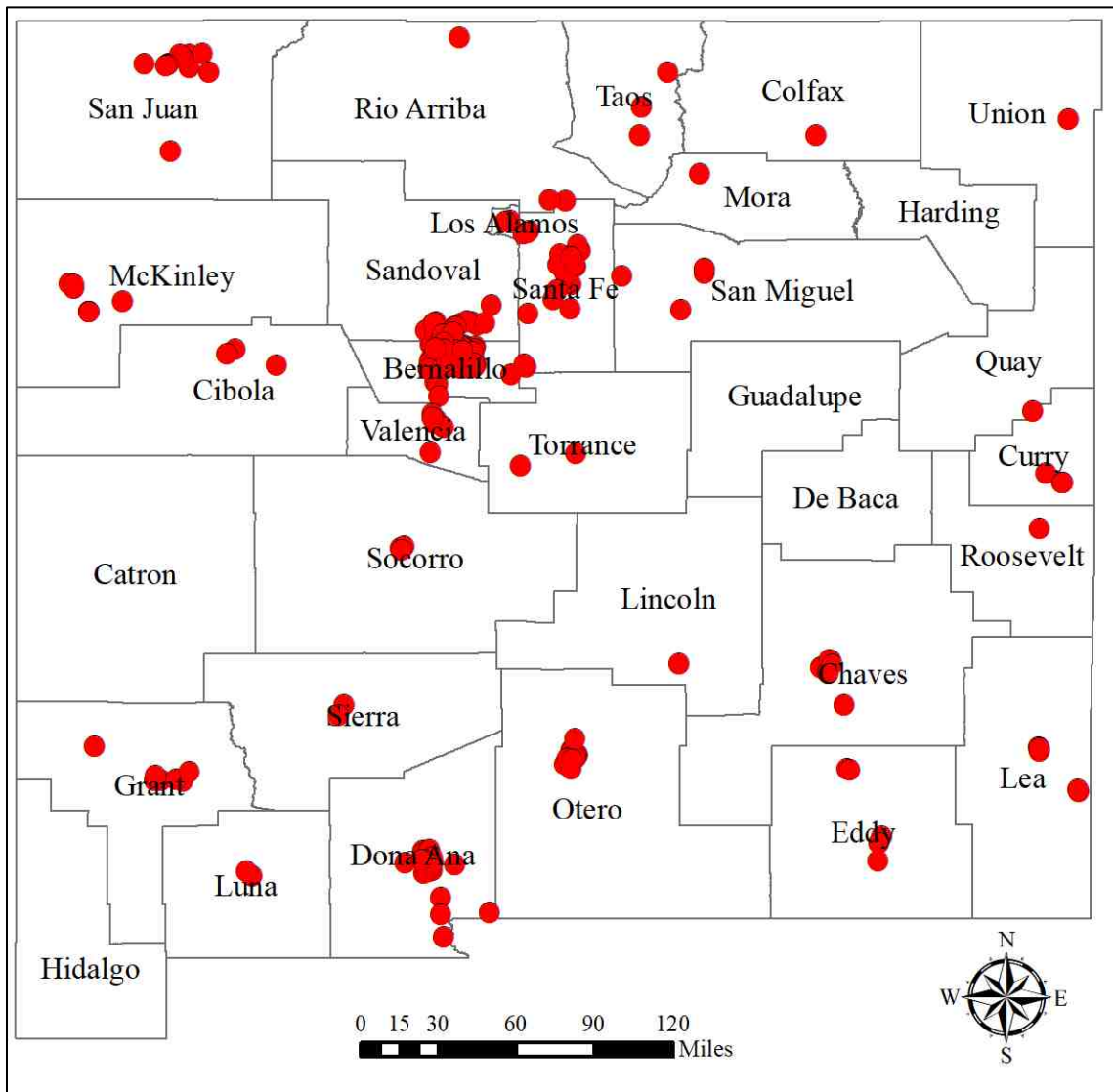
At this phase, I conducted the survey to the 1,300 households. I also uploaded the survey online where only the respondent invited by mail is allowed to participate as the online survey was protected by an individualized password. The individual password of the online survey is sent to the respondent via mail. I communicated with the respondents five times during the survey period. At the end of the survey, there was a 22.2 to 23.5% response rate calculated based on American Association for Public Opinion Research

(2016). Altogether, the sample includes 306 individuals completing 894 useable choice questions.

2.2.3 Survey Questionnaire

The survey questionnaire consists of five sections. The first section asks about the general perception of the New Mexico energy future. The second section informs the respondent about different attributes and their current levels. It also subsequently asks some questions about attributes. The third section consists of three choice questions with three alternatives, where one of them is the status quo or current plan (CP). Just after each choice question, the certainty of choice question answer and attribute non-attendance (ANA) related question are asked. The fourth section starts with an importance ranking question and then asked some attitudinal questions. The survey questionnaire ends with demographic information collection.

The success of a DCE largely depends on the development of attributes and their levels (Abiiro, Leppert, Mbera, Robyn, & De Allegri, 2014; Coast et al., 2012), which requires rigorous and iterative approaches, including qualitative methods (Coast et al., 2012; Helter & Boehler, 2016). The DCE attributes and levels were selected based on a meticulous and iterative process using literature review, expert opinion, interview with potential respondents, and pre-tests. Table 2-1 presents the selected attributes and their levels. The main component of RPS is the share of electricity from renewable sources. I used three levels of share of electricity from renewable sources (20%, 50%, and 80%). The RPS target of 20% by 2020 is the lowest category to continue till 2040 as it was mandated rule during the survey. The highest level of 80% is chosen based on the

proposed bill in 2017. The current form of RPS law is mandated after the survey is

conducted. Hence, the survey does not include 100% RPS.

Table 2-1: Discrete choice experiment attributes and levels

Attributes	Levels
Required share of electricity from renewables by 2040	**20%**, 50%, 80%
Electricity generation from nuclear power	0%, **18%**, 36%
Change in water usage for electricity generation	10% increase, **No change**, 10% decrease
Change in number of New Mexico jobs	Lose 2000 jobs, **No change**, Create 2000 jobs
Change in monthly electricity bill	**No change**, $5, $10, $20, $40, $60

Note: * status quo levels are shown in bold.

The other attributes in the choice questions are the consequences of different

energy plans of the state. Although nuclear electricity is clean (producing zero carbon

emission), the definition of renewable electricity does not include nuclear electricity.[4]

The choice of state energy plan will likely impact the consumers' decision on nuclear

electricity. The current level of New Mexico nuclear electricity distribution in 2017 is

18% (calculated from the distribution plan of the three largest utility companies in New

Mexico). I included 18% as the base, 0% as low and doubled the base (36%) for high

nuclear electricity. The perception of nuclear electricity can be different for different

consumers depending on the fact that (1) it produces zero emission; (2) all the nuclear

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[4] Note that, the 2019 RPS of New Mexico does not restrict nuclear in the RPS portfolio.

electricity of New Mexico is imported from Pale Verde, Arizona; and (3) consumers'

negative perception regarding nuclear electricity due to health and waste concern and fear

of nuclear accidents. The choice of a state energy plan is also impacted by the perception

of water usage for electricity generation. Water is a very important resource in New

Mexico for being a desert state. On average, 96% of New Mexico is affected by drought

in 2018 (National Integrated Drought Information System, 2019). Research suggests that

renewable electricity technology can reduce water withdrawal and consumption

(Macknick, Newmark, Heath, & Hallett, 2012). I included a 10% increase, 10% decrease,

and no change of water uses for the levels of water attribute. Another important factor is

the economic consideration of the state plan. The economic consideration is captured

through number of jobs changes by implementing the plan. Developing and maintaining

renewable electricity will have an impact on number of jobs in the energy sector of New

Mexico. Research shows that $1 million investment shifted from fossil fuel to renewables

can create five jobs (Garrett-Peltier, 2017). I used 2,000 jobs increase, 2,000 jobs

decrease, and no change as the levels of jobs attribute. The final attribute is the increased

cost that the consumer needs to pay through monthly electricity bills. Implementing state

energy plan is likely to increase the cost of electricity as the renewable electricity cost is

higher than conventional sources. I used six levels of cost increase ranging from no

change to $60/month.

Figure 2-4 presents a sample choice card. The respondents are asked to choose

between three alternatives, where the last one is the current plan. The respondents are

reminded of giving serious consideration to the cost and assume that they are paying the

mentioned amount. After every choice question, I asked two choice related questions. The first one is to know the certainty of the respondent making a choice. The second one is to get the stated attribute non-attendance (ANA) of the respondent for that particular choice situation. After all the choice questions, I included an attribute importance ranking (AIR) question, where respondents are asked to choose the importance of attributes on a scale of 1 to 5. Next, the survey asked about environmental attitude using 6-point, modified version of new ecological paradigm (NEP) (Thornton, 2013; Whitmarsh, 2009; Whitmarsh & O'Neill, 2010) and concludes with collecting demographic information such as education, age, sex, voting pattern, and income. Responses are used to explain the sources of heterogeneity for the respondent.

■ Theoretical and analytical framework

2.3.1 Theory underlying discrete choice experiment

The discrete choice experiment hinges on two broad economic theories. Lancaster's modern consumer theory states that the good itself does not provide utility, rather the characteristics of the good rise in utility (Lancaster, 1966). It allows one to decompose a good into several attributes and obtain the value of each attribute. The random utility maximizing (RUM) is a variant of the utility-maximizing theory of economics. It states that individual rational agents choose a good whose overall characteristics raises the utility to the maximum and the variation of individual choice can be captured through random factors.

Figure 2-4: An example of a choice card

Which State Plan Do You Prefer?

Now we will ask you to make 3 choices over 3 competing state plans and ask which

you prefer: Plan A, Plan B, or the Current Plan.

Pick the state plan that you think is best, giving serious consideration to the costs;

assume you are paying the mentioned amount. If you do not like any, choose the

one with which you are most able to live.

Consider these three possible state plans. Which plan would you prefer? *Check Plan A*

or Plan B or Current Plan.

	Plan A	Plan B	Current Plan
Required share of electricity from renewables by 2040	50%	80%	20%
Electricity generation from nuclear power	0%	18%	18%
Change in water usage for electricity generation	10% ▮	No change	No change
Change in number of New Mexico jobs	No change	2000 jobs ▮	No change
Change in monthly electricity bill	No change	$10 ▮	No change
I would choose Plan ⟶	◯	◯	◯

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Consider a rational, utility-maximizing individual or agent (i) is faced with a discrete choice situation ($s \in \boldsymbol{S}$). Given a set of alternatives ($\boldsymbol{J}$), the individual maps a utility (U_{ij}) with each alternative ($j \in \boldsymbol{J}$) and chooses the alternative that provides maximum utility. The utility given by equation (2.1) has a systematic observable component, V_{ij}, and a random and unobservable stochastic component, ϵ_{ij}.

$$U_{ijs} = V_{ijs} + \epsilon_{ijs} = X_{ijs}^T \beta_i + \epsilon_{ijs} \qquad (2.1)$$

In equation (2.1), the observed variable related to alternative j and choice situation s is represented by X_{ijs}. The idiosyncratic error term, ϵ_{ijs} follows independent and identically distributed (i.i.d.) extreme value type 1 distribution. As β_i is unobserved for each i, I assume that β_i is distributed multivariate normal, $\beta_i \sim MVN(\beta, \Omega)$. The basic form of equation (2.2) for this study can be formulated as:

$$\begin{aligned} U_{ijs} = {} & \beta_1 ASC + \beta_2 RE\_share + \beta_3 Water + \beta_4 Nuc\_in \\ & + \beta_5 Nuc\_de + \beta_6 Job + \beta_7 Job\_sq + \beta_8 Cost \\ & + \epsilon_{ijs} \end{aligned} \qquad (2.2)$$

Following maximizing utility theory, the individual's probability of choosing alternative $j \in \boldsymbol{J}$ over alternative $k \in \boldsymbol{J}$ in choice situation s is based on equation (2.3):

$$P_{ijs} = Prob(U_{ijs} > U_{iks} \; \forall \; j \in \boldsymbol{J}, j \neq k) \qquad (2.3)$$

In equation (2.2), ASC represents alternative specific constant. RE_share is the share of electricity from renewable sources. Water represents changes in water usage. Nuc_in and Nuc_de are categorical variables indicating a change in nuclear electricity.

Job variable is defined as the change in number of jobs. Job_sq is square of Job variable,

included to obtain the non-linear effect of employment. The Cost variable represents a

monthly change in electricity bill. Table 2-2 provides the definition and statistics of the

variables used in equation (2.2).

Table 2-2: Definition of variables used in the econometric models

Variable	Description	Mean	Standard Deviation
ASC	=1 if Status Quo; 0 otherwise	0.33	0.47
RE_share	Required share of electricity from renewables by 2040	0.40	0.25
Water	Change in water usage for electricity generation	0.0001	0.07
Jobs	Change in number of New Mexico jobs	-0.03	1.33
Cost	Change in monthly electricity bill in dollar/household	15.26	21.67
Nuc_in	The increase in nuclear. Effect coding is used to construct this variable. Nuc_in = 1 if the level of nuclear increased from the status quo level of 18%. Nuc_in = -1 if it is status quo level of 18%. Nuc_in = 0 if it decreased to 0%.	0.09	0.81
Nuc_de	The decrease in nuclear. Effect coding is used to construct this variable. Nuc_de = 1 if the level of nuclear decreased from the status quo level of 18%. Nuc_de = -1 if it is status quo level of 18%. Nuc_de = 0 if it increased to 36%.	-0.34	0.82
Job_sq	Square of Jobs variable	1.78	1.99
Geospatial variables			
Distance_RE	Distance in km from the household location to the nearest renewable power plant. Data is collected from EIA (2018b)	27.28	32.85
Distance_Con	Distance in km from the household location to the nearest conventional power plant. Data is collected from EIA (2018b)	15.74	21.41
Distance_Oil_Gas	Distance in km from the household location to the nearest centroid of oil and gas lease area. Data is collected from NMSLO (2018).	42.89	43.48
Socioeconomic variables			
Age	The age of the respondent	58.13	16.00
Hispanic	=1 if Hispanic	0.27	0.45
Male	=1 if the respondent is male	0.58	0.49
High_income	=1 if the respondent's household income is 100,000 or greater	0.43	0.50
Bachelor	=1 if the respondent has at least a bachelor degree	0.60	0.49
Environmental and ecological attitude			
EA	Ecological Attitude. Based on Thornton (2013), I have asked six ecological attitudinal questions. Each question has 5 points. The continuous variable is defined as the obtained points divided by the maximum point possible. The variable is bounded to 0-1.	0.63	0.14
E_prac	Environmental Practice. E_prac = 1 if the respondent or household member falls in one of the following categories: (1) has a hybrid car, or rooftop solar panel, or wind turbine; (2) work in energy or environment sector; or (3) contributed to environmental protection group	0.47	0.50

2.3.2 Data Analysis Methods

2.3.2.1 The generalized multinomial logit (GMNL)

The most straightforward estimation method based on Random Utility

Maximization (RUM) models is conditional or multinomial logit model (MNL)

(McFadden, 1974). Although MNL has a closed-form choice probability and a globally

concave likelihood function, it imposes constant competition across alternatives (IIA

property) and cannot allow for individual specific preferences. The mixed logit model

(MIXL) generalizes and extends the MNL model by allowing for preference or taste

heterogeneity (McFadden & Train, 2000; Train, 2009). While MNL can be estimated

using maximum likelihood estimation (MLE), MIXL requires simulated maximum

likelihood estimator (SMLE) as it does not have a closed-form solution. MIXL is

practically a random parameter logit (RPL) model, where the taste heterogeneity of an

individual is captured thorough continuous distribution of parameters. MIXL

approximate RUM model and improves MNL by eliminating IIA property, while keeping

independent and identically distributed (IID) extreme value type 1 error term. However,

researchers argue that individual not only have differing taste, they also exhibit

heterogeneous consistency of choices depending on their ability to choose stemming

from various factors such as familiarity with the good, the complexity of the choice task,

and cognitive ability (Christie & Gibbons, 2011). Fiebig et al. (2010) proposed the scale

multinomial logit model (SMNL), where the individual coefficient is adjusted based on a

random scale. The SMNL is essentially a restricted case of MIXL with symmetrical

mixing distribution (e.g., normal distribution; not log-normal) where the individual

coefficient is not multiplied by negative values. While scale heterogeneity can better explain individual behavior than random taste heterogeneity in some context (J. J. Louviere et al., 2008; J. Louviere et al., 2002), adjusting for scale heterogeneity in the absence of treatment for taste heterogeneity results in a statistically inferior model (Greene & Hensher, 2010; S. Hess, Rose, & Bain, 2009). The generalized multinomial logit (GMNL) model is a flexible model that can allow for both individual scale and taste heterogeneity (Fiebig et al., 2010).

The model estimation depends on how the parameter β_i in equation (2.4) is distributed. For the GMNL model, the parameters vary across individual according to:

$$\beta_i = \sigma_i \beta + [\gamma + \sigma_i(1 - \gamma)]\eta_i \tag{2.4}$$

In equation (2.4), σ_i is the scale of the idiosyncratic error term across individual, γ is a scalar controller of the variance of residual taste heterogeneity η_i. The positive real value of scale (σ_i) is ensured by assuming the log-normal distribution of σ_i, with a mean and standard deviation of $\bar{\sigma}$ and τ:

$$\ln(\sigma_i) = \bar{\sigma} + \tau v_i, \text{ where } v \sim N(0,1) \tag{2.5}$$

Fiebig et al. (2010) note that the estimation performance can be improved by restricting the distribution of $v \sim TN[-2, +2]$. In this study, I am allowing the mean of scale to differ based on individual choice specific observed variables. Given the parameter distribution and constraints, the utility function that needs to be estimated is given in equation (2.6).

$$U_{ijs} = (\beta_{0j} + \eta_{0ij}) + X_{ijs}^T[\sigma_i\beta + \{\gamma + \sigma_i(1-\gamma)\}\eta_i] + \epsilon_{ijs} \qquad (2.6)$$

Note that, equation (2.6) has flexibility such that it can be reduced to different

sub-models (MNL. MIXL, SMNL) based on the value of structural parameters

$(\sigma_i, \gamma, var(\eta_i))$ of the model. In this study, I estimated all these models and compared

their results and performance. I choose the model that gives the best fit in terms of

Akaike information criteria (AIC), Bayesian information criteria (BIC), and log-

likelihood. The best fit model (ensuring 'statistical efficiency') is then used as a base case

to tackle 'response efficiency' by using the stated information.

2.3.2.2 Incorporating attribute non-attendance (ANA) and attribute important ranking (AIR)

The previous section discussed the statistical efficiency of the analysis, whereas

there is another type of efficiency that needs to be achieved. Various cognitive effects

that result in poor quality responses can cause measurement error. The measurement error

can arise from various sources. Although measurement error cannot be totally controlled

for, the survey design and implementation should be well thought so that it can reduce

some of the measurement errors (F. R. Johnson et al., 2013). For example, a respondent

can become fatigued when there is a large number of choice questions. I eliminated this

by incorporating block design so that one respondent has to answer only three sets of

choice questions and I also keep the questionnaire length to 20 minutes. I tested these in

individual interviews. However, there can be some issues associated with DCE that

cannot be solved through survey design and implementation, as it relates to the

behavioral component of respondents in applying different heuristics and decision rules

to identify a preferred choice alternative. It needs additional elicitation and technique to

incorporate those issues. Often cases, respondent choose to ignore some information that is presented to them (e.g. attribute non-attendance) (Balcombe, Fraser, & McSorley, 2015; Balcombe, Fraser, Williams, & McSorley, 2017; Chavez, Palma, & Collart, 2017; Y. Chen, Caputo, Nayga, Scarpa, & Fazli, 2015; Hensher, Rose, & Greene, 2005; Hole, 2011; Hole, Kolstad, & Gyrd-Hansen, 2013; Krucien, Ryan, & Hermens, 2017; Lagarde, 2013; Puckett & Hensher, 2009; Scarpa, Zanoli, Bruschi, & Naspetti, 2013; Van Loo et al., 2015), selecting alternative based on one specific attributes (e.g. lexicographic choice) (Campbell, Hutchinson, & Scarpa, 2006; S. Hess, Rose, & Polak, 2010; Rouwendal & de Blaeij, 2004; Sælensminde, 2006; Veisten, Navrud, & Valen, 2006), or selecting the same alternative such as status quo alternative (e.g. no-trading) (S. Hess et al., 2010). In this paper, I focus on attribute non-attendance (ANA).

Although there is no consensus on how ANA will be accounted for in DCE, the ANA literature implies that ignoring ANA while maintaining passive boundary rationality assumption leads to potentially biased welfare estimates and poor model performance (Alemu, Mørkbak, Olsen, & Jensen, 2013).[5] The ANA literature has looked into stated ANA by asking questions if the respondents ignore an attribute(s) (Hole, 2011; Lagarde, 2013); inferred ANA by incorporating econometrics tools to make the zero utility for the attribute(s) that is ignored (Hensher et al., 2005; Hole et al., 2013; Puckett & Hensher, 2009; Scarpa et al., 2013); and visual ANA by using eye tracking or brain imaging devices (Balcombe et al., 2015, 2017; Chavez et al., 2017; Y. Chen et al., 2015; Krucien et al., 2017; Van Loo et al., 2015). I have opted for stated ANA technique by

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[5] Bounded rationality coined by Simon (1957), refers to individuals limited rationality when making choices due to tractability of the problem, limitations of time and cognitive ability. The passive bounded rationality model, proposed by Deshazo & Fermo (2004), assumes that respondents has an increasing tendency of making mistakes due to increasing complexity of the choice sets.

eliciting an ANA question after every choice question. Dealing with stated ANA has several limitations such as ignoring an attribute may mean that a respondent has very low importance on that attribute, not totally ignoring it (Balcombe, Bitzios, Fraser, & Haddock-Fraser, 2014; S. Hess & Hensher, 2010; S. Hess, Stathopoulos, Campbell, O'Neill, & Caussade, 2013). For this reason, incorporating additional information along with dichotomous stated ANA question is common (Balbontin, Hensher, & Collins, 2017; Byrd, Widmar, & Ricker-Gilbert, 2017; Caputo, Nayga, Sacchi, & Scarpa, 2016; Chalak et al., 2016; Heidenreich, Watson, Ryan, & Phimister, 2018; Sandorf, Campbell, & Hanley, 2017). I have incorporated attribute importance ranking (AIR) data with dichotomous stated ANA information. Research on AIR found that model performance is better when AIR data is used (Balcombe et al., 2014). Chalak, Abiad and Balcombe (2016) is the only study that used both ANA and AIR information together to estimate DCE. Unlike Chalak, Abiad and Balcombe (2016) and Balcombe et al. (2014), I have used AIR data such that two different attributes can have the same rank or same importance. In the questionnaire, I have not forced the respondent to provide a unique rank for each attribute; rather there is a flexibility of considering the same importance.

Following Chalak, Abiad and Balcombe (2016), I have designed a 'contracted' model where ANA and AIR data are used as a weight factor. According to MIXL model the random utility of person i for alternative $j \in \boldsymbol{J}$ and for choice situation $s \in \boldsymbol{S}$ is:

$$U_{ijs} = \widetilde{x_{ijs}^T}\beta_i + \epsilon_{ijs} \tag{2.7}$$

In equation (2.7), the parameter β_i varies according to equation (2.4). The latent variables $(\widetilde{x_{ijs}^T})$ is found after multiplying with weight matrix (Λ_i) with original latent variables (x_{ijs}^T). The weight factor, Λ_i is defined as a diagonal matrix comprised of the weights (λ_{ik}), where $k = 1\ to\ K$ attribute. The diagonal element of weights for individual i and attribute k is comprised of the multiplication of two weight factor of ANA and AIR. The ANA weight factor is defined as:

$$\overline{\lambda_{ik}} = \rho\phi_{ik} + (1 - \phi_{ik}) \tag{2.8}$$

In equation (2.8), $\phi_{ik} = 1$ if non-attendance is stated and $\phi_{ik} = 0$ otherwise. The value of ρ will be in between (0, 1), where $\rho = 1$ makes no use of ANA data, $\rho = 1$ means ANA corresponds to zero utility and $\rho = [0,1]$ means the use of ANA data. Another weight factor from AIR data is constructed based on the following equation:

$$\dot{\lambda}_{\iota k} = (1 - \mu) + \mu \frac{K - v_{ik}}{K - 1} \tag{2.9}$$

v_{ik} is the importance of the kth attribute by the ith individual, where v_{ik} can have a value of 1 to 5 and the rank of the importance is not forced. The individual i can have the same importance for more than one attributes. The value of μ represents the AIR parameter that varies between (0, 1). When $\mu = 0$, the value of $\dot{\lambda}_{\iota k}$ becomes 1 and AIR data has no use. The corresponding value of multiplicative weights is:

$$\lambda_{ik} = \overline{\lambda_{ik}} \times \dot{\lambda}_{\iota k} \tag{2.10}$$

Now I can estimate equation (2.7) given the set of equations (2.8) - (2.10). However, the value of ρ and μ are not known beforehand. I have employed a grid-search heuristic to find the optimal value of ρ and μ such that the MIXL system has maximum log-likelihood. I have incorporated ANA and AIR data systematically in 5 different restrictive models based on values of ρ and μ:

Model - 1: no use of ANA or ranking data: $\rho = 1, \mu = 0$

Model - 2: use of ranking data only: $\rho = 1, \mu = [0,1]\ free$

Model - 3: use of ANA data only, under ANA equals zero utility: $\rho = 0, \mu = 0$

Model - 4: use of ANA data only: $\rho = [0, 1],\ \mu = 0$

Model - 5: joint use of both ranking and ANA data: $\rho = [0, 1],\ \mu = [0, 1]$

Within the five models, the model with the best fit is used for calculating marginal willingness to pay (MWTP) measure. I have used a 95% confidence interval of MWTP using the delta method. The MIXL model incorporating ANA and AIR data can provide whether taste and/or scale heterogeneity present in the preference. It cannot explain the source of that heterogeneity. I dig more into the source of heterogeneity using geospatial technique and latent class models (LCM). The individual MWTP is used to conduct heterogeneity analysis using the geospatial technique, whereas LCM is used to explain the sources of heterogeneity in preference space.

2.3.2.3 Latent Class Models

The GMNL, along with using ANA and AIR data, can provide individual specific coefficients by capturing both taste and scale heteroscedasticity. Although GMNL model

has flexibility in terms of efficiency, latent class model (LCM) is a more powerful tool to interpret the results based on several classes. The LCM is simplifying the results of GMNL by making the respondent segments discrete. LCM can be considered as a restrictive case of GMNL, where scale heterogeneity (σ_i) is not considered and taste heterogeneity is based on some distinct classes ($c \in \boldsymbol{C}$). Mathematically, if $\sigma_i = 1$ and $\beta_i = \beta_c$, then GMNL turns into LCM. Alternatively, LCM is MIXL with discrete mixing distribution. Recently Greene and Hensher, (2013) and Keane and Wasi, (2013) extended LCM by taking advantage of both LC and MIXL model. Greene and Hensher (2013) proposed the model as LC-MIXL, where MIXL is nested within LCM by double mixing of the logit model. LC-MIXL has taken advantage of simpler and useful interpretability of LCM and statistical flexibility of MIXL. Considering $\sigma_i = 1$ in equation (2.4) and I have classes within the respondents ($c \in \boldsymbol{C}$), the distribution of β_i will be:

$$\beta_i \sim N(\beta_c, \Sigma_c) = f_c(\beta_{i \in c}) \tag{2.11}$$

Consider a choice situation $s \in \boldsymbol{S}$ for respondent i. The probability that respondent i in class $c \in \boldsymbol{C}$ chooses alternative $j \in \boldsymbol{J}$ is:

$$P_{ijs|c} = \frac{e^{\beta_c X_{ijs}}}{\sum_{j=1}^{J} e^{\beta_c X_{ijs}}} \tag{2.12}$$

The use of socioeconomic and behavioral information in LCM models are common (Borger & Hattam, 2017). If the vector Z specifies the set of socioeconomic and behavioral information, then equation (2.13) defines the probability of class membership for respondent i.

$$P_{is} = \frac{\theta_s Z_i}{\sum_{s=1}^{S} \theta_s Z_i} \tag{2.13}$$

If the individual classes have distinct preferences, then the socioeconomics and attitudinal information can explain factors of preference heterogeneity of respondents.

2.3.2.4 Geospatial Analysis

I also consider spatial heterogeneity using a Hotspot analysis. Hotspot analysis is a spatial analysis tool that identifies clusters of points in space. It extends the density analysis by providing statistical significance of spatial autocorrelation. Hotspot analysis allows a researcher to detect spatial pockets or clusters of high (or low) MWTP values by examining the local spatial autocorrelation. There are several local indicators for spatial association (LISA) that can be used to conduct hotspot analysis. I have adopted Getis-Ord G_i^* statistics to determine statistically significant high (low) MWTP surrounded by high (low) MWTPs. Statistically significant high and low MWTPs are called hotspot and Coldspot, respectively. Getis-Ord G_i^* is a Z-scores that reflects the statistical significance of the MWTPs. The positive and negative G_i^* represent hotspot and coldspot, respectively. G_i^* is defined as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j} \right)^2 \right]}{n}}} \tag{2.14}$$

In the above setup, x_j is the MWTP for any attribute for individual j, $w_{i,j}$ is the spatial weight for MWTP of individual i and j, n is the total number of individual, $\bar{X}$ and S represents mean and standard deviation. The spatial weight $w_{i,j}$ is a component of the spatial weight matrix, W, which is calculated based on k nearest neighborhood and

threshold distance, d. A minimum value of $k = 8$ is required to ensure normality of G_i^*

(Nelson & Boots, 2008). The threshold distance can be between the minimum and the

maximum nearest neighbor distance. The results of hotspot analysis can be linked to

spatial and socioeconomic variables to compare the difference of those variables between

hotspot and coldspot. Spatial interpolation can be used to convert a cluster of points to a

continuous raster surface. There are several interpolation techniques, such as simple

inverse distance weighting. Ordinary kriging is a powerful interpolation tool if data is

stationary, having no trend, and normally distributed. Kriging interpolation is used to

transform a vector of G_i^* to a continuous raster surface.

■ Results and Discussion

2.4.1 Ensuring statistical efficiency

The choice data are analyzed using several models to obtain the best model. Table

2-3 reports the results of multinomial logit (MNL), scaled multinomial logit (SMNL),

mixed logit (MIXL), and generalized multinomial logit models (GMNL). The different

models are essentially estimating equation (2.2) using various structures of coefficients

(β). Table 2-2 provides a definition of variables used and their descriptive statistics. The

alternative specific constant (ASC) is included to measure the willingness to stay with the

status quo or current state. The RE_share, Water, and Job variables are continuous where

Nuc_in and Nuc_de are categorical variables for Nuclear energy increase and decrease,

respectively. I have used effect coding to create categorical variables. The effect coding

is similar to dummy variable coding except for the interpretation of the results is easier

with effect coding in the presence of status quo (Bech & Gyrd-Hansen, 2005; Daly,

Dekker, & Hess, 2016). I have used the Job_sq variable to capture the non-linearity in change in number of jobs. The Job_sq variable is defined as the square of Job variable.

Table 2-3 presents results of econometric models in preference space. Column 2 presents results of multinomial logit. The multinomial logit is dependent on the assumption of IIA. I tested the IIA property using the Hausman-McFadden test and report the results in Table 2-4. I dropped each package from the choice set and recorded the chi-square value of Hausman-McFadden test. The Hausman-McFadden test shows that I can reject the absence of IIA in the data at 90% confidence level. I cannot reject it with a higher confidence level indicating the possibility of IIA does not hold. I can circumvent this IIA property in MIXL and GMNL model by estimating the model using simulation technique. Column 3 of Table 2-3 presents the results of MIXL model. In MIXL model, all the variables are random, and the mixing distribution is normal. The MIXL model uses simulated maximum likelihood estimation (SMLE) technique with 1,500 conventional Halton draws, where the first 15 primes are dropped. I have used a GMNL model to account for scale heterogeneity along with the taste heterogeneity. The estimation of the GMNL model is dependent on the choice of several inputs into the model. There are four possible input sources (random seed, number of draws, estimation method, and starting values) that can lead to computational issues in the GMNL model (Gu, Hole, & Knox, 2013). Appendix A provides details discussion on my choice of these four inputs for GMNL model. I have used 1,500 conventional Halton draws along with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) estimation method and basic GMNL starting values to compute the GMNL results shown in column 4 of Table 2-3. Finally, the results of SMNL model are shown in column 5 of Table 2-3.

Table 2-3: Results of different models in preference space

Parameter	MNL	MIXL	GMNL	SMNL
Cost	-0.0213***	-0.0921***	-0.0849***	-0.0215***
	(0.0026)	(0.0225)	(0.0221)	(0.0029)
ASC	-0.1327	-1.2058***	-1.1032***	-0.1336
	(0.1379)	(0.4075)	(0.4019)	(0.1384)
RE_share	1.1187***	2.4388**	1.9434**	1.1256***
	(0.2118)	(0.9714)	(0.9774)	(0.2171)
Water	-1.4089**	-4.6614**	-3.5826*	-1.4168**
	(0.6295)	(2.0005)	(2.1107)	(0.6340)
Jobs	0.2825***	0.9375***	0.8911***	0.2849***
	(0.0328)	(0.2151)	(0.2140)	(0.0358)
Job_sq	-0.0486*	-0.2412***	-0.2654***	-0.0500*
	(0.0259)	(0.0936)	(0.0954)	(0.0270)
Nuc_in	-0.1356*	-0.7035***	-0.5602**	-0.1352*
	(0.0749)	(0.2610)	(0.2674)	(0.0756)
Nuc_de	0.0321	0.4016*	0.3810	0.0336
	(0.0707)	(0.2373)	(0.2467)	(0.0717)
sd.Cost		0.0945***	0.0808***	
		(0.0235)	(0.0310)	
sd.ASC		2.2270***	2.5283***	
		(0.6165)	(0.9707)	
sd.RPS		10.4691***	11.6600***	
		(2.4254)	(4.2459)	
sd.Water		13.4600***	14.5439**	
		(4.2775)	(6.5901)	
sd.Jobs		0.8174***	0.8560**	
		(0.2556)	(0.3786)	
sd.Job_sq		0.2734*	0.2888	
		(0.1629)	(0.2019)	
sd.Nuc_in		0.3374	0.4968	
		(0.7466)	(0.5694)	
sd.Nuc_de		0.8579**	0.8318*	
		(0.3617)	(0.4293)	
Tau			0.2871	-0.1702
			(0.5123)	(0.4834)
Gamma			2.3117	
			(3.5083)	
N	894	894	894	894
Log-likelihood	-898.0372	-774.6164	-774.3267	-898.0081
$\|g\|_\infty$	8.0597E-10	8.2773E-04	3.3505E-02	4.29E-02
$g'H^{-1}g$	-1.0971E-23	-1.1855E-06	-3.7511E-05	-4.66E-07
K(H)	9.8496E+04	4.1214E+05	1.0773E+06	9.7162E+04
AIC	1812.074	1581.233	1584.653	1814.016
BIC	1850.44	1657.964	1670.976	1857.177
AICc	1812.237	1581.853	1585.435	1814.22

Note:
a. MNL, MIXL, GMNL, and SMNL represents multinomial logit, mixed logit, generalized multinomial logit and scaled multinomial logit, respectively
b. *** $p<0.01$, ** $p<.5$, * $p<0.1$. Standard errors are in parenthesis
c. MIXL and GMNL assumed Cost, ASC, RPS, Water, Jobs, Job_sq, Nuc_in, and Nuc_de are normally distributed
d. $\|g\|_\infty$, $gH^{-1}g$, and K(H) are used to know the condition of gradient and Hessian matrix so that I can infer on the convergence of simulated maximum likelihood. $\|g\|_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, K(H) is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$, respectively.

Table 2-4: Hausman-McFadden test for independence of irrelevant alternatives (IIA)

Alternative dropped	Chi-squared	Degrees of Freedom	p-value
Package A	13.97	8	0.0824
Package B	16.27	8	0.0386

The best fit model, in terms of statistical efficiency, is determined based on the statistics provided in the lower panel of Table 2-3. The MIXL provides the lowest corrected Akaike Information Criteria (AICc) value. The AICc improves on AIC by imposing a penalty on the number of parameters estimated. The MIXL model improves upon the MNL model by allowing the parameter(s) to be random and bypassing the IIA property. The GMNL model estimates the scale parameters, τ and γ, in addition to the random taste parameters. However, I find that the scale parameters are not significant in the model, suggesting that I did not find scale heterogeneity in the data. I have run SMNL model which confirms that the scale parameter is not significant in the data. Given all these considerations and having the best statistical efficiency with MIXL model, I go forward with MIXL model to account for additional stated information.

The coefficients and significance are overall similar in all the models. As the magnitudes of the coefficients are not readily explainable in the logistic model, I comment on the sign and the significance of the coefficients. The cost coefficients are negative and significant in all the models, as expected. If the coefficient of any variable has the opposite (same) sign of the cost coefficient, that means this variable contributes to utility (disutility). The significant negative coefficient ASC is interpreted as the household, on average, having disutility staying with the current plan. The significant RE_share coefficient indicates a positive preference for an increase in the share of

renewable electricity. An increase in water usage has significant disutility, which is reasonable in a high desert area. On average, a household associated utility (disutility) with a decrease (an increase) in nuclear electricity. The increase in Jobs is linked with utility where the Job_sq coefficient implies that the increase of utility is at a decreasing rate. The significant standard deviation of the variables shows the presence of taste heterogeneity of the consumer preference. The insignificant scale parameter indicates there is no scale heterogeneity present in the data.

2.4.2 Response efficiency

In DCE, respondents often ignore attribute(s) due to their limited cognitive ability while making rational choices. Respondents also have differing importance of attributes. Incorporating attribute non-attendance and attribute information ranking information can increase response efficiency in DCE. I used stated attribute non-attendance data and stated importance data asked in the survey. At least one attribute is ignored in 29% of the choice sets. The jobs attribute is ignored the most frequently (8%) and the water attribute is ignored the least frequently (5%). The average importance of the attributes shows that RE_share is the most important attribute, followed by Water. Compared to Chalak, Abiad and Balcombe (2016), my ANA data has less ignored attribute. For example, in their study, one attribute is ignored in 55% of the choice situation. Since the attributes in this study were chosen following best practices of survey design, only the most important attributes were included in the survey, which reduces the number of occurrences of ignoring an attribute. I used five variety of MIXL models to incorporate ANA and AIR data. Table 2-5 presents the summary statistics of the contracted models. Model 1 does not account for any new information. Model 2 only uses AIR information. Model 3

estimate ANA using the inferred technique by making zero utility if the respondent has

ANA on that attribute. Model 4 uses ANA data only and model 5 is based on both ANA

and AIR data. The contraction factors for AIR and ANA (μ and ρ, respectively) are

estimated heuristically using grid search approach. A detailed description of the heuristic

optimization for estimating ρ and μ is provided in Appendix B. If the value of μ and ρ is

equal to 0 and 1, respectively, then the data has no contraction. The estimated value of μ

is 0.91 in model 2 and 0.93 in model 5 signifies that there is very high contraction based

on AIR. The estimated ρ are 0.47 and 0.48 in model 4 and model 5, respectively

representing a significant contraction of data based on AIR information. Appendix B

provides detailed information on μ and ρ.

Table 2-5: Summary statistics of contracted MIXL models

Statistics	M(1): No ANA or AIR	M(2): AIR data only	M(3): ANA data only (ANA=zero utility)	M(4): ANA data only	M(5): Both ANA and AIR data
N	863	863	863	863	863
Log-likelihood	-740.8465	-722.2269	-743.8989	-736.3773	-718.9366
$\|g\|_\infty$	5.17E-06	5.65E-08	6.58E-06	1.30E-05	4.09E-06
$g'H^{-1}g$	5.31E-10	2.61E-15	4.10E-10	3.32E-09	1.53E-10
K(H)	5.30E+05	4.31E+05	3.99E+05	3.85E+05	3.26E+05
AIC	1513.693	1476.454	1519.798	1504.755	1469.873
BIC	1589.86	1552.62	1595.964	1580.921	1546.04
AICc	1514.336	1477.097	1520.441	1505.398	1470.516
μ	0	0.91	0	0	0.93
ρ	1	1	0	0.47	0.48

Note:
a. ρ is the contraction parameter for ANA and μ is the contraction parameter of AIR
b.   The number of choice questions is reduced to 863 because I have deleted those choice question for which a respondent did not provide an answer to subsequent ANA and/or AIR questions.
c. $\|g\|_\infty$, $gH^{-1}g$, and K(H) are used to know the condition of gradient and Hessian matrix so that I can infer on the convergence of simulated maximum likelihood. $\|g\|_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, K(H) is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$, respectively.

The best fit model is chosen based on Log-likelihood, AIC, BIC, and AICc

values. Model 2 reduces the AIC value significantly compared to model 1. This signifies

that incorporating AIR information fits the model significantly better. When ANA

45

information is used in model 3 and model 4, the AIC values reduce compared to model 1. However, model 4 fits better than model 3, where ANA is used as having zero utility for that attribute. Finally, taking both ANA and AIR together fits the model best as evident by lower Log-likelihood, AIC, BIC, and AICc values. Compared to the base case MIXL model where neither ANA nor AIR data is considered, the direction and significance of the parameters of model 5 are similar. Note that, some of the standard deviations are significant, suggesting that there are heterogeneities of these parameters.

I have estimated the marginal willingness to pay (MWTP) using model 5 that considers the ANA and AIR information. Hole (2007) compared the confidence interval of MWTP measures in four ways: delta, Fieller, Krinsky Robb, and bootstrap method. I have used the first three methods to compute the MWTP confidence interval. Table 2-6 reports the MWTP with a confidence interval. I have used the delta method for further analysis[6] (estimating individual MWTP for spatial analysis) and explaining the MWTP as it is most accurate when data is well conditioned (Hole, 2007). In this case, the delta method provides the narrowest confidence interval among all the three methods I have employed. The presented prices to the respondents range from -$25.26 to $36.53. Figure 2-5 presents the marginal willingness to pay (MWTP) and confidence interval using the delta method. The box plot is constructed using a 95% confidence level.[7] The whisker represents a 99% confidence level. The negative and significant MWTP for alternative specific constant shows that the households have a negative value associated with staying

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[6] Note that, the simulated maximum likelihood estimation results differ based on software packages and different computers as indicated by Gu, Hole and Knox (2013); Lancsar, Fiebig and Hole (2017). The confidence interval (CI) and MWTP measures are computed using Stata®. All other analysis is conducted using R, gmnl package developed by Sarrias and Daziano (2017). The difference in MWTP CI and MWTP is very minimal (<0.01%).
[7] Significant at 90% confidence level.

at the status quo level. In other words, the households are willing to pay to move away

from the current plan. They are willing to support another state plan that is different from

the current plan.

Table 2-6: Monthly MWTP estimates and confidence intervals from Model 5 using Delta, Fieller, and Krinsky Rob method

Parameter	Estimate	Delta		Fieller		Krinsky Rob	
		Lower	Upper	Lower	Upper	Lower	Upper
Alternative specific constant	-3.03*	-6.55	0.49	-7.20	0.75	-7.45	0.73
share of renewables	31.49***	17.51	45.47	17.48	49.23	17.89	49.47
Change in water usage for electricity generation	-66.86***	-101.07	-32.65	-109.19	-31.70	-107.17	-33.52
Change in number of jobs	10.07***	7.09	13.04	7.14	13.91	7.10	13.89
Square of change in number of jobs	-1.55**	-3.00	-0.10	-3.21	0.07	-3.17	0.06
Increase of nuclear electricity	-6.24***	-10.69	-1.79	-11.25	-1.21	-11.21	-1.23
Decrease of nuclear electricity	4.49**	0.18	8.80	-0.46	9.26	-0.91	9.36

Note:
1. The confidence intervals are based on 95% confidence level.
2. *** p<0.01, ** p<.5, * p<0.1

Figure 2-5: Willingness to pay estimate ($/month/household) for different variables
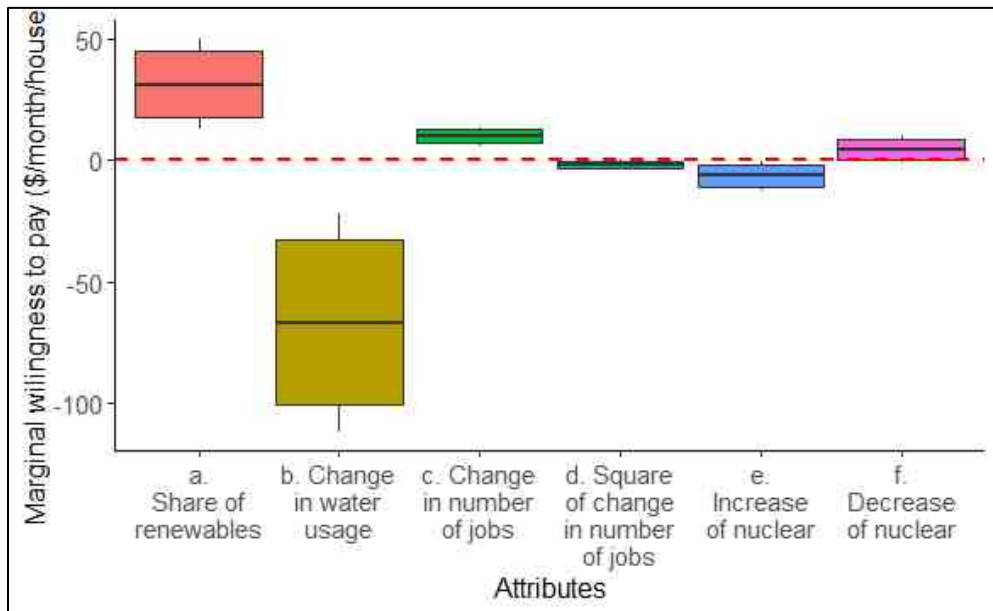
The significant MWTP for share of renewables shows that households are willing to pay for renewable energy. On average, the MWTP for share of renewables is $0.32/month/household for a 1% increase in share of renewables. The average household uses 655 KWh of electricity a month with an average price of 11.37 cents/KWh. The willingness to pay measure translates to 4.23% increase in retail prices of electricity for 10% increase in renewable energy in the form of RPS. This is within the bound of cost-benefit studies (Greenstone & Nath, 2019; Morey & Kirsch, 2013; Tra, 2016; Upton Jr & Snyder, 2017; H. Wang, 2016). The PNM Sky Blue, a voluntary renewable electricity program of PNM, New Mexico, sells 100 KWh for $1.70. The premium charge is 3.31% compared to the average electricity price of 11.37 cents/KWh. New Mexico household on average willing to pay more than the premium charged by voluntary program. Household has more MWTP for water usage for electricity generation than share of renewables. The MWTP for water usage for electricity generation is -$67/month/household, which means that households are willing to pay $6.70/month/household if there is a decrease in water usage by 10%. This high value associated with water usage for electricity generation attribute is as expected in a high desert like New Mexico. Households are willing to pay $10/month/household for an increase of 1,000 jobs in electricity generation and distribution sector of New Mexico. However, the negative MWTP for square of change in number of jobs shows that the WTP for job increase will be increasing at a decreasing rate. The household shows a negative value associated with an increase in nuclear energy. This can be attributed to two reasons: (1) all the nuclear energy distributed in New Mexico is currently imported from Pale Verde, Arizona; and (2) household generally has a fear of nuclear accident and environmental concern regarding nuclear waste. The

consumer is willing to pay $4.49/month/household if there is a decrease in nuclear energy

distribution in New Mexico. This can be explained as the household's preference on non-

reliability of imported nuclear electricity, rather be self-sufficient on electricity

production especially using renewable sources.

2.4.3 Explaining sources of heterogeneity

2.4.3.1 Preference heterogeneity

The standard deviations of some of the variables are significant. It shows that

there is considerable heterogeneity of the parameter estimates among the individual. I

have conducted the LCM and LC-MIXL model to explain the sources of heterogeneity. I

have included socioeconomic and behavioral information to construct the class

characteristics. Our perception is that the pro-ecological and pro-environmental

household will have a positive preference for RPS policies. I have used 6-point new

ecological paradigm (NEP) questions to obtain the ecological perception of the

respondent (Thornton, 2013). The ecological perception variable has six statements with

a 5-point Likert scale. The continuous ecological attitude (EA) variable is defined as the

points attained by a respondent divided by maximum total points available (30). Often

cases, ecological or environmental attitude differs from the environmental practice of the

individual. The environmental practice (E_prac) is a dummy variable set equal to 1 if the

respondent either (a) has a hybrid car, rooftop solar panel, wind turbine, or (b) work in

energy or environment sector, or (c) contributed to the environmental protection group.

The socioeconomic variables included in LCM are Age, Male, Hispanic, High_income,

and Bachelors degree. The definition and summary statistics of these variables are

presented in Table 2-2.

The results from LCM and LC-MIXL are presented in Table 2-7. Both the LCM and LC-MIXL model reconfirms the presence of heterogeneity. Both the LCM and LC-MIXL model uses two classes, where class 2 is the reference class.[8] The upper panel of Table 2-7 shows the preferences and the lower two panels report the class membership and summary statistics. The class membership links the preferences with a socioeconomic and behavioral profile of the household. The slightly dominant class, as indicated by the class probability (0.584) in LCM, shows different preferences compared to the reference class. The dominant class prefers to move away from the current plan, to have a significant increase in RE_share, and decrease in nuclear whereas the reference class prefers to stick with the current plan, no significant preference for RE_share and Nuclear. Both the groups share a similar preference for Water and Jobs variables. Class 1 is tied with the characteristics of being pro-ecological, demonstrated the environmental practice, and younger compared to class 2. It is expected that the pro-ecological class will show an inclination towards pro-environmental policy such as RPS. The result of LC-MIXL is similar to LCM in some respect. The LC-MIXL model shows that households in class 1 do not evaluate any attribute other than the cost attribute. The characteristics of class 1 households comprise of being less pro-ecological, demonstrated less environmental practice and older compared to class 2 where household prefers to move away from the current plan and have a significant preference towards RE_share.

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[8] The number of classes used is usually dictated by the data. LC and LC-MIXL models are usually carried out with a varying number of classes. The optimal number of classes is based on the corrected Akaike Information Criteria. and the Bayesian Information Criterion (W. Y. Chen, Hua, Liekens, & Broekx, 2018). In this study, I use two classes for simpler interpretability and convergence. The preference heterogeneity results presented in this chapter are limited.

Table 2-7: Results of the latent class model (LCM) and the latent class mixed logit model (LC-MIXL)

Model	LCM		LC-MIXL	
	Class 1	Class 2	Class 1	Class 2
Cost	-0.0436***	-0.1218***	-0.3034*	-0.0773**
	(0.0076)	(0.0293)	(0.1835)	(0.0365)
ASC	-1.7660***	0.6168*	-0.1457	-1.6918**
	(0.2921)	(0.3473)	(1.1424)	(0.6992)
RE_share	3.0743***	-0.0667	0.3693	5.8924***
	(0.4360)	(1.1035)	(5.4753)	(2.1516)
Water	-3.9928***	-7.3504**	-4.4201	-14.1942**
	(1.3985)	(3.6108)	(6.2397)	(5.7771)
Jobs	0.4596***	2.7649***	3.2979	1.1775**
	(0.0897)	(0.9636)	(2.0623)	(0.4897)
Job_sq	-0.1130*	-0.9177*	-0.8273	-0.2757
	(0.0653)	(0.4946)	(0.7921)	(0.2362)
Nuc_in	-0.8621***	0.1340	2.4728	-3.5427***
	(0.2106)	(0.4655)	(1.9736)	(1.3578)
Nuc_de	0.4749**	-0.5442	-2.8632	2.6625**
	(0.1872)	(0.5818)	(1.9796)	(1.1109)
Class membership				
EA	5.1353***		-5.8738***	
	(0.7484)		(1.1939)	
E_prac	0.4961***		-0.6270**	
	(0.1916)		(0.2972)	
Age	-0.0210***		0.0148*	
	(0.0064)		(0.0082)	
Male	0.1954			
	-0.2034	Reference class		Reference class
Hispanic	0.1493			
	-0.2267			
High_income	0.0685			
	-0.2005			
Bachelor	-0.0075			
	-0.207			
Intercept	-2.1631***		3.4211***	
	(0.6299)		(0.7618)	
Summary Statistics				
Class probability	0.584	0.416	0.556	0.444
N	741		741	
Log-likelihood	-604.9718		-580.4801	
BIC	1368.5356		1398.8483	
AIC	1257.9436		1232.9603	

Note:

a. *** p<0.01, ** p<.5, * p<0.1. Standard errors are in parenthesis

b. The number of choice questions reduced to 741 because I have deleted those choice question for whom I do not have socioeconomic and/or behavioral data that I have used in LCM models.

c. The standard deviation results are not presented for LC-MIXL model. Some of the standard deviations are significant.

d. The preference heterogeneity results presented are limited because the number of classes is not determined based on the data. Two classes are used because the LC_MIXL model fails to converge when three or more classes are used and the ease of simpler interpretation of the results.

2.4.3.2 Geospatial heterogeneity

The individual MWTP is estimated based on the MIXL model after considering

both ANA and AIR information to conduct hotspot analysis. I have focused only to

MWTP f RE_share. The aim of hotspot analysis is to find statistically significant clusters

of high and low MWTP. The spatial weight matrix for Getis-Ord G_i^* is calculated using

$k = 10$ neighbors and $d = 10,000$ meters (90th percentile distance using the nearest

neighborhood analysis). The results of hotspot analysis and kriging interpolation are

shown in Figure 2-6. The left panel shows that there is a hotspot in Bernalillo and Santa

Fe County, whereas a coldspot exists in near to Chavez, Eddy, and Lea County. The right

panel shows kriging interpolation of the hotspot and coldspot.

Figure 2-6: Geospatial heterogeneity for marginal willingness to pay (MWTP) of RE_share
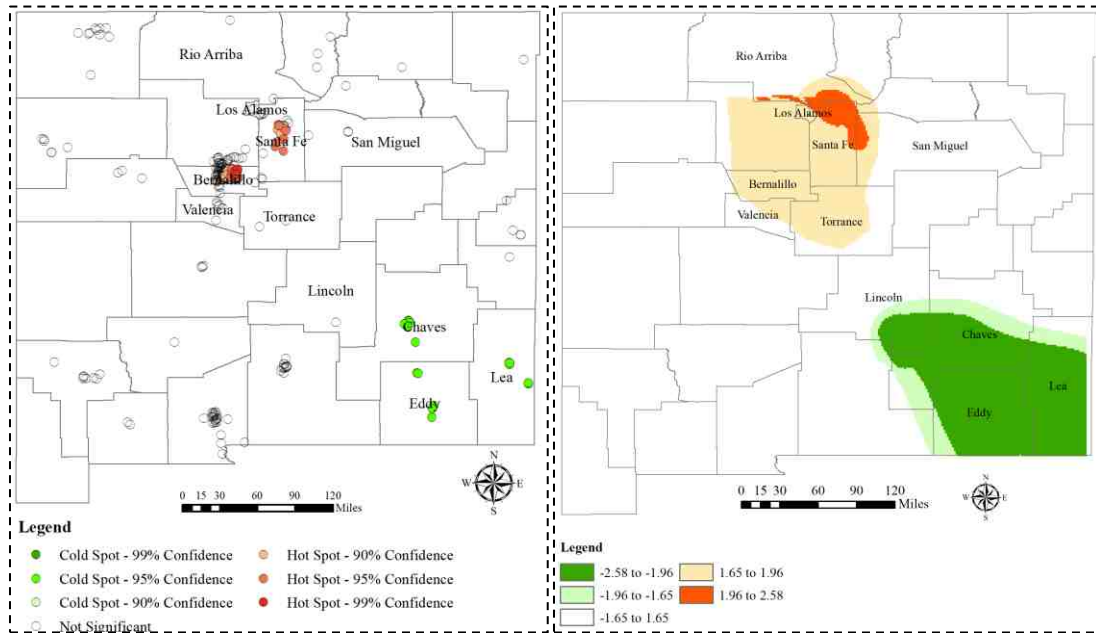
The spatial and demographic differences of households in hotspot and coldspot

are presented in Table 2-8. The spatial variables I have presented include household

distance from the renewable power plant, distance from the conventional power plant, and distance from oil and gas lease location. Table 2-2 presents the definition and summary statistics of these variables. Spatially the hotspot households are characterized by living near to renewable power plants and farther away from oil and gas lease locations compared to households in the coldspot. A similar conclusion is found by Meyerhoff (2013). The households that live further from wind turbines are more likely to be opponents of wind power generation (Meyerhoff, 2013). The location of the coldspot is on the Permian basin (Chaves, Eddy, and Lea county). A household that lives there most likely working in the oil and gas sector thus has a higher likelihood of supporting conventional electricity rather than RPS policies. The demographic differences suggest that the hotspot households are pro-ecological, not pro-environmental, slightly older and more educated than the coldspot households. The finding regarding being pro-ecological and educated is as expected. The LCM and LC-MIXL results also confirm that pro-ecological households prefer to support RPS policy.

Table 2-8: Spatial, Socioeconomic, and behavioral variable comparison of hotspot and coldspot household

Variables	Unit	Hotspot (n=77)	Coldspot (n=20)	Insignificant (n=195)	All sample (n=292)	Significance
Distance to renewable power plants	Km	15.52	80.25	26.50	27.28	***
Distance to conventional power plants	Km	7.58	11.65	19.38	15.74	
Distance to oil and gas lease	Km	35.56	6.38	49.53	42.89	***
Ecological Attitude (EA)	-	0.66	0.55	0.64	0.64	***
Environmental Practice (E_prac)	-	0.43	0.70	0.47	0.47	**
Age	Years	58.74	51.35	54.55	55.44	*
Male	-	0.57	0.65	0.58	0.58	
Hispanic	-	0.21	0.35	0.26	0.25	
High income	-	0.31	0.35	0.44	0.40	
Bachelor	-	0.73	0.35	0.54	0.58	**

Note:
a. All sample includes 292 households that are included in the hotspot analysis
b. The significance levels indicate if the Hotspot and Coldspot group means are significantly different. The significance levels are estimated using Welch two-sample t-test. *** $p<0.01$, ** $p<.5$, * $p<0.1$

■ Policy communication and Conclusion

The objective of this study is to estimate the welfare measure of RPS policy to inform policymakers in taking further decisions regarding this policy. The literature concentrated on estimating welfare measures using cost-benefit analysis. This study uses the discrete choice experiment to map the household preferences of RPS policy in New Mexico. This study answers some of the policy questions that the policymaker might have in regard to updating RPS policies. The target time of New Mexico's RPS policy was 2020. The legislators proposed a bill in 2017 to increase the RPS requirement to 80% by 2040. The proposed bill was rejected by the New Mexico Senate. Subsequently, in the 2019 Senate, the policymaker enacted 100% clean energy by 2045. The 100% clean energy requirement also includes electricity generated from nuclear sources. The policymaker might wonder what could the share of renewables excluding nuclear preferred by New Mexico residents look like. The survey defines RPS requirement excluding electricity generated from nuclear. The result of the survey shows that New Mexico residents prefer an average of 36.15% by 2040 when asked about the preferred share of renewable electricity.[9] This result indicates that out of 100% clean energy, New Mexico residents preferred 36.15% from renewable sources. The remaining clean energy requirement can be met using nuclear and other forms of clean energy. Note that, California and Hawaii also have a 100% clean energy requirement by 2045. While California mandated 100% clean energy requirement, it does not mean the optimum level of RPS in California is 100%. Research on California RPS showed that 27% RPS

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[9] Note that, the average preferred share of renewables is calculated based on the weighted average of responses from the household. The respondents are asked about what is their preferred share of electricity from renewables. The reported average preferred share of renewables does not indicate an optimal level.

requirement provides higher social welfare when CO_2 social cost is moderate and 50%

RPS requirement is better when CO_2 social cost is high (Rouhani, Niemeier, Gao, & Bel,

2016). However, the analysis I have performed does not allow to comment on the optimal

level but preferred level by New Mexico residents, which provides an indication

regarding share of renewables in clean energy requirement of New Mexico.

     The subsequent question this study seeks is if New Mexico residents are willing

to pay for an increase in RPS requirement. The negative and significant MWTP for ASC

indicates that New Mexico residents are willing to pay to move away from the current

plan. The MWTP for RPS is \$31.5/month/household, which translates to a 4.23%

increase in retail prices of electricity. The cost-benefit studies of RPS policies show 3%

to 11% increase in retail prices. This study fits within the boundary to cost increases

indicating that New Mexico residents are willing to pay a moderate amount to increase

the RPS level. The New Mexico Public Regulation Commission (NMPRC) is responsible

for setting a reasonable cost threshold provision that allows electric load-serving utility

flexibility of not procuring renewable electricity if the cost exceeds a certain level. The

2018 reasonable cost threshold is 3% of the total revenue. As the New Mexico residents

are willing to pay a 4.23% increase in retail electricity prices, this can guide the NMPRC

to formulate the reasonable cost threshold. In fact, the Energy Transition Act, 2019 sets a

fixed reasonable cost threshold of \$60/MWh, which is 50% lower than the average

willingness to pay for renewable electricity.

     In addition to the willingness to pay for renewable electricity, households are

willing to pay if the intended plan increases employment in New Mexico. Investment in

renewables increases the number of jobs compared to fossil fuels (Garrett-Peltier, 2017).

However, this does not account for the possible secondary employment loss due to increases in retail electricity prices. Policymakers need to consider the trade-off between the primary and secondary change of employment while formulating RPS policy. The preference for nuclear electricity showed that households have disutility associated with an increase in nuclear electricity. The policymaker can think of a way to communicate regarding nuclear electricity. The RPS policy can bring significant water savings and households are willing to pay for a decrease in water usage by electricity generation. The policymaker can devise the RPS policy 'carve-outs' inclined to the renewable technology that saves the water most.

The survey is conducted in New Mexico, which has one of the most aggressive RPS requirements. However, the results of this study can be valuable to policymakers of other states that are planning to update the RPS policies. Findings in terms of MWTP of individual attributes hold for other regions if the conditions are similar to the study area. For example, the study finds that respondents are willing to pay significantly for a decrease in water usages by electricity generation. This finding holds for the Southwest United States that are frequently affected by drought. Findings in terms heterogeneity of preferences are particularly useful for policymakers of other regions. Results of the study suggest that pro-ecological and pro-environmental groups have significantly higher WTP for renewable energy compared to other groups. Findings from geospatial heterogeneity suggest that individual who lives close to oil and gas-rich areas are tended to have less WTP for renewable energy. Policymakers and utility companies in other states can use this information to establish their policy and plan accordingly. Note that, the results of the study indicate a considerable preference and geospatial heterogeneity of household WTP.

The policymakers need to be cautious about differing socio-demographic characteristics of the population when using this study for other regions using benefit transfer method[10]. The policymakers also need to adjust for differing environmental contexts.

The mismatch between New Mexico residents' preferred share of renewable electricity and recently mandated RPS level that includes nuclear creates a room for meeting the demand using nuclear electricity. Minimum carve-outs set by the policy states that 55% of the RPS requirement needs to be fulfilled using specific types of renewable electricity. In the case of 100% clean energy RPS, minimum 55% must be from renewable sources, which is also almost 20% higher than New Mexico resident's preference. The results also suggest that New Mexico residents show disutility towards nuclear energy. The future distributed electricity mix and diversification of electricity will be highly dependent on the comparative cost of clean energy generation.

The preference heterogeneity analysis presented in this study is limited because the number of classes required for the latent class models are not determined optimally. The number of classes needs to be guided by the data. In this analysis, two number of classes are chosen for simpler interpretability and convergence of the models. However, the convergences of the models can also be achieved if reduced number of sociodemographic variables are used. Future studies can determine the optimal number of classes in the latent class models using the relevant and reduced number of sociodemographic variables.

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[10] Benefit transfer refers to use of welfare estimates for a region to predict welfare estimates in other region for which primary research for welfare estimates is not available.

The result of this study hinges on the fact that the cost of electricity generated from renewable sources is higher than conventional sources. The U.S. Energy Information Administration (2019a) predicts that by 2050, the renewable generation collectively will be approximately double of the U.S. state-level renewable portfolio standards (RPS) due to steep declining of the cost of renewable electricity especially the solar PV costs. Following the U.S. Energy Information Administration (2019a) prediction, the RPS might not be a binding requirement for many states. Future studies can look into the effect of the declining cost of renewable electricity on RPS requirements.

Joint Production of Natural Gas and Oil in the Presence of Externalities

Abstract

Technological advancement in extraction processes such as horizontal drilling and hydraulic fracturing have made it possible to extract from unconventional reservoirs. Unconventional reservoirs are low-porous and permeable reservoirs with a low concentration of hydrocarbons. Unconventional shale gas now accounts for a major share of natural gas production in the United States. Increased production in turn makes natural gas prices competitive compared to coal. However, there are externalities associated with unconventional shale development. This chapter develops a model that considers joint production of oil and gas from shale along with externalities associated with shale development. The well manager will extract at a higher rate without externality case. Results show that gross production is sensitive to change in prices, discount rate, and differing pollution contribution. The well manager who operates several wells within a geographic area can shut-in wells to meet the regulatory requirement of internalizing externality or for a response to unfavorable prices. Leasing agencies such as Bureau of Land Management can use this type of model to develop oil and gas field leasing policies.

■ Introduction

As a relatively clean and abundant energy source, natural gas is becoming more important energy source because governments and consumers grow more concerned about climate change. The International Energy Agency (2014) estimates that global gas use will grow, with the demand of 5.4 trillion cubic meters (tcm) by 2040 and become the second-largest fuel in the global energy mix, after oil. The production of natural gas is increasing over time due to technological advancement in the extraction process. Reservoirs formerly thought to be economically unyielding due to their low porosity and permeability can now be tapped using unconventional extraction processes. A combination of horizontal drilling and hydraulic fracturing have made it possible to extract from reservoirs with low concentrations of gas extended over a large land area. Of these unconventional reservoir types, shale reservoirs is the most widely developed in the United States. Shale deposits are sedimentary rocks that have been found to harbor natural gas, as well as petroleum. Nearly 57 % of U.S. natural gas withdrawal in 2017 was from shale gas wells (U.S. Energy Information Administration, 2019c).

Amidst the natural gas boom, academicians and professionals have worked to optimize production, transportation, and marketing of the product. Zheng et al. (2010) provide a recent survey on optimization models in the natural gas industry. Most such models focus on the engineering aspect of extracting natural gas from shale formations. For example, Wong and Larson (1968) use dynamic programming, and Borraz-Sánchez and Ríos-Mercado (2005) propose a hybrid meta-heuristic approach for natural gas pipeline network optimization. These approaches do not consider economic factors. Considering economic factors in optimizing natural gas extraction is a relatively recent

phenomenon, but it gained attention so quickly that dynamic optimization in extraction of natural gas has become a prototypical example in Natural Resources Economics textbooks (Sweeney, 1992).

The economic theory and application evolve around the theory of exhaustible resources, also known as Hotelling theory. The simplest form of the theory of exhaustible resources states that the price of an exhaustible resource should rise over time at roughly the same pace as interest rates. Note that, this theory does not consider demand and often fails to explain reality (e.g., Halvorsen & Smith, 1991). Chermak & Patrick (2001) extend Halvorsen & Smith's (1991) test where Chermak & Patrick (2001)consider raw and final product in the natural gas industry. However, these are some examples of testing Hotelling theory using econometric technique. Chermak, Crafton, Norquist, & Patrick (1999) integrate exhaustible resources theory with reservoir engineering theory and analyze effective natural gas extraction decision from tight sands. Soemardan, Purwanto, & Arsegianto (2013) present a production optimization model using marginal cost analysis. Adhikari (2017) and Bernknopf et al. (2019) provide proof of concept for net resource valuation while considering externalities of hydrocarbon development.

While shale development supplies hydrocarbons such as oil and gas, it also creates externalities (Ferrell & Sanders, 2013). A growing body of research shows that unconventional shale development has positive and negative externalities. Proponents argue that shale gas development contributes to employment and wage growth. Examples of negative externalities include greenhouse gas emissions, groundwater contamination, unintended health outcomes, and seismic disturbances, among others. Stakeholders such

as policymakers, regulatory bodies, the public, and the media have mixed reactions to the positive and negative impacts of shale development.

Stakeholders who support shale development emphasize positive economic impacts in terms of reduced emissions, increased jobs and local investment, poverty alleviation, energy independence, and service improvements (Thomas, Pidgeon, et al., 2017). Shale development often faces restrictions from stakeholders due to perceived secondary negative impacts. The most commonly cited perceived risks are environmental and health concerns. Perceived risks often lead to changes in law and regulation that affect shale development. For example, Colorado recently passed a law mandating that oil and gas companies must evaluate external impacts such as health and environmental degradation. A federal judge temporarily halted unconventional oil and gas leases in Wyoming to allow for consideration of climate change effects (Duncombe, 2019). The scientific facts of externalities and stakeholders' perceptions of shale development emphasize the importance of considering externalities of shale development while modeling unconventional oil and gas extraction.

This chapter develops a model that considers externalities in unconventional oil and gas development. The literature mostly concentrates on models where profit is maximized while ignoring the cost of externalities. However, few dynamic optimization models compare price paths, and extraction paths of both private and social optimization. Since the U.S. Energy Information Administration estimates that more than 50% of natural gas is produced jointly with oil, I consider joint production of natural gas and oil. Furthermore, the extracted natural gas and oil from shale is not readily marketable. It

needs to go through processing. This chapter extends the literature by considering joint production, processing costs, and externalities.

Results from the model presented here show that extraction of shale gas decreases over time. The gross extraction path is lower if external costs are considered. Consideration of joint production reduces the hyperbolic curvature of gross extraction, because oil production, which is produced at a later stage, is more profitable than natural gas production. The net present value of the extracting firm is sensitive to changes in prices of natural gas and oil and discount factor. The net present value of the firm also increases with a decrease in pollution effects. Results have implications for well managers and leasing agencies.

The rest of the chapter is organized as follows: section 3.2 provides a brief introduction to unconventional shale development process and a literature review on externalities associated with shale development and stakeholders' perceptions. Sections 3.3 discusses a theoretical model of a profit-maximizing oil and gas firm where the well manager considers externalities. A simplified numerical analysis is carried out in section 3.4 to show a well manager's decisions while considering externalities and section 3.5 concludes the chapter.

▊ Background

3.2.1 Unconventional shale development process

Conventional hydrocarbons can be easily tapped using vertical wells because of the highly porous and permeable nature of reservoirs. Unlike conventional hydrocarbons, unconventional hydrocarbon resources are found in low concentrations in low porous, and permeable reservoirs extending over large land area. Unconventional hydrocarbon

reservoirs include shale, coalbed methane, and tight sandstone, among others. The United States has more shale gas reserves compared to other unconventional sources. Proven shale gas reserves were approximately 26 times proven coalbed methane reserves in 2017 (U.S. Energy Information Administration, 2019c). While extraction from unconventional reservoirs requires horizontal drilling and stimulation by hydraulic fracturing, the extraction processes differ depending on geological location and reservoir depth.[11] For example, coalbed methane is found at a shallow depth (600 ft to 3200 ft), whereas shale reservoir has a depth of 5000 ft to 10,000 ft.

Shale development involves extracting oil and gas from shale formations using unconventional ways. One of the most common unconventional processes is hydraulic fracturing. Hydraulic fracking is nothing new, but technological innovation in hydraulic fracturing combined with horizontal drilling makes unconventional shale development economical. Figure 3-1 presents the locations of shale gas within the United States. The United States had a proven reserve of 42 billion barrels (bbl) and 464.3 trillion cubic feet (tcft) crude oil and natural gas in 2017, respectively. Among others, the Permian in western Texas, the Eagle Ford in southern Texas, the Marcellus in Appalachian Basin, and the Niobrara in South Dakota, Colorado, Nebraska, and Wyoming are examples of some of the largest shale plays in the United States.

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[11] For discussion of the difference between coalbed methane and shale reservoirs, read Lea & Rowlan (2019).

Figure 3-1: Location of shale formations in the United States
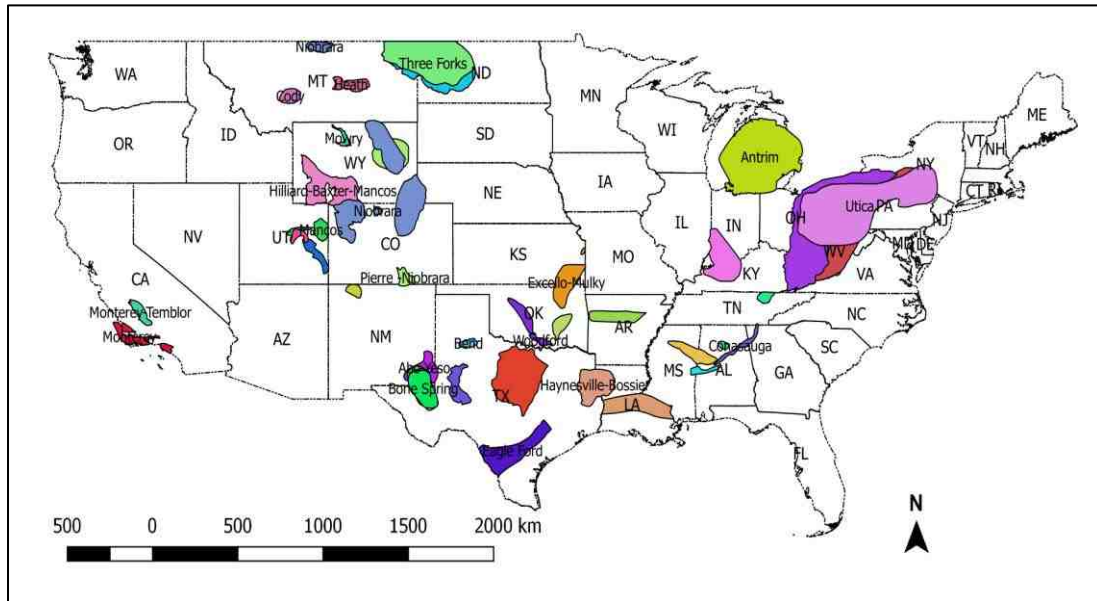
After exploration and approval of development, oil and gas companies build well pads that are typically 3 to 7 acres. A well pad may be constructed to drill multiple wells. A typical well is drilled vertically 5,000 ft to 10,000 ft depending on the depth of shale formation. Next, the well is drilled horizontally up to 10,000 ft. The well is now ready for hydraulic fracturing. A mixture of water, hydraulic fracturing fluids, and proppant is pumped in a controlled and monitored manner into the shale formation to fracture the shale. A wide variety of chemicals are used as hydraulic fracturing fluids, including dilute acids, biocides, and breakers. Each of the chemicals in hydraulic fracturing fluids serves a specific engineering purpose. The role of proppant is to keep the fractures open for natural gas and oil. Proppants can vary in composition and use, but most commonly used proppant is silica sand. A well can be fractured multiple times depending on the pressure and availability of hydrocarbons. After the hydraulic fracture, the well is ready for production.

As the pumping of fluids into the reservoir stops, the pressure is released. As a result of pressure differentials, the gas and oil trapped within the rocks now flow freely to the surface. The fluid and injected water that return to the surface within a short time is called flowback water. Productions from a well are produced water and hydrocarbons in the form of oil and natural gas. Flowback and produced water are much similar in chemical composition, but the timing of their return to the surface is different. The production of hydrocarbons depends on the formation of the reservoirs, pressure of hydrocarbons, and changing the relative volume of produced fluids. The production from a well usually declines over time, and the graphical representation of the declining production is known as Arp's curve.

3.2.2 Positive externalities of shale development

Positive externalities of shale development are primarily economic. Most of the literature is concentrates on local and regional economic development in terms of value addition impact, and employment and wage externalities. The total value added by shale gas to GDP is predicted to exceed $231 billion by 2035 (Bonakdarpour et al., 2011). Weber (2012) suggested that every million dollars in gas production creates 2.35 jobs in the county of production, which leads to an annualized increase in employment of 1.5% of the pre-boom level. Feyrer, Mansur and Sacerdote, (2017) found even smaller employment and wage effects – 0.85 jobs per million dollars in gas production. Considering non-wage income, Bartik and Knittel (2017), meanwhile, found larger effects: a 4.4 to 6.9% wage effect and a 3.6 to 5.4% employment effect. Krupnick and Echarte (2017) provide a literature survey on the economic impact of unconventional oil and gas development and find that most of the literature that studies economic impact

reports a positive employment effect. Studies found a wide range of employment and

wage effects – ranging from 0.3 to 16.7% for wage and 0.16 to 23% for employment

(Krupnick & Echarte, 2017). The wide variation and overestimation of effects in some

studies are due to differences in scope and methodological limitations of studies. A major

part of the studies uses input-output models that provide ex-ante estimates and may

misrepresent the actual economic impact (Lee, 2015). Input-output models typically

consider lease and royalty payments as windfall income and ignore the effect of non-local

purchases of goods. Furthermore, input-output models estimate direct employment while

ignoring the continuation of employment (Lee, 2015). Thus, input-output models

overestimate wage and employment effects. The economic and employment effect also

can be temporary (Komarek, 2016; Weinstein, 2014). Some of the studies that evaluate

long-term growth and economic development found evidence of 'resource curse' and no

economic effect at all (Krupnick & Echarte, 2017). While debate exists among academic

scholars on the size of economic and employment effects of unconventional shale

development, researchers have generally found positive effects.

The climate benefit of shale development is dependent on multiple factors,

including fuel switching, market demand, and life-cycle emissions. Note that, literature

typically does not isolate the effect of shale development but rather reports effects of

increased natural gas production (Mason, Muehlenbachs, & Olmstead, 2015). The

climate benefit can be largely attributed to shale development as the major share of

natural gas production comes from shale development (U.S. Energy Information

Administration, 2019c). Being cleaner than coal in combustion, natural gas can be

considered as a 'bridge fuel' to the future (Howarth & Ingraffea, 2011; Howarth, Santoro,

& Ingraffea, 2011; Mac Kinnon, Brouwer, & Samuelsen, 2018; Zhang, Myhrvold, Hausfather, & Caldeira, 2016). Comparing life-cycle greenhouse gas emissions of different fuels, Burnham et al. (2012) found that shale gas has 6% and 33% lower emissions compared to conventional natural gas and coal, respectively. Oil produced from shale also has lower life-cycle emissions compared to coal (Zhou, Yang, Zhu, Song, & Zhang, 2019). Other than economic and climate benefits, studies also find service improvements and social development attributed to shale development.

3.2.3 Negative externalities of shale development

Unconventional shale gas development has several negative externalities associated with the process. Primarily, the negative concerns are associated with environmental degradation. Litovitz et al. (2013) estimated conventional air pollutant emissions, and the monetary value of the associated environmental and health damage, from the extraction of unconventional shale gas in Pennsylvania. Ethridge et al. (2015) provide an inventory of volatile organic compounds (VOC) that includes many toxic chemicals. One particular concern is methane emissions into the atmosphere. Although life-cycle analysis of shale gas shows favorable greenhouse gas emissions compared to coal, unconventional shale gas development is responsible for methane emissions (Allen et al., 2013; Hausmann, Sussmann, & Smale, 2015; Howarth & Ingraffea, 2011; Karion et al., 2013), which are short-lived but highly potential for global warming (Alvarez et al., 2018; Intergovernmental Panel on Climate Change, 1996).

Vulnerability of groundwater and surface water due to shale development is often cited in literature. The hydraulic fracturing process requires a high amount of water and fracturing fluids to inject into the borehole with high pressure. Groundwater and surface

water contamination can occur in various stages of unconventional shale development. Contentious issues include management of produced water that is often contaminated with brine and toxins (Gregory et al., 2011), and the chemical composition of fracturing fluids. Entrekin et al. (2011) argue that surface water close to gas wells could be impacted. Elevated sediment runoff from pipelines and roads and alteration of stream flow as a result of water contamination are potential impacts (Entrekin et al., 2011). Warner et al. (2012), Engelder, Cathles and Bryndzia (2014), and Harkness et al. (2017) observe the presence of saline in groundwater near shale wells. Toxic chemicals can leak into groundwater from mineral deposition and used hydraulic fracking fluids (Colborn, Kwiatkowski, Schultz, & Bachran, 2011; Vengosh et al., 2015). Methane contamination of groundwater is prevalent throughout the United States (Caulton et al., 2014; Grieve et al., 2018; Harkness et al., 2017; Osborn, Vengosh, Warner, & Jackson, 2011; Vengosh, Warner, Jackson, & Darrah, 2013; Vidic, Brantley, Vandenbossche, Yoxtheimer, & Abad, 2013; Woda et al., 2018). Darrah *et al.* (2014) showed that due to the extraction of shale natural gas, fugitive gas contamination occurred, the relative proportions of thermogenic hydrocarbon gas were significantly higher, and the proportions of atmospheric gases were significantly lower relative to background groundwater. McMahon et al. (2018) even found methane leakage from abandoned wells. However, using isotopic tracing, Botner et al. (2018) found that methane contamination cannot be attributed to shale development. While this finding sounds a cautionary note, studies have generally found evidence of water contamination due to shale development.

Air quality and water contamination from shale development have negative consequences for human health. Health concerns associated with shale development

includes general health problems and hospitalization (Denham, Willis, Zavez, & Hill, 2019; Elliott et al., 2018; McKenzie, Witter, Newman, & Adgate, 2012; Schmidt, 2011; Weinberger, Greiner, Walleigh, & Brown, 2017), asthma and respiratory problems (Rasmussen et al., 2016; Willis, Jusko, Halterman, & Hill, 2018), cancer risk (Elliott et al., 2017), birth outcome (Casey et al., 2016; McKenzie et al., 2015), and infant health (Hill, 2018). For example, McKenzie *et al.* (2015) estimated associations with proximity to natural gas wells and congenital heart defects (CHDs), neural tube defects (NTDs), oral clefts, preterm birth, and term low birth weight.

Seismic activity, and ecosystem and wildlife damages have also been reported as negative externalities from shale development. The coincidence of seismic activities with hydraulic fracturing documented in Louisiana (Walter, Dotray, Frohlich, & Gale, 2016), Ohio (Friberg, Besana-Ostman, & Dricker, 2014), Oklahoma (Holland, 2013) and other places raises the question of a valid causal relationship. Production of oil and gas is responsible for the loss of ecosystem services from crop and rangelands (Haggerty et al., 2015). In addition to environmental and health outcome negative externalities of shale development include traffic congestions and accidents (Goodman et al., 2016; Graham et al., 2015; Rahm, Fields, & Farmer, 2015) and rising housing prices (Muehlenbachs, Spiller, & Timmins, 2016).

3.2.4 Stakeholders' perceptions regarding shale development

Stakeholders' perceptions regarding shale development are shaped by the scientific facts of the positive and negative impacts of shale development. It is also impacted by the survey wording and analysis methodology used to understand stakeholders' perceptions. A systematic review of 58 studies of stakeholders' perceptions

of shale development found that the perceived benefits tend to be economic and perceived risks environmental and social (Thomas, Partridge, Harthorn, & Pidgeon, 2017). Boudet *et al.* (2014) show that individuals who support shale development are less aware of the environmental impacts. Exposure to shale development plays a crucial role in individual perceptions (Theodori, 2009).

Even while expressing apprehension over negative impacts of shale development such as public health and safety, local leaders tend to highly acknowledge economic benefit of unconventional shale development (Anderson & Theodori, 2009). While local leaders and residents often have similar perceptions of shale development, their perceptions sometimes differ (Crowe, Silva, Ceresola, Buday, & Leonard, 2015; Sangaramoorthy, 2019). Sometimes, residents and local leaders both have paradoxical perceptions of scientific facts (Theodori, 2018). Silva and Crowe (2015) show that leaders embrace shale development as a solution to economic malaise, although their intention is not backed by the structure of the economy and society.

Stakeholders perceptions at individual and local community level translate into regulations. Mayer and Malin (2019) show that support for restrictive oil and gas regulations largely depends on natural resource dependence, underlying local economic conditions, and perceived economic benefits. Considering both positive and negative perceptions from residents and local leaders, Buse et al. (2019) suggest that regulators should consider mandating social and environmental impact assessment at a minimum. In line with this policy recommendation, Colorado recently passed SB19-181, requiring oil and gas companies to consider environmental and health outcomes of oil and gas development.

3.2.5 Optimization efforts

Increased production and consumption of natural gas has drawn the attention of academicians and researchers to optimize different stages of natural gas production: exploration, extraction, processing, transport, storage, distribution, and marketing. These research have been conducted from diverse fields of science and technology. For instance, Berkhout (1987) focused on a seismic survey to optimize the exploration of oil and gas, while Tang, Chen, Zhang, Guo, & Chu (2013) designed optimal exploration from a chemistry perspective.

These optimization studies have ignored economic factors until recently. Economists recently explored the external costs of extraction but limited to several industries. For example, Cacho and Hean (2005) considered externalities in an agroforestry system. External costs are not borne by the extracting firm itself, because they do not affect the firm directly. Instead, the cost may be borne by the public, other firms, government, etc. When the external costs of an activity are borne widely within society, the external cost is referred as social costs. A good example of social cost will be health impact of pollution.

The externalities due to natural resources extraction are scientific facts. They are rarely considered in the existing dynamic optimization models. Also, external costs are not accounted for by private firms. Firms do not internalize the cost of externalities unless they are bound to do so by the law. These costs are not directly measurable and can only be perceived. Various non-market valuation techniques can be employed to calculate these costs. Whenever costs of externalities are internalized in the cost function, it can be referred to as 'social cost function.' This paper incorporates social costs in

optimizing natural gas and oil extraction. It extends the literature by incorporating externalities, considering the joint production of natural gas and oil, and explicitly modeling the raw and final product.

■ Theoretical Model

Let's consider a profit-maximizing shale gas and oil extraction company that is a price taker in terms of inputs and outputs. Let's start with the positive half of the objective function; the revenue of the firm. The firm receives revenue by selling the final product natural gas, $N(s)$ and oil, $O(s)$. The revenue function takes the following form:

$$M(S(t); t) = P_N(t)N(S(t)) + P_O(t)O(S(t)) \tag{3.1}$$

Where: $M(S(t)) \equiv$ revenue of the firm at time t;

$P_N(t) \equiv$ price of natural gas at time t;

$P_O(t) \equiv$ price of oil at time t;

$S(t) \equiv$ extraction of water and hydrocarbons (gross production) at time t;

$N(S(t)) \equiv$ production function of natural gas from shale; and

$O(S(t)) \equiv$ production function of oil from shale.

There are three sources of costs, and let's assume that they are additively separable. The extraction cost is defined as $C^E(S(t); R(t))$, where $R(t)$ is the reserve at time t, $C_S^E(t) > 0$, $C_{SS}^E(t) > 0$, $C_R^E(t) < 0$, and $C_{RR}^E(t) \gtrless 0$. The cost of extraction increases at an increasing rate with respect to extraction and decreases with the reserve. The cost of processing is defined as $C^P(S(t))$, where $C_S^P(t) > 0$ and $C_{SS}^P(t) = 0$. I assume a constant marginal cost of processing. The externality cost, $C^H(D(t))$ is

assumed to be logarithmic. Hence, $C_D^H(t) > 0$ and $C_{DD}^H(t) < 0$. Total cost function is

shown in equation (3.2).

$$C(S(t); R(t); P(t); t)$$
$$= C^E(S(t); R(t)) + C^P(S(t)) + C^H(D(t)) \qquad (3.2)$$

The law of evolutions of two stocks, reserve and pollution is given by equations

(3.3) and (3.4).

$$\dot{R} = -S(t) \qquad (3.3)$$

$$\dot{D} = \epsilon S(t) - \delta D(t) \qquad (3.4)$$

The reserve of hydrocarbons decreases as the production of hydrocarbons along

with produced water continues. The extraction of shale and its processing increases

pollution (D) at constant rate ϵ and δ is the natural degeneration capacity of pollution.

Our objective is to maximize the profit of the firm by taking all the costs into account.

The maximization problem is given by:

$$\max_{S(t)} \int_0^T e^{-rt}[M(S(t), t) - C(S(t), R(t), D(t), t)] \qquad (3.5)$$

subject to: $R(0) = \overline{R_0}, \ R(T) \geq 0,$

$$\dot{R} = -S(t),$$

$$\dot{D} = \epsilon S(t) - \delta D(t),$$

$$D(0) = \overline{D_0}, \ D(T) \geq 0, \text{T free}$$

Replacing $M(S(t); t)$ and $C(S(t); R(t); D(t); t)$ from equation (3.1) and (3.2), the maximization problem becomes:

$$\max_{S(t)} \int_0^T e^{-rt}[P_N(t)N(S(t)) + P_O(t)O(S(t)) - C^E(S(t); R(t))$$

$$- C^P(S(t)) - C^H(D(t))]$$

(3.6)

$$\text{subject to: } R(0) = \overline{R_0}, \ R(T) \geq (0),$$

$$\dot{R} = -S(t),$$

$$\dot{D} = \epsilon S(t) - \delta D(t)$$

$$D(0) = \overline{D_0}, \ D(T) \geq 0, \text{ T free}$$

I solve this dynamic optimization problem using the Hamiltonian method. The Hamiltonian function is:

$$H = e^{-rt}[P_N(t)N(S(t)) + P_O(t)O(S(t)) - C^E(S(t); R(t))$$

$$- C^P(S(t)) - C^H(D(t))] - \lambda(t)S(t)$$

(3.7)

$$+ \mu(t)[\epsilon S(t) - \delta D(t)]$$

Here, $\lambda(t)$ is the costate variable or shadow price of reserve and $\mu(t)$ is the shadow cost of pollution. As pollution is an economic bad the value of $\mu(t)$ will be negative. The First Order Necessary Conditions using Pontryagin maximum principle are[12]:

$$H_S = e^{-rt}[P_N N_S + P_O O_S - C_S^E - C_S^P] - \lambda + \epsilon\mu = 0$$

(3.8)

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[12] Subscripts denote the partial derivative with respect to the subscripted variable. Time dimensions are suppressed for clear presentation.

$$-H_R \ = \ e^{-rt} \, C_R^E \ = \ \dot{\lambda} \tag{3.9}$$

$$-H_P \ = \ e^{-rt} C_P^H \ - \ \delta\mu \ = \ \dot{\mu} \tag{3.10}$$

$$H_\lambda \ = \ -S \ = \ \dot{R} \tag{3.11}$$

$$H_\mu = \epsilon S \ - \ \delta D \ = \ \dot{D} \tag{3.12}$$

Equation (3.8) relates the marginal benefit of extracting today to the marginal cost of keeping the reserve in the ground for future extraction. It expressed that the present value of the profit stream (revenue minus costs) is equal to the shadow value of reserve in the ground after subtracting benefit due to reducing the secondary future negative cost of externality, represented by μ. Equation (3.9) equates the present value of the marginal effect of the reserve on the extraction cost to the change is the shadow value of the reserve. Equation (3.10) and (3.11) simply give back the law of evolutions. The change in reserve is simply the shale extraction, and the pollution dynamics consists of two parts, contribution of shale extraction to pollution level and natural degeneration of pollution. As I have two stocks and one control, there is no closed form solution of the maximization problem. Let's further define the functional form and use a numerical solver[13] to get the time path of extraction.

◼ Numerical Analysis

To perform empirical analysis, I need functional forms in discrete term. Let's first derive the shale gas extraction process. Extracting shale from the reserve produces

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[13] I use Powersim® Studio 10 Academic in the Windows 10 environment

natural gas with impurities, oil with impurities, and brine (saltwater) as shown in

equation (3.13).

$$S(t) = G(S(t)) + L(S(t)) + W(S(t)) \tag{3.13}$$

where, $G(S(t)) \equiv$ natural gas with impurities at time t and $G_S(t) = \gamma_1 > 0$ and

$G_{SS} = 0$,

$L(S(t)) \equiv$ liquid oil with impurities at time t and $L_S(t) = \gamma_2 > 0$ and $L_{SS} =$

0, and

$W(S(t)) \equiv$ brine with impurities at time t and $W_S(t) = \gamma_3 > 0$ and $W_{SS} = 0$.

In order for equation (3.13) to hold I need $0 < \gamma_1 < 1, 0 < \gamma_2 < 1$ and $\gamma_1 +$

$\gamma_2 < 1$. Sale-able products-natural gas, $N(G(t))$ and oil, $O(L(t))$- are obtained after

processing. Let's say, the impurities are a certain percentage of natural gas and oil. I

define, $N(S(t)) = \theta_1 \gamma_1 S(t)$ and $O(S(t)) = \theta_2 \gamma_2 S(t)$, where, θ_1 and θ_2 are

percentages of natural gas and oil, respectively and $0 < \theta_1 < 1$ and $0 < \theta_2 < 1$.

Equations (3.14), (3.15), and (3.16) define the cost functions, whereas equation (3.17) is

the revenue function.

$$C^E(S; R) = \frac{S_t^2}{R_t} \tag{3.14}$$

$$C^P(S_t) = G_t^\alpha L_t^{1-\alpha} = (\gamma_1 S_t)^\alpha (\gamma_2 S_t)^{1-\alpha} = \gamma_1^\alpha \gamma_2^{1-\alpha} S_t \tag{3.15}$$

$$C^H(D_t) = \ln(D_t) \tag{3.16}$$

$$M(S_t) = P_N \theta_1 \gamma_1 S_t + P_O \theta_2 \gamma_2 S_t \tag{3.17}$$

I use simple extraction cost function as described in Conrad and Clark (1987), which maintains the property I discussed before. The extraction cost increases with an increase in extraction and with a decrease in reserve over time, because the firm has to go greater depth to extract more. I use a constant return to scale Cobb-Douglas cost function for processing of impure natural gas and impure oil. The externality cost has a logarithmic form. So, the discrete Hamiltonian becomes:

$$H = \left(\frac{1}{1+r}\right)^t \left[P_N\theta_1\gamma_1 S_t + P_O\theta_2\gamma_2 S_t - \frac{S_t^2}{R_t} - \gamma_1^\alpha \gamma_2^{1-\alpha} S_t - ln(D_t)\right]$$

$$+ \left(\frac{1}{1+r}\right)^{t+1} [\lambda_{t+1}(-S_t + R_t - R_{t+1}) + \mu_{t+1}(\epsilon S_t$$

$$- \delta D_t) + D_t - D_{t+1}]$$

(3.18)

First order necessary conditions using Pontryagin maximum principle are:

$$H_S = \left(\frac{1}{1+r}\right)^t \left[P_N\theta_1\gamma_1 S_t + P_O\theta_2\gamma_2 S_t - \frac{2S_t}{R_t} - \gamma_1^\alpha\gamma_2^{1-\alpha}\right] - \left(\frac{1}{1+r}\right)^{t+1} [\lambda_{t+1} + \epsilon\mu_{t+1}]$$

$$= 0$$

$$\Longrightarrow S_t = \frac{R_t}{2}[P_N\theta_1\gamma_1 + P_O\theta_2\gamma_2 - \gamma_1^\alpha\gamma_2^{1-\alpha} - (1+r)(\lambda_{t+1}$$

$$+ \epsilon\mu_{t+1})]$$

(3.19)

$$H_R = \left(\frac{1}{1+r}\right)^t \frac{S_t^2}{R_t^2} + \left(\frac{1}{1+r}\right)^{t+1}\lambda_{t+1} - \left(\frac{1}{1+r}\right)^t \lambda_t = 0$$

$$\Longrightarrow \lambda_{t+1} = (1+r)(\lambda_t - \frac{S_t^2}{R_t^2})$$

(3.20)

$$H_D = \left(\frac{1}{1+r}\right)^t \frac{1}{D_t} + \left(\frac{1}{1+r}\right)^{t+1}\mu_{t+1}(1-\delta) - \left(\frac{1}{1+r}\right)^t \mu_t$$

$$=\gg \mu_{t+1} = (1+r)(\mu_t - \frac{1}{D_t}) \tag{3.21}$$

Equation (3.19) is the extraction path for shale gas, which is not an analytical

solution, rather a function of parameters and endogenous variable. Using equations (3.3),

(3.4), (3.19), (3.20), and (3.21) I can simulate the model.

3.4.1   Data Selection

3.4.1.1   Economics prices

The historical prices of oil and natural gas are collected from the U.S. Energy

Information Administration (2019d) and the U.S. Energy Information

Administration(2019c), respectively. The U.S. Energy Information Administration

(2019a) provides a prediction of oil and gas prices under different scenarios. Figure 3-2

and Figure 3-3 represent historical and predicted natural gas and oil prices under different

scenarios, respectively. The reference case scenario assumes that prices will change

based on expected improvement in oil and gas resources and technology. The high and

low oil and gas resources and technology scenarios assume that the price predictions are

driven by high and low technological improvements. If technological improvement is

high (low), the prices of oil and gas is low (high). For the reference case, the high oil and

gas resources and technology case and the low oil and gas resources and technology case

the WTI crude oil (Henry Hub spot) prices will be 104 $/bbl, 88 $/bbl, and 119 $/bbl

(4.87 $/Mcft, 3.39 $/Mcft, and 8.24 $/Mcft), respectively. Note that, the historical WTI

crude oil prices and Henry Hub spot prices are more volatile than the price predicted by

the U.S. Energy Information Administration (2019a).

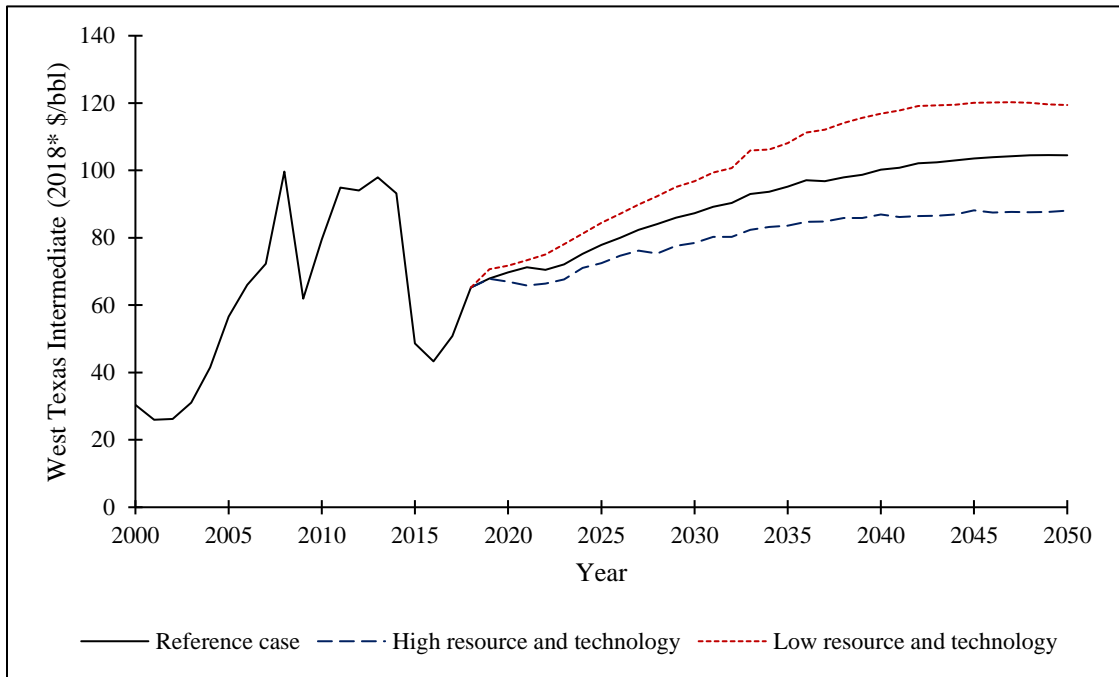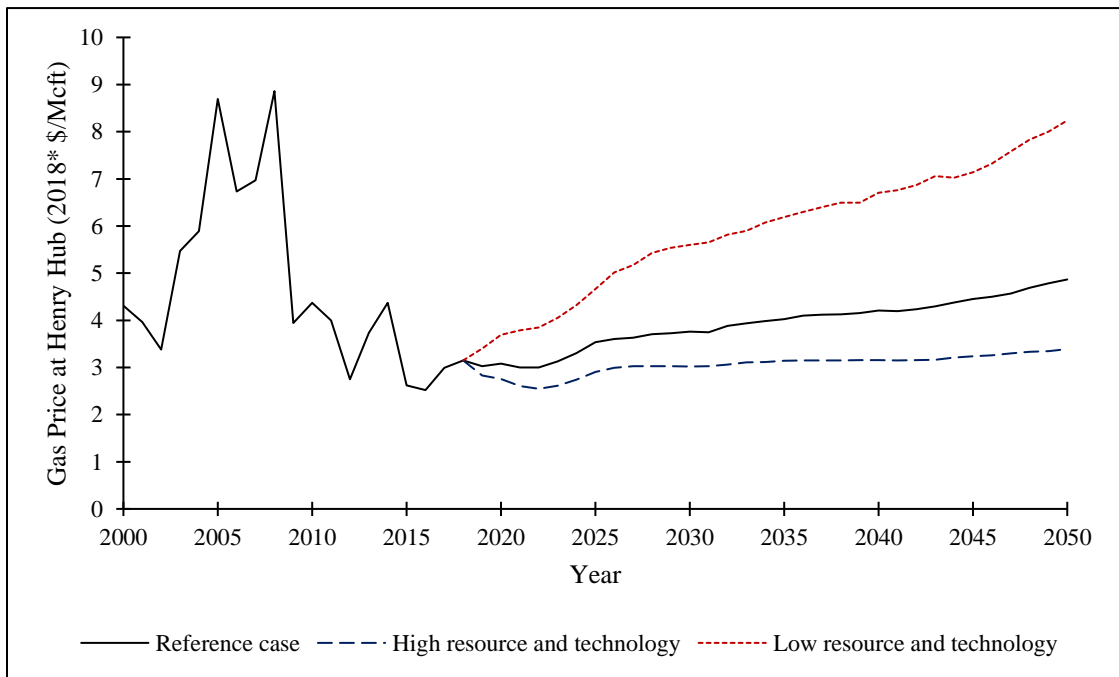Figure 3-2: Price of crude oil at West Texas Intermediate under different scenarios

Figure 3-3: Spot prices of natural gas at Henry Hub under different scenarios

3.4.1.2 Well characteristics

The lifespan of a shale gas well depends on the rate of extraction, initial reserves, well characteristics, and economic conditions. The life of a natural gas well varies from 20 to 30 years (Encana Corporation, 2011). However, the Encana Corporation (2011) does not differentiate between conventional and unconventional wells. The lifespan of an unconventional well is shorter than the lifespan of a conventional well.[14] The Colorado Oil and Gas Conservation Commission (2019) publishes well completion and production data for oil and gas wells in Colorado. There are 446 shale wells that have plugged and abandoned status (PA) in 2018 and producing status (PR) in 2017. The difference between abandoned status date and first production date is considered the lifespan of the well. On average, the lifespan of shale wells is 10.78 years with a range of 2.17 to 35.92 years. In this study, I simulate extraction from 2018 to 2032, assuming 15 years of lifespan. The reserve in the shale well is very diverse in nature. In the analysis, I take a typical well and hence use average reserves, calculated as total US reserve divided by the number of producing wells. The total US reserves and number of 'producing'[15] wells of natural gas is the average for the last five years (2013-2017) data available in the U.S. Energy Information Administration (2019c). The average reserve is 679,482 Mcft. I use 700,000 Mcft as reserve. However, I am maximizing the shale extraction (gross product), not just natural gas or oil extraction. I am estimating jointly. As average water proportion

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[14] There is an argument that the lifespan of unconventional well can be significantly increased using refracturing. Refracturing can even provide a production bump of about 30% (Cafaro, Drouven, & Grossmann, 2016).

[15] Number of wells explored data is not available. A number of producing wells data is used as a proxy. However, this should get a reasonable estimate as production decision is heavily dependent on well characteristics such as pressure and permeability of the reserve.

in shale extraction is 70%, I have an estimated reserve of shale=700,000/30% = 2.33

Million Mcft.

3.4.1.3 Gas to oil ratio dynamics

The proportion of impure natural gas and impure oil is calculated using dynamic

gas to oil ratio (GOR). GOR depends on temperature, pressure, bubbling point, depth of

well, and reserve. There is growing scientific literature on how to quantify the GOR over

the lifespan of well. For example, Liqiang, Feng, Jianhai, Guoqing, & Hang (2014)

calculated a methodical relationship between GOR, gas layer area, and oil layer area. As

the depth increases, the oil layer area increases. Thus, as I drill more depth, the GOR

decreases. I use a simple assumption to estimate the GOR. In the model, the GOR

decreases at the same rate the reserve decreases. The dynamics of GOR is given by

equation (3.22). As reserves, $R(t)$, decrease with time, $GOR(t)$ decreases too.

$$GOR_{t+1} = GOR_t \times \left(1 + \frac{R_{t+1} - R_t}{R_t}\right) \tag{3.22}$$

The Colorado Oil and Gas Conservation Commission (2019) provides GOR data.

In January of 2018, 79 shale wells are completed in the Niobrara and the Willian Fork –

Cameo shale plays in Colorado. Based on the 2018 production data, the gas to oil ratio is

212 Mcft/bbl. I use 212 Mcft/bbl as initial GOR. I calculate the value of γ_1 and γ_2 by

using equation (3.23) and (3.24), where $\gamma_3 = 70\%$, as 70% of extraction of shale is

water.

$$\gamma_1 = (1 - \gamma_3) \times \frac{GOR}{1 + GOR} \tag{3.23}$$

$$\gamma_2 = (1 - \gamma_3) \times \frac{1}{1 + GOR} \qquad (3.24)$$

3.4.1.4 Processing parameters

The extracted natural gas is wet and contains impurities. The U.S. Energy

Information Administration (2006) estimates that 20.4 Tcf of wet natural gas was

converted into the 18.9 Tcf of dry natural gas that was put into the pipeline system in

2004. Also, Bullin & Krouskop (2008) report that non-hydrocarbon in the Barnett,

Marcellus, Fayetteville, and New Albany shale gas is 1.8-9.3%, 0.4-1.3%, 1.7%, and 5.6-

10.4%, respectively. I use this processing conversion as $\theta_1 = 90\%$. Oil from shale is

chemically different from conventional crude oil. It has lower API gravity[16] than light oil.

Hence, the heavier crude oil from shale contains more impurity than the conventional

light crude oil. On a weight basis, the Green River shale has 40% hydrocarbons with API

gravity of 18.6 degrees (Guo, 2009). I assume $\theta_2 = 40\%$.

3.4.1.5 Accounting for externalities

The literature claims an increase of several pollutants due to hydraulic fracturing.

However, these claims are not always published in peer-reviewed journals. Howarth,

Ingraffea and Engelder (2011) discussed these claims in detail and concluded that

methane pollution is the most serious one. In this study, I only consider methane

pollution in drinking water near the well. Howarth, Ingraffea and Engelder (2011) show

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[16] API gravity is a specific gravity scale developed by the American Petroleum Institute (API). It measures the relative density of various petroleum liquids compared to water. Although it is unitless, but it is expressed in degrees. Lower API gravity signifies that the petroleum liquid is heavy and contains heavy materials other than light hydrocarbons.

that the life-cycle methane emission from shale is much higher than other fossil fuels. They also show that shale gas and conventional gas have higher methane emission than coal or diesel. Emissions are even higher for shale gas, more than 60 grams of CO_2 equivalent per MJ of heat energy in the high estimate.

Osborn et al. (2011) found about 75% of groundwater wells sampled within 1 km of gas drilling in the Marcellus shale in Pennsylvania were contaminated with methane from deep shale formations. Although methane is not as persistent greenhouse gas as CO_2, it is deadlier than CO_2 in the near term. The U.S. Department of the Interior, Office of Surface Mining suggests that wells with methane concentrations below 10 mg/L are generally considered safe for use, while 28 mg/L is considered very unsafe and between 10 and 28 mg/L wells need regular monitoring (Eltschlager, Hawkins, Ehler, Baldassare, & Dep, 2001). I use initial methane concentration as 10 mg/L.

3.4.1.6   Other parameters

I use $\alpha = 0.5$, assuming cost share of natural gas and oil processing is the same. The long-run US treasury bill yield is around 2%. However, considering the risky investment in the oil and gas sector, the base case r is assumed to be 0.03 and I simulate 0.00, 0.03, and 0.05. The key parameter values used in this analysis are shown in Table 3-1.

Table 3-1 : Key parameter values and sources

Parameter	Symbol	Value	Source
Oil price	$P_N(0)$	$65.23/bbl	U.S. Energy Information Administration (2019d)
Natural gas price	$P_O(0)$	$3.15/Mcft	U.S. Energy Information Administration (2019c)
Shale reserve	R(0)	2.33 Million Mcft	U.S. Energy Information Administration (2019c)
Water Proportion	γ_3	70%	U.S. Energy Information Administration
Gas to Oil ratio	GOR(0)	212 Mcft/bbl	Colorado Oil and Gas Conservation Commission (2019)
Natural gas purity	θ_1	92%	U.S. Energy Information Administration (2006) and Bullin & Krouskop (2008)
Oil purity	θ_1	40%	Guo (2009)
Discount rate	r	3%	Long term bond rate
Extraction contribution to pollution	ϵ	0.00001	Assumed using Howarth, Ingraffea and Engelder (2011)
Natural degeneration of pollution	δ	0.000001	Assumed using Howarth, Ingraffea and Engelder (2011)

3.4.2 Simulation Results and Discussion

3.4.2.1 Base results

I use Powersim Studio 10 Academic in the Windows 10 environment to simulate.

First, I present the results of the base case scenario. The base case scenario uses price

prediction from the U.S. Energy Information Administration reference case and

parameter values as indicated in Table 3-1.

Figure 3-4 shows the reserve of shale over time for two scenarios. The two

scenarios are different in terms of the well manager's decision to consider externalities.

The finding shows that shale reserves decrease over time. The shale reserves decrease

quickly if the well manager does not consider externalities in production decisions.

Figure 3-5 shows the gross production over time. The gross production decreases over

time. Initially, the firm produces more natural gas and oil. With time, production decreases as the increased health costs are considered. However, the gross production path is less steep than the case where the shale well manager ignores externalities. As the well manager does not consider externalities, the manager does not have any incentive to keep the resources underground. On average, 70% of the reserve is extracted in the first few years. Lake, Martin, Ramsey, & Titman (2013) discussed the empirical hyperbolic production function from a well. In my simulation, the extraction path is not as hyperbolic as empirically found in the literature, because I consider joint production, and the profitable oil products are extracted later.

Figure 3-6 shows the revenue, total cost, and profit of the firm. As the extraction goes down, the revenue and costs go down as those are functions of extraction. The profit of the firm increases over time because the GOR decreases over time. Extracting more oil means more profit, while the extraction of natural gas provides less profit. This is realistic because the sale price of natural gas is lower than oil in terms of the heat energy they produce.

Figure 3-7 shows the net present value of the firm over the period of operation. The Net Present Value (NPV) of the firm in the base case and the case without considering externalities is 0.31 and 0.34 million dollars, respectively.

Figure 3-4: Shale reserve over time
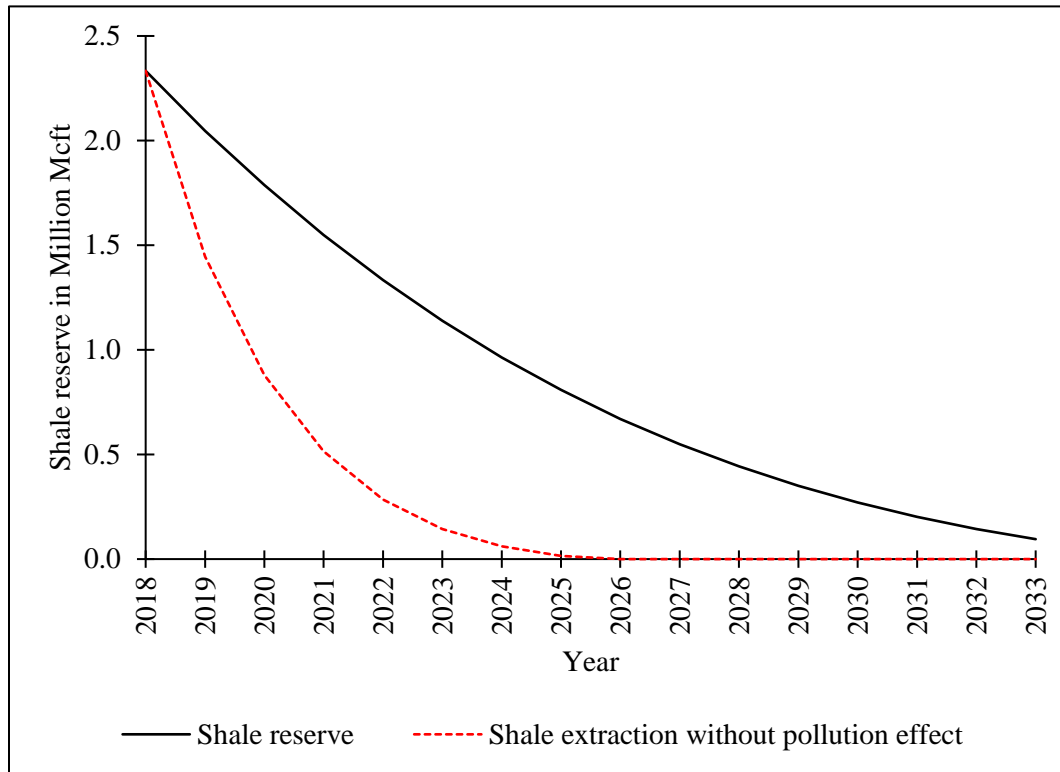
Figure 3-5: Gross production over time
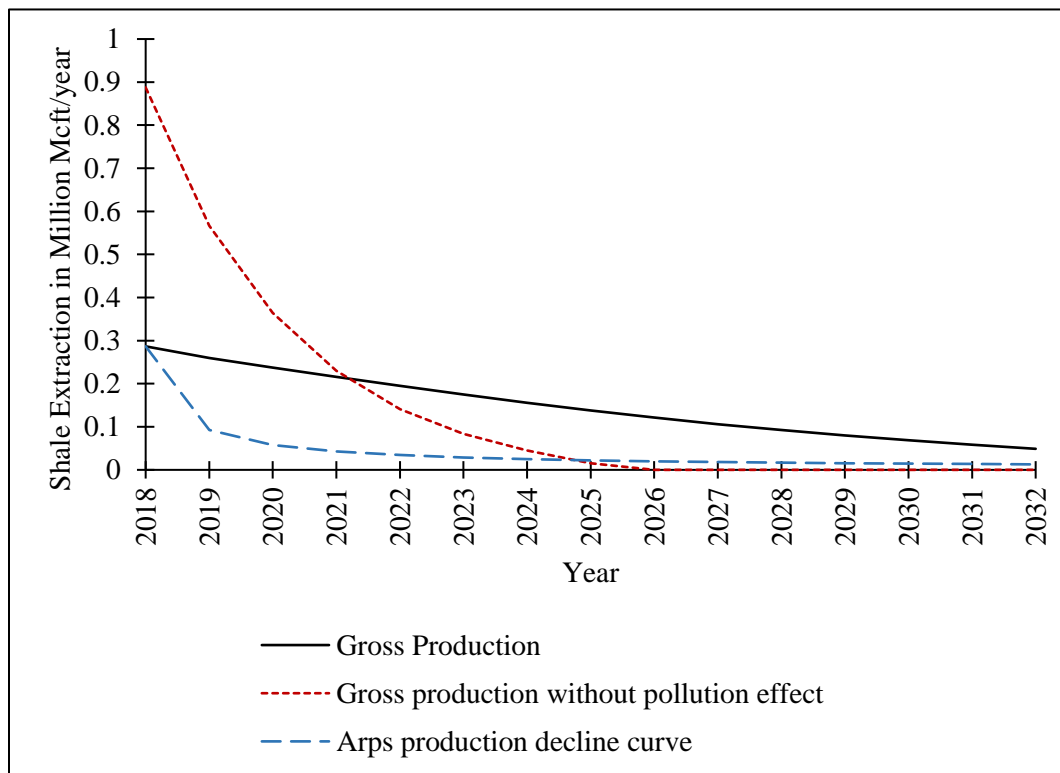
Figure 3-6: Revenue, Cost, and Profit of the firm
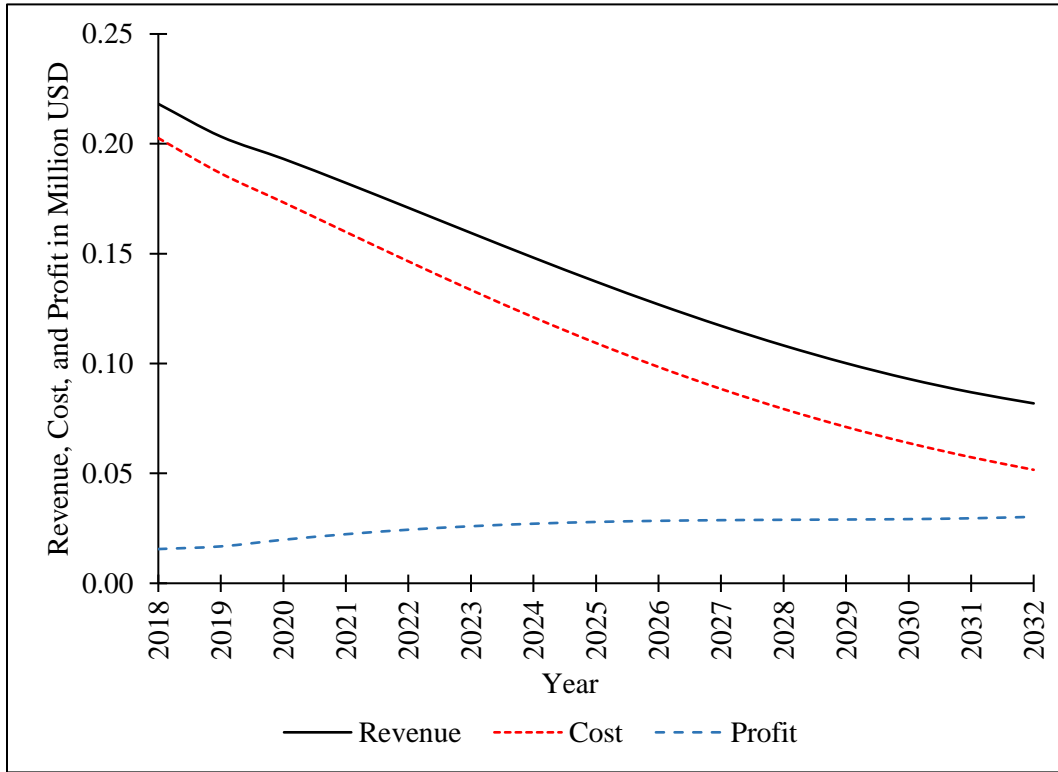
Figure 3-7: Net Present Value of the firm over time
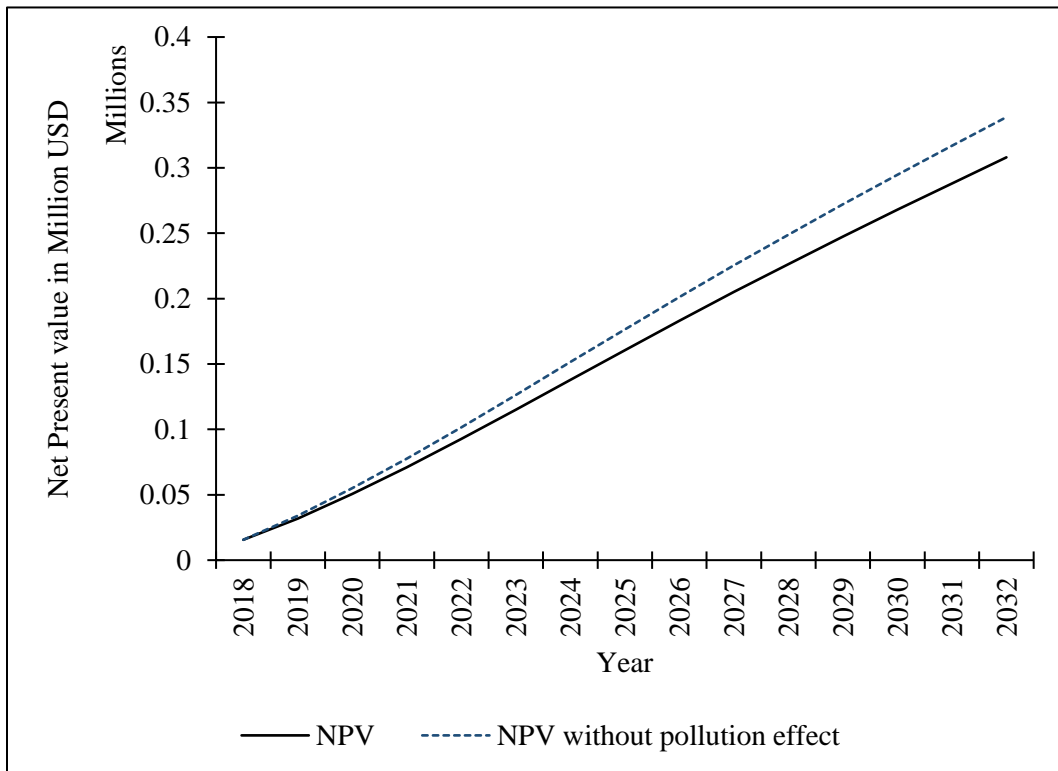
3.4.2.2 Results of alternative assumptions

I perform a sensitivity analysis based on a change in price, effect of pollution, and discount rate. In addition to the reference case price prediction, The U.S. Energy Information Administration (2019a) modeled cases for high and low resources and technology for oil and gas. These cases are based on technological development and resource abundance. Oil and gas price predictions for these cases are shown in Figure 3-2 and Figure 3-3. The prices of oil gas are predicted to be high (low) compared to reference case in low (high) resource and technology of oil and gas. Figure 3-8 shows the sensitivity of NPV with respect to change in price prediction. As the price of natural gas and oil increases rapidly, the NPV increases too. The NPV for the low resource and technology case, the reference case, and the high resource and technology case is 0.45, 0.31, and 0.24 million dollars, respectively.

The sensitivity of NPV with respect to the discount rate is shown in Figure 3-9. I simulate a discount rate of 0%, 3%, and 5% for the low case, the base case, and the high case, respectively. As the firm discounts its future stream of profits heavily, the NPV increases. The NPV for the low case, the base case, and the high case is 0.26, 0.29, and 0.35 million dollars, respectively.

Figure 3-8: Oil and gas resource and technology sensitivity of NPV

EIA reference case

EIA high resource and technology case

EIA low resource and technology case
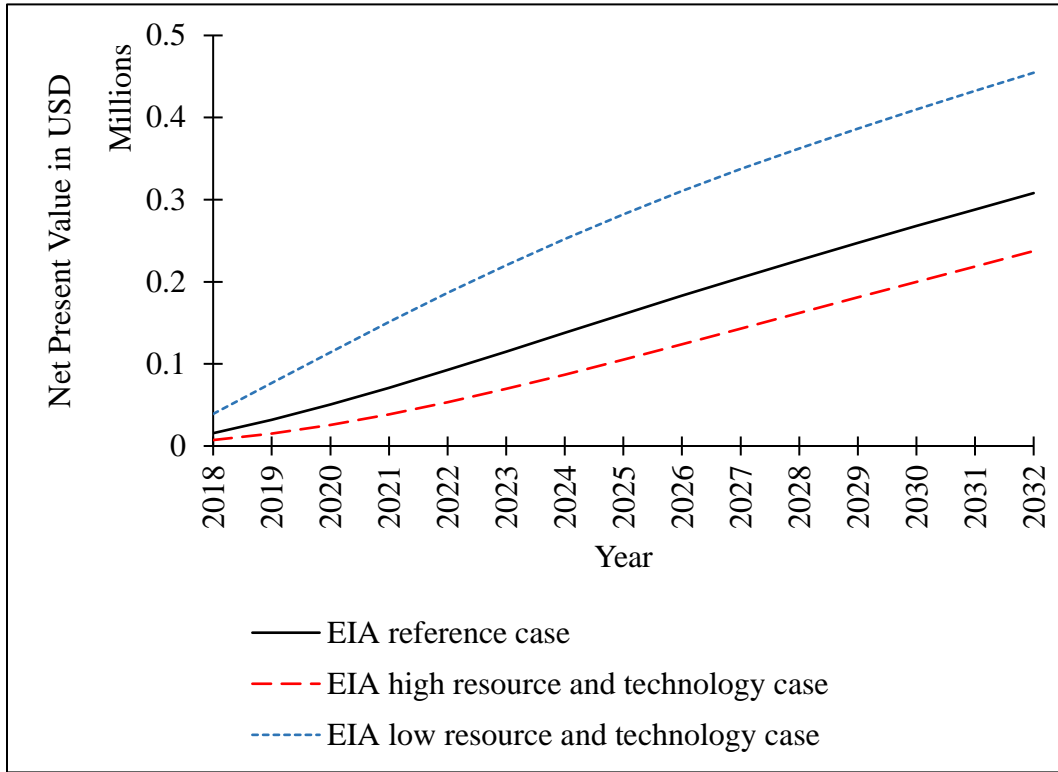
Figure 3-9: Discount rate sensitivity of NPV

Base case [r=3%] High case [r=5%] Low case [r=0%]
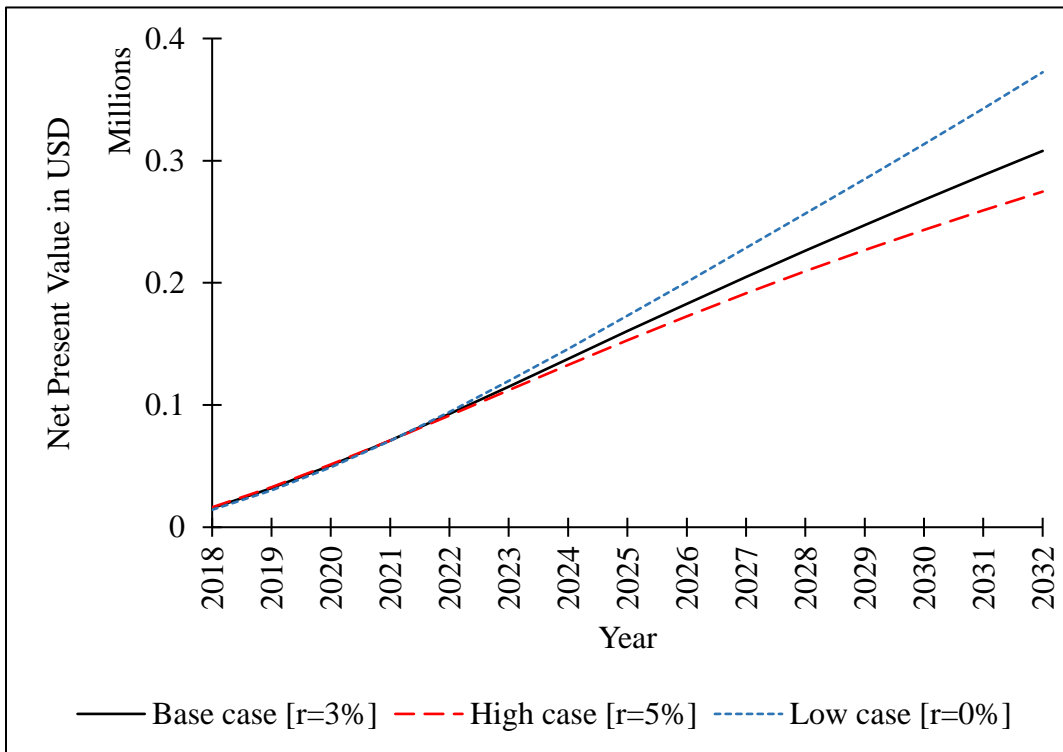
Figure 3-10 shows the sensitivity of the level of pollution (left panel) and the sensitivity of net present value (right panel) with respect to pollution contribution (ϵ). The without pollution case does not change the methane concentration in groundwater. Methane concentration in groundwater is less than 28 mg/L in the low pollution case, which is not very unsafe but requires continuous monitoring of groundwater. Methane concentrations reach an unsafe level in the base case and the high pollution case. Net present values of the firm decrease with an increase in pollution contribution. However, the relationship is non-linear as a higher level of pollution has higher marginal health costs.

Figure 3-10: Level of pollution in different scenarios (left panel) and changes in NPV with pollution contribution (right panel)
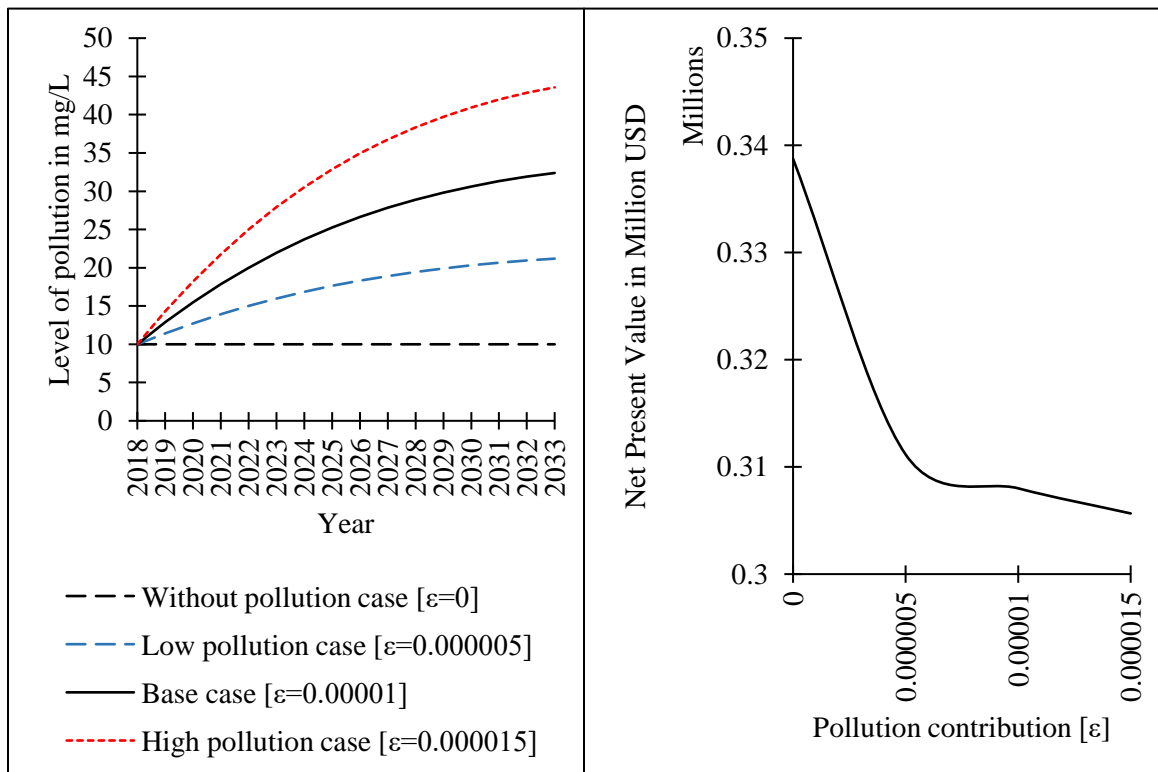
Findings from base scenarios show that the well manager produces less when he/she is internalizing externalities. The well manager has no incentive to curb the production on his/her own. From a societal perspective, laws and regulations can force the well manager to internalize externalities and hence curb production. The well manager also produces less in response to unfavorable prices of oil and gas. The well manager faces two issues if he/she wants to produce less. First, the production from a shale well is largely dependent on well characteristics. Second, the major share of shale development cost is already incurred before production begins. In this sense, a manager will not curb production. However, findings from this chapter have implication for managers who manage several wells.[17] The externalities considered in this analysis are not specific to a single well. The well manager can temporarily shut-in some wells so that aggregate production from a series of wells incorporate production curbing requirements.[18]

The result also has implications for the mineral rights owner if the land is public land. For example, the Bureau of Land Management (BLM) has significant public land within shale plays. BLM's leasing process includes environmental considerations and public hearings. The environmental regulation of BLM (43 CFR § 3162.5-1) requires onshore oil and gas operators to comply with the pertinent orders of an authorized officer and with the standards and procedures set by existing laws. It also requires an authorized officer to prepare an environmental record of review or an environmental assessment,

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[17] In Colorado, oil and gas companies manages 54 wells on average in 2018 (Colorado Oil and Gas Conservation Commission, 2019).

[18] In Colorado, 14% wells have shut-in (SI) status in 2018. Shut-in wells are completed well that are not producing but are mechanically capable of production (Colorado Oil and Gas Conservation Commission, 2019).

whichever is applicable. The results of this chapter can help the authorized officer in preparing an environmental assessment. Also, BLM already has an unsuitability criterion for coal mining that restricts operators from extracting in areas highly vulnerable to environmental degradation. Application of this type of model with site-specific inputs can help BLM to develop such unsuitability criteria for onshore oil and gas operation from shale.

Conclusion and Way Forward

With the development of technology, natural resources extraction from shale reservoirs becomes a reality. This technological change shapes the future of natural gas and oil extraction. A significant portion of natural gas is extracted using fracturing and horizontal drilling. However, there is growing concern about negative externalities associated with this technology and with overall extraction from shale. I model the joint extraction of natural gas and oil in the presence of externalities.

In an empirical setting, findings suggest that the gross production path is lower if the well manager considers externalities. I find that stock of natural gas, extraction, and user cost are sensitive to discount factor and future prices. If the price trend is high, then the firm would like to extract the resources rapidly. In the case of the discount factor, I find that at a high discount factor, then it would be beneficial to keep the resources in the ground for a long time because investments in other assets are generating a high return. The model only considers methane contamination in groundwater while ignoring other externalities associated with shale development. The magnitudes of the cost of externalities, gross production, and net present value are not representative of actual

reality. In this sense, the results from this simplistic model are only valid for comparison purposes among the cases.

The model does not consider the lease cost of extraction. There is a cost associated with the lease of the mineral state of the land. Usually, the lease cost is a percentage of revenue and depends on various negotiation processes. A typical lease can cost 10-15% of revenue. It can further shrink the extraction path. In this model, the extraction costs depend on extraction and reserve at any time t. For a single well, I can also define a more complex econometric result based on functional forms for extraction cost as estimated by Chermak and Patrick (1995). It will be interesting to use such functional forms to further validate the results found in this chapter.

Supply, Operational, and Market Risk Reduction Opportunities of a Cellulosic

Biorefinery for Sustainable Bioeconomy

Abstract

Variability in feedstock characteristics, feedstock supply, and selling prices are major sources of risk facing a cellulosic biorefinery. This paper evaluates supply, operational- and market-risk reduction opportunities if a biorefinery adapts a supply chain design based on a distributed depot concept. In contrast to the conventional feedstock-supply system, a supply-chain design based on a network of depots providing feedstock to a biorefinery employs geographically distributed depots where the feedstock is preprocessed into densified pellets, allowing feedstock to be transported a greater distance. Geographically distributed depots may reduce supply risk by drawing feedstock from larger area and, hence reducing the operational risk. The market risk may be reduced because the densified pellets have potential of selling to alternative markets. Results show that combining the effects of contract management and feedstock supply configuration create alternative market opportunities, which can lead to a reduction of

95

supply, operational, and market risk by approximately 48, 69, and 35%, respectively, thus improving the role of cellulosic biofuels in sustainable production. The expected return on investment increases from -4 to 33%. However, this positive return on investment for a cellulosic biorefinery largely depends on whether densified pellets can be turned into commodity to sell to alternative markets.

■ Introduction

Why are cellulosic biofuel refineries, facilities that convert non-food materials into liquid fuel, not springing up across the United States? Research finds that biofuels can play a critical role in reducing carbon emissions; one lifecycle analysis found that a fleet of biodiesel-powered vehicles can reduce emissions up to 74% over fossil-derived diesel (Tilman et al., 2009; U.S. Department of Energy, 2019). And yet today, a single facility operates in Iowa, and using Intellulose, six other plants are operational.[19] With domestic enthusiasm for environmentally friendly technologies, combined with government investments and policy geared towards sustainable fuels, one would expect more. Studies show that biomass feedstocks like municipal solid wastes, woody biomass, dedicated crops for energy, and agricultural residues—feedstocks for bioenergy—can be obtained in sufficient abundance for cellulosic biofuels to be an important, sustainable, and environmentally friendly component of the cellulosic industry (U.S. Department of Energy, 2005, 2011, 2016). Moreover, the Renewable Fuels Standard (RFS) imposes fuel requirements. RFS requires a certain percentage ethanol to be blended with gasoline. RFS capped annual corn grain ethanol at 56.78 billion liters (15 billion gallons) and calls for

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[19] Intellulose technology uses corn kernel fiber to produce cellulosic ethanol. It is approved by the U.S. Environmental Protection Agency as cellulosic biofuel for Renewable Portfolio Standards. It is advantageous as it uses byproduct of corn grain ethanol and can be processed in corn grain ethanol plant.

production, annually and by 2022, of advanced biofuels to hit 60.57 billion liters (16

billion gallons) (Schnepf & Yacobucci, 2010). Because corn grain ethanol is at a "blend

wall", cellulosic fuels are an important part of a renewable-fuels strategy in the United

States.[20]

Recent experience in today's operating cellulosic biorefineries illustrates barriers

remain to be resolved in order for the cellulosic biofuels industry to expand; they are off

to a bumpy start. By May 2015, annualized production of three facilities hit 3% of

nameplate capacity, a combined value of $2.6 million (Rapier, 2015). The annualized

production reached 38.04 million liters in 2017 (U.S. Environmental Protection Agency,

2018), which is much lower than the desired 60.57 billion liters called for in the RFS.

Eight of the sixteen facilities registered with the Environmental Protection Agency in the

United States (US EPA) are producing commercially as of April 2018, but two of the

facilities are permanently idle (Lane, 2017; Schill, 2018; Voegele, 2015).

The cellulosic biorefinery failed to attract investors in part due to its inability to

match risk and return. The biorefinery faces risks from different sources.

Figure 4-1 shows the sources of risks and their intricacies with the biorefinery.

There can be potential risks from biomass yield, the participation of the growers, and

drought that can impact the availability of biomass (Altman, Bergtold, Sanders, &

Johnson, 2015; Bergtold, Fewell, & Williams, 2014; Fewell, Bergtold, & Williams, 2016;

Kucharik & Ramankutty, 2005; Porter & Semenov, 2005; Ray, Gerber, Macdonald, &

West, 2015). The uncertain characteristics of the available biomass can be a potential

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[20] Blend wall refers to the upper limit of ethanol that can be blended to the gasoline. For more information about blend wall, read Yacobucci (2010).

source of risk to the biorefinery. Key characteristics of biomass, such as ash content, dry-matter loss, and moisture content, can affect cellulosic biofuel production (Liu, Ye, Womac, & Sokhansanj, 2010; Weiss, Farmer, & Schell, 2010; Williams, Westover, Emerson, Tumuluru, & Li, 2016). Another source of risk is from the market itself: price volatility of ethanol and the combination of price volatility and availability of other merchandisable product intermediates (MPIs) (Serra, Zilberman, & Gil, 2011). As the sources of risk suggest, cellulosic biorefinery risk can be delineated into three categorical risks: (1) supply risk, the risk of not having enough feedstock; (2) operational risk, the risk of not producing cellulosic biofuel within a minimum cost threshold due to quality variation of the feedstock; and (3) market risk, the risk of not obtaining a return on asset above a certain threshold.

Industry deployment hinges on the ability to quantify, mitigate and manage risk at the biorefinery (Searcy et al., 2015). The biorefinery has the option to shift some risk to other parties. Insurance for inventory mitigation can fully or partially share the burden of supply risk to insurance companies. However, as the cellulosic biorefinery is in infancy, the lack of data to determine insurance premiums is discouraging insurance companies from offering this risk-shifting mechanism (Searcy et al., 2015). Managers at the cellulosic biorefinery can mitigate risk in how they configure the feedstock supply chain. Managers can employ contract-management strategies, such as over-contracting to reduce supply risk. In the conventional herbaceous-feedstock supply system, managers contract for cellulosic feedstock with local growers, store it at the edge of the grower's field and then transport the feedstock to the local biorefinery in raw format.

Figure 4-1: Biorefinery risk sources and their intricacies.
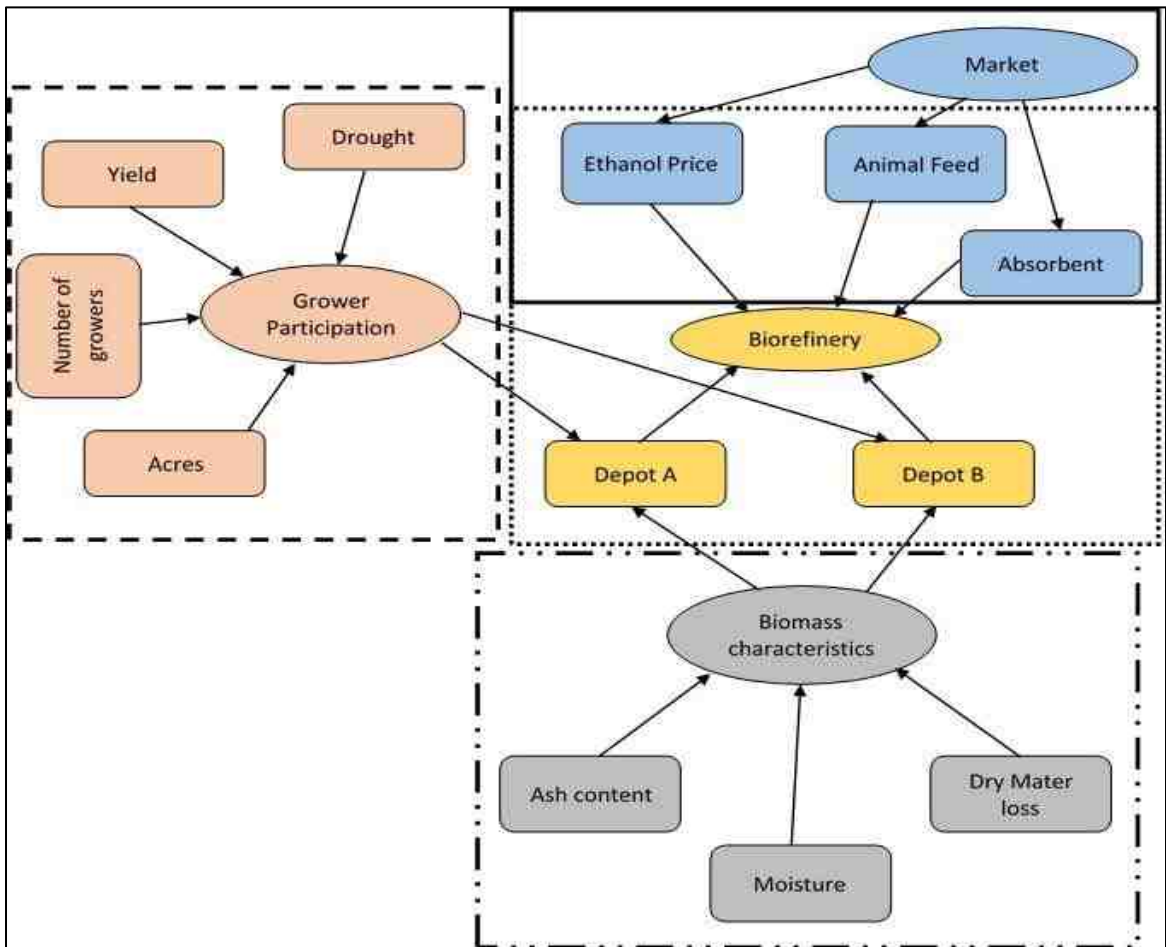
Note: The sources of risks stemming from uncertainty in grower participation, characteristics of biomass, biorefinery configuration, and market condition.

Note that, woody biomass may be stored on the stump until needed and stored short-term as logs, chips, or hog fuel (unprocessed mixture of barks and fiber chips). As opposed to the practice of conventional supply systems, in distributed depot-based feedstock supply system, outlined by R. J. Hess, Kenney, Ovard, Searcy, & Wright (2009) at the Idaho National Laboratory, biomass feedstock is transformed into a commodity, such as a densified, herbaceous pellet that can be stored, handled, and transported across a greater distance, be traded in a market, and meet conversion in-feed

specifications for various conversion processes (R. J. Hess et al., 2009; Lamers, Roni, et al., 2015; Lamers, Tan, et al., 2015). In this paper, I explore operational- and market-risk reduction opportunities should a biorefinery adopt the distributed-depot-based supply chain design.

Research on risk analysis at the cellulosic biorefinery concentrates on two strands. The first strand of research explores the optimal design size and location of a cellulosic biorefinery under uncertain conditions (Bowling, Ponce-Ortega, & El-Halwagi, 2011; Dal-Mas, Giarola, Zamboni, & Bezzo, 2011; Huang, Ramaswamy, Al-Dajani, Tschirner, & Cairncross, 2009; Larasati, Liu, & Epplin, 2012; Leboreiro & Hilaly, 2011; López-Díaz, Lira-Barragán, Rubio-Castro, Ponce-Ortega, & El-Halwagi, 2017; Sesmero & Sun, 2016; Tay, Ng, & Tan, 2013). The design size and location of a cellulosic biorefinery is a crucial component for investing in the biorefinery because a growing concern regards economic availability of feedstock. A major part of cellulosic-biorefinery risk studies, apart from selecting facility-specific attributes like size and location, encompass the uncertainty of the supply biomass (Golecha & Gan, 2016b, 2016a; J. K. Hansen, Jacobson, Lamers, Roni, & Cafferty, 2015; Searcy et al., 2015; Y. Wang et al., 2018). Using a systems-dynamics approach, Hansen et al. (2015) argued that supply risk can be reduced by using a distributed-depot-based feedstock supply system. Using Monte-Carlo simulation, Searcy et al. (2015) reach the same conclusion. Golecha and Gan (2016a), Golecha and Gan (2016b), and Wang et al. (2018) show the effect of contract management on supply uncertainty. The operational- or market-risk studies consider different aspect of risk at a cellulosic biorefinery. Wang et al. (2018) looked into the uncertainty of return on investment (ROI) from a biomass grower's perspectives. Zhao,

Brown and Tyner (2015) and Zhao, Yao and Tyner (2016) estimated the uncertainty of break-even prices under different fuel pathways. Cheali et al. (2016) analyzed biorefinery profitability and risk among different conversion processes.

Although several studies look into cellulosic-biorefinery risk, few studies investigated operational- and market-risk reduction opportunities in the biorefinery's distributed-depot-based supply-chain design. To date, much feedstock supply-system research compares feedstock-supply systems, assuming deterministic processes (Argo et al., 2018; Chugh et al., 2016; Lamers, Roni, et al., 2015; Lamers, Tan, et al., 2015; Muth et al., 2014). Hansen et al. (2015) and Searcy et al. (2015) are two studies that compared supply systems and estimated supply risk. Our paper builds on this line of research. The purpose of this analysis is to evaluate quantitatively the extent to which distributed supply-chain management at a cellulosic biorefinery can mitigate supply, operational and market risk.

This paper has two primary contributions. It is the first study that identifies operational- and market-risk reduction opportunities if a biorefinery adopts the supply-chain design based on a distributed depot. Second, this paper articulates the sources of risk in a stylized cellulosic biorefinery and potential risk-mitigation techniques available. The results from this paper will help investors and financiers to make informed decisions as they seek to invest in a cellulosic biorefinery, considering risk, potential risk-management strategies and expected ROI.

■■ **Materials and Methods**

4.2.1 Distributed-depot supply-chain

A supply chain organized around a distributed-depot design of a biorefinery employs geographically distributed depots where the feedstock is preprocessed into densified pellets, because transportations costs decrease with densification, greater distance for transportation of feedstock is economically attainable (Figure 4-2). This design, much like the supply system in the grain industry, allows management an alternative to managing feedstock-supply risk. Conventional feedstock-supply systems are constrained by volume, but in the distributed-depot-based supply chain weight is the constraint (R. J. Hess et al., 2009; Searcy et al., 2015). At the depot, production enables value added intermediates that can be suitable for multiple markets, including biofuel.

The example illustrates how diversification lets the manager mitigate feedstock-supply risk due to drought. The same logic applies to mitigating risk from pests or other extreme weather events. In the conventional supply system, odds are that the unwanted event applies to all contract feedstock; in the distributed-depot-based supply system, geographic diversification mitigates how the unwanted event applies.

Figure 4-3 shows what a diversified supply portfolio means in the presence of drought. For a design based on a conventional supply system, the radius from the biorefinery in which feedstocks can be sourced is represented by the dotted line around the green point. The sourcing radius in the distributed depot-based supply system is represented by wider, solid black lines and includes a network of preprocessing depots. In Year A, neither the conventional supply system nor the distributed-depot-based supply system is impacted by drought. In Year B, drought covers the entire sourcing radius of

the conventional supply system, but in the distributed depot-based supply system, much of the sourcing radius is unaffected. By diversifying the supply portfolio, the contracting manager reduces the risk of feedstock shortage from any one location.

Figure 4-2: Distributed-depot-based feedstock-supply system for herbaceous lignocellulosic biomass.
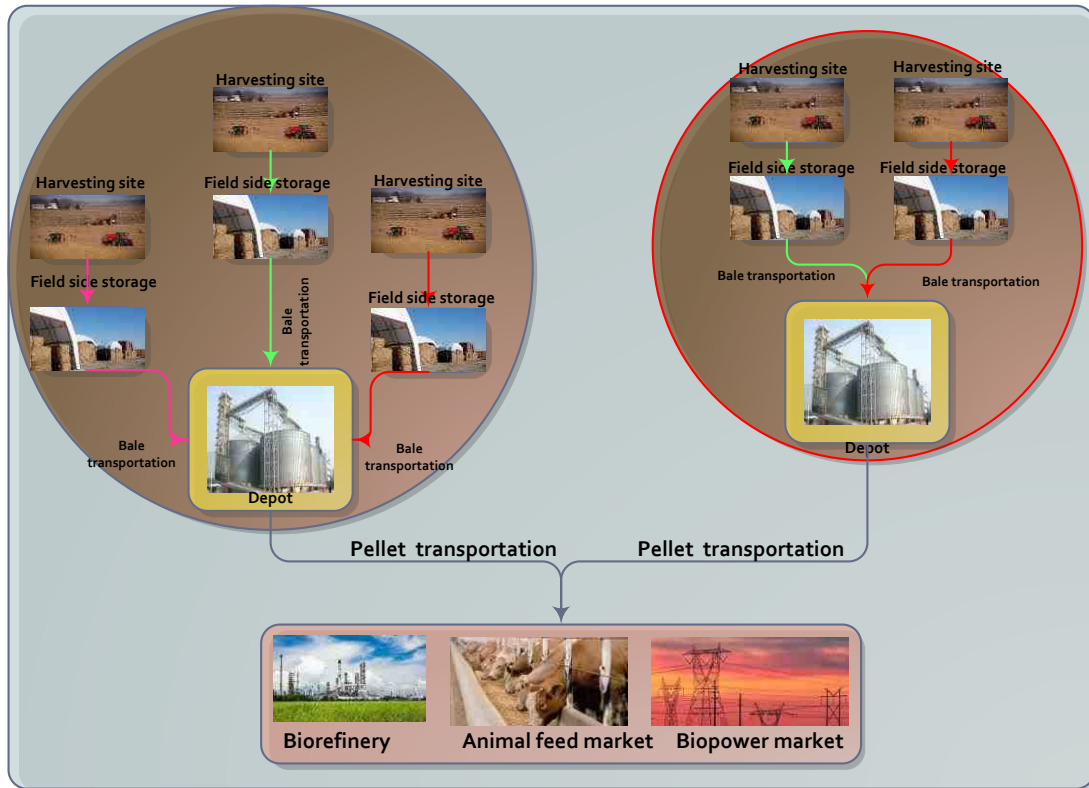
Note that, preprocessing operations are done at the depot. Pellets from depot can be transported to different market.

The example illustrates how diversification lets the manager mitigate feedstock-supply risk due to drought. The same logic applies to mitigating risk from pests or other extreme weather events. In the conventional supply system, odds are that the unwanted event applies to all contract feedstock; in the distributed-depot-based supply system, geographic diversification mitigates how the unwanted event applies.

Figure 4-3: Impact of increased-draw radius in the distributed-depot-based supply-chain design.
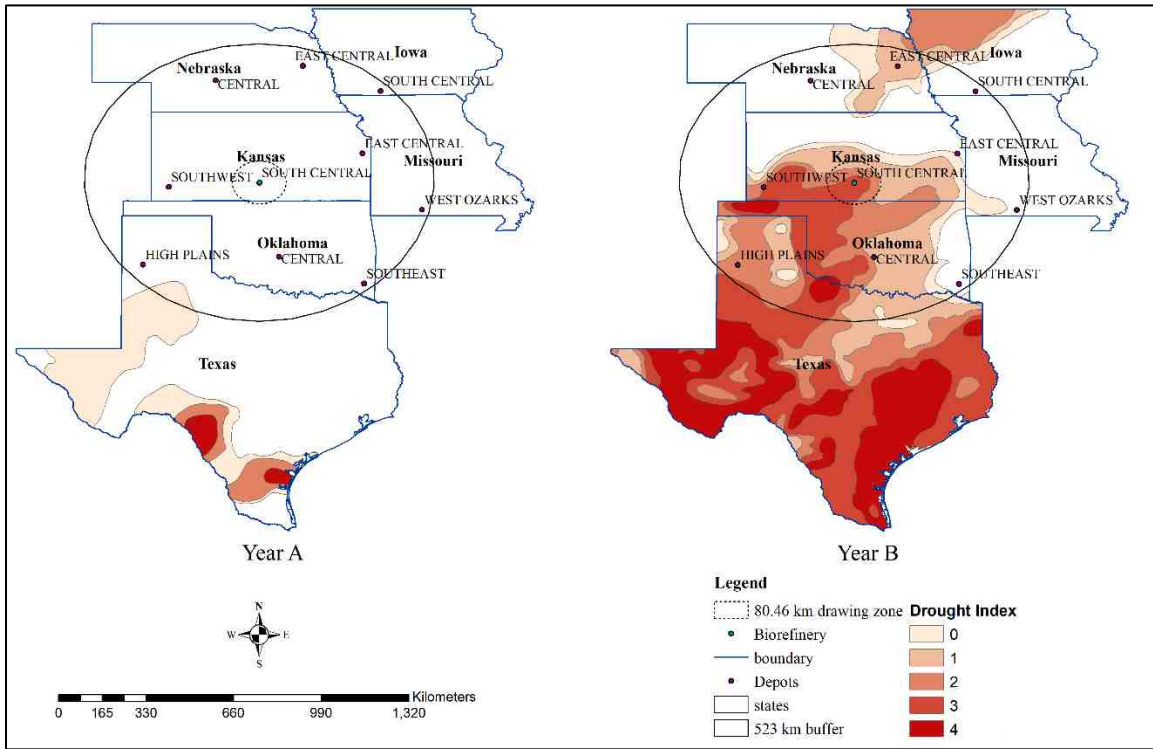
Note: In the conventional supply system, the biorefinery sourcing radius is represented by the dotted line around the green point. The sourcing radius in the distributed-depot-based supply-chain design is represented by a large solid black line. It includes a network of preprocessing depots. The drought-index map data were obtained from the National Drought Mitigation Center (2018). The drought index represents severity of drought, where 4 is an 'Exceptional Drought' and 0 represents 'Abnormally Dry,' as defined by National Oceanic and Atmospheric Administration.

4.2.2 Risk Definition and Management Strategies

In this section, I describe the baseline scenario used throughout the analysis. I define the use of the terms operational risk, market risk, and supply risk, then discuss management options.

4.2.2.1 Defining Risk

Investors are interested in a reward for taking on risk. For an investment in a cellulosic biorefinery, investors will require an accurate assessment of the inherent risk

and the expected reward. To provide this, at least two broad categories of risk must be analyzed. Non-systematic risk, also called idiosyncratic or diversifiable risk, is risk unique to a specific project or policy (J. Hansen & Lipow, 2013). For example, in evaluating the biorefinery's supply-chain design, there is a risk that the design will not perform as planned. Non-systematic risk arises from uncertainties not correlated with performance in the economy. On the other hand, systematic risk measures how the biorefinery performs in the economy. For example, there is a risk that market demand will not support the biorefinery's production costs. Measuring systematic risk assesses the project's "riskiness" relative to market risk. For well-established industries, where sufficient data is available, financial analysts rely on tools such as the capital-asset pricing model (Varian, 1992) to assess systematic risk. Then a risk premium—i.e., the reward for taking on risk—is established. The cellulosic biofuels industry is not, however, well established yet, so an alternative analysis is called for to measure risk and assess reward.

This paper uses a definition of risk based on the combined answers to three questions. They are: what is the unwanted event that can go wrong, how likely is the unwanted event, and what are the consequences of the unwanted event? (Kaplan, Garrick, Kaplin, & Garrick, 1981) Based on this foundational construct, the definitions of risk that follow are measured with probability statements.

4.2.2.2 Supply Risk

In the feedstock supply chain, lots of things can go wrong, creating unwanted events, because of the inherent uncertainty in the environment. Weather events—for which the timing is outside of an expected range (like rain, hail, or frost) or which

involve extreme and deleterious events (such as drought, flood, tornadoes, wind, or pests)—affect biomass at its source. Uncertainty in these events drives uncertainty in factors that matter to the biorefinery: biomass production and attributes of feedstock quality like ash, moisture content and dry-matter loss. These variables affect the biorefinery in two important ways. The certainty of the feedstock-supply requirement is jeopardized and conversion efficiency falls, both of which bear on biorefinery costs. Therefore, uncertainty in the environment leads to risk because uncertain environmental factors lead to uncertainty in factors that define the quality and quantity of the feedstock supply. I term this supply risk. The quantitative definition of supply risk is defined in equation (4.1), which states the probability of feedstock supply falling shorter than a certain threshold level where Mg (Megagram) is unit for mass of dry matter.

$$\Pr(Supply < 635029 \; Mg) \qquad\qquad (4.1)$$

4.2.2.3   Operational Risk

Operational risk is based on the relationship between the minimum fuels selling price (MFSP) relative to a threshold. The MFSP represents the price the cellulosic biorefinery must receive in the marketplace to cover the expenses of producing biofuels. Many components influence MFSP, including the quantity of feedstock needed, quality of feedstock required by the conversion process, the conversion technology used, environmental sustainability, and both products and by-products generated. In this analysis, I focus on the feedstock-supply requirement. In the model developed, I describe how uncertainty in biomass yield, moisture content, ash content, and dry-matter loss impact the supply requirement and, therefore, MFSP. A delivered feedstock-cost target of $93.05/Mg is required to meet the fuel-cost target of $0.84/liters per gasoline equivalent

(LGE) (Bioenergy Technologies Office (BETO), 2015). I use the targets for a quantitative approach to operational risk. Operational risk is defined in equation (4.2), which states the probability of MFSP exceeding the fuel cost target.

$$\Pr(MSFP > \$0.84/LGE) \tag{4.2}$$

4.2.2.4 Market Risk

Uncertainty in the market price of ethanol underlies market risk because of the relationship between the MFSP to the price of ethanol. Like MFSP, market ethanol price is a random variable that I incorporate into the model. I use ROI to measure the biorefinery's market risk. The quantitative definition of market risk is defined in equation (4.3), which measures the probability of ROI not meeting target ROI threshold.

$$\Pr(ROI < 10\%) \tag{4.3}$$

The ROI threshold for risk is set at 10% because it represents the risk premium on an investment in a cellulosic biorefinery. In the design report for a biochemical conversion facility, Humbird et al. (2011) assume a loan rate of 8% with financing over 10 years. Assume the bond rate for the biorefinery is equal to the loan rate. Then, following Hirschey (2008), add a 4% risk premium to the bond rate to determine the equity cost of financing. The risk-free rate on US government bonds for 10 years is 2% (U.S. Department of Treasury, 2015). Subtract this from the 12% sum computed above. What remains is 10%, the net risk premium—i.e., the reward to investors for financing the biorefinery.

4.2.3 Risk Management Strategies

4.2.3.1 Contract Management

The local availability of biomass does not guarantee the adequate supply of feedstock. Supply of feedstock depends on contract management and growers' willingness to participate (Altman et al., 2015; Bergtold et al., 2014; Fewell et al., 2016; Golecha & Gan, 2016b; Ray et al., 2015). Feedstock-supply risk can be managed by the amount of biomass resources put under contract and through understanding the liquidity of the uncontracted supply. Contract management is related to the profitability of the biorefinery (Golecha & Gan, 2016a). Adequate feedstock delivered to the biorefinery is important because a shortage means production shuts down and payment must be made for unused capacity. The contract manager can contract an average number of farmers to get required feedstock. However, due to the variation in the feedstock availability and quality, the biorefinery will get an uncertain amount of feedstock supplied. This can be more than, equal to, or less than the capacity of the biorefinery. In this circumstance, the manager has the option to set the level of contracts such that enough feedstock enters the biorefinery to engage production.

4.2.3.2 Configuration of Feedstock-supply System

A fundamental risk-management decision for the investor to evaluate is how the feedstock supply chain is configured because this determines which market opportunities will be available in the future. In its current form in the conventional supply system, biomass is not a commodity, so it is not 'fungible' (because of its varying characteristics) (Olsson, Lamers, Schipfer, & Wild, 2016), which means its potential applications are limited. The excess biomass in baled form does not have a market value other than selling

as salvage. Excess biomass sold in alternative markets can offset biofuels production cost; hence, the distributed-depot-based feedstock-supply system enables risk mitigation because of broader market access.

The biomass-feedstock commodity has value outside of the biofuels supply chain and becomes an MPI (merchandisable product intermediate). In the case of excess biomass, management can sell MPIs to alternative markets. I consider two MPI markets, the animal feed market and the absorbent market, to evaluate how access to alternative markets allows risk mitigation I maintain the assumption that the biorefinery's primary purpose is to produce biofuels; hence, I consider sales to MPI markets only when the biorefinery ends up with excess feedstock supply. However, by considering these two markets, I consider how management could divert product from one MPI to another based on market price.

Demand for animal feed grows steadily, particularly the demand for nutrient content. I compare nutrient contents of animal feed to approximate the market for pelleted corn stover. Dried distiller's grain with solubles (DDGS) and alfalfa cubes are two potential candidates that closely match nutrient contents of pelleted corn stover. Dale et al. (2009) examined the market for animal feed in terms of protein content in materials used for feed products. They suggest that feedstock from herbaceous biomass, such as corn stover, can be used to generate leaf protein content (LPC) at about 10%. To place this in context, LPC in alfalfa is about 15.4% and in corn grain, it is 9.6% (Dale et al., 2009). The corn-ethanol production process yields DDGS is a co-product. There is no differentiable effect of corn stover and DDGS in growing cattle (Chapple, Cecava, Faulkner, & Felix, 2015; Gramkow et al., 2016; Harding, Bittner, Burken, Erickson, &

MacDonald, 2015). Because of similar protein content, the market for DDGS may approximate market conditions for animal-feed products that may come from the cellulosic industry. However, Preston (2015) compared the nutrient content of 280 animal feeds in terms of energy, protein, and fiber. Table 4-1 presents a comparison of alfalfa cubes, dehydrated alfalfa, distiller's dried solubles, and distiller's grain with the pelleted whole corn plant. Alfalfa cubes are more similar to pelleted whole corn plant than distiller's dried solubles and distiller's grain in terms of total dissolved nutrient (TDN), net energy for growth (NEG), net energy for lactating (NEL), and other categories. In this context, following Preston (2015), I assume that of the two alternative candidate market conditions, the alfalfa cube's market better approximates the condition of pelleted corn stover.

The market for industrial absorbents is another MPI market alternative that biorefinery managers might exploit. Research finds animal health improves with quality bedding materials (Collins, 2012; Davis, Purswell, Columbus, & Kiess, 2010). In the dairy industry, animal health improves with compost-bedding packed barns (Collins, 2012); however, the primary constraint on the widespread use of composting is the availability of sawdust for litter material. Herbaceous materials like corn stover and switchgrass have water-holding capacity conducive for litter material (Collins, 2012). In the poultry industry, research suggests switchgrass is a viable alternative to pine shavings (Davis et al., 2010). Comparison of production characteristics finds that footpad dermatitis decreases with switchgrass litter (Davis et al., 2010). Straw pellets have the highest density and second highest absorption capacity among bedding materials used for horse-manure management (Westendorf & Krogmann, 2013).

Table 4-1: Nutritional comparison of selected animal feeds

Feedstuff	Unit	Alfalfa Cubes	Alfalfa Dehydrated 17% CP	Corn Whole Plant Pelleted	Distiller's Dried Solubles	Distillers Grain
DRY MATTER	Percent	91	92	91	93	Corn with Solubles
ENERGY						
TDN	Percent	57	61	63	87	91
NEM	MJ/Kg	5.3	5.7	5.9	8.9	8.9
NEG	MJ/Kg	2.3	2.9	3.1	5.9	10.1
NEL	MJ/Kg	5.3	5.6	5.9	8.4	6.8
PROTEIN						
CP	Percent	18	19	9	32	100
UIP	Percent	30	60	45	40	31
FIBER						
CF	Percent	29	26	21	4	55
ADF	Percent	36	34	24	7	9
NDF	Percent	46	45	40	22	14
eNDF	Percent	40	6	6	4	30
ETHER EXTRACT						
EE	Percent	2	3	2.4	13	4
MINERALS						
Ash	Percent	11	11	6	8	10.8
Ca	Percent	1.3	1.42	0.5	0.35	5
P	Percent	0.23	0.25	0.24	1.2	0.21
K	Percent	1.9	2.5	0.9	1.8	0.82
Cl	Percent	0.37	0.45		0.28	0.9
S	Percent	0.33	0.28	0.14	1.1	0.18

TDN: total digestible nutrients; NEM: net energy—maintenance; NEG: net energy—growth; NEL: net energy—lactation; CP: crude protein; UIP: undegradable intake protein; CF: crude fiber; ADF: acid detergent fiber; NDF: neutral detergent fiber; eNDF: effective neutral detergent fiber; EE: ether extract; Ash: total mineral content of a feed; Ca: Calcium; P: phosphorus; K: potassium; Cl: chlorine; S: sulfur. For more information about the calculation procedure of the nutrients, see Preston (2015).

Although the market for absorbents produced from herbaceous biomass is not yet widely understood, the industry is emerging. In Pennsylvania, a vendor offers switchgrass pellets for sale for use as industrial absorbent and animal bedding (Ernst Biomass, 2015). These two market opportunities do not represent an exhaustive list of all possible MPI markets. Commodity feedstocks may be used in coal-fired power plants or sold in international markets. But these markets serve as proxies to illustrate how expanding product offerings lets management mitigate market risk.

■ Model Development

A model is needed to compare risk across alternatives. This subsection outlines the theory and Monte Carlo simulation model that serves as the basis for comparison. Let, Q_f represent the total feedstock quantity, in Dry Mg, delivered to the biorefinery on an annual basis. It is based on the total number of farmer contracts, F, the average size of each farm, S, corn stover yield, y, and quality attributes such as dry matter loss, b, and moisture content, c. The equation to compute annual feedstock supply follows:

$$Q_f = \sum_{i}^{D} \sum_{j}^{F} S_{ij} y_{ij} (1 - b - c) \tag{4.4}$$

where i indexes the number of depots from which the biorefinery draws, and j indexes the total number of farmers. Quality attributes, which take the form $0 \leq b, c < 1$ and $b + c < 1$, reduce the total biomass available for conversion.

To compute the quantity of biofuel produced, Q_e in LGE, based on Q_f, I assume the following relationship:

$$Q_e = Q_f \times E_c \, LGE/Mg \tag{4.5}$$

where, E_c is the ethanol conversion factor. I have used 367.20 LGE/Mg, which is similar to that reported in Bioenergy Technologies Office (BETO) (2015). Converting Q_f to Q_e allow us to focus on how the supply risk impacts the unit cost of biofuels, MFSP, and the ROI.

The total cost function is the sum of the cost of biofuel production (cost at the refinery) and logistic cost of the feedstock. I model the average cost of producing a unit

of biofuel, AC_e', based on economies of scale in feedstock intake up to the point of design capacity, which in this model is assumed to be 635,029 Dry Mg (700 thousand DMT) per year, with diseconomies beyond design capacity up to 662,245 Dry Mg (730 thousand DMT). The step function described here shows how AC_e' decrease up to the production of 233.18 million (MM) LGE and then increase up to the point of maximum production, 243.40 MM LGE.

$$AC_e' = \begin{cases} 503.31 Q_e^{-1.25} + \dfrac{\beta_s}{E_c} & for \ Q_e \leq 233.18 \ MM \ LGE \\[2ex] 0.01 Q_e^{0.75} + \dfrac{\beta_s}{E_c} & for \ 233.18 \ \leq Q_e \leq 243.40 \ MM \ LGE \end{cases} \tag{4.6}$$

In equation (4.6), the logistic cost, β_s is dependent on the method of the supply system. I argue that the distributed-depot-based feedstock-supply system can deliver at $93.05/Dry Mg (Bioenergy Technologies Office (BETO), 2015).

Kenney et al. (2013) develop an "ash dockage" that quantifies the impact of poor-quality feedstock on biorefinery costs. Dockage is based on the rate that costs increase for each percentage increase in ash content above a designed capacity. The dockage equation from Kenney et al. (2013) is in terms of $/(%*DMT). It converts to $0.01057/(%*LGE). Let a and a_s measure the weighted average ash content of the feedstock and ash content based on design specification. I assume the design specification for a biochemical conversion facility as 5% ash content. The equation for the average cost of biofuels, in terms of quantity and quality, follows:

$$AC_e = AC_e' + 0.01057 \times \max\{(a - a_s), 0\} \tag{4.7}$$

MFSP, the minimum price for biofuels the biorefinery must receive to break even, depends on AC_e, but also on revenue attained from MPI market opportunities. Recall that the maximum feedstock the biorefinery can process annually, if it operates 365 days per year, is 662,245 Dry Mg. Further, the contract manager over-contracts feedstock to ensure adequate feedstock supply. This means that, depending on the number of contracts issued, the biorefinery may end up with more feedstock than it can use at the biorefinery. Let $Q_x = Q_f - 662245$ for $Q_f > 662245$ and zero otherwise. Let β_s represent the logistic cost the biorefinery pays for delivered feedstock and let p_a stand for the price the biorefinery receives in the MPI market for Q_x. The MFSP ($/LGE), the price the biorefinery must receive to break even follows:

$$MFSP = AC_e + (\beta_s - p_a)\frac{Q_x}{Q_e} \qquad (4.8)$$

From equation (4.2), the MFSP is part of the metric to assess operational risk.

ROI is based on the relationship of total profits to total costs. Because my aim is to enable the biorefinery to compete in the market for biofuel, ROI depends on the market price of ethanol, p_e, relative to MFSP. Moreover, since this model collapses all costs of production into MFSP, the simple per-unit formulation of ROI follows:

$$ROI = \frac{p_e}{MFSP} - 1 \qquad (4.9)$$

From equation (4.3), the ROI is a part of the metric to assess market risk. MFSP and ROI are random variables because underlying variables describing each are uncertain. Next, I describe the data used to approximate model uncertainty.

■■■ **Case Study Using Simulation**

Consider a stylized nth-of-a-kind cellulosic biorefinery using biochemical-conversion technology and located in south-central Kansas with a design capacity to process 635,029 Dry Mg per year (up to 662,245 Dry Mg with overtime production). Based on logistics and economies of scale, the assumption on size is at the lower bound for a distributed-depot-based supply-system biorefinery (Argo et al., 2018). Whereas the biorefinery can process a variety of herbaceous biomass, this analysis assumes corn stover is the primary feedstock. Assume 350 normal operating days per year, with the potential to operate 365 days per year if circumstances and economics warrant. Based on a conversion yield of 367.20 LGE units per Dry Mg of feedstock, the biorefinery produces 233.18 MM LGE annually with a maximum capacity to produce 243.40 MM LGE. Conversion yield may vary, but for simplicity, I assume 367.20 LGE/Dry Mg, consistent with projections (Bioenergy Technologies Office (BETO), 2015) to focus on feedstock implications.

The contract manager at the biorefinery places hectares of farmland under contract to meet the supply requirement. Recognizing uncertainty in factors that impact supply, the contract manager issues contracts for more feedstock than the biorefinery can process to meet the minimum supply requirement. In this analysis, I assume an $93.05/Dry Mg (2015$) total delivered feedstock cost. This represents the cost paid to the grower and covers all logistics cost for getting the biomass from the field to the biorefinery. It is consistent with cost targets for 2022 (Bioenergy Technologies Office (BETO), 2015). Hectares under contract and logistic cost serve as points of comparison in the results.

The data used to parameterize the family of equations developed above is summarized in Table 4-2. Historical data represent the basis for the uncertainty model. The mean, standard deviation, minimum, and maximum are calculated based on historical data found in different sources. The scenarios involving the distributed-depot-based supply system draw feedstock supply from six states and ten different climate divisions. Nine of the ten climate divisions each have one depot, and south-central Kansas has the biorefinery. The summary statistics presented in Table 4-2 are hence divided into ten climate divisions for some of the parameters for which they differ from each other. Finally, historical data are used to fit a family of known distribution. The best fit distribution is used in the simulation.

4.4.1   Farm Size and Corn Stover Yield

Corn stover yield data provides the basis for the probability model for each climate division included in the simulation. The yield data represent climate-division averages across the time frame gathered from the United States Department of Agriculture (U.S. Department of Agriculture, 2018a). The data are arranged by agricultural districts. I have matched the data with climate division, which is the geographic basis of this analysis. All climate districts match with climate division except the Texas high-plain climate division. This climate division is divided into two agricultural districts. For this climate division, I have used the average corn grain yield. The data are recorded based on the corn grain yield measured in bushel/acre. Following Kim and Dale (2004), I convert corn-grain yield to corn-stover yield using a 1:1 ratio and a conversion factor of 56 lb/bushel. For each climate division listed in the data, I model the yield uncertainty by best fitting the data with a series of known distributions. Average

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farm size varies across states. The data do not allow us to infer farms of different types. In reality, corn farm size may differ from farms of other crops. I model farm size as a deterministic parameter and assume that one farmer equals one farm.

Table 4-2: Parameters and their sources used in the simulation.

Data	Mean	St. Dev.	Min	Max	Units	Sources
Corn stover yield						
South Central Kansas	9.44	1.73	5.45	12.78		
Southwest Kansas	2.58	2.08	0.40	8.97		
East Central Kansas	2.87	2.00	0.47	7.20		
Central Oklahoma	8.68	2.44	3.00	12.62		U.S. Department of Agriculture (2018a); Kim & Dale (2004)
Southeast Oklahoma	6.14	2.24	1.88	10.36	Mg/hectare	
Southern Missouri	4.93	1.73	2.02	8.56		
South Central Iowa	5.04	3.79	0.11	12.22		
East Central Nebraska	4.48	3.18	0.16	12.24		
Central Nebraska	3.70	2.69	0.04	10.42		
North Texas	4.71	2.73	0.83	11.48		
Average firm size						
average farm size, KS	296					
average farm size, OK	163					
average farm size, MO	115				hectare	U.S. Department of Agriculture (2016)
average farm size, IA	143					
average farm size, NE	384					
average farm size, TX	230					
Biomass characteristics						
ash content	5	-	-	-		
moisture content, IA	16.31	4.98	6.15	32.83		Idaho National Laboratory
moisture content, KS	20.75	4.98	10.48	34.40	percent	
moisture content, mean	16.08	3.48	8.32	25.97		
dry matter loss	13	10	3	25		R. J. Hess et al. (2009)
Economic prices						
price, ethanol	0.92	0.25	0.32	1.66	USD/LGE	U.S. Department of Agriculture (2018b)
price, Alfalfa cube	257.94	25.79	128.97	386.91	USD/Mg	Online sources
price, absorbent	197.89	9.08	188.16	214.62	USD/Mg	Online sources

Note: The mean, standard deviation, minimum, and maximum are based on historical data. The historical data is used to fit a family of distributions. The best fit distribution is used in the simulation.

4.4.2 Drought Data

The corn stover yield is controlled for drought condition. I have collected the Palmer drought severity index (PDSI) for all climate divisions in six states from the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration, 2017).[21] This is a monthly index that indicates the severity of wet and dry spells. The historic monthly data range from January 1895 to January 2017. The index ranges from -7 to +7. PDSI values of 0 to -0.5, -0.5 to -1.0, -1.0 to -2.0, -2.0 to -3.0, and -3.0 to -4.0 are considered normal, incipient drought, mild drought, moderate drought, severe drought, and extreme drought, respectively. The PDSI distribution is bimodal in the data for positive and negative PDSI values. I have used a mixture of distributions and their proportion of occurrence to represent this bimodal distribution. I choose each part of bimodal distribution based on the best fitting to the underlying data for a series of known continuous and discrete distributions.

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[21] For more information about data, please read: ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/divisional-readme.txt

Table 4-3 presents the probability of different severities of droughts. Note that, as the severity of drought increases, the probability of incurring this severe drought gets lower.

Figure 4-4 shows the hypothetical location of depots in different climate divisions and the probability of at least mild drought occurrence. Climate divisions have a varying probability of having at least mild drought for a given period, which ranges from 0.25 to 0.49. Although the quality of biomass changes with drought condition (Hoover et al., 2018), I assumed that yield only varies. I assumed that yield varies according to levels of drought: mild, moderate, severe, and extreme drought as 95%, 90%, 75%, and 50% of the yield of crops with normal weather condition, as shown in Table 4-3..

Figure 4-4: Hypothetical depot location and corresponding at least mild drought probability
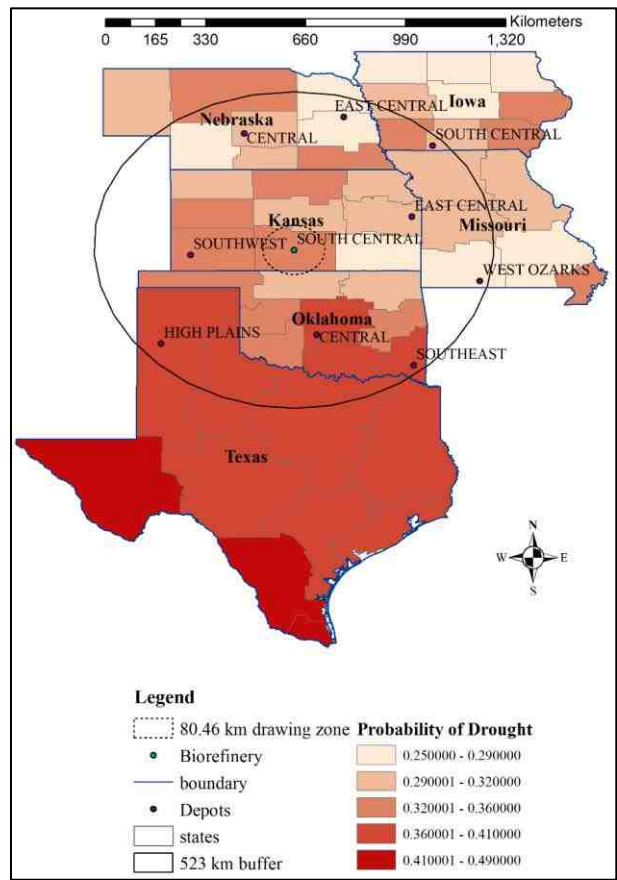
Table 4-3: Probability of different type of droughts and their corresponding yields.

Climate division	CLIMDIV	Mild	Moderate	Severe	Extreme
South Central Kansas	1408	0.13	0.11	0.06	0.04
Southwest Kansas	1407	0.16	0.09	0.05	0.04
East Central Kansas	1406	0.13	0.08	0.07	0.04
Central Oklahoma	3405	0.14	0.11	0.07	0.04
Southeast Oklahoma	3409	0.17	0.12	0.06	0.04
Southern Missouri	2306	0.17	0.10	0.05	0.03
South Central Iowa	1308	0.12	0.09	0.06	0.05
East Central Nebraska	2506	0.12	0.07	0.03	0.06
Central Nebraska	2505	0.13	0.07	0.03	0.07
North Texas	4103	0.17	0.11	0.06	0.03
Yield (percent of normal)	-	95%	90%	75%	50%

Note: CLIMDIV represents the National Oceanic and Atmospheric Administration assigned identification number. Note that, as the severity of drought increases the probability of occurring this severe drought is getting lower.

4.4.3 Biomass Characteristics

The ash content data collected from the Idaho National Laboratory show a wide range of variability. The densification process that converts biomass into pellets, involved in the distributed-depot-based supply system has the option to mitigate ash content to the specification of the biorefinery. The simulation uses a deterministic 5% for the distributed-depot-based supply system. The data for moisture content were collected by the Idaho National Laboratory from Kansas and Iowa. I have used the best-fit distribution for those two states. For other states, I have used the mean of the distribution.

I use a lognormal distribution, parameterized with reported parameters, to represent dry-matter loss. R. J. Hess et al. (2009) report statistics on dry-matter loss for various storage types. Those recorded in Table 4-2 are for 'on ground' storage in bale form. The extent of dry-matter loss depends on physical characteristics of the biomass, storage methods and weather conditions, among other factors (He et al., 2014). The

length of time biomass needs to be stored in bale form will be much lower in the distributed-depot-based supply system. The physical characteristics of baled and pelleted biomass are much different. Hence, I assume that dry-matter loss will be much lower in the distributed-depot-based supply system, and I approximate uncertainty in dry-matter loss with a uniform distribution that ranges from 1% to 2%.

4.4.4 Economic Prices

United States Department of Agriculture (2018b) reports monthly price data for ethanol. The data represent gamma distribution with a mean of $0.92/LGE. The prices of the alternative market are very hard to model as there is no established market. I have used two alternative MPIs: animal-feed market and the absorbent market for corn-stover pellets. A close approximation of the animal-feed market is the market for alfalfa cubes. I have searched online to find prices of bulk and retail alfalfa cubes. I assume that the biorefinery can attain bulk price with a margin and processing cost (such as branding and distributing) of 40%. I represent the uncertainty in the absorbent market with a normal distribution, parameterized with a mean of $257.94/Mg and a standard deviation of 10% of the mean. I use the prices of bedding pellets to model the prices of the absorbent. The bulk and retail prices of bedding pellets are similar22. I use 40% margin and processing cost. I fit the data to get the distribution and parameterize the uncertainty model for the bedding pellets with a mean of $197.89/Mg and standard deviation of $9.08/Mg.

The distributions described here allow us to simulate the family of equations described previously. I iterate the model 10,000 times using the software @Risk,

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[22] Price of 40 lb and 1ton (packaged or non-packaged) is $5.95 and $297.5, respectively that yields same price per pound (https://kingdombiofuel.com/bedding-pellets).

published by the Palisade Corporation. The equations, data, and simulation let us quantify operational and market risk, which I report in the next section.

■■■ Results

The distributed-depot-based feedstock-supply system has two contrasting possibilities: baseline and over-contract scenarios. The baseline scenario represents the case of average contracting. Here, the management contracts with 920 farmers distributed across nine regional supply depots in six states, placing 635,029 Dry Mg on contract. The over-contract scenario represents a case in which management issues more contracts than are needed to reduce the risk of a supply shortage. In this case, management contracts with 1,444 farmers, evenly distributed across the nine supply depots, to place 907,185 Dry Mg under contract. Whereas the baseline alternative contracts based on average assumptions, the other scenario represents an attempt to mitigate supply risk using over-contracting. Over-contracting not only mitigates supply risk but also creates a commodity supply for MPI markets. In the first set of results, I add the restriction that there be no MPI market possibilities. In the second set of results, I relax the restriction and extend market possibilities by allowing excess biomass that remains under contract after the supply requirement is met to be sold in alternative MPI markets. Each market opportunity has two possibilities for excess feedstock based on the contracting assumption. For the case of average contracting, baseline with animal feed market scenario represents excess biomass sold in the animal-feed market and baseline with absorbent market scenario represents sale to the market for absorbents. Baseline with alternative market represents the situation where the manager sells excess in either the animal feed market or the absorbents market, based on where the greater price obtains. For the case of over-

contracting, over-contract with animal-feed market scenario, over-contract with absorbent

market scenario, and over-contract with alternative market stand for sales of excess

biomass in the feed market, the absorbent market, and switching markets, respectively.

Altogether, I have two scenarios in which the simulation assumes restricted access to

alternative MPI markets and six scenarios allowing different alternative MPI-market and

contract-management strategies. Table 4-4 summarizes the attributes of various

scenarios.

Table 4-5 presents the key results for the eight different simulation scenarios. The

risk type and measure columns represent the type of risk and definition of risks as

indicated in equation (4.1)–(4.3). The risk-value column represents the cumulative

probability in percentage for the biorefinery's not meeting the threshold value defined in

risk measure. The mean and standard deviation show the mean and standard deviations of

the parameters for 10,000 runs. I have explained these key results in the subsections using

graphs and specific tables.

Table 4-4: Summary of scenarios and risk measurement criteria.

Scenario name	Description	Risk type	Measurement criteria
Baseline	Biorefinery contracts with 920 farmers distributed across 9 regional supply depots in 6 states, placing 635,029 Dry Mg on contract. Biorefinery does not have access to the merchandisable product intermediate market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Over-contract	Biorefinery contracts with 1,444 farmers, evenly distributed across the 9 supply depots, to place 907,185 Dry Mg under contract. Biorefinery does not have access to the merchandisable product intermediate market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Baseline with animal feed market	Same as baseline but biorefinery has access to the animal feed market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Over-contract with animal feed market	Same as over-contract but biorefinery has access to animal feed market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Baseline with absorbent market	Same as baseline but biorefinery has access to the absorbent market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Over-contract with absorbent market	Same as over-contract but biorefinery has access to the absorbent market.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Baseline with alternate market	Same as baseline but biorefinery has access to both animal feed market and absorbent market. It can sell excess densified pellets to whichever market provide a higher price.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%
Over-contract with alternate market	Same as over-contract but biorefinery has access to both animal feed market and absorbent market. It can sell excess densified pellets to whichever market provide a higher price.	Supply	Q<635029 Mg
		Operational	MFSP > $0.84/LGE
		Market	ROI < 10%

Table 4-5: Key simulation results indicating risk type, mean values, and standard deviations of parameters.

Scenario	Risk type	Risk value (%)	Mean value	Standard deviation
Baseline	Supply	54	628,318	116,697
	Operational	91.5	$0.97	$0.14
	Market	71.3	-3.87%	29.24%
Over-contract	Supply	6	905,563	182,229
	Operational	97.1	$0.99	$0.11
	Market	73.5	-5.53%	27.80%
Baseline with animal feed market	Supply	54	628,318	116,697
	Operational	74	$0.94	$0.16
	Market	66.3	0.20%	31.77%
Over-contract with animal feed market	Supply	6	905,563	182,229
	Operational	22.6	$0.73	$0.16
	Market	36	33.01%	52.12%
Baseline with absorbent market	Supply	54	628,318	116,697
	Operational	77	$0.95	$0.15
	Market	67.6	-0.96%	30.81%
Over-contract with absorbent market	Supply	6	905,563	182,229
	Operational	30.5	$0.80	$0.12
	Market	45	18.65%	37.57%
Baseline with alternate market	Supply	54	628,318	116,697
	Operational	74	$0.94	$0.16
	Market	66.3	0.20%	31.77%
Over-contract with alternate market	Supply	6	905,563	182,229
	Operational	22.6	$0.73	$0.16
	Market	36	33.02%	52.12%

Note: The measure column represents the definition of the risk. The risk column quantifies the cumulative probability (in percentage) of the risk thresholds not met. The values of mean and standard deviation of supplied biomass, operational MFSP, and market return are in Dry Mg, $/LGE, and percentage, respectively.
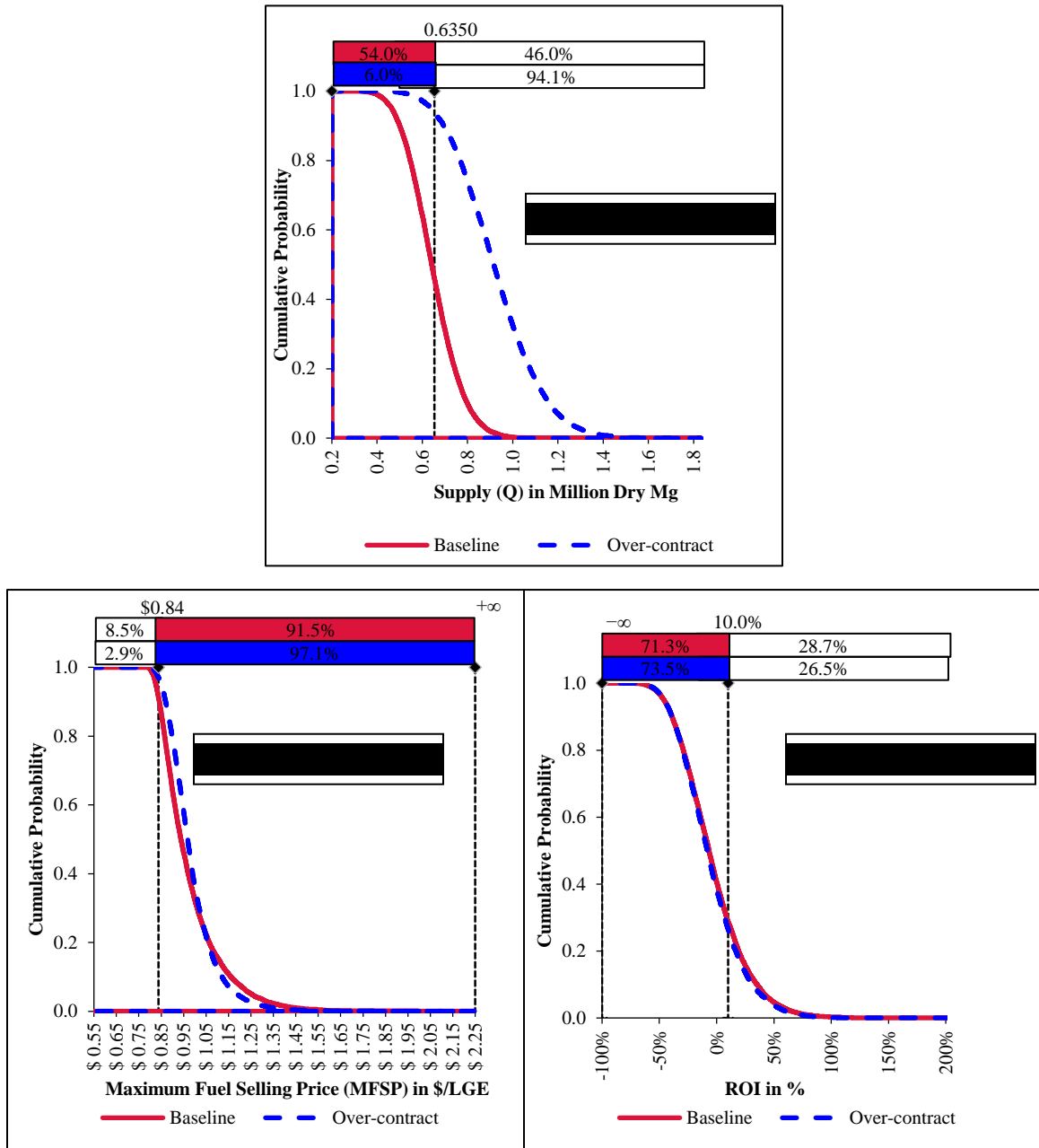
4.5.1 Supply, Operational, and Market Risk without Alternative MPI Markets

Figure 4-5 illustrates a quantitative assessment of supply, operational, and market risk for the baseline and over-contract scenarios. The red, descending cumulative-probability graph of panel (a) shows that the probability of supply shortage is about 54%

in the baseline scenario. The blue line represents the cumulative probability of the over-contract scenario, which has less probability of supply shortage. Comparing cumulative probabilities illustrates that by over-contracting, management can reduce feedstock-supply risk. But the figure also shows that the chance of contracting for excess biomass is 46% and 94%, respectively. In the over-contract scenario, the manager can reduce supply risk, but this reduction obtains at the expense of paying for much more biomass than is needed.

The panels (b) and (c) of Figure 4-5 show how supply risk translates to operational and market risk. Operational risk is 91.5% in the baseline and 97.1% in the over-contract scenario. By over-contracting, management reduces supply risk at the expense of increasing operational risk. The expected MFSP are $0.97/LGE and $0.99/LGE in the baseline and over-contract scenarios, respectively. Cost is incurred for biomass that does not produce revenue other than at salvage value. The market risk also remains high: 71 and 73% in the baseline and over-contract scenarios, respectively. The market risk shown in panel (c) remains similar in both cases, with a two percent increase in the over-contract scenario.

Figure 4-5: The supply (a), MFSP (b), and ROI (c) of Baseline and Over-contract Scenario

4.5.2 Operational and Market Risk with Alternative MPI Markets

Figure 4-6 shows outcomes for the case of average contracting (baseline

contracts) with MPI market opportunities. In each panel, the curves for market scenarios

are essentially the same, having a very small reduction in risk when allowing for

alternative market opportunity. In the baseline with alternative market scenario, operational risk and market risk are 26% and 67%, respectively. Market opportunities cannot reduce operational and market risk significantly as there is much less opportunity to sell excess biomass in MPI markets. The average contract targets to attain 635,029 Dry Mg. But the operating assumption of the biorefinery is that it is designed to operate for 350 days each year, and the ability to operate 365 days. If the biorefinery never shuts down, then it can process 662,245 Dry Mg. Thus, access to alternative MPI market is only available when the biorefinery gets more than 662,245 Dry Mg of pelleted feedstock.

Figure 4-7 shows how biorefinery economics are impacted when the manager over-contracts in the presence of MPI opportunities. The best result is achieved when the biorefinery has access to alternative market opportunities in the over-contract with alternative markets scenario. The operational risk and market risk are 23% and 36%, respectively.

Figure 4-6: Comparison of operational and market risk of Baseline with different MPI market
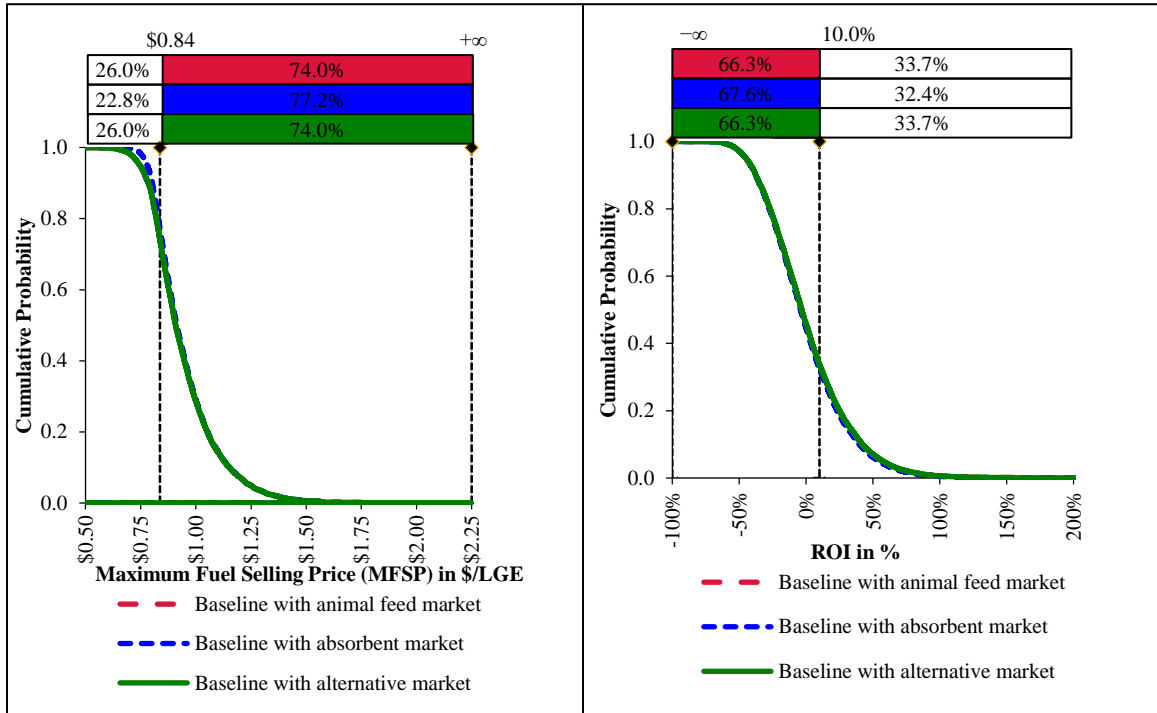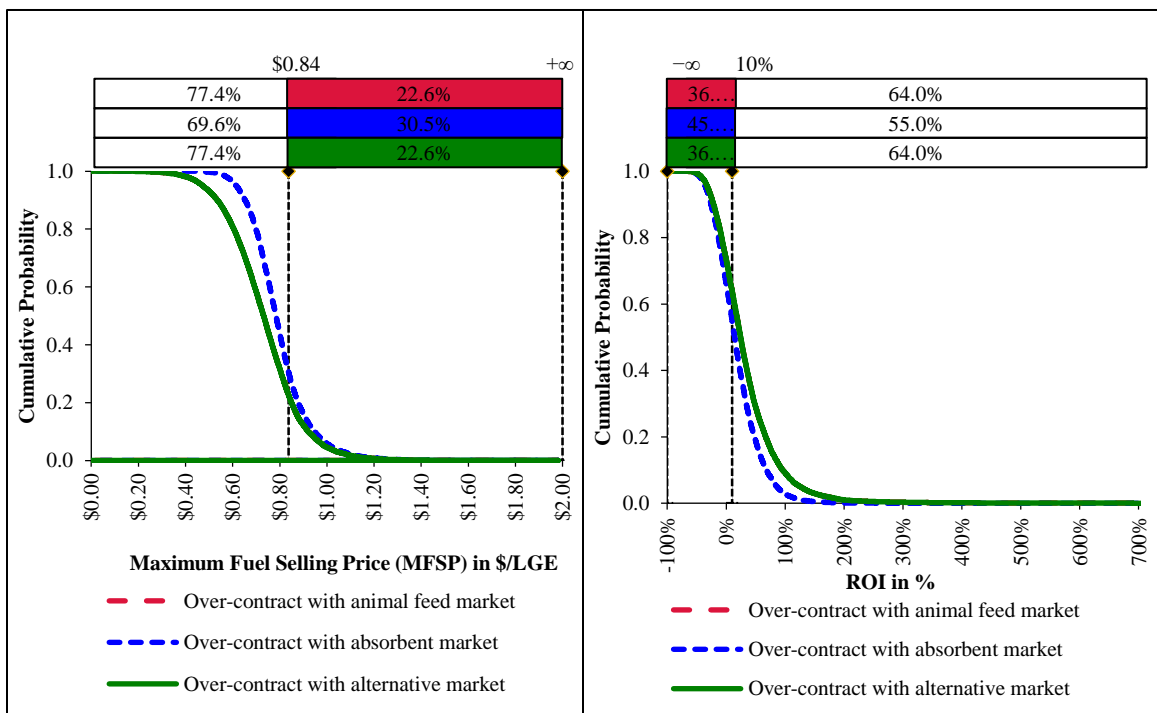

Figure 4-7: Comparison of operational and market risk of over-contracting with different MPI market

4.5.3 Risk Comparison among Risk Management Strategies

Table 4-6 shows risk reduction using different strategies. The over-contracting strategy can reduce supply risk significantly. The supply risk decreases from 54 to 6%. However, without market opportunity, the operational risk increases significantly, and market risk remains similar. Using alternative logistic configuration, allowing for MPI market opportunity can lead to a decrease in operational risk of 17.5% and a market-risk reduction of 5% compared to a baseline without MPI opportunity. However, it does not have any effect on supply risk. The use of over-contracting and allowing for an alternative market for densified pellets has the highest effect in reducing supply risk, operational risk, and market risk. It can reduce supply risk by 48%, operational risk by 68.9%, and market risk by 35.3% compared to baseline.

Table 4-6: Supply risk, operational risk and market risk reduction using different strategies

Strategy	Supply Risk[†]	Operational Risk[†]	Market Risk[†]
Over-contract without market opportunity	-48%	5.6%	2.2%
Baseline with market opportunity	0%	-17.5%	-5%
Over-contract with market opportunity	-48%	-68.9%	-35.3%

Note: [†]Negative values represent a reduction in risk and positive values represent an increase in risk. The risks are compared with the baseline scenario without alternative market opportunities where supply risk, operational risk, and market risk are 54%, 91.5%, and 71.3%, respectively.

4.5.4 Balancing Risk and Return

Table 4-7 shows the market risk and corresponding expected-return profile with a standard deviation for each scenario evaluated. The investors and financiers are willing to take on risk if the corresponding return receives an appropriate premium. In the baseline scenario and the over-contract scenario without alternative MPIs, the risk is similar, and

the baseline scenario has slightly higher but still negative, returns. The range of average

negative returns in the baseline and over-contract scenario without MPI opportunities is -

5.53 to -3.87%, respectively. These results are similar to the literature estimated ROI

(Chugh et al., 2016; Zhao et al., 2015, 2016). However, when I allow the distributed-

depot-based feedstock-supply system to have access to MPI market opportunities, the risk

is lower, and the return is higher and positive. The lowest market risk of 36% and the

highest return of 33% are observed in the over-contract with alternative market scenario.

Thus, the success of attracting investors and financiers in cellulosic biorefinery largely

depends on creating MPI markets. Although in this analysis, I have assumed that the

distributed-depot-based feedstock-supply system can turn the feedstock into a

commodity, several features of commoditization of the feedstock market are missing

(Olsson et al., 2016).

Table 4-7: Market risk and return profile of alternate scenarios

Scenario	Market Risk (ROI<10%)	Return	Standard deviation
Baseline	71.3%	-3.87%	29.24%
Over-contract	73.5%	-5.53%	27.80%
Baseline with animal feed market	66.3%	0.20%	31.77%
Over-contract with animal Feed market	36%	33.01%	52.12%
Baseline with absorbent market	67.6%	-0.96%	30.81%
Over-contract with absorbent market	45%	18.65%	37.57%
Baseline with alternate market	66.3%	0.20%	31.77%
Over-contract with alternate market	36%	33.02%	52.12%

Note: Market risk represents the percentage of occurrences when the return will be less than
10% that is needed to attract investors and financiers. Return and standard deviation represent
the mean and standard deviation of ROI among 10,000 runs.

■ Discussion

The current state of the cellulosic biorefinery is in its infancy. It has potential because regulation has set a high target for the use of advanced biofuels. In reality, however, the cellulosic biofuel industry has yet to overcome barriers and to attract financiers. Much of the work within the field is directed towards successful development of technology, but the industry is not thriving; rather, failure of several biorefineries led to concern over the risks associated with this industry. The cellulosic biorefinery industry faces supply, operational, and market risk. Financiers are not fully aware of these risks and do not employ mechanisms to mitigate them. Successful mitigation can lead to an increase in profitability and thereby attract more investment in the cellulosic biofuel industry.

A biorefinery can handle risks by shifting the burden of risk by insuring the operations at different stages to outside companies, rather than to internalize risk. However, as the industry is in infancy, there is little or no interest from underwriters to work with cellulosic biorefineries as they cannot accurately price the risk premiums. An alternate is to internalize the risk and then attempt to mitigate it using management techniques and technological solutions. In this paper, I evaluated two management strategies that the cellulosic biorefinery can employ to reduce risk. A contract-management strategy can be employed such that the supply risk of the cellulosic biorefinery is reduced. This can ensure that biorefinery gets a smooth supply of feedstock. Distributed-depot-based feedstock-supply systems have the potential to reduce operational and market risk by allowing an alternative MPI market for pelletized feedstock.

Much of the research on risk and return for the cellulosic biorefinery shows that the investors are taking on high risk and getting very little or negative returns on average, indicating the industry is unstable in the long term (Chugh et al., 2016; Zhao et al., 2015, 2016). However, by employing risk-management strategies, the management at cellulosic biorefineries can reduce risk and increase profitability. The strategy can attract future investments in the industry to make it sustainable. However, both risk reduction and profitability enhancement depend on the availability of alternative MPI market.

■ Concluding Remarks

The objective of this paper is to explore supply, operational, and market risk at a cellulosic biorefinery. Two risk-management strategies were analyzed and compared. Management at biorefineries can employ over-contracting and change the feedstock-supply configuration such that it allows them to tap into other markets where they can sell their surplus pelleted feedstock. Using over-contracting, management can reduce supply risk, but operational risk would increase correspondingly. Using distributed-depot-based supply systems, management can reduce operational and market risk. Combining both strategies, which are not mutually exclusive, management can reduce supply, operational, and market risk simultaneously. In the business-as-usual scenario, which I called the baseline, supply, operational, and market risk are 54, 91.5, and 71.3%, respectively. In the best-case scenario—over-contracting with alternative market opportunities—supply, operational, and market risk are 6, 22.6, and 36%, respectively. The results suggest that managers can reduce supply risk by 48%, operational risk by 68.9%, and market risk by 35.3%. Management also can increase the expected profitability of the biorefinery while mitigating risk. The business-as-usual and best-case

scenarios have expected ROI of -3.87 and 33.02%, respectively. The distributed-depot-based feedstock-supply system with over-contracting has the potential to reduce risk and to offer suitable returns, but this hinges on the successful commoditization of the pelleted feedstock.

Conclusion and Future Works

Energy policy and development needs to address the dual objectives of providing energy security while reducing greenhouse gas emissions. Stakeholders play a key role in formulating energy policies and the implementation of energy development projects. This dissertation presents the implication of three energy policies and developments on the stakeholder's decision. Chapter 2 employs a discrete choice model to analyze household preference of renewable portfolio standards. Households preferences for renewable portfolio standards can potentially help policymakers and electricity distributors to take an informed decision. Chapter 2 also presents implications of preference heterogeneity on the decision of legislators and distributors.

Drawing on the stakeholders' perception about shale development, Chapter 3 analyzes a well manager's hydrocarbon production decision in the presence of externalities. It also has implication for a regulatory body such as Bureau of Land Management (BLM) on their lease granting decision process while facing restriction from stakeholders. For an example of restriction, Colorado legislators recently passed

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SB19-181 that mandated oil and gas companies to consider health and environmental impact of hydrocarbon extraction. This type of restrictive law can impact a hydrocarbon well manager's decision to optimize production while considering social objective instead of private objective. I set up a dynamic optimization problem where well manager's oil and gas production decision accounts for externalities associated with the production process.

Discussing the influence of renewable fuel standards on sustainable development of cellulosic biorefinery, I analyze risk mitigation techniques available for a cellulosic biorefinery manager in Chapter 4. While there are abundant resources and technological advancement, the cellulosic biorefinery did not flourish as expected in part due to the industry's inability to attract investors by offering balanced risk and return. Cellulosic biorefinery manager can potentially mitigate risk by using feedstock configuration system and contract management. Geographically distributed depot-based supply chain system and over contracting can reduce supply-, operational- and market risk of a cellulosic biorefinery. Applying numerical simulation technique on uncertain parameters, I quantify the performance of risk mitigation strategies.

In the sections that follow I summarize key findings in section 5.1 and provide limitation and future work in section 5.2.

▮ Key findings and general conclusion

The objective of this dissertation is to investigate stakeholders' decision making while energy policy aims to achieve environmental goals. I have analyzed the implication of three policy on stakeholders' decision. Chapter 2 deals with renewable portfolio standards, a specific state policy aiming to renewable electricity development. I take a

consumer-centric approach by employing a discrete choice experiment to analyze the effectiveness of the policy. I find that New Mexico residents want an increase in the level of RPS. The legislators of New Mexico already increase the RPS level more than the survey suggests. The results also show that New Mexico residents willing to pay a 4.23% premium for 10% increase in the RPS, which is within the boundary of cost-benefit studies in the literature. New Mexico legislator subsequently passed a bill in 2019 that imposes 100% clean electricity by 2045. New Mexico residents have a positive marginal willingness to pay for an increase in employment opportunity. New Mexico has an unemployment rate of 5.0% in April 2019, placing the State on the second position after Alaska among 50 States. Residents of a State with high local unemployment rate welcome a higher share of renewables that has the potential to create employment opportunities. New Mexico residents have a disutility associated with water requirement for electricity generation. This is no surprise for a desert State such as New Mexico. New Mexico has 0.2% of land covered with surface water, which is the lowest among 50 States. This result implies that New Mexico residents are not only interested in an increase of RPS level, but they also show a preference for renewable technologies that have the potential to save water. New Mexico residents also have a disutility for electricity generation from nuclear. The disutility can be attributed to the fact that New Mexico import all of its nuclear electricity from Arizona and there is a concern about the safety of nuclear technology. The newly passed bill in 2019 Senate session imposes 100% clean energy by 2045, which creates a room for nuclear electricity development. There is considerable heterogeneity of preferences for RPS in part due to respondents' attitude towards renewable energy.

Chapter 3 presents a summary of positive and negative externalities and perceptions of stakeholders regarding shale development. I present a theoretical optimization model where social cost, including the cost of externalities, is considered. A numerical analysis is also conducted to show the production path, revenue, profit, and net present value. Numerical analysis shows that the gross production decreases over time and production path the lower if externalities are internalized. This conforms with other natural resource studies that consider externalities. I find the hyperbolic curvature of gross production is lower than usual Arps curvature. This is due to the consideration of the joint production of oil and gas. The net present value of the firm is sensitive to change in prices of natural gas and oil and discount factor.

Chapter 4 evaluates the performance of two risk reduction opportunities for a cellulosic biorefinery manager. Biorefinery manager can reduce supply risk while increasing operational and market risk if the over-contracting strategy is employed along with no access to an alternative market. In this scenario, the biorefinery manager is stuck with an excess densified feedstock that does not have marketable value. In the case of baseline contracts with access to alternative markets, biorefinery manager cannot mitigate supply risk, but operational risk and market risk mitigation are possible. Result of these to cases implies that performance of either of the strategies alone does not provide intended results of supply-, operational- and market-risk reduction. Biorefinery manager can reduce all three forms of risks if both he risks mitigation strategies are available. The best-case scenario of employing both risk reduction strategies also provide significant improvement in return on investment. However, this improvement of return on investment largely depends on the successful creation of alternative markets.

██   **Limitations and future works**

In this section, I discuss the limitations of each of the chapters in this dissertation. Some of the limitations can be investigated in future works. In Chapter 2, respondents are forced to choose a plan over other plans even if they do not like any of the plans presented in a choice set. This coercion of choice implies that respondents might be uncertain about the choice they made. Accounting for this uncertainty of choice has the potential to provide better precision of random utility models. In the current form, due to the limited response rate, data is not adjusted for the uncertainty of choice. Future discrete choice models can gain precision by incorporating choice uncertainty. In addition, I discuss the superiority of visual attribute non-attendance over stated attribute non-attendance technique implemented in Chapter 2. However, I could not implement visual attribute non-attendance technique due to logistic limitation. Moreover, the study presented in Chapter 2 assumes that the cost of renewable electricity is higher than the cost of conventional electricity. Steep declining of renewable electricity cost indicates that this assumption might not hold in the future. US Energy Information Administration (2019) predicts that collectively renewable electricity generation will be approximately double of RPS requirement in 2050. This prediction implies that State mandated RPS might not be a binding requirement in the future. Future studies can analyze the effect of the declining cost of renewables on RPS requirements. Furthermore, the definition of renewable electricity in Chapter 2 does not include nuclear electricity. This definition of renewable electricity conforms with applicable legislation during the survey. After the survey implementation, New Mexico legislators updated renewable portfolio standards in 2019 that sets a goal for clean electricity instead of renewable electricity. This can, in

turn, create a room for the development of nuclear electricity subject to comparative costs of nuclear and renewable electricity.

I consider joint production of oil and gas in Chapter 3 where both oil and gas have marketable value. The U.S. Energy Information Administration estimates that more than 50% of natural gas is produced jointly with oil. If one of the hydrocarbons produced from a well does not have economic value due to minimal production, the results of the model can change significantly. For example, future studies can model a scenario where natural gas production is very minimal such that it does not have economic value. In addition, the cost functions presented in Chapter 3 are simplified to avoid complexity. I assume that costs are additively separable. Moreover, I only consider the net effect of positive and negative externalities in the theoretical model. In addition, only health cost due to methane concentration in groundwater is considered. While simplification assumptions lead to a clear presentation of the model, the introduction of complex functional forms might represent reality better in some contexts. Moreover, Chapter 3 presents a simulation model for a representative well. However, attributes of a well can be heterogeneous in nature. An agent-based model can address the heterogeneity of well attributes. Hence, future studies warrant for agent-based modeling technique. Furthermore, the parameter values used in Chapter 3 has uncertainty associated with it. I presented the simulation model where those parameters are deterministic. While I report the sensitivity of some of the parameters in some cases, future studies can employ a simulation model that accounts for the uncertainty of parameters.

Risk reduction opportunity presented in Chapter 4 largely depends on the successful creation of alternative markets. At present those markets are not readily

available but there is an indication of such markets. Given very limited evidence of alternative markets, this study relies on limited price data available for alternative markets. The availability of alternative market information can help to a better understanding of cellulosic biorefinery risks. In addition, Chapter 4 assumes that a biorefinery manager can sell to alternative markets if there is an excess of feedstock. This restrictive assumption limits competition for feedstock between biorefinery and alternative markets. Finally, the risk mitigation strategies presented in Chapter 4 are not implemented in the cellulosic industry. Future studies can build on the practical experience of these risk mitigation strategies.

Appendices

Appendix A

Computational issues in GMNL model

The GMNL model is dependent on the choice of several input parameters (Gu et al., 2013). The GMNL model can be sensitive on the randomization seed. I have used 4105 for randomization seed. I have also tested two other seeds, but results do not change very much in magnitude and direction. The second computational issue can arise from the number of draws and method of draws used for random parameters. Halton draws has better chances of convergence compared to random or pseudorandom draws. I have used deterministic Halton draws after burning first 15 primes for reliable estimation as argues by Sarrias and Daziano (2017). Table A 1 present results of using a varying number of draws. Gu, Hole and Knox (2013) suggests starting from 500 draws. I have simulated using 500 draws to 2000 draws with an increment of 250 draws. The goal of the exercise is to get a minimum number of draws that provides a consistent estimation. The choice of the number of draws depends on the quality of convergence. The first criterion is based on the 2-norm condition of the Hessian matrix, K(H). If the K(H) is negative, the convergence signifies a non-stable saddle point instead of the maximum. If the K(H) is more than 1.00E+07, then the Hessian is ill-conditioned (Hole & Yoo, 2017). The second criterion is to choose the number of draws that has sufficiently lower infinity norm of the gradient ($\|g\|_\infty$) and $gH^{-1}g$ matrix. Using both criteria, a draw of 1,500, 1,750, and 2,000 are candidate for number of draws. I choose the minimum of 1,500 as number of draws in GMNL model.

Table A 1 : Summary statistics of GMNL model with varying number of Halton draws

Draws	R_500	R_750	R_1000	R_1250	R_1500	R_1750	R_2000
N	894	894	894	894	894	894	894
Log-L	-771.1871	-771.9652	-774.0919	-772.9316	-775.0731	-773.2138	-774.5997
$\|g\|_\infty$	9.01E-01	1.85E-01	2.64E-02	2.64E+00	3.86E-02	5.16E-02	3.69E-02
$g'H^{-1}g$	6.69E-03	-2.33E-02	-4.80E-05	-1.99E-02	-2.07E-06	-1.33E-05	-3.27E-05
K(H)	-1.44E+04	1.72E+07	7.56E+05	-1.11E+04	3.12E+05	6.19E+05	5.00E+05
AIC	1578.3740	1579.9300	1584.1840	1581.8630	1586.1460	1582.4280	1585.1990
BIC	1664.6970	1666.2530	1670.5060	1668.1860	1672.4690	1668.7500	1671.5220
AICc	1579.1560	1580.7120	1584.9650	1582.6450	1586.9280	1583.2090	1585.9810

$\|g\|_\infty$, $gH^{-1}g$, and K(H) are used to know the condition of gradient and Hessian matrix so that I can infer on the convergence of simulated maximum likelihood. $\|g\|_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, K(H) is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of $-H$, respectively.

The second issue associated with GMNL model is the starting point. The convergence of GMNL models is highly sensitive to the starting point. I have followed Hole and Yoo (2017) to get the starting point using the conventional method. The parameter choice is shown in Table A 2 and the result of the simulation is shown in Table A 3. Based on the quality of convergence criteria, I choose a GMNL model where the starting point of GMNL model will be the base case of GMNL model. Although GMNL II staring values provide better AICc, it is ill-conditioned as indicated by a K(H) more than 1.00E+07.

Table A 2: The starting parameter values for MGNL models

Parameter	MNL	SMNL	MIXL	GMNL I	GMNL II	GMNL
Coefficients (β)	Est	Est	Est	Est	Est	Est
Standard deviation (σ)	0.1	0.1	Est	Est	Est	Est
Scale parameter – τ	0.1	Est	0.1	Est	Est	Est
Scale parameter – γ	0.1	0.1	0.1	0.1	0.1	Est

Note: Est means that parameters are estimated using the specified model

Table A 3: The summary statistics of GMNL model with different starting values

Starting value	MNL	SMNL	MIXL	GMNL I	GMNL II	GMNL
N	894	894	894	894	894	894
Log-L	-775.07	-774.52	-774.35	-774.35	-771.73	-774.33
$\|g\|_\infty$	4.32E-05	9.90E-05	1.46E-05	1.96E-04	3.24E-04	3.75E-05
g'H^{-1}g	3.08E-08	2.77E-07	3.37E-09	5.05E-07	1.86E-06	2.54E-08
K(H)	3.12E+05	3.67E+07	1.24E+06	6.06E+05	1.80E+07	1.08E+06
AIC	1586.15	1585.03	1584.69	1584.69	1579.45	1584.65
BIC	1672.47	1671.35	1671.01	1671.01	1665.78	1670.98
AICc	1586.93	1585.81	1585.47	1585.47	1580.23	1585.44

Note:

1. *$\|g\|_\infty$, gH^{-1}g, and K(H) are used to know the condition of gradient and Hessian matrix so that I can infer on the convergence of simulated maximum likelihood. $\|g\|_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, K(H) is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and λ_{min} are the largest and smallest eigenvalues of −H, respectively.*

2. *GMNL I and GMNL II have three different starting values. GMNL I or GMNL II model predicted with (1) MNL starting values; (2) SMNL starting values; and (3) MIXL starting values. Only the best of GMNL I and best of GMNL II starting values are reported.*

The last issue in GMNL model that I have taken care of is the method of optimization. There are four popular optimization methods in simulated likelihood estimation: (1) Newton-Raphson (NR). (2) Berndt–Hall–Hall–Hausman (BHHH); (3) Davidon–Fletcher–Powell (DFP), and (4) Broyden–Fletcher–Goldfarb–Shanno (BFGS). I have tested three of them as BFGS is a refined DFP method where BFGS nearly always works better (Train, 2009). The results of alternative optimization methods are shown in Table A 4.

Table A 4: The summary statistics of GMNL model for varying optimization method

Parameter	NR	BHHH	BFGS
N	894	894	894
Log-L	-775.7276	-775.66019	-775.0731
$\|g\|_\infty$	2.2852E+02	2.8699E+01	3.8626E-02
$g'H^{-1}g$	-1.8322E-01	-2.2983E+01	-2.0748E-06
K(H)	-1.1408E+04	6.9215E+05	3.1153E+05
AIC	1587.455	1587.32038	1586.146
BIC	1673.778	1673.64308	1672.469
AICc	1588.237	1588.10209	1586.928

$\|g\|_\infty$, $gH^{-1}g$, and K(H) are used to know the condition of gradient and Hessian matrix so that I can infer on the convergence of simulated maximum likelihood. $\|g\|_\infty$ is the infinity norm of the largest gradient, which is the largest element of the gradient matrix in absolute value. The 2-norm condition of the Hessian, K(H) is defined as $\lambda_{max}/\lambda_{min}$. λ_{max} and $\lambda_{min}$are the largest and smallest eigenvalues of $-H$, respectively.

All three methods tested (NR, BFGS, and BHHH) provide similar results in terms of coefficients, significance, and AICc. The time taken to get the results is fast with BHHH and very slow with NR compared to BFGS. The infinity norm ($\|g\|_\infty$) and $g'H^{-1}g$ of NR and BHHH method is much higher compared to the BFGS method. The higher values

of these lead to unstable convergence, where it reached a flat region. Moreover, Train

(2009) argued that BFGS works better than all other methods. In this note, we have

chosen to use BFGS method.

Appendix B

**Fitting response efficiency (ANA and AIR) data**

Table B 1 provides the summary statistics of ANA and AIR information. At least one attribute is not considered in 28.92% of the choice situation. We have analyzed five different restrictive models where we have considered ANA and/or AIR information. Table 2-5 presents the summary statistics of the restrictive models. Model 1 does not use ANA and AIR data. Model 2 uses AIR data only where we have found the value of μ using heuristic optimization. The grid search value of μ with corresponding AIC values are presented in the left panel of Figure B 1. As the μ increases, the AIC values increases up to the value of μ is 0.91. After that, the AIC value bounces back.

Table B 1: Summary statistics of ANA and AIR data

Attributes	ANA	AIR
RE_share	0.066741	3.881188
Nuclear	0.074527	3.184564
Water	0.054505	3.765101
Jobs	0.082314	3.601329
Cost	0.061264	3.413333

Note: ANA and AIR represent attribute non-attendance and attribute important ranking, respectively

Figure B 1: The AIC value corresponding contraction factor of AIR (μ) and ANA (ρ) in model 2 and 4, respectively
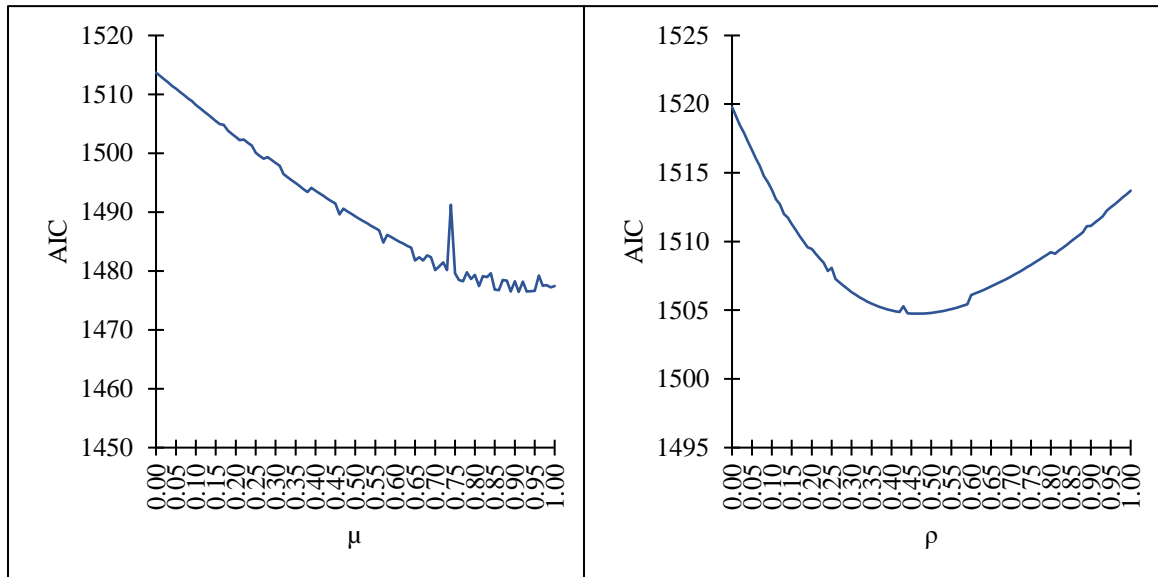

The heuristics grid search optimization of ρ shows that the minimum AIC value is attained when ρ is equal to 0.47. When considering both μ and ρ, the model 5 heuristic optimization gives the lowest value of AIC when μ and ρ are 0.93 and 0.48, respectively. These values are used to get the optimized model 5, where we consider both ANA and AIR information.

Survey Questionnaire

Have Your Say: New Mexico's Renewable Energy Future
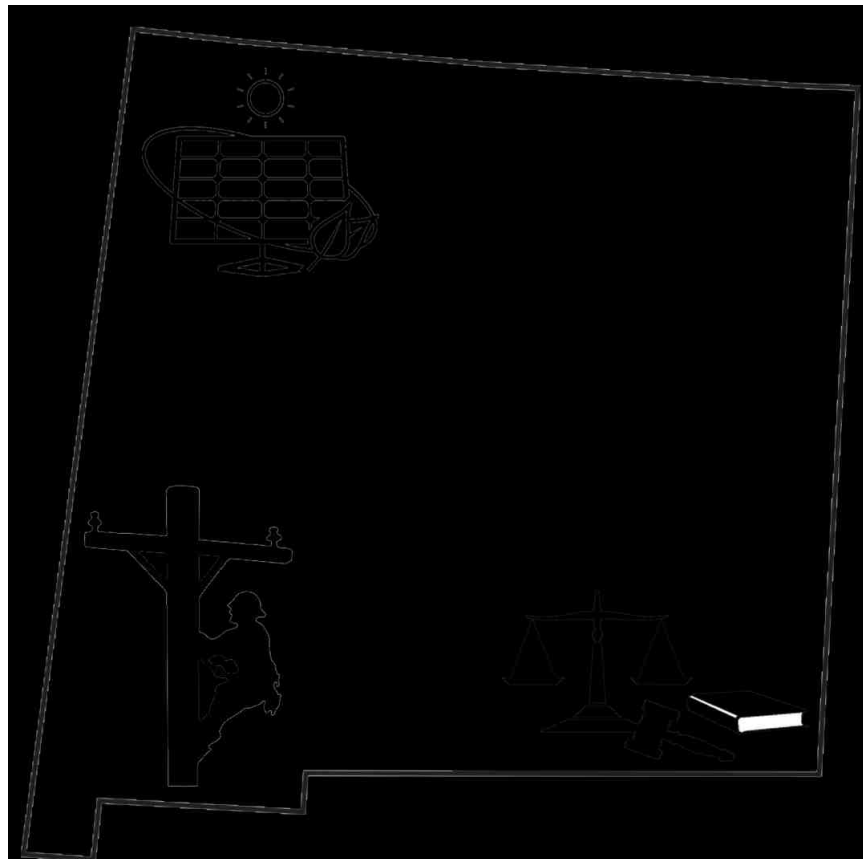
The survey will take approximately 20

Your Opinions on Energy Use and Production

We are interested in knowing the opinion of New Mexico residents about the energy sources used to generate electricity. There is currently a discussion at the state level and expected proposed legislation on these issues, which could affect your electricity bill.

To inform this discussion, we are asking a sample of state residents to take this survey. Responses will be shared with policymakers.

1. **Over the next 25 years, would you favor an increase, no change, or decrease in reliance in the United States on each of the following energy sources? Check one response** *for each.*

	Increase	No Change	Decrease
Coal	●	●	●
Natural gas	●	●	●
Oil	●	●	●
Wind	●	●	●
Solar	●	●	●
Nuclear	●	●	●

2. **Which of the following statements best describes your view?** *Check one.*

   ● We can protect land and water and have a strong economy with good jobs, without having to choose one over the other.

   ● Sometimes protections for land and water and a strong economy are in conflict and we must choose one over the other.

Renewable Portfolio Standards

Like many states, New Mexico has adopted Renewable Portfolio Standards. This law requires that a certain percentage of electricity sold by utilities must come from renewable sources (such as wind and solar).

Under New Mexico's Renewable Portfolio Standards, all large electric utilities are required to have 20% percent of electricity come from renewables by 2020.

Currently, approximately 10% of total electricity consumed in New Mexico comes from renewable energy sources.

3. **To what extent do you oppose or support New Mexico having Renewable Portfolio Standards? Check one.**

   ● Very opposed
   ● Somewhat opposed
   ● Neither oppose or support
   ● Somewhat supportive
   ● Very supportive

There are discussions about modifying New Mexico's energy plan to increase the share of electricity coming from renewable sources.

4. **Which of the following is your preferred renewable energy source? Check one.**

   ● Wind
   ● Solar
   ● Whichever is cheaper
   ● Other _____

5. **Which of the following best captures your perception about government subsidization of energy?** *Check one.*

    ☐   The oil and gas industry is highly subsidized.

    ☐   The renewable energy industry is highly subsidized.

    ☐   Both are highly subsidized.

    ☐   Neither are highly subsidized.

Using more renewable sources of energy means less coal will be used to generate electricity.

Reducing the use of coal will reduce carbon emissions. The EPA has identified carbon as a pollutant and contributor to climate change.

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6. **To what extent do you oppose or support substituting renewable energy for coal to generate electricity in New Mexico?** *Check one.*

    ⬤ Very opposed

    ⬤ Somewhat opposed

    ⬤ Neither oppose or support

    ⬤ Somewhat supportive

    ⬤ Very supportive

7. **Which of the following best captures your opinion about climate change?** *Check one.*

    ☐   Climate change is NOT occurring.

    ☐   Climate change is occurring but it is NOT due to human activity.

    ☐   Climate change is occurring.

8. **How worried are you about climate change?** *Check one.*

- ❏ Very worried
- ❏ Moderately worried
- ❏ Somewhat worried
- ❏ Slightly worried
- ❏ Not worried at all

9. **How much do you trust or distrust climate scientists as a source of information about climate change?** *Check one.*

- ❏ Strongly trust
- ❏ Somewhat trust
- ❏ Neither trust or distrust
- ❏ Somewhat distrust
- ❏ Strongly distrust

A State Energy Plan

In the following pages, we will ask your opinion about the following possible components of a state energy plan:
- Required share of electricity from renewables by 2040
- Electricity generation from nuclear power
- Change in water usage for electricity
- Change in number of New Mexico jobs
- Change in monthly electricity bill.

Required share of electricity from renewables by 2040

As noted earlier, under current law, large electric utilities (e.g, PNM) must ensure that 20% of the electricity sold comes from renewable resources in 2020 and beyond.

Small cooperative utilities have a requirement that is always 10% lower than that of large electric utilities. Thus, by 2020, 10% of the electricity sold by cooperatives must come from renewable sources. Note that, the percentage numbers hereafter is representing required share of renewables for large utilities.

There is a discussion about increasing the share of electricity that utilities are required to distribute from renewables by 2040.

There is significant renewable energy potential across the state. Renewable energy does not produce any carbon emissions.

10. **Do you think New Mexico should increase, decrease, or make no change in the required share of electricity from renewables by 2040?** *Check one.*

   ⬤ Increase
   ⬤ Decrease
   ⬤ Make no change

11. **Suppose the cost of renewable energy was twice as much as the cost of energy produced from fossil fuels. In this case, which of the following would be your preferred share of electricity from renewables?** *Check one.*

   ⬤ <10%
   ⬤ 11-20%
   ⬤ 21-40%
   ⬤ 41-60%
   ⬤ 61-80%
   ⬤ 81-90%
   ⬤ >91%

Electricity generation from nuclear power

Nuclear energy does not produce any carbon emissions. It is not considered a renewable energy.

Currently, approximately 18% of NM's electricity comes from the Palo Verde nuclear power plant in Arizona.

12. **To what extent do you oppose or support the use of nuclear-generated electricity?** *Check one.*

   ⬤ Very opposed
   ⬤ Somewhat opposed
   ⬤ Neither oppose or support
   ⬤ Somewhat supportive
   ⬤ Very supportive

13. **To what extent do you oppose or support increasing the share of New Mexico electricity from Palo Verde?** *Check one.*

   ⬤ Very opposed
   ⬤ Somewhat opposed
   ⬤ Neither oppose or support
   ⬤ Somewhat supportive
   ⬤ Very supportive

14. **What drives your answer to question 13?** *Check one.*

   ☐ Impact on jobs in New Mexico
   ☐ Environmental concerns
   ☐ Health concerns
   ☐ Cost concerns
   ☐ Other _____

Water usage

Water usage varies for electricity generation, depending on the technology and resources used to generate electricity.

Currently, electricity generation consumes an amount of water that is equivalent to serving 415,000 Albuquerque residents for a year.

15. **How concerned are you about the amount of water used to generate electricity in New Mexico?** *Check one*

◉ Very concerned
◉ Moderately concerned
◉ Somewhat concerned
◉ Slightly concerned
◉ Not concerned

16. **Given the limited water resources in New Mexico, which one of the following uses of water do you think most important?** *Check one.*

◉ Agriculture sector
◉ Electricity generation
◉ Industrial sector
◉ Oil and gas industry
◉ Residential sector

Number of New Mexico jobs

Changes in the state energy plan may impact New Mexico jobs in two ways.
Depending on the technology used, the number of New Mexico jobs associated with
generating electricity and the corresponding inputs may increase, decrease, or stay the
same.

Changes to the state energy plan may change electricity prices, which in turn could change
the number of jobs in industries that use electricity. Depending on the size of the effect, the
number of jobs in New Mexico could increase, decrease, or stay the same.
Rural and urban areas may be affected differently.

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17. **How important a concern should the number of jobs be in any choice of a state energy plan?** *Check one*

  - ● Very important
  - ● Moderately important
  - ● Somewhat important
  - ● Slightly important
  - ● Not at all important

18. **Which one of the following statements best describes your view regarding New Mexico jobs due to changes in state energy plan?** *Check one.*

  - ◻ Rural job creation should be emphasized
  - ◻ Urban job creation should be emphasized
  - ◻ Rural and urban job creation should have an equal emphasis

---

Monthly electricity bill

A change to the state energy plan could increase, decrease, or have no change on your monthly electric bill.

---

19. **What is your best approximation of the cost of your July electric bill?** *Check one*

- ⬛ Less than $39
- ⬛ $40 to $69
- ⬛ $70 to $99
- ⬛ $100 to $129
- ⬛ $130 to $159
- ⬛ $160 or greater

20. **If your monthly electric bill increased by the following amounts, how much hardship would it cause your household?** *Check one for each.*

	No hardship	Some hardship	A great hardship
$5/month	⬛	⬛	⬛
$10/month	⬛	⬛	⬛
$20/month	⬛	⬛	⬛
$40/month	⬛	⬛	⬛
$60/month	⬛	⬛	⬛

Which State Plan Do You Prefer?

Now we will ask you to make 3 choices over 3 competing state plans and ask which you prefer: Plan A, Plan B, or the Current Plan.

Pick the state plan that you think is best, giving serious consideration to the costs; assume you are paying the mentioned amount. If you do not like any, choose the one with which you are most able to live.

21. **Consider these three possible state plans. Which plan would you prefer?** *Check Plan A or Plan B or Current Plan.*

	Plan A	Plan B	Current Plan
Required share of electricity from renewables by 2040	50%	80%	20%
Electricity generation from nuclear power	0%	18%	18%
Change in water usage for electricity generation	10%	No change	No change
Change in number of New Mexico jobs	No change	2000 jobs	No change
Change in monthly electricity bill	No change	$10	No change
I would choose Plan ⟶	◼	◼	◼

22. **How certain are you of your choice? Check one. It's ok to be uncertain – Your reply will be no less valuable for that reason!**

- ⬢ Very uncertain
- ⬢ Uncertain
- ⬢ Neither certain nor uncertain
- ⬢ Certain
- ⬢ Very certain
- ⬢ Don't know

23. **In deciding among the state plans presented above did you NOT consider any of the following components?** *Check any that you did NOT consider.*

- ☐ Required share of electricity from renewables by 2040

- ☐ Electricity generation from nuclear power

- ☐ Water usage for electricity generation

- ☐ Change in number of New Mexico jobs

- ☐ Change in monthly electricity bill

- ☐ I didn't ignore any of the components

24. **Consider these three possible state plans. Which plan would you prefer?** *Check Plan C or Plan D or Current Plan.*

	Plan C	Plan D	Current Plan
Required share of electricity from renewables by 2040	50%	20%	20%
Electricity generation from nuclear power	18%	0%	18%
Change in water usage for electricity generation	10%	10%	No change
Change in number of New Mexico jobs	2000 jobs	2000 jobs	No change
Change in monthly electricity bill	$60	$20	No change

I would choose Plan $\longrightarrow$

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25. **How certain are you of your choice?** *Check one*
It's ok to be uncertain – Your reply will be no less valuable for that reason!

- ☐ Very uncertain
- ☐ Uncertain
- ☐ Neither certain nor uncertain
- ☐ Certain
- ☐ Very certain
- ☐ Don't know

26. **In deciding among the state plans presented above did you NOT consider any of the following components?** *Check any that you did NOT consider.*

- ☐ Required share of electricity from renewables by 2040

- ☐ Electricity generation from nuclear power

- ☐ Water usage for electricity generation

- ☐ Change in number of New Mexico jobs

- ☐ Change in monthly electricity bill

- ☐ I didn't ignore any of the components

27. **Consider these three possible state plans. Which plan would you prefer?** *Check Plan E or Plan F or Current Plan.*

	Plan E	Plan F	Current Plan
Required share of electricity from renewables by 2040	50%	20%	20%
Electricity generation from nuclear power	0%	36%	18%
Change in water usage for electricity generation	10%	10%	No change
Change in number of New Mexico jobs	No change	2000 jobs	No change
Change in monthly electricity bill	No change	$60	No change

I would choose Plan ⟶ ☐ ☐ ☐

28. **How certain are you of your choice? Check one. It's ok to be uncertain – Your reply will be no less valuable for that reason!**

- ⭕ Very uncertain
- ⭕ Uncertain
- ⭕ Neither certain nor uncertain
- ⭕ Certain
- ⭕ Very certain
- ⭕ Don't know

29. **In deciding among the state plans presented above did you NOT consider any of the following components?** *Check any that you did NOT consider.*

- ☐ Required share of electricity from renewables by 2040
- ☐ Electricity generation from nuclear power
- ☐ Water usage for electricity generation
- ☐ Change in number of New Mexico jobs
- ☐ Change in monthly electricity bill
- ☐ I didn't ignore any of the components

30. **For each of the following possible components of the state energy plan, please indicate the level of importance to you in choosing your preferred state plan.** *Check one for each*.

	Extremely Important	Very Important	Moderately important	Somewhat Important	Not at all important
Required share of electricity from renewables by 2040	▢	▢	▢	▢	▢
Electricity generation from nuclear power	▢	▢	▢	▢	▢
Water usage for electricity generation	▢	▢	▢	▢	▢
Change in number of New Mexico jobs	▢	▢	▢	▢	▢
Change in monthly electricity bill	▢	▢	▢	▢	▢

Your Attitudes and Information

31. **Listed below are statements about the relationship between humans and the environment. For each one, please indicate if you strongly agree, mildly agree, are unsure, mildly disagree, or strongly disagree with it.** *Check one for each.*

	Strongly Agree	Mildly Agree	Unsure	Mildly Disagree	Strongly Disagree
The balance of nature is very delicate and easily upset.	☐	☐	☐	☐	☐
Modifying the environment for human use seldom causes serious problems.	☐	☐	☐	☐	☐
Plants and animals exist primarily to be used by humans.	☐	☐	☐	☐	☐
The earth is like a spaceship with only limited room and resources.	☐	☐	☐	☐	☐
There are limits to economic growth even for developed countries like ours.	☐	☐	☐	☐	☐
Humans are meant to rule over the rest of nature.	☐	☐	☐	☐	☐

About You and Your Household

Not all New Mexico residents will have the opportunity to complete this survey. Thus, we need to know how similar you and other survey respondents are to New Mexico residents. Your answers to the following questions will help us to do this.

All the information collected in this survey will be kept completely confidential. No individual results will be reported.

32. **Does your or anyone in your family's job relates to any of the following sectors in New Mexico?** *Check all that apply.*

    ☐   Energy
    ☐   Environmental Protection
    ☐   None of the above

33. **Have you ever contributed (such as volunteering, donating money, etc.) to an environmental protection group (such as 350 New Mexico, Greenpeace International, Environmental Working Group etc.) working in the US?** *Check one.*

    ● Yes
    ● No

34. **Do you or anyone in your household have any of the following?** *Check all that apply.*

    ☐   Hybrid car
    ☐   Rooftop solar panel
    ☐   Wind turbine
    ☐   None of the above

35. **Which of the following best describes the type of utility from which you purchase your electricity.** *Check one.*

⬤ Large electric utilities (e.g. PNM or EPE)

⬤ Small cooperative utilities (e.g. Farmers Electric or Jemez Mountain Electric)

36. **Have you voluntarily agreed to pay more to purchase electricity generated by renewable resources (such as PNM Sky Blue)?** *Check one.*

❑ Yes

❑ No

37. **What is your gender?** *Check one.*

⬤ Male
⬤ Female

38. **What is your age?**

_____ **years**

39. **Do you have children?** *Check one.*

❑ Yes

❑ No

40. **Have you lived in the United States your whole life?** *Check one.*

⬤ Yes → Skip to Question 41
⬤ No ⌐

a. **What year did you move to the United States?** *Write the year.*

_____

41. **Have you lived in New Mexico your whole life?** *Check one.*

⬤ Yes → Skip to Question 42
⬤ No ───┐
         │
         └──→   **a.   What year did you come in New Mexico?** *Write the year.*

               _____

42. **Which languages are regularly spoken in your home?** *Check all that apply.*

☐   English

☐   Spanish
☐   Native North American Languages
     → *Please identify language*: _____
☐   Other → *Please identify language*: _____

43. **Are you Spanish/Hispanic/Latino?** *Check one.*

⬤ Yes
⬤ No

44. **The last question deals with ethnicity while this one deals with race. Please check the race(s) you consider yourself to be. These race categories may not fully describe you, but they are the standard categories used by the Census Bureau.** *Check all that apply.*

☐   White
☐   Black or African American
☐   American Indian or Alaska Native
         → *Print Tribe*: _____
☐   Asian

☐   Pacific Islander
☐   Multiple races

45. **What is the highest degree or level of school you have completed?** *Check one.*

- ⬤ Less than 5th grade
- ⬤ 5th-8th grade
- ⬤ 9th-11th grade
- ⬤ 12th grade, no diploma
- ⬤ High school diploma or GED
- ⬤ Some college, but no degree
- ⬤ Associate degree
- ⬤ Bachelor's degree
- ⬤ Master's degree
- ⬤ Professional degree (e.g., MD, DDS, JD)
- ⬤ Doctorate degree (e.g., Ph.D.)

46. **Have you ever called or emailed your US Senator or US representative to communicate your opinion on an issue?** *Check one.*

- ⬤ Yes
- ⬤ No

47. **In which of the following elections, if any, did you vote?** *Check all that apply.*

- ☐ 2012 general election
- ☐ 2014 midterm election
- ☐ 2016 primary election
- ☐ 2016 general election
- ☐ None of the above

48. **With which political party do you primarily identify?** *Check one.*

- Democrat
- Green
- Independent
- Libertarian
- Republican
- Other → *Print party*: _____

49. **In the 2016 general election who did you vote for?** *Check one*

- Hillary Clinton
- Donald Trump
- Gary Johnson
- None of the above

50. **What is the range that best describes your total household income before taxes in 2016? (Please include wages, interest, and any other income.)** *Check one.*

- Less than $14,999
- $15,000 to $24,999
- $25,000 to $34,999
- $35,000 to $49,999
- $50,000 to $74,999

- $75,000 to $99,999
- $100,000 to $124,999
- $125,000 to $149,999
- $150,000 to $199,999
- $200,000 or greater

Thank you very much for your help!

If you have any additional comments, please write them below. When you are finished, please place the survey in the postage-paid return envelope and mail it back to us.

If the return envelope was misplaced, please send the completed survey to:
        Professor Jennifer Thacher
        Department of Economics
        University of New Mexico
        MSC05 3060
        Albuquerque NM 87131-000122

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