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Market and Non-Market Valuation of Renewable Energy

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MARKET AND NON-MARKET VALUATION OF RENEWABLE ENERGY

BY

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DISSERTATION

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Dedication

This is for my loved ones, my family: my dearest aunt, Baji Tuba; my mother, Amin; my love, Jordan Hoile; my dad and uncle, Omar and Osman; my brothers: Arsalan, Shoresh, and Kamal; my sisters: Kuestan, late Gelavej, Mlook, and Sirwe; and my dearest nephews to whom I wish the best in achieving their potentials, Rizgar and Karwan.

To my people, the nicest, strongest, most underappreciated people in the globe, the Kurds, the biggest nation in the globe without a state. I sincerely hope I can be a valuable asset and give something back to the society in general, and my people in particular. As we say:

بەرەو بەرزای دەچم گەرچی وردم، خاکی بەر پێی تێکۆشەرێکی کوردم

لای هەڵۆی، بەرزە فڕی بەرزە مژی، چۆن بژی شەرتە، نەوەک چەندە بژی

To everyone who said I cannot do it, who said I will never achieve my dreams. I tell them, "Impossible even itself says I'm Possible; you can do it too!" and "Don't be a dream-killer, rather be a dream-chaser." To those who made me stretch knowingly or unknowingly.

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ABSTRACT

This dissertation is an assessment of market and non-market valuation of renewable energy, specifically within the electricity sector. It contributes to the energy and economics literature through a battery of three chapters. This dissertation utilizes New Mexico as a case study, which is an economically poor and natural-resource rich state that produces and consumes electricity in the southwestern United States. It is also one of the four states that have adopted a policy for 100% clean energy by 2045.

The **first** chapter models state- and county-level economic (e.g., employment, economic output, etc.) and environmental (e.g., externality, health impact, water use, greenhouse gases, etc.) impacts of the switch from fossil fuel generation to renewables on a state's economy. This chapter provides a roadmap of how to measure the economic and environmental impacts of different energy scenarios by integrating various methodologies such as econometrics, GIS, and input-output into a unique system dynamics model. Findings from this chapter suggest that renewable energy intensive scenarios are only economically viable when market failure (externalities) is taken into

account. Further, counties with varying energy potential and population density will experience variation in impacts.

The following two chapters are based on a discrete choice experiment survey conducted in New Mexico in 2017. The **second** chapter estimates people's willingness to pay (WTP) for renewable energy, particularly solar energy. Results suggest that respondents support an increased renewable portfolio standard solar requirement and they have a positive marginal WTP for rooftop solar and smart meter installation. These values are impacted by several factors, including location, environmental worldview, and proximity to solar. We observe a distance decay effect on respondents' marginal WTP for different solar plans.

As there are often questions concerning the validity of survey responses, the **third** chapter focuses on the impact of response under two alternative mechanisms: with and without having respondent sign an oath prior to taking a survey. Hypothesis testing results show no evidence that the oath lowers valuation measures in this setting.

There are three major lessons from this dissertation. First, 100% clean energy policies are more desirable when internalizing external costs and hence correct for market failure. Second, consumers are willing to pay a premium to accompany the move towards a higher level of renewable energy diffusion. Third, an oath script may have limited application outside of the experimental lab and is not effective under every condition. This research will provide improved information to enact sustainable energy policies that are effective for the economy, environment, and individual consumers.

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Chapter 1: Introduction

1.1. Overview

Electricity is essential to support our society. From industry to home life, electricity is used to advance technology, medicine, provide entertainment, and support activities of daily living. The methods of electricity generation we have used to date, however, have created numerous detrimental effects on the environment and on human health. Fossil fuels, including coal, natural gas, and petroleum, have contributed extensively to climate change, premature human morbidity and mortality, avian mortality, and increased water consumption. These substantial externalities along with continuing costs to maintain aging facilities lead to market failure. In other words, as the equilibrium price of electricity does not accurately account for true costs of generation, fossil fuel combustion externalities lead to market failure.

Renewable energy (RE) has been a growing, attractive alternative in electricity generation particularly over the past decade. Taking into account generation externalities and advancing technology, RE is becoming more cost-effective than fossil fuels. This is accompanied by legislators in the U.S. implementing numerous policies encouraging increased electricity generation from RE. Renewable Portfolio Standards (RPSs) are one such group of policies, which mandate electric providers generate a portion of their generation or sale from renewable energy within a certain time frame. The main goal of these types of policies is to address climate change by reducing greenhouse gases, air pollution, and water consumption through the use of less fossil fuel.

These policies have the potential to make considerable impacts on state economies, including but not limited to employment, electricity prices, lower greenhouse gases, improved air quality, health and wellness of residents, and reduced water usage. However, these policies have been enacted without studying the short and long-term economic ramifications nor the preference of consumers affected by such mandates. How can energy policies be implemented to optimize societal objectives? What are consumers preferences and willingness to pay (WTP) for a transition to higher level of RE? Furthermore, given the concern for validity in current survey methods, how can we monitor for sincerity of respondents' answers?

This dissertation aims to address the above questions through market and non-market valuation methodologies, with the use of state-of-the-art modeling techniques and a discrete choice experiment survey (with and without implementing an oath). This work will provide improved information to enact sustainable energy policies that are effective for the economy, environment, and individual consumers.

1.2. Background

Electricity generation in the United States is progressively moving away from coal-fired generation to cleaner fossil fuels and, increasingly, towards RE. As depicted in

Figure 1-1, coal-fired generation has been experiencing a decreasing trend since 2009, while electricity generation from natural gas and renewables have concurrently experienced a positive trend. In 2018, natural gas provided the largest share of total generation in the United States with 35.1%, followed by coal (27.4%), nuclear (19.3%), and renewables (17.1%, of which 7% was hydropower).[1] Compared to a decade ago, electricity generation from RE sources increased by approximately 100% with the majority of the growth from wind and solar energy.[2]

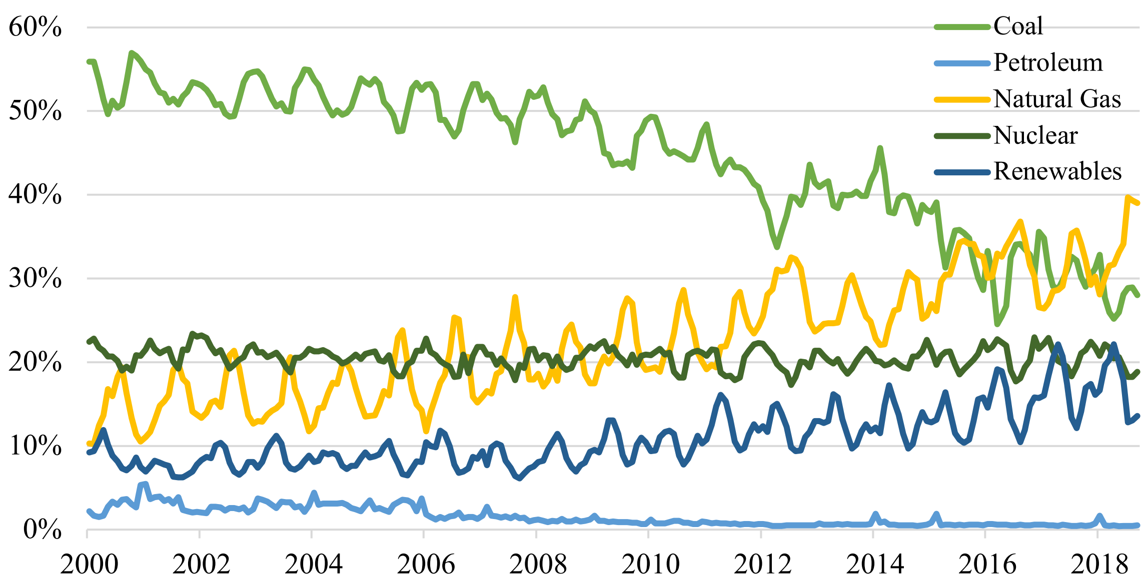

Figure 1-1: Monthly electricity net generation in the electric power sector from January 2000 to November 2018. Source: Energy Information Administration

As a result, employment and economic output via the RE sector have amplified and are expected to continue growing in the future. In fact, Bureau of Labor Statistics introduces "solar photovoltaic installers" and "wind turbine service technicians" as the

[1] Source: https://www.eia.gov/tools/faqs/faq.php?id=427&t=3 (accessed 03/22/2019)
[2] Source: https://www.eia.gov/todayinenergy/detail.php?id=38752 (accessed 03/22/2019)

top two fastest growing occupations in the next decade nationwide.[3] In 2018, the solar industry alone supported more than 242,000 jobs across all 50 states[4], while the wind industry sustained more than 105,000 employments nationwide. In the last decade, $145 billion has been invested in the wind industry for additional wind turbine installation[5], and $17 billion investment was spent in the solar industry in the United States in 2018.[6]

The growth in RE sector is attributed to various factors. This includes state and federal policies, such as various tax incentives (production tax credit[7] and investment tax credits[8]), net metering, state-mandated RPSs, as well as declining renewable technology costs. Net metering programs, implemented in 44 states[9], allow RE customers sell back their excess electricity generated from qualified RE sources. This program is a vital reason as to why citizens want to install distributed renewable energy.

State-mandated RPSs, currently mandated in 29 states and Washington D.C., require electric utility companies to generate a share of their electricity generation from renewable sources with progressive targets over time. Iowa was the first state to regulate an RPS in 1983. In the decades since, states have considered modifying or even repealing their RPS requirements. For example, Hawaii, California, Washington D.C., New Mexico, and Washington extended their RPSs to 100% clean energy (carbon-free) by

[3] Source: https://www.bls.gov/ooh/fastest-growing.htm (accessed 03/22/2019)
[4] Source: https://www.solarstates.org/#states/solar-jobs/2018 (accessed 03/22/2019)
[5] Source: https://www.awea.org/wind-101/basics-of-wind-energy/wind-facts-at-a-glance (accessed 03/22/2019)
[6] Source: https://www.seia.org/solar-industry-research-data (accessed 03/22/2019)
[7] A production tax credit provides a tax rebate based on the amount of electricity production by a RE source. The federal government provides a production tax credit of $0.015 per kilowatt-hour in 1993 dollars for certain technologies such as solar and wind energy technologies. Different states have different production tax credit incentives. For more detail, for example see http://www.dsireusa.org/.
[8] An investment tax credit provides a tax rebate of a certain percentage of the investment in a qualified RE asset. The federal government provides investment tax credits of 19% and 12% for qualified solar and wind energy investments respectively in 2019. For more detail, for example see http://www.dsireusa.org/.
[9] Beside Idaho, Texas, South Dakota, Tennessee, Alabama, and Mississippi, the remaining states have some sort of net metering policy in place.

2045[10], New York and New Jersey[11] extended their RPSs to 50% by 2030, and Connecticut to 48% and Massachusetts to 35% by 2030[12]; Kansas altered its mandatory RPS to a voluntary policy; West Virginia and Ohio repealed their RPSs in 2015 and 2017 respectively.[13] In addition to the four states and Washington D.C. that have mandated policies, the governors of New York and New Jersey signed executive orders to achieve 100% clean electricity by 2045 and 2050 respectively. Further, seven other governors have made promises (CO, CT, IL, MA, ME, OR, and PR) to join the 100% clean electricity movement sometime between 2045 and 2050.[14]

While the primary objective of these regulations is to address climate change through environmental motives, such as greenhouse gas mitigation and/or saving water, there can be potential impacts on regional economy (i.e., state- and county-level). To meet the requirements of RPSs, the majority of utility-scale RE development will be located primarily in rural areas (Brown et al. 2017). These regions have limited access to transmission lines, and investment in installing new transmission lines causes electricity rates to rise (Upton and Snyder, 2017). Consequently, rural areas will benefit more from RE development than urban areas. While there are ongoing debates regarding the

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[10] Sources: https://www.eia.gov/todayinenergy/detail.php?id=38492, https://www.nmlegis.gov/Sessions/19%20Regular/bills/senate/SB0489.pdf, and http://lawfilesext.leg.wa.gov/biennium/2019-20/Pdf/Bills/Senate%20Bills/5116.pdf#page=1 (accessed 04/18/2019)

[11] Source: https://www.energy.gov/savings/renewables-portfolio-standard-0 (accessed 03/22/2019)

[12] Source: https://www.eia.gov/todayinenergy/detail.php?id=38492

[13] RPS designs are unique to each state and mainly focus on wind and solar energy. Some RPSs have distinct goals solely for solar energy. Among the 29 states with RPS requirements, 18 states have mandated that electric providers within respective states include a minimum amount (carve-out) from solar energy. For example, New Mexico's RPS has mandated that by 2020, 20% of energy production derive from renewables, including a 23% solar carve-out. Similarly, Nevada's RPS has mandated that by 2025 25% of energy production result from renewables, with a 5% solar carve-out

[14] Source: NREL, https://www.nrel.gov/docs/fy19osti/73234.pdf , page 7. (accessed 04/20/2019)

effectiveness of RPSs policies, scientists agree RPSs are expensive and might directly (e.g., electricity price) or indirectly (e.g., tax) impact citizens (ibid).

As far as RE technology cost is concerned, installation costs of wind and solar energy have declined coupled with increasing their technologies' efficiency level. Median price to install solar energy has decreased by more than 60% since 2010, and 16% since 2016 (\$4.43/W_{DC} in 2010 to \$1.56/W_{DC} in 2017) (Bolinger & Seel, 2018, p. 15), and installation cost of wind projects has fallen by 33% since 2010 (\$2,403/kw in 2010 to \$1,611/kw in 2017) (Wiser and Bolinger, 2018, 50). Not only have wind and solar energy installation costs fallen in the last decade, but their technology efficiency levels have risen as well. For example, capacity factor of wind energy increased by 10% (32.5% to 42.5%) from 2010 to 2016 (Wiser and Bolinger, 2018, 42). National Renewable Energy Laboratory, Energy Information Agency, and Lawrence Berkeley National Laboratory are all predicting that wind and solar technology costs will continue to decline.[15]

Further, the move toward integrating more renewables into the electricity grid is complemented by citizens' positive attitudes and WTP toward development of RE sources such as wind and solar energy. Stated preference studies commonly find electricity consumers around the globe have positive WTP for the move to RE (e.g., Soon and Ahmad, 2015).[16] Since there is no actual expenditure at issue while asked

[15] For the latest available prices of wind and solar energy, among others see Wiser and Bolinger (2018), Barbose et al. (2018), and Cole et al. (2018).
[16] For instance, Soon and Ahmad (2015) conducted a meta-analysis of thirty studies from all continents from 2000 and beyond and found a mean WTP of \$7.16/month to increase electricity from RE. Among others see Sundt & Rehdanz (2015), Ma et al. (2015), and Soon and Ahmad (2015) for meta-analysis on WTP for RE.

hypothetical questions, as is the case with the stated preference approach, these studies may be biased upward, meaning respondents may overstate their WTP.

Overall, it is easy for a society to pass long-term policies a decade into the future, as is the case with RPSs, and not quantify the economic and environmental impacts associated with them. It is also common for states and the federal government to provide tax incentives and subsidies for energy industry without analyzing consequences. However, if these policies eventually affect tax/rate payers through higher electricity prices and/or taxes, the future of the RE diffusion will be dependent upon how supportive citizens are toward RE development and the gains/losses from different energy policies. Lastly, consumers' behaviors and attitudes might vary under different administrations (in favor or opposed) or survey settings for a nonmarketed publicly provided good, such as electricity generation from RE, leading to understating or overstating one's true WTP.

This dissertation focuses on various aspects of RE, specifically in electricity generation. This dissertation contributes to the electricity and economics literature through a battery of three main chapters. The first chapter assesses the economic and environmental impact of RE and the tradeoffs on an economy. The second chapter estimates people's WTP for RE, particularly solar energy. As there are often questions concerning the validity of survey responses, the third chapter focuses on the impact of response under two alternative mechanisms: with and without having respondent sign an oath prior to taking a survey. This research utilizes New Mexico as a case study, which is an economically poor and natural-resource rich state that produces and consumes electricity in the southwestern United States. New Mexico is also one of the four states that has mandated a policy for 100% clean electricity by 2045. This dissertation contributes to the current body of literature in three ways. First, not only does it assess different energy scenarios by considering the underlying dynamics within the energy sector, but also it assesses these impacts at lower granular level (i.e., county-level) for the first time. Second, it finds that citizens are in favor of the movement towards clean electricity and are willing to pay a premium on top of their monthly electricity bill to help the movement. Third, it finds no evidence that an oath script lowers respondents' WTP for clean electricity. This dissertation will assist local policymakers with determining the optimal packages for stakeholders and develop effective cost-control strategies for the electricity sector.

1.3. Chapter Two

This chapter models state- and county-level economic and environmental impacts of the switch from fossil fuel generation to RE on a state's economy. Economic impacts include employment and gross economic output (direct, indirect, and induced impact) during installation and operating phases of additional and existing power plants. Environmental impacts include greenhouse gas and water usage reduction and their corresponding impacts on social welfare (e.g., human and avian mortality, human morbidity, etc.). This chapter is an attempt to answer various complex questions that electric utility companies face, in particular: 1) What are the environmental and economic impacts of an X%-RPS by a certain deadline, where X can be any number from 0 to 100%? 2) How much electricity, when, where, and from what source do we need to fulfill an X% RPS? To answer these questions, we integrate several methodologies to develop a system dynamics (SD) model. We are the first to construct such a thorough model that enables estimation of environmental and economic impacts of different energy scenarios in such a granular level. The model is developed for the state of New Mexico, which has existing capacity for traditional fossil fuels, as well as renewables.

SD is a derivative of the work developed by Forrester (1971), in which he commenced an innovative approach to integrate multi-loop feedback systems. So long as relationship among variables are known, this approach makes modeling complex systems, such as electricity, possible. We integrate results from various modeling approaches such as input-out, econometrics, and GIS to form a unique SD model. To assess different scenarios, we use multiple programs such as: Jobs and Economic Development Impact (JEDI) coupled with Impact Analysis for Planning (IMPLAN) to calculate employment and economic output multipliers by energy type and by county; Stata to estimate the electricity demand by various sectors; ArcGIS to estimate RE and electricity production by natural gas potential, as well as the optimal location for siting additional power plants; lastly, Powersim Studio to assess various energy portfolio scenarios. Combining these methodologies in an innovative approach to analyze the SD model is the key contribution of this chapter.

Data used in the analysis are from multiple sources, such as, Energy Information Administration (various survey forms, 2018 Annual Energy Outlook, and Layer Information for Interactive State Maps shapefiles), Emissions and Generation Resource Integrated Database of Environment Protection Agency, National Renewable Energy Laboratory (JEDI, Annual Technology Baseline, Wind Data, and Solar Data), Public Regulation Commission, United States Geological Survey, Bureau of Economic Analysis, United States Census Bureau, Western Electricity Coordinating Council, and the energy literature. Further, we acquired the employment and economic output multipliers for each energy source at the county-level through purchasing the IMPLAN 2016 data.

Under the fossil fuel intensive scenarios, our findings suggest supporting jobs in primarily in the fossil fuel sector in urban counties with existing infrastructure, the RE intensive scenarios support jobs in rural counties that are most suitable for future RE installation. Further, our results indicate that the fossil fuel intensive scenarios will be the most beneficial scenarios, with the highest employment and economic output impacts, without considering their consequential environmental impacts. However, considering environmental impacts, such as water usage, greenhouse-gases, air pollution, and human and avian mortalities and morbidities, will reverse the results: the higher the RPS level, the higher the overall benefits to the state. Although the employment values appear to have minimal impacts, the disparity in job and economic output distribution across counties and energy sources suggest that counties with different energy potential and population density will experience a variation in impacts. Given the rural nature of New Mexico and variable economic outlook across its counties, higher RE diffusion may become an economic tool to stimulate growth in economically-depressed areas.

1.4. Chapter Three

The objective and contribution of this chapter is to answer multiple questions in the literature, including I) Are citizens willing to pay a premium to go beyond the mandated state-determined RPS levels? II) Is there a difference in WTP for different types of solar energy (rooftop solar verses solar farm)? III) Does proximity to solar installation (both rooftop solar and solar farm) impact WTP for RE in general and solar energy in particular? IV) Does commitment to environmental conservation, as measured by the New Ecological Paradigm[17], lead to higher support for environmental attributes? V) Are citizens willing to pay a premium for advanced smart meter[18] installation? The answers to these research questions extend the literature by differentiating solar energy types, employing the New Ecological Paradigm scale in primary research of RE valuation in a choice experiment setting, and assessing preferences on smart meter and higher-level RPS. We test the impact of the actual distance to the nearest solar location (both solar farm and rooftop solar) post-survey, rather than an artificially-introduced distance through the survey instrument.

To answer the aforementioned questions, we implemented a choice experiment survey to gain understanding of consumer preferences and their preference heterogeneity. The survey is conducted in New Mexico, a state with RPS and great potential for renewables, particularly in solar where it ranks third in the United States for that potential. We administered the survey, developed following the Tailored Design Method (Dillman, Smyth, & Christian, 2014) to 1,300 randomly selected consumers of the state's largest electricity utility from 13 counties across New Mexico. The choice experiment considers an increase in RE and preference for different types of solar energy (rooftop solar and solar farm). In addition to assessing households' WTP for higher level of RPS, we evaluate respondents' attitudes towards advanced smart meters installation in New

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[17] New Ecological Paradigm is a scale that is designed to capture the relationship between humans and the environment. The literature suggests that this scale is strongly correlated with high levels of pro-environmental behaviors.

[18] Advanced smart meters are electrical meters that can directly transfer electricity consumption information two ways, to both the customer and the corresponding utility company. This real-time communication will allow utility companies to dictate different time-of-use prices on electricity, which may encourage some customers to switch their use from peak hours (expensive) to low-use hours (less expensive) to save money. Further, advanced smart meter facilitates the use of renewables in the grid and prevents the need for additional power plants to accommodate peak-hour times (peaking natural gas power plants), which results in lower carbon emissions and water usage.

Mexico. We control for factors that are expected to be responsible for variation in preference such as exposure and proximity to solar installations (solar farm and rooftop solar), location (rural versus urban), and environmental worldview.

With a response rate of 37.2% with responses from 10 of the 13 counties that Public Service Company of New Mexico provides service, we analyzed the data utilizing multinomial logit coupled with random parameter logit models. We used GIS to calculate spatial heterogeneity variables: the distance to the closest rooftop solar and solar farm as the crow flies.

Results suggest respondents support an increased RPS solar requirement and they have a positive marginal WTP for rooftop solar and advanced smart meter installation. These values are impacted by several factors, including location and exposure to solar. We also observe a distance decay effect on respondents' marginal WTP for solar farms, that is, the farther away a respondent lives from a solar farm installation the lower her marginal WTP for its development. Additionally, rural respondents are statistically significantly more supportive of solar farm improvements than urban respondents. Lastly, we find that respondents with a higher (modified) New Ecological Paradigm score possess higher support for our environmental attributes. For regulators considering additional RPS levels, or utilities considering solar installations, the results provide improved information on consumer preferences, heterogeneity of response, and marginal WTP for solar energy.

1.5. Chapter Four

Stated preference approaches such as discrete choice experiment and contingent valuation method are commonly used to monetize non-marketed publicly provided goods. One drawback for utilizing these approaches is that respondents commonly overstate their WTP and might not reveal their true preferences for acquiring the nonmarket good in question. Thus, these methods could be subject to biases, in particular hypothetical bias – the gap between WTP from a hypothetical question to a real incentive. The issue of hypothetical bias challenges the validity of stated preference results, which can lead to development of ineffective policies.

A recently offered *ex ante* approach to address hypothetical bias is the “solemn oath script”, where survey respondents sign or initial a solemn oath at the start of the survey to provide honest answers to valuation questions (Jacquemet et al., 2009, 2013). While the efficacy of solemn oath script is still debatable, the objective of this analysis is to provide an initial field setting test of the solemn oath script to a particular discrete choice experiment survey application to solar energy.

We divided our sample into two treatment groups: with and without having respondents sign the solemn oath prior to taking the survey. Data used in the analysis are different than the data used in the previous chapter; we collected 78 additional responses (34 with and 44 without the solemn oath) for the current study. Overall, we gathered 482 responses (221 with the solemn oath and 261 without).

Utilizing random parameter logit models in both preference-space and WTP-space, our results provide no evidence that the solemn oath script lowers respondents’ willingness-to-pay for the good in question. Either there is no hypothetical bias in this solar energy case study, which we are unable to test as there is no real expenditure at issue, or the solemn oath script may have limited application outside of the experimental lab and is not effective under every condition. Lastly, this calls for more research on the efficacy of the solemn oath script.

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Chapter 2: 100% Renewable-Electricity Demand: A Dream or Dreaming a Dream

2.1. Introduction

Electric utility companies in the United States are transitioning toward integrating more renewable energy (RE) sources in their energy mix. In April 2018, 23% of the USA's electricity generation came from renewable sources.[19] This is partly a result of policies and regulations aimed at mitigating greenhouse-gas (GHG) emissions through programs like the Regional Greenhouse Gas Initiative, and through Renewable Portfolio Standard (RPS) at the state level. While the primary objective of these regulations is to address global warming, there can be potential impacts on the economy at a micro-level

[19] Source: https://www.eia.gov/electricity/monthly/ (accessed 01/11/2019)

(i.e., state- and county-level). For rural western states, this has become increasingly important, as they strive to diversify their economies.

Debates are ongoing in the literature as to whether RPS policies have positive (i.e., job creation, GHG and air pollution reduction), negative, or no impact on an economy and the environment (e.g., Slattery, 2011; Yi, 2015; Barbose et al., 2016; Wiser et al., 2016; Divounguy et al. 2017; NYSERDA 2013; Upton & Snyder, 2017). For example, NYSERDA (2013) assesses New York's RPS impact and finds a gain of 24,000 job-years during 2002 to 2037; Divounguy et al. (2017) investigate Ohio's 12.5% by 2025 RPS and find that it would result in a loss of more than 134,000 jobs; Upton and Snyder (2017) evaluate states with an RPS versus without and find RPS has no significant impact on increasing RE or GHG reduction. Further, most of the existing literature has focused on either too generic of a scope (e.g., nation-wide) or state-specific assessments and has not considered assessment of impacts at lower level jurisdictions (e.g., county-level). Lastly, much of what is in the literature overlooks the fundamental dynamics within the energy sector. The objective of this paper is to contribute to this line of research and assess the economic and environmental impact of renewable energy and the tradeoffs on a regional economy.

Particularly, we are interested in answering questions such as: 1) How can we achieve an X%-RPS by a certain timeframe, where X can be any number from 0 to 100%? 2) What are the tradeoffs in terms of jobs and the environment in each scenario? 3) How much electricity, from what source, when, and where (by county) do we need to fulfill an X% RPS? These are rather complex questions and answering them requires the use of system simulation (Ford & Bull, 1989; Olaya & Dyner, 2005; Tidwell et al., 2009;

Qudrat-Ullah, 2013; Qudrat-Ullah & Seong, 2010). Thus, we develop, validate, and utilize a system dynamics-based (SD) simulation model that integrates results from various methodologies such as input-out, econometrics, and GIS. Combining these methodologies in an innovative approach to analyze the SD model is the key contribution of this paper. We execute our analysis in our case study of New Mexico (NM), a southwestern state in the U.S. with an RPS and high potential for both fossil fuel (FF) and RE sources.

Our findings suggest a net increase of jobs in rural counties that are most suitable for future RE installation. Depending on scenario, our model estimates increasing 137 – 156 thousand cumulative full-time equivalent jobs, $19 to $24 billion (2017$) cumulative gross economic output, and 3,431 to 3,492 and 257 to 296 billion gallons of cumulative withdrawal and consumption respectively from 2017 to 2050. These scenarios result in increasing millions of avian mortalities, as well as millions of tons of GHG emissions and thousands of tons of air pollutants, which each lead to billions of dollars in climatic and air-quality costs (social cost). Lastly, we find that higher levels of RPS will lead to greater benefits to the state when externalities and social benefits/costs are taken into account.

2.2. Background

FF combustion is the main source of GHG emissions in the U.S., which contributes to climate change.[20] Combusting FF for electricity generation not only emits air pollution, but also requires an immense amount of water. There is an extensive

[20] Source: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions (accessed 01/14/2019)

literature that demonstrates the correlation between air pollution and premature mortality/morbidity (Woodruff et al., 1997; Krewski et al., 2009; Lepeule et al., 2012; EPA, 2016a; Sovacool, 2009; Steinberg et al. , 2012). Maupin et al. (2014) shows that roughly 40% of all of the U.S. freshwater withdrawal was used for thermoelectric power plants in 2010. Policymakers, as a result, are seeking to promote policies that lead to integrating more environmentally friendly generation sources with less externalities.

Electricity generation is moving towards integrating a higher level of RE and lower combustion-based FF (e.g., oil, natural gas, and coal) in the U.S. due to not only regulatory mandated laws such as the RPS but also cost competitiveness. Twenty-nine states and D.C. currently have an RPS in place (Barbose, 2018). RPS mandates electric utility companies source a portion of their generation from RE within a certain timeframe. Although the main goal of RPS is environmentally-oriented, that is, to mitigate GHG emissions and/or save water, these policies have the potential to impact an economy. Previous research on the impact of RPSs shows that these policies are capable of yielding positive economic impact if positive externalities (zero or close to zero water usage, zero emission, etc.) are taken into account (Barbose et al., 2016; Wiser et al., 2017). Barbose et al. (2016) demonstrates that meeting requirements mandated by RPSs led to supporting 200 thousand jobs in 2013 and a reduction of 59 million metric tons of CO2 in the U.S. in 2013. Wiser et al. (2017) quantifies positive externalities of RE and estimates that existing RPSs policies lead to improving air quality and reducing climatic damages ($258 billion), which not only compensate the increase in electric system costs ($23 to $194 billion) but also exceeds those costs over the period of 2015–2050.

There are a handful of peer-reviewed papers and national laboratory reports that look at the feasibility of providing global energy through RE (e.g., Jacobson et al., 2015; Heard et al., 2017; Shaner et al., 2018; Cole et al., 2018). For example, Jacobson et al. (2015) estimates a portfolio mix that enables the United States to sustain its entire energy needs- including electricity, transportation, heating/cooling, and industry-with renewable energy by 2050. Similarly, Cole et al. (2018) assesses different scenarios of achieving various levels of RE in only the power sector by 2050. Further, previous economic impact studies of constructing and operating RE projects suggest that economic impacts to states are considerable (Lantz et al, 2011; Steinberg et al., 2012; Wiser et al., 2015; Godby et al., 2016). Similarly, studies on environmental impact of RE show significant climate and air quality benefits. For instance, Millstein et al. (2017) finds that solar and wind development resulted in benefits of \$30–\$113 billion (2015\$) and \$5–\$107 billion from air quality and climate respectively, while avoiding 3,000–12,700 premature mortalities from 2007–2015. Most of these studies have produced state-level or nation-wide job/environmental impact estimates, which have produced less understanding of lower-level dynamics like job/environmental impacts across counties. These studies also do not consider the underlying dynamics within the energy sector.

To address the aforementioned gaps in the literature, we combine various methodologies to develop an SD model. SD is a derivative of the work developed by Forrester (1971), in which he introduced a novel approach to integrate multi-loop feedback systems. So long as relationships among variables are known, this approach makes modeling complex systems, such as electricity, possible (Sterman, 2000). The SD model of this paper integrates results from input-out, econometrics, and GIS and form a unique framework that can provide both the public and policymakers improved information with which to make informed decisions. This model is developed at a monthly time-step starting from January 2004 to January 2050. Multiple programs are used to analyze the complex electricity problems common to most utilities. Namely, Jobs and Economic Development Impact (JEDI) coupled with Impact Analysis for Planning (IMPLAN) are used to calculate job multipliers by energy type and by county; Stata is used to estimate the electricity demand; ArcGIS is utilized to estimate the potential of RE and natural gas (NG) electricity generation by county, as well as the optimal location for siting additional power plants; lastly, results from previous models are all embodied in Powersim Studio, which is used to analyze various energy mix scenarios.

The objective of the SD model is to estimate electricity generation and consumption by different fuel sources and various sectors respectively. We provide a roadmap to assess the explicit and implicit impacts of various energy mix scenarios at the state and county level and at different points in time. Explicit impacts may include potential jobs and economic gross output associated with current and potential future electricity generation, and implicit impacts may include positive health effects and social benefits of reducing ambient emissions. We apply this roadmap to our case study of NM.

2.2.1. Study area: New Mexico

NM contains considerable potential for both FF and RE resources. It holds about 3%, 4%, and 5% of the United States' total estimated recoverable coal reserves, proved crude oil, and NG respectively and it possesses the second-largest uranium reserves in the nation. Most of the state's NG and crude oil are located in the San Juan and Permian

Basins in the northwestern and southeastern part of NM respectively, while coal reserves are mainly located in the San Juan and Raton Basins in northern NM (EIA, 2018). The vast areas of NM with available geo-physiological landmass that receives high wind and sunlight levels is optimal for increasing RE usage. NM ranks third in both solar[21] and wind (NREL, 2018) potential in the U.S.

NM's economy is ranked 46th in the nation.[22] The energy industry, especially oil and NG extraction, is one of the main contributors of NM's economy. NM obtains $2 billion and $300 million in direct (e.g., severance, property taxes, royalty, and rental income) and indirect (sales and income taxes) revenues respectively per year from oil and gas production. Depending on the state of the economy, revenues from oil and gas can result in 40% of NM's general fund revenue (NM Legislature, 2018). Thus, fluctuating oil and gas prices affect NM's economy immensely.[23]

On one hand, the energy industry is responsible for emitting GHG and ambient pollution as well as increased water usage in NM. GHG contributes to climate change, air pollution causes premature mortality and morbidity, and freshwater has historically been insufficient in NM.[24] On the other hand, RE is becoming more and more cost-competitive

[21] After Nevada and Arizona, NM has the highest energy potential for solar power in the U.S. Source: http://www.neo.ne.gov/statshtml/201.htm (accessed 01/13/2019)
[22] Source: https://www.usnews.com/news/best-states (accessed 01/13/2019)
[23] "A dollar increase in the per barrel price of oil translates into about $9.5 million for the general fund, while a 10 cent increase in the price per thousand cubic feet of natural gas translates into $6.5 million in additional revenue" Source: https://www.nmlegis.gov/Entity/LFC/Natural_Resources. For more information on NM's legislations including historical NM's general fund revenue see https://www.nmlegis.gov/ (accessed 01/13/2019)
[24] In 2018, roughly 90% of the state was faced with severe drought conditions that affected the entire population Sources: https://www.env.nm.gov/water/ and https://www.drought.gov/drought/states/new-mexico (accessed 12/25/2018)

relative to FF technologies.[25] Thus, it makes logical and economic sense for policymakers to promote policies, such as RPS, to integrate more RE into NM's energy mix.

At the time of analysis, NM's RPS required all the large electric utilities to generate 20% of their in-state electricity sales from RE resources by 2020.[26] Although it did not pass, a bill (Senate Bill 312) was introduced to increase NM's RPS previous level to 25% by 2020, 35% by 2025, 50% by 2030, 65% by 2035, and 80% by 2040 in the 53rd legislative session in 2017 (Stewart & Small, 2017).[27] A modified version of this bill was reintroduced in January 2019 (House Bill 15) and passed in the 54th legislative session in March 2019 (Senate Bill 489).[28] In addition to the requirements set by Senate Bill 312, Senate Bill 489 sets a 100% RPS by 2045 that is sourced from zero carbon resources. This makes NM the third state in the U.S. after California and Hawaii and before Washington to mandate a 100% RPS.[29] Thus, as of March 2019, NM's current RPS policy requires 20% in-state electricity sales from RE resources by 2020, 40% by 2025, 50% by 2030, 80% by 2040, and 100% by 2045.

Currently, there are three large electric utilities in NM: Public Service Company of New Mexico, El Paso Electric, and Xcel Energy, with the first serving the largest

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[25] For the latest available prices of wind and solar energy, among others see Wiser and Bolinger (2018), Barbose et al. (2018), and Cole et al. (2018).
[26] RPS requires the NM's rural electric distribution cooperatives to generate 10% of their in-state electricity sale from renewable sources. We do not consider rural cooperatives constraint in our analysis.
[27] Further details on Senate Bill 312 can be found at: https://www.nmlegis.gov/Sessions/17%20Regular/bills/senate/SB0312.pdf (accessed 03.12.2019)
[28] Further details on House Bill 15 and Senate Bill 489 can be found at: https://www.nmlegis.gov/Sessions/19%20Regular/bills/house/HB0015.pdf and https://www.nmlegis.gov/Sessions/19%20Regular/bills/senate/SB0489.pdf see p. 60 for more information on the updated RPS requirements (accessed 04.05.2019)
[29] Washington State joined the 100%-clean-energy movement on April 11, 2019. "It is the policy of the state that nonemitting electric generation and renewable resources supply one hundred percent of all retail sales of electricity to Washington customers by January 1, 2045." Source: http://lawfilesext.leg.wa.gov/biennium/2019-20/Pdf/Bills/Senate%20Bills/5116.pdf#page=1 (accessed 04/18/2019).

customer pool in the state. Further, as NM has considerable potential in both wind and solar energy, Public Regulation Commission set diversity targets (carve-outs) on different types of RE to create a diversified portfolio. Based on this portfolio, utility companies are to source at least 30%, 20%, and 3% of their in-state electricity sales from wind, utility-scale photovoltaic solar (PV), and residential photovoltaic solar (RPV) respectively by 2020 (see Table 2-1).[30]

Table 2-1: Carve-Outs regulated by Renewable Portfolio Standard.

Source	**Minimum amount**
Wind	30%
Utility-scale solar (PV)	20%
Residential/Distributed solar (RPV)	3%

The reminder of the paper is organized as follows. Section 2.3 defines the assessed scenarios in this paper. Section 4 contains methodologies and assumptions utilized in estimating: 4.1) electricity demand, 4.2) electricity supply, 4.3) the gap between demand and supply of electricity, 4.4) employment, and 4.5) environmental impact. Section 5 summaries the sources of data, while Section 6 presents economic (economic impacts) and environmental (water usage and air pollution and greenhouse-gas emissions) impacts of different scenarios and provides a summary of overarching results.

[30] For more information NM's RPS, visit: http://programs.dsireusa.org/system/program/detail/720 (accessed 01/13/2019).

The paper concludes with a discussion of results and conclusion in the last section, Section 7.

2.3. Scenario definitions

Our analysis investigates the number of jobs and their locations by energy source, as well as environmental impact based on thirty-four prices, three technological-costs, and four RPS scenarios. Each of these scenarios are described briefly below.

We adopted 34 price scenarios (electricity price by sector, Henry Hub natural gas price, and electric sector fuel cost [coal and natural gas]) developed by Energy Information Administration's (EIA) Annual Energy Outlook 2018 (AEO, 2018), along with three technology cost scenarios developed by National Renewable Energy Laboratory (NREL) (Cole et al., 2018). A list of AEO2018 scenarios are summarized in Table 2-2 below. The cost scenario includes Low, Mid, and High (constant) cost and performance estimates for wind, PV, RPV, NG (both baseload and peaker), and coal from 2016 to 2050. Low-cost wind and solar scenarios utilize low-cost estimates for land-based wind, along with PV and RPV technologies, while High-cost scenarios use constant costs at or near the 2018 cost estimates. The Mid-case scenario assumes prospective advances in the RE arena technology. Low- and high-cost scenarios for FF beyond 2016 relies on "High Oil and Gas Resource and Technology" and "Low Oil and Gas Resource and Technology" estimates respectively from AEO (2018). The Mid-case scenario serves as a reference case for FF technology costs adopted from AEO (2018).[31]

[31] For more information on AEO2018 and NREl's technology cost scenarios see: AEO 2018 (2018) and Cole et al. (2018).

Table 2-2: US EIA Annual Energy Report Price Scenarios (AEO, 2018)

No.	**AEO2018 Scenarios**	No.	
1	Reference case	**18**	Nuclear costs 20% higher low resources
2	High economic growth	**19**	Nuclear costs 20% lower high resources
3	Low economic growth	**20**	Nuclear costs 20% higher high resources
4	High oil price	**21**	$15 carbon allowance fee
5	Low oil price	**22**	$25 carbon allowance fee
6	High oil and gas resource and technology	**23**	ANWR mean resources
7	Low oil and gas resource and technology	**24**	ANWR low resources
8	Reference case with Clean Power Plan	**25**	ANWR high resources
9	High economic growth with Clean Power Plan	**26**	New efficiency requirements
10	Low economic growth with Clean Power Plan	**27**	No new efficiency requirements
11	High oil price with Clean Power Plan	**28**	PTC/ITC extension
12	Low oil price with Clean Power Plan	**29**	Early PTC/ITC sunset
13	High resource with Clean Power Plan	**30**	Solar PV tariff
14	Low resource with Clean Power Plan	**31**	Autonomous battery electric vehicle
15	Nuclear costs 20% lower Reference case	**32**	Autonomous hybrid electric vehicle
16	Nuclear costs 20% higher Reference case	**33**	AEO2017 without Clean Power Plan
17	Nuclear costs 20% lower low resources	**34**	AEO2017 with Clean Power Plan

We develop four RPS scenarios, namely: i) Status Quo RPS, ii) 1% Incremental RPS, iii) Senate Bill RPS, and iv) Decrease RPS. The "Status Quo RPS" assumes an RPS policy where electric utility companies are required to generate at least 20% of their in-state sell electricity from renewables by 2020[32] and to stay at this level until 2050.[33] The second scenario, "1% Incremental RPS", builds on the first scenario where it assures the 20% RPS by 2020 and 1% increment per year afterwards (50% by 2050). The "Senate

[32] At the time we developed the SD model and analysis, the 20% RPS by 2020 was the status quo and the new RPS had not yet been introduced.
[33] In the Status Quo RPS scenario, additional RE will be installed only when RPS 20% requirement and/or carve-outs are not met.

Bill RPS" scenario is a modified version of NM's newly-accepted Senate Bill of 80% RPS by 2040 (see above), which extends the RPS level to 100% by the end period. Lastly, we assume a hypothetical future where the 20% RPS by 2020 will decrease to 10% by 2050 ("Decrease RPS").

Overall, the SD model is capable of assessing 1,224 (34x3x3x4) different scenarios. For the purpose of brevity, we focus on the four most plausible future scenarios. Under the first scenario, *Scenario 1*, we assume a future with abundant fossil fuel and adequate RE resources and technologies that make 1% Incremental RPS (50% by 2050) possible. Second scenario, *Scenario 2*, is where there are scarce natural resources with costly FF and cheap RE technologies. Third scenario*, Scenario 3*, is the opposite of the second scenario: abundant natural resources with cheap FF and expensive RE technologies and hence a decreased RPS (10% by 2050). Lastly, we implement a status quo scenario, *Reference Case Scenario*, that assumes reference case AEO prices with Mid-case technology cost of FF and constant RE technology cost, along with business as usual RPS (RPS 20% by 2020 and on). Below we summarize each scenario.

I. ***Scenario 1***: AEO Price= High Oil and Gas Resource and Technology; RE Cost=Mid; FF Cost=Low; RPS=1% Incremental RPS (50%)

II. ***Scenario 2***: AEO Price= Low Oil and Gas Resource and Technology; RE Cost=Low; FF Cost=High; RPS= Senate Bill RPS (100%)

III. ***Scenario 3***: AEO Price= High Oil and Gas Resource and Technology; RE Cost=High; FF Cost=Low; RPS= Decrease RPS (10%)

IV. ***Reference Case Scenario***: AEO Prices= Reference Case; RE Cost=High; FF Cost=Mid; RPS= Status Quo RPS (20%)

2.4. Methods and assumption

Our model consists of more than 900[34] variables that altogether composed five sub-models: 1) Demand; 2) Supply; 3) Gap between supply and demand (hereafter, "Gap"); 4) Jobs; and 5) Environmental Impact. The first sub-model consists of two modules that together estimate electricity demand beyond 2016. The second sub-model includes six modules that altogether project megawatt-hour (MWh) generation. The Gap and the Job sub-models each contain seven modules. Finally, the Environmental Impact sub-model encompasses only one module. Below, we briefly describe each of these sub-models and corresponding modules and assumptions. Figure 2-1 summarizes the causal loop diagram utilized in the entire model.

[34] List of the variables can be accessed upon request from the corresponding author.

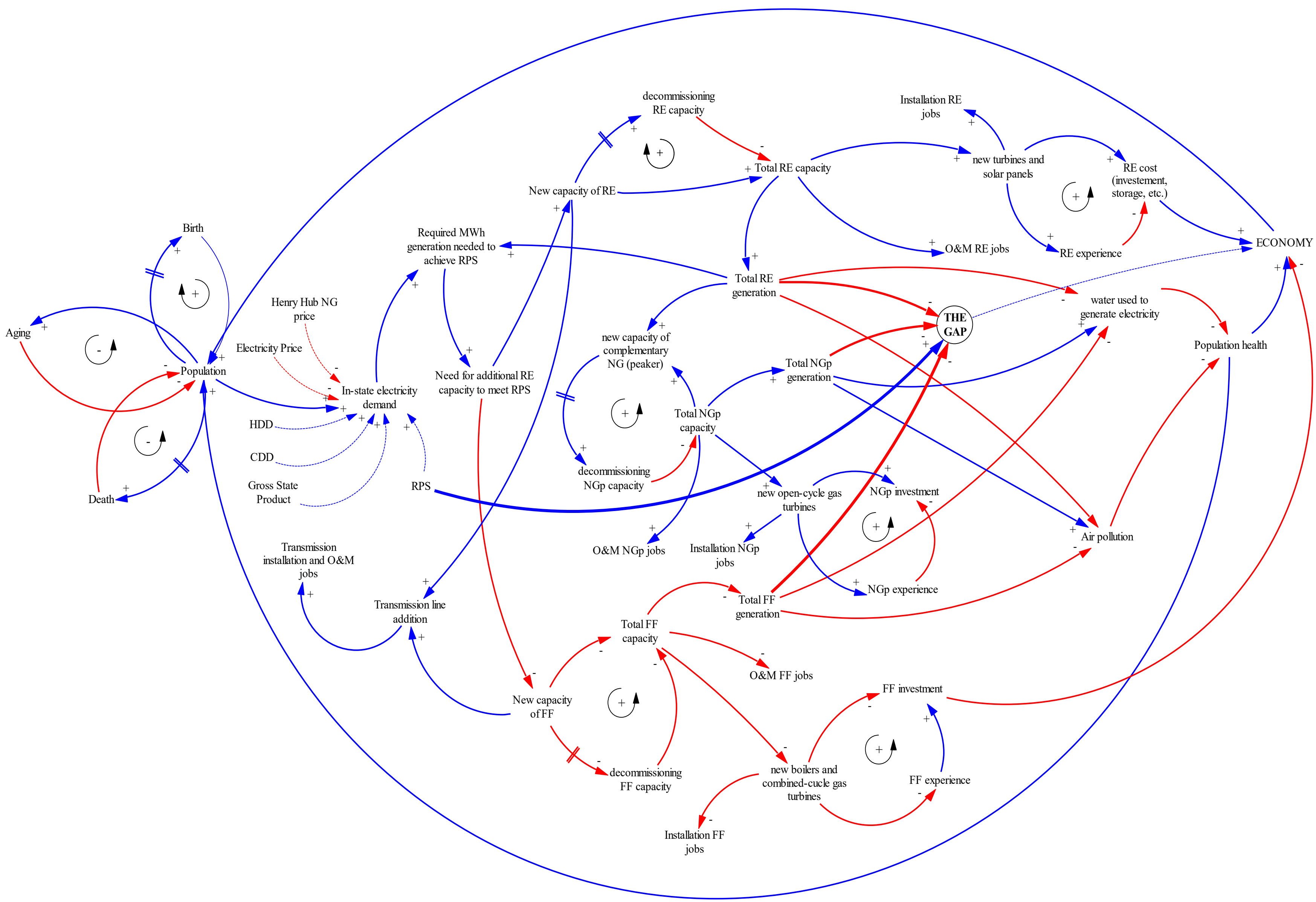

Figure 2-1: Causal loop diagram

In order to read the causal loop diagram depicted in Figure 2-1, imagine the variable at the base of the arrow increasing in value; the sign at the arrow head indicates the increase (+) or decrease (-) in the variable at the arrow head, all other variables unchanged. Lastly, parallel lines crossing an arrow indicates delay in impact from the variable at the base of the arrow to the variable in the head of the arrow. The causal loop diagram presents the logic behind our SD model. The following is an explanation of one path in the diagram.

Required generation to achieve a certain level of RPS increases as in-state electricity demand increases, which increases the need for additional RE capacity to meet the corresponding RPS level. The higher the need for additional RE capacity, the higher the new capacity of RE. As the new capacity of RE rises, total RE capacity rises and the capacity that will be decommissioned in the future will increase with a delay. Higher level of RE capacity that will be decommissioned decreases total RE capacity creating an enforcing loop (see Figure 2-1). On one hand, the higher the RE capacity, the higher the RE generation, hence the higher the need for peaker NG and storage and transmission lines. On the other hand, if we assume a higher level of RE generation replaces FF generation, then a higher level of RE generation results in lower GHG and air pollution, and thereby lowers population mortality and morbidity (social cost). Higher level of RE generation can also decrease the gap caused by a discrepancy between supply and demand for electricity and/or RPS requirement. The same logic holds true for the remaining components of the causal loop diagram.

2.4.1. Demand

The population module coupled with electricity demand module create the Demand sub-model. The former estimates population projection by county and the latter uses that information to forecast electricity demand. Below, we first describe the electricity demand module and then the population.

Recall that RPS policy regulates all the large electric utilities to source 20% of their electricity sold in-state from RE in NM by 2020. In order to extrapolate in-state electricity consumption beyond historical values, we estimate NM's monthly electricity demand and use the derived coefficients in the SD model. Following the literature (e.g., Holtedahl & Joutz (2004)), we apply a linear form using electricity price, Henry hub NG price, temperature, gross state product, population, and recession period as independent variables in the empirical analysis. Thus, in the empirical study the following specification (1) for state electricity demand is employed:

$$ED_t = \beta_0 + \beta_1 P_t + \beta_2 HHP_t + \beta_3 HDD_t + \beta_4 CDD_t + \beta_5 GSP_t + \beta_6 Pop_t + \sum_{i=2}^{12} \gamma_i month_i + \varepsilon_t \quad (1)$$

where ED_t is the state consumption for electricity at time t, P_t is real electricity price, HHP_t is real Henry Hub NG price, HDD_t and CDD_t are heating and cooling degree days respectively, GSP_t is real gross state product, Pop_t is population, $month_i$ is a dummy variable for experienced recession months[35] of the year, and ε_t is the error term. This analysis is executed utilizing monthly data for NM for the period of 1/2001 –

[35] Recession occurred from March to November 2001 and December 2007 to June 2009. Thus, it's "1" for those months and "0" for the remaining period.

12/2015. Table 2-3 presents the descriptive statistics of the data, while Table 2-4 summarizes the estimated coefficients for electricity demand. Estimated variables form the main body of the electricity demand module variables.

*Table 2-3: Descriptive statistics of state electricity demand from January 2001 to December 2015.**

Variables	Mean	SD	Min	Max
Total state MWh consumption	1,794,770	209,656.9	1,361,108	2,305,957
Real total price $/MWh	93.6	6.2	81.7	111.1
Real Henry Hub NG price	7.1	3.6	2	20.3
Heating degree days	373.7	335.6	0	1,024
Cooling degree days	84.5	118.7	0	401
Real Gross State Product	92,215.6	6,367.2	77,801.6	97,572.9
Population	2,082,706	167,597.5	1,831,690	2,356,236

*Number of observations=180

Table 2-4: Regression results on state's electricity demand

Variables	State
Real total price $/MWh	-2,769***
	(875.2)
Real Henry Hub NG price	1,288
	(1,397)
HDD	147.3**
	(63.05)
CDD	971.2***
	(157.9)
Real GSP	6.956***
	(1.309)
Population	0.551***
	(0.0578)
month = 2	-139,197***
	(16,451)
month = 3	-96,835***
	(23,855)
month = 4	-102,333***
	(34,894)
month = 5	-19,232
	(48,583)
month = 6	33,947
	(59,850)
month = 7	144,972**
	(65,472)
month = 8	210,689***
	(61,644)
month = 9	145,704***
	(51,839)
month = 10	42,148
	(40,695)
month = 11	-92,164***
	(20,253)
month = 12	-7,231
	(12,451)
Constant	109,480
	(109,494)
AIC	4342.5
Obs.	180
R-Squared	0.967

Note: Robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1

Moreover, future electricity demand is partially driven by population (see equation 1). Thus, to be able to forecast future electricity demand beyond 2015, we develop the population module that takes into account the following drivers: fertility; mortality; and aging. Figure 2-2 and Figure 2-3[36] summarize the stock/flow and causal loop diagrams of population module.

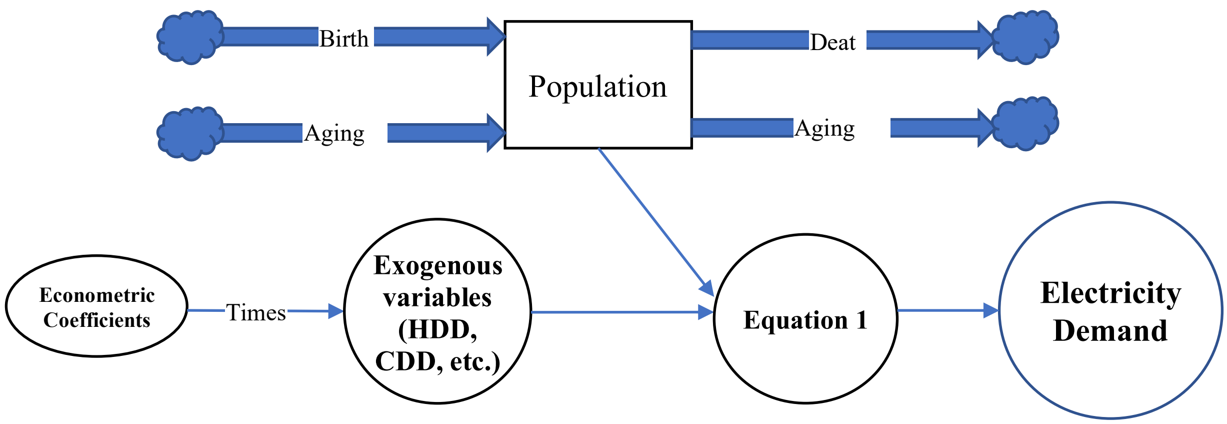

Figure 2-2: Population and Electricity Demand Stock/Flow Diagram

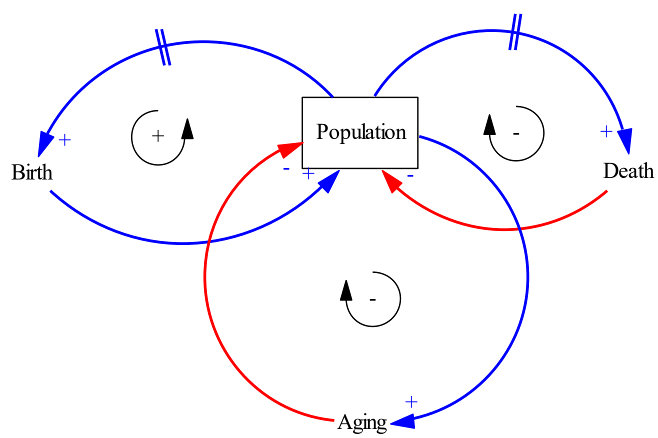

Figure 2-3: Population causal loop diagram.

[36] As population rises, the number of births increase with a delay, and population will grow as the number of births increase, leading to a reinforcing loop. Additionally, as population grows, the number of deaths also increase (with a delay) and population will shrink as the number of deaths increase, leading to a balancing loop. Similarly, as population increases, so does the number of individuals who age, thereby decreasing overall population and results in another balancing loop.

Assumptions made in the Demand sub-model include: 1) EIA's forecasts beyond 2015 for electricity and Henry Hub NG prices (all 34 scenarios) are used; 2) heating and cooling degree days (HDD and CDD) will either be the same as, 5%, or 10% higher than those of January 1916 to December 1950; 3) We use $GSP = 5{,}887.8 ln(t) + 14{,}738$ function (t for time) derived from Stata based on historical data to forecast real gross state product beyond historical data; and 4) population module is used beyond historical data. Figure 2-4 depicts electricity demand calibration.

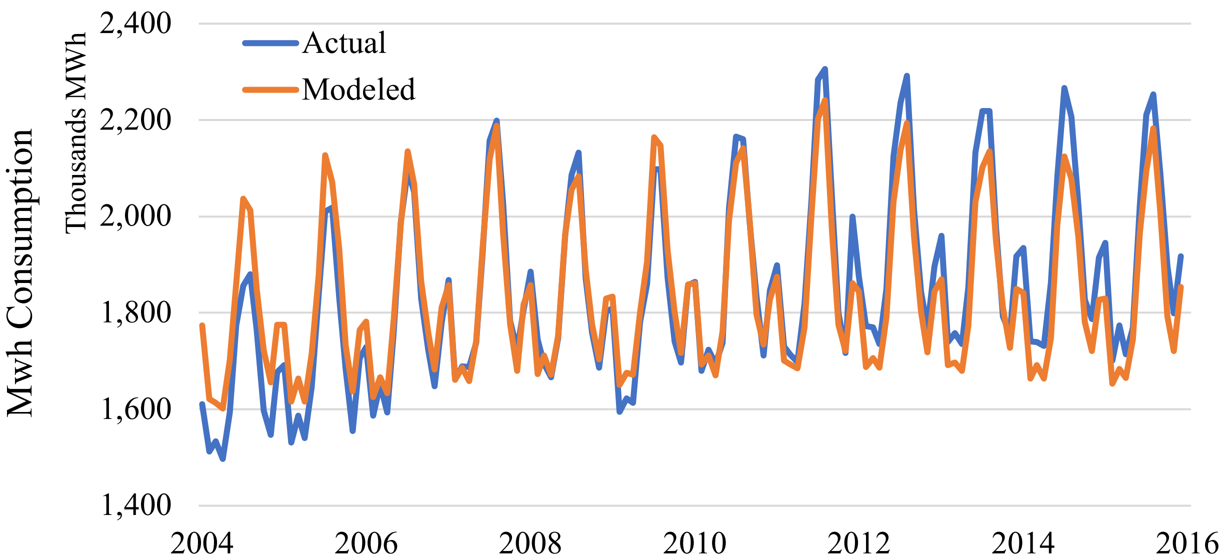

Figure 2-4 State Monthly Electricity Demand Historical versus Modeled

2.4.2. Supply

As mentioned earlier, the Supply sub-model consist of six modules. Each module estimates monthly electricity generation by one of our six main energy sources, namely: baseload coal, peaker NG, baseload NG, wind, PV, and RPV. Base-load is the amount of electricity that is constantly required (over a period of 24 hours), while peak-load is the daily fluctuation of electricity usage. Base-load is usually supplied by coal-fired, nuclear, and/or combined-cycle NG power stations (also known as baseload plants), whereas peak-load is normally delivered by open-cycle NG (also known as peaker NG). Additional peaker NG capacity is tied to RE development: the higher level RE capacity is installed, the higher peaker NG is needed to address the additional RE intermittency issue. On the other hand, baseload NG capacity is installed when it is the cheapest energy source (more on this below). Existing power plants are assumed to maintain similar power production to capacity ratios (i.e., capacity factors) as were measured and recorded in the eGRID database for 2014 and EIA-861. To allow for technology improvement and thus more efficient power plants, capacity factors are defined in a way that can be changed over time in the SD model. Figure 2-5 shows the capacity factors for wind for each 5-year period.

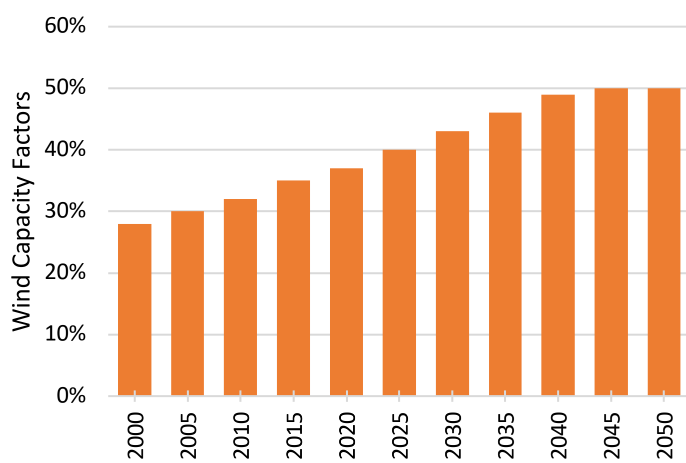

Figure 2-5: Adjustable capacity factor for wind energy.

In each of the six generation modules, we first convert plant-level data to county-level, that is, we aggregate existing megawatt nameplate capacities of all the power plants that are fueled the same in each county. This process is called "historical capacity –

convert plant to county" in the SD model. Second, we model the construction of new power plants, which is driven by increased demand for electricity, exogenous RPS policy, or both. Specifically, new power plants are ordered when the demand exceeds the existing electrical power generation, RPS is not met, or both happen simultaneously (more detail in the next subsection). We show this process in the "Permitting, Construction, to Delivery Plants". Next, we model the additional nameplate capacity by source and county. Finally, utilizing equation (*2*), we estimate electricity generation:

$$MWh = nameplate\ capacity\ (MW) \times capacity\ factor\ (\%) \times (1 - Not\ Accounted) \times timestep \tag{2}$$

where, not accounted is 5.15% which is the fraction of the electricity generated at the source place (power plant location) that is not accounted for due to *direct use*, *losses*, and *unaccounted*.[37] Further, *timestep* in our model is 1 month. Figure 2-6 depicts a snapshot of the wind module and Figure 2-7 illustrates the supply sub-model calibration.

[37] 3.52% losses, 0.55% direct use, and 1.08% Unaccounted, overall 5.15%. These values are from EIA "Table 10. Supply and disposition of electricity, 1990 through 2015".

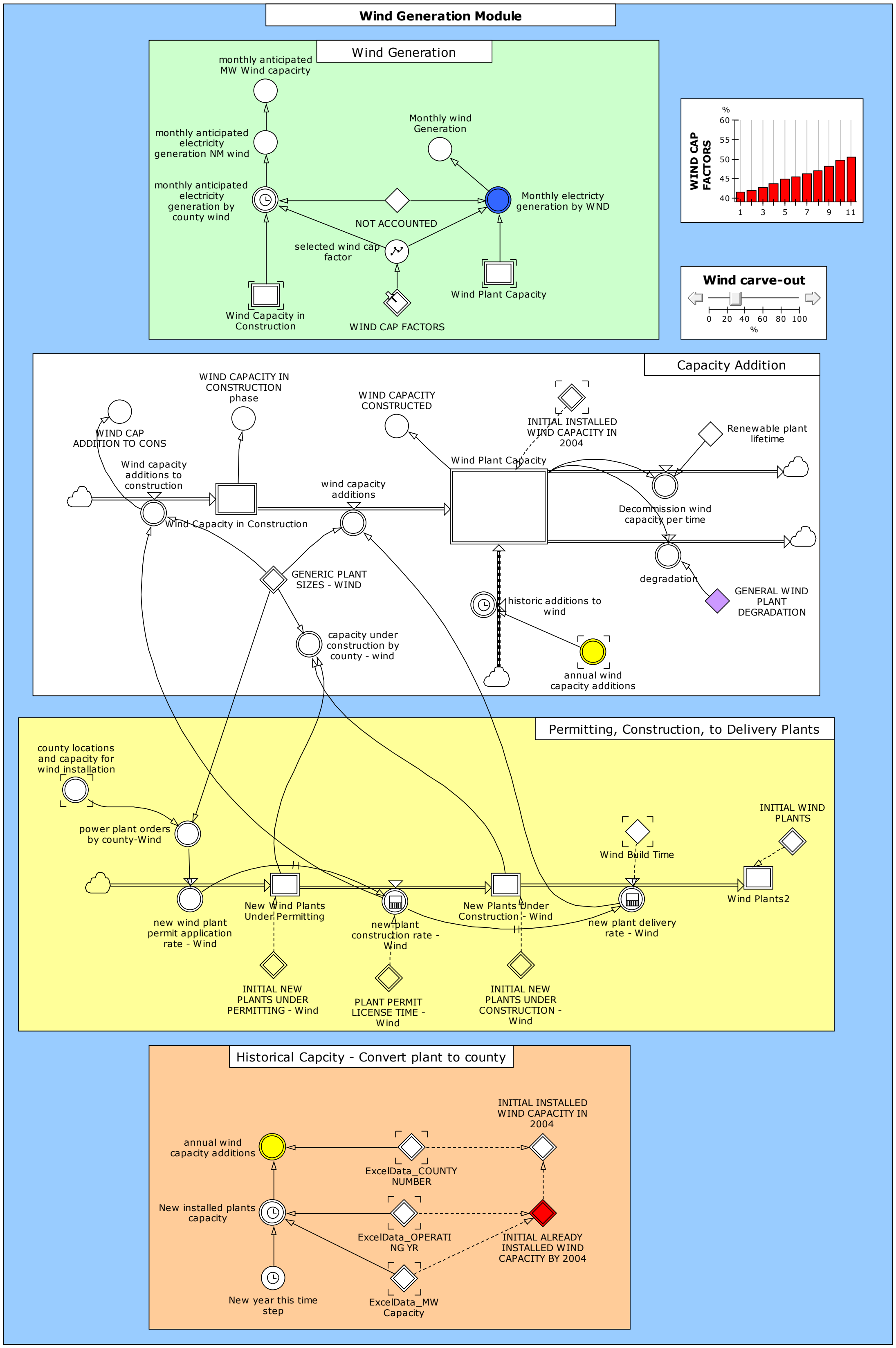

Figure 2-6: Wind generation module snapshot

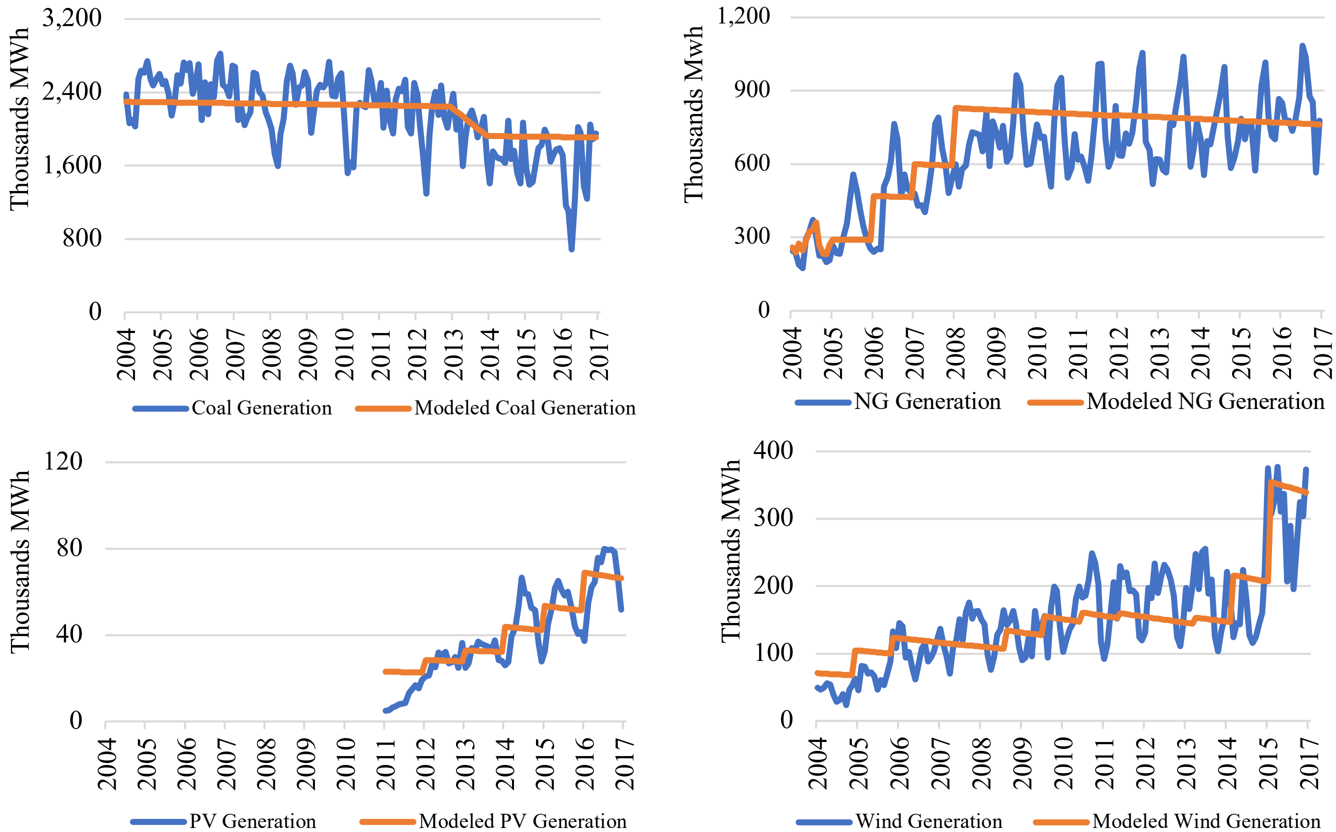

Figure 2-7: Generation calibration, modeled versus historical data for coal, NG, wind, and PV.

2.4.3. The Gap between Supply and Demand

In this subsection, we discuss the Gap sub-model and ways to address it. To better understand this sub-model, we start with explaining assumptions used in the calculation of the gap between generation and electricity demand. We then describe each of the seven modules that together solve the Gap sub-model.

As mentioned in the Background section, NM has three main electricity providers: PNM, EPE, and SPS. These electric utility companies import 17.71% of their in-state electricity consumption from nuclear power from Arizona.[38] Historically, approximately 35% of net NM electricity generation is exported to neighboring states.[39] Total in-state electricity consumption, net electricity generation, total in-state electricity consumption, net in-state generation, and gap in electricity demand are summarized in equation (*3*), (*4*), (*5*), and (*6*) respectively.

$$\begin{aligned} &Total\ in\_state\ electricity\ consumption \\ &\qquad = State\ electricity\ demand - Total\ imported\ electricity\ from\ AZ \end{aligned} \tag{3}$$

$$\begin{aligned} &Net\ generation \\ &\qquad = Total\ generation - (direct\ use + unaccounted + losses \\ &\qquad + international\ export) \end{aligned} \tag{4}$$

$$Net\ in\_state\ generation = Net\ generation - Net\ interstate\ exports \tag{5}$$

$$\begin{aligned} &Gap\ in\ electricity\ demand \\ &\qquad = Net\ instate\ generation - Total\ in\_state\ consumption \end{aligned} \tag{6}$$

As mentioned earlier, a gap occurs when RPS policy is not satisfied, the demand exceeds the existing electrical power generation, or both happen simultaneously. Recall that NM's RPS mandates electric utility companies generate their in-state sales from RE sources. Thus, we call a shortage in fulfilling the in-state sales requirement also a "gap"

[38] Public Service Company of New Mexico: Total distribution is 9,692,000 MWh, out of which 23% is coming from Nuclear. [source: Link] El Paso Electric: Total nonrenewable sales (NM+TX) is 10,699,000 MWh and 5,136,686 MWh is from nuclear. Nonrenewable sales in NM is 1,422,365 MWh and total distribution is 1,652,042 MWh. Given proportional nuclear in nonrenewable, nuclear sales in NM is 41.43% [source: 1. 2015 10-K] Excel: has total distribution of 5,097,988 in NM and no nuclear. [source: Link]

[39] Table 10. Supply and disposition of electricity, 1990 through 2015 (EIA 2017)

that needs to be addressed. To overcome a potential gap between power generation and electricity demand, we need to know *when* the gap occurs, *how much* capacity of *what* energy source(s) we need to fulfill the gap, and *where* to add the new capacity. Hence, we develop the Gap sub-model, which consist of seven modules. The first module calculates the Gap (equations *(3)* to *(6)*). The second module checks to see if RPS policy is satisfied and whether RE carve-outs are met. The third module finds the cheapest energy source in case RPS is satisfied and yet there is a gap to be fulfilled. The fourth module computes capacity needed to satisfy the carve-outs first and then RPS. The fifth module calculates the additional capacity needed to fill the gap by each energy source. The sixth module estimates counties' potential energy for each source. Finally, the last module allocates the capacity from the fifth module amongst desirable counties with potential. To address the additional RE intermittency issue, we add 5% (can be modified to add more, less, or nothing) peaker NG in "the best" counties.[40] Figure 2-8 summarizes this process.

[40] The intermittency issue of RE can be resolved by either storage, peaker NG, or both.

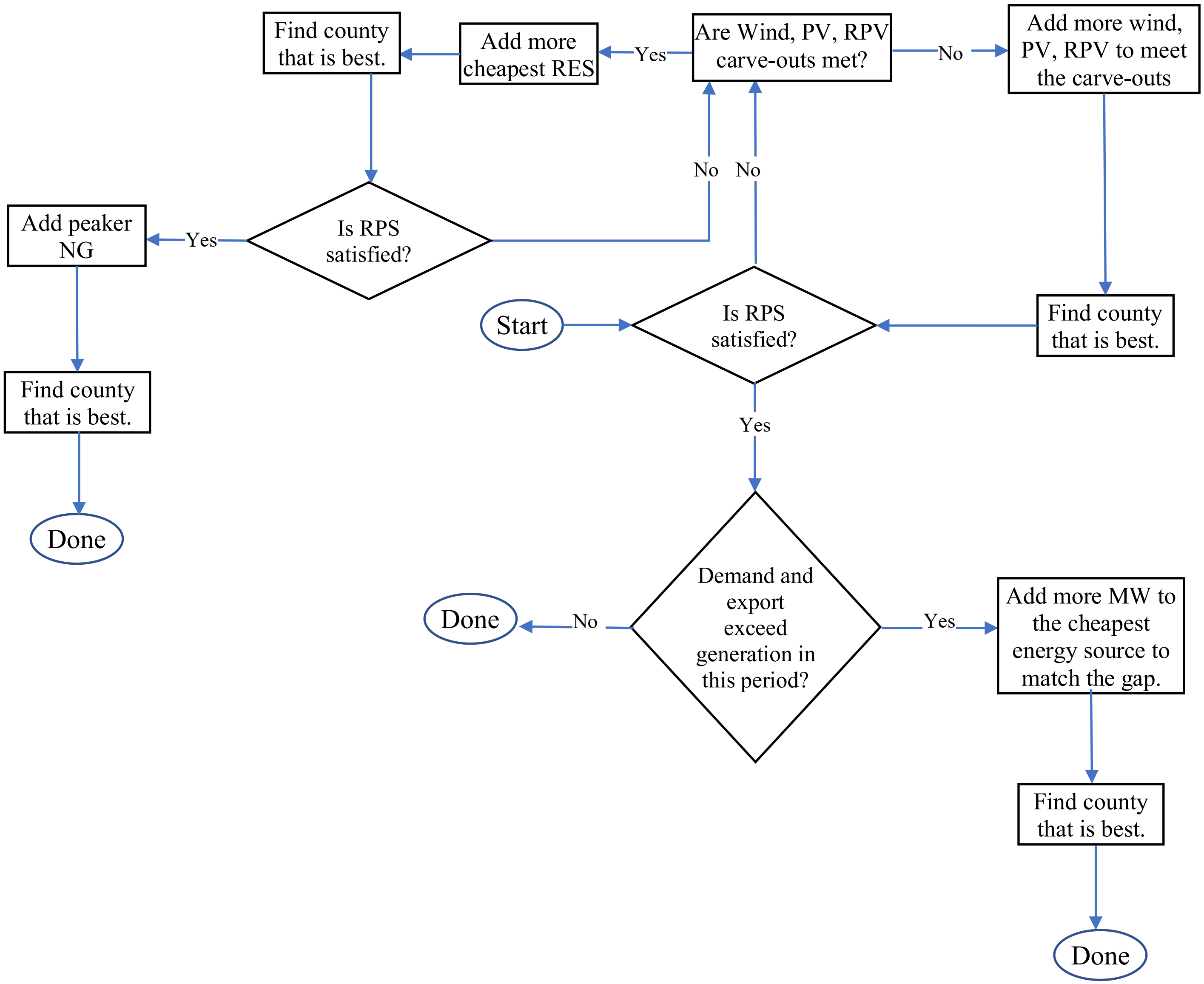

Figure 2-8: Flow diagram that depicts how to overcome the gap.

Regarding energy potential spatial analysis, we utilize GIS to estimate NM's potential for wind, PV, and NG. The analysis included only private land[41] for the preliminary buffers. For renewables (wind & PV), transmission lines were buffered at 5- and 10-mile increments and intersected with private land. PV estimates are total potential (kilowatt-hour) by county using area weighted buffers and solar radiation data from NREL, while wind estimates are total land available for different heights (80 m, 100 m, and 140 m) and efficiency levels (capacity factors of 30%, 35%, and 40%). For NG, both transmission lines and NG pipelines were buffered at 5- and 10-mile distances. Only the areas that also intersected private land were included. NG potential is total land area available for NG plants based on the buffers. Moreover, we assume San Juan county is the only county with potential for more coal-fired power plant installation or recommission. Lastly, we use the NREL's "solar for all" map, which estimates the RPV potential for each county (Gagnon et al., 2018).

In regard to "the best" county selection process, wind and PV are assumed to be installed in the least populous (most rural) counties, while RPV in the more populous counties first. Following Brown et al. (2017), we assume that additional utility-scale RE capacity will be located primarily in rural areas of NM. Further, the more populous the county, the higher the number of buildings, thus the larger the RPV potential. For additional NG capacities, we assume the counties with existing infrastructure[42] have priorities over those without. Lastly, new coal-fired power plants, if any, are assumed to be built only in San Juan county, where most of the state's coal reserves are located. Similar to PNM's

[41] As none of the existing RE power plants are on federal, public, or BLM lands, we excluded those types of lands.
[42] Bernalillo, Dona Ana, Eddy, Grant, Hidalgo, Lea, Los Alamos, Luna, McKinley, San Juan, and Valencia counties.

latest integrated resource plan, we assume every 200 MW (can be varied from 100 to 500 MW in the SD model) additional RE capacity is accompanied with a 40-MW, four-hour battery storage.[43] The SD model overcomes the intermittency issue of RE or the need for additional quick-start generation capacity by either storage, peaker NG, or both.

2.4.4. Jobs

Sub-model Jobs includes six modules to calculate number of jobs for each energy source (i.e., coal, NG peaker, NG baseload, wind, PV, and RPV).

To measure the change in economic activity, the JEDI[44] model of NREL is used to determine the impact of constructing and operating a renewable generator based on size of generation, renewable source (number of turbines or photovoltaic cells), location, and year of construction for twelve planned wind and solar power plants (Mamkhezri et al., 2017). From this, we estimate the job multipliers by energy type at a county level during construction and operations using IMPLAN.[45] Utilizing job multipliers derived from IMPLAN[46] and NREL's technology cost scenarios (see Scenario definitions Section) along with Transmission Cost Calculator developed by Western Electricity

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[43] PNM's latest integrated resource plan can be found at: https://www.pnm.com/documents/396023/396193/PNM+2017+IRP+Final.pdf/eae4efd7-3de5-47b4-b686-1ab37641b4ed, see p.67 for information on storage cost.

[44] JEDI model is a spreadsheet tool that applies the IMPLAN (Impact Analysis for Planning) Input-output economic impact system to calculate consumption and spending patterns and project costs (i.e., specific expenditures) as well as economic activity that will accrue to the state being analyzed. JEDI models can be accessed on NREL's webpage at: https://www.nrel.gov/analysis/jedi/models.html (accessed 11/15/18)

[45] IMPLAN is an economic impact modeling tool for forecasting the effect on a local, regional, or national economy of a given economic change or event in the economy's activity. IMPLAN is a derivative of the work developed by Leontief (1986), in which he utilized a matrix mathematical approach to predict/project standard input-output modeling, conjunct with social accounting matrices and multipliers.

[46] Not all the counties have energy related multipliers, especially rural counties. To overcome this issue, we modified IMPLAN multipliers and instead used counties with similar characteristics (potential for energy, population, etc.) multipliers.

Coordinating Council[47], each module estimates the number of full-time equivalent (FTE) jobs associated with different RPS policy requirements and any combination of carve-outs during construction and operating and maintenance (O&M) phases. Construction phase is a temporary time-period (1-2 years, depending on size of projects) that installation of a power plant occurs, while O&M phase is permanent (20-50 years, depending on type of power plant) and starts when a facility starts generating electricity. Figure 2-9 summarizes the model structure.

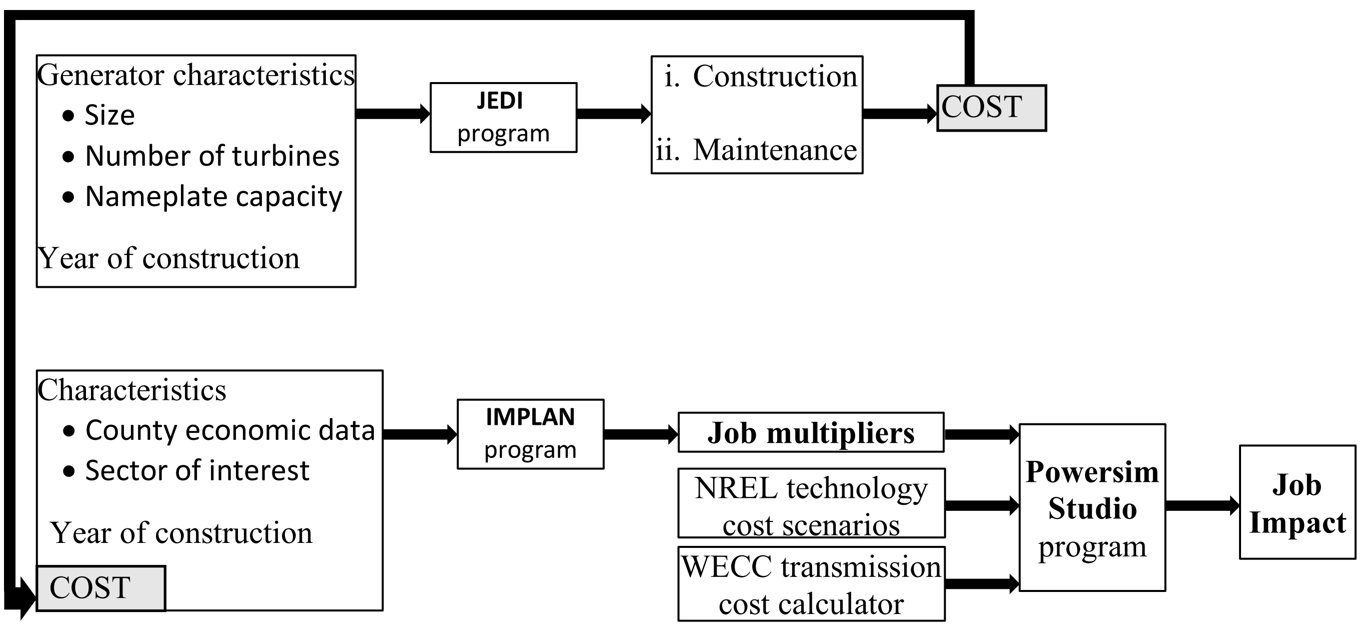

Figure 2-9: Using multiple analytic methods to assess the impact of renewable energy source.

Different studies assume different percentage of construction employment is from local crew. For example, Lantz et al. (2008, p. 9) assume 70% of construction employment are local residents in their default scenario (90% in the Medium scenario), while Godby et al. (2016, p. 60) assumes 80% of construction employment are

[47] Calculator can be accessed on WECC's webpage at: https://www.wecc.biz/Reliability/ (accessed 11/15/18)

nonresident. We assume all construction and O&M workers are local labor. The 100%-local-worker assumption is attainable when NM policymakers implement workforce training programs across counties, especially rural counties, to ensure that local workers are skillful and competitive. Such programs are already in place for example in San Juan County. Moving forward in the timeline, this assumption can be more realistic.

2.4.5. Environmental Impacts

Environmental Impact sub-model consists of one module, which calculates primary GHG emissions (CO2), air pollution (SO2, NOx, and PM), and water usage (withdrawal and consumption) under different scenarios. This module follows Equations (*7*) and (*8*) to capture existing and potential future environmental impacts of different scenarios.

$$\text{Gallon } water = MWh \ generation \times conversion \ factor(gallon/MWh) \tag{7}$$

$$\begin{aligned} &Ton \ GHG \ emission \ \& \ air \ pollution \\ &\quad = MWh \ generation \times conversion \ factor(ton/MWh) \end{aligned} \tag{8}$$

where MWh is megawatt-hour electricity generation and different energy sources have different conversion factors. These factors are calculated from actual data when exist (historical EIA, EPA data, and utility companies integrated resource planning), or else from the energy literature. Table 2-5 summarizes the conversion factors utilized in the environmental impact estimation and their corresponding sources. Note that all of the conversion factors for coal-fired power plants are higher than those of NG.

Table 2-5: Conversion factors used in estimating water usage, GHG emission, and air pollution.

	NG (peaker)	NG (baseload)	Coal	Source
Mercury (lbs/GWh)	0	0	0.0172	PNM (2014, p. 37); EIA; EPA
PM (lbs/MWh)	0.0975	0.0628	0.094	PNM (2014, p. 37); EIA; EPA
CO2 (lbs/MWh)	1,569.27	961.84	2,150.7	PNM (2014, p. 37); EIA; EPA
NOx (lbs/MWh)	2.8879	0.1293	6.77	PNM (2014, p. 37); EIA; EPA
SO2 (lbs/MWh)	0.008	0.005	1.691	PNM (2014, p. 37); EIA; EPA
Water Withdrawal (gallon/MWh)	250	250	10,180	Tidwell et al. (2009, p. 17); EIA; EW3 (UCS, 2012)
Water Consumption (gallon/MWh)	160	160	630	Tidwell et al. (2009, p. 17); EIA; EW3 (UCS, 2012)

Once potential environmental impacts are estimated, we calculate the potential GHG and air pollution reduction relative to the reference case scenario. From these values, we quantify economic benefits/costs based on GHG and air pollution's social cost. In so doing, we utilize USD/ton multipliers used in the U.S. regulatory agencies such as Environmental Protection Agency (EPA, 2016a, 2016b) and academic literature (Sovacool, 2009; McCubbin & Sovacool, 2013; Wiser et al., 2015; Heo et al., 2016; Heo et al., 2016b; Millstein et al., 2017) and multiply them by the estimated ton emissions (CO2, SO2, NOx, and PM) to calculate dollar values.

To estimate social benefit of air pollution and GHG emission, we use multipliers from the Estimating Air pollution Social Impact Using Regression (EASIUR) model, developed by Heo et al. (2016a, 2016b), and EPA (2016b) respectively. The EASIUR[48] predicts marginal benefits of "primary" and "secondary" PM2.5, where secondary PM2.5 includes SO2 and NOx. Similarly, the EPA model predicts social benefits of avoiding CO2 emissions. As acknowledged by Wiser et al. (2015), these models are common practice and are based on the state-of-the-art air-quality models, which best serves our purpose.

The EASIUR model estimates marginal social cost of "primary" and "secondary" PM2.5 in USD per ton. As avoiding air pollution (SO2, NOx, and PM) reduces corresponding risk of premature mortality, the derived EASIUR multipliers can be viewed as marginal social benefit as well. We use three sets of marginal social benefit estimates for NOx, SO2 and PM2.5 at ground-level and by county. Although EPA takes a similar approach in estimating social benefit of CO2, it is rather less finely determined spatial resolution. EPA values (USD/ton) are developed for the entire U.S. We follow Wiser et al. (2016) but only use the central set of estimates, which are calculated based on a 3-percent discount rate.[49] The social benefit of reducing carbon is intended to capture (but is not limited to) changes in net agricultural productivity, human health, avoiding property damages from increased flood risk, and the value of ecosystem services due to climate change (EPA, 2016b).

EPA (2016a) estimates premature mortality, morbidity, and non-fatal heart attack incidence per ton of NOx and SO2 for three US regions: East, West, and California. We

[48] The EASIUR model and multipliers can be find at: https://barney.ce.cmu.edu/~jinhyok/easiur/ (accessed 1/8/19)
[49] See Table A1 of EPA (2016, p. 25) report for a description of the multipliers. Note that those values are 2007 USD/metric ton and ours are converted to 2010 USD/ton. We use US$45 per tCO2 in 2017, US$57 per tCO2 in 2030, and US$79 per tCO2 in 2050. These multipliers are national estimates and are not specific to New Mexico.

use EPA's West incidence-per-ton estimates to assess human premature mortality and morbidity reduction relative to baseline scenario.[50] Lastly, we utilize estimated multipliers by Sovacool (2009, p. 2246), McCubbin & Sovacool (2013, p.437), and Walston et al. (2016, p. 411)[51] to estimate avian mortality reduction caused by coal, NG, wind turbines, and PV panels.

2.5. Data

Data were obtained from numerous sources including: EIA (various survey forms, AEO2018, and Layer Information for Interactive State Maps shapefiles), Emissions and Generation Resource Integrated Database (eGRID) of EPA, NREL (JEDI, Annual Technology Baseline, Wind Data, and Solar Data), NM Public Regulation Commission, United States Geological Survey, Bureau of Economic Analysis, United States Census Bureau, Western Electricity Coordinating Council, and the energy literature. Except for RPV data, we obtained generation data from EIA-923 and EIA-861. The data includes historical nameplate capacity of the existing power plants, generation, power plants' locations (county and latitude/longitude), operating and planned retirement year times, and capacity factors. The data for existing RPV capacity were obtained from NM Public Regulation Commission. Further, we purchased the IMPLAN 2016 data to calculate jobs and output multipliers for each energy source. Lastly, economic benefit/cost of air

[50] See tables: Table 4A-3 to Table 4A-7 of EPA (2016, pages 242 to 245).
[51] See tables 3, 4, and 1 respectively. Following McCubbin & Sovacool (2013), we assume NG kills half as many birds as coal-fired power plants. Coal, NG, wind and PV avian mortality multipliers are: 5.18, 5.18/2, 0.4, and 0.23 birds per gigawatt-hour electricity generation respectively.

pollution and GHG reduction multipliers came from the energy literature. Table 2-6 summarizes the key data sources.

Table 2-6: Sources of data for key variables.

Data for	Source
Electricity demand	EIA
Population	United States Census Bureau
Gross state product	Bureau of Economic Analysis
Generation data	EIA-860, EIA-861, EIA-923
Existing RPV capacity	New Mexico Public Regulation Commission
RPV potential	Solar for all – NREL
Wind Potential	Wind Data – NREL
PV Potential	Solar Data – NREL
NG Potential	Layer Information for Interactive State Maps – EIA
Levelized Cost of Energy	Cole et al., (2018) – NREL
Job multiplier	IMPLAN and JEDI (NREL)
Output multiplier	IMPLAN
GHG social benefit multipliers	EPA (2016b)
Air pollution social benefit multipliers	Heo et al. (2016a, 2016b)
Human mortality and morbidity multipliers	EPA (2016a), Krewski et al. (2009), Lepeule et al. (2012), and Woodruff et al., (1997)
Avian mortality multipliers	Sovacool (2009); McCubbin & Sovacool (2013); Walston et al. (2016); Dissanayake and Ando (2014)

2.6. Results

In this section, we present our results. We first review electricity generation under the four modeled scenarios. Next, we discuss state-level and then county-level economic and environmental impacts. Economic impact results are presented for FTE employment and gross economic output, wherein we distinguish between the construction and operation periods respectively. The construction period represents a short-term infusion of investment and economic activity. The operations period represents a more modest, but longer-term infusion of dollars into the local and state-wide economy. Environmental impacts, on the other hand, are reported in terms of GHG emissions, air pollution, water usage, and human and avian mortality associated with each of our four modeled scenarios. These impacts are experienced once the plants are in the O&M phase. Thus, environmental impact results are reported for operations period solely and on a state- and county-level basis. In what follows, results are presented in this order: state- and county-level job and output impact, state- and county-level water usage impact, state- and county-level GHG-reduction benefits, state- and county-level air pollution impact, lastly state-level human and avian mortality associated with each of our four modeled scenarios.

2.6.1. Generation

Figure 2-10 shows total electricity generation under four modeled scenarios and Figure 2-11 presents the generation mix through 2050 in the four modeled scenarios. Based on the reference case scenario, as with the other three scenarios, RE and FF generations encompassed 17% and 83% of total generation in 2017. In 2030, generation shares are 15% and 85% for RE and FF respectively. Relative to the reference case scenario, RE generations will comprise 2% and 9% higher in the generation mix under Scenario 1 (17%) and Scenario 2 (24%) respectively, and 5% lower under Scenario 3 (12%). All scenarios estimate a dip in electricity generation from 2036 until the end of 2037. This is due to the decommissioning of the existing coal-fired power plants in that period. As presented in Figure 2-11, scenarios estimate the amount and type of energy source to replace the foregone coal generation. By 2050, RE generation increases to 52%, while FF generation drops to 48% under the reference case scenario. Scenario 1 (55%) and Scenario 2 (59%) result in 7% and 11% higher and Scenario 3 (4%) to 48% lower RE generation compared with the reference case scenario. Recall that RPS requires utility companies generate a portion of their in-state sales from RE. Thus, it is possible to have FF generation even under the 100% RPS scenario (Scenario 2). Figure 2-12 presents RE generation versus required generation to meet RPS constraints by the four modeled scenarios. Take away here is that different energy scenarios will lead to different energy mix, thus different environmental and economic impacts.

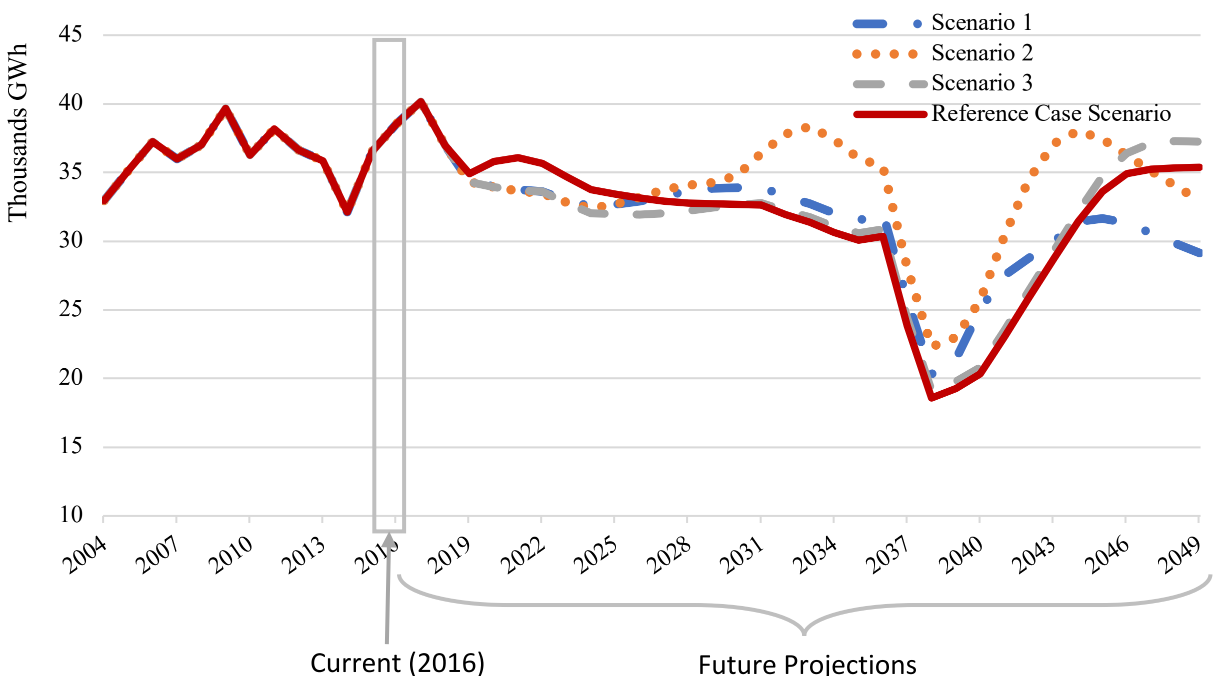

Figure 2-10: Total annual electricity generation under four modeled scenarios.

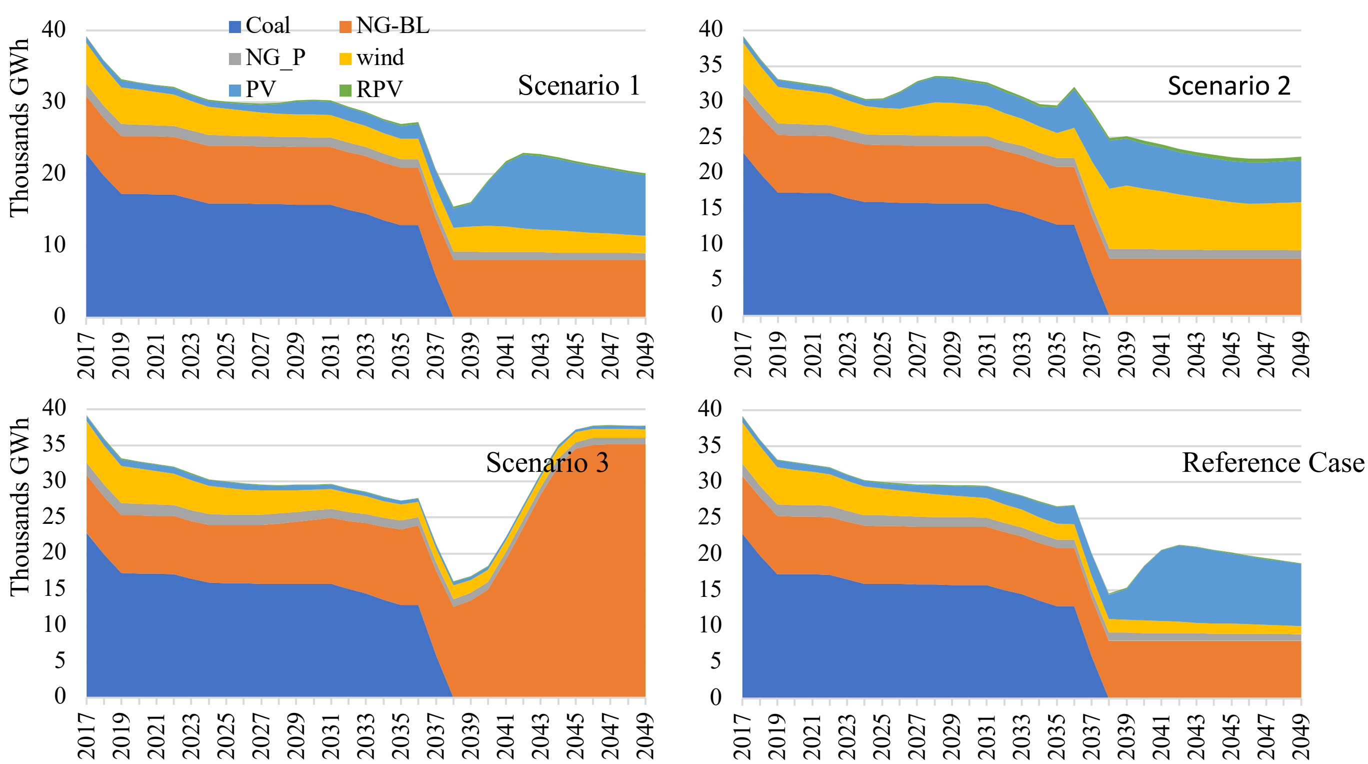

Figure 2-11: Annual electricity generation by all six energy sources under four modeled scenarios.

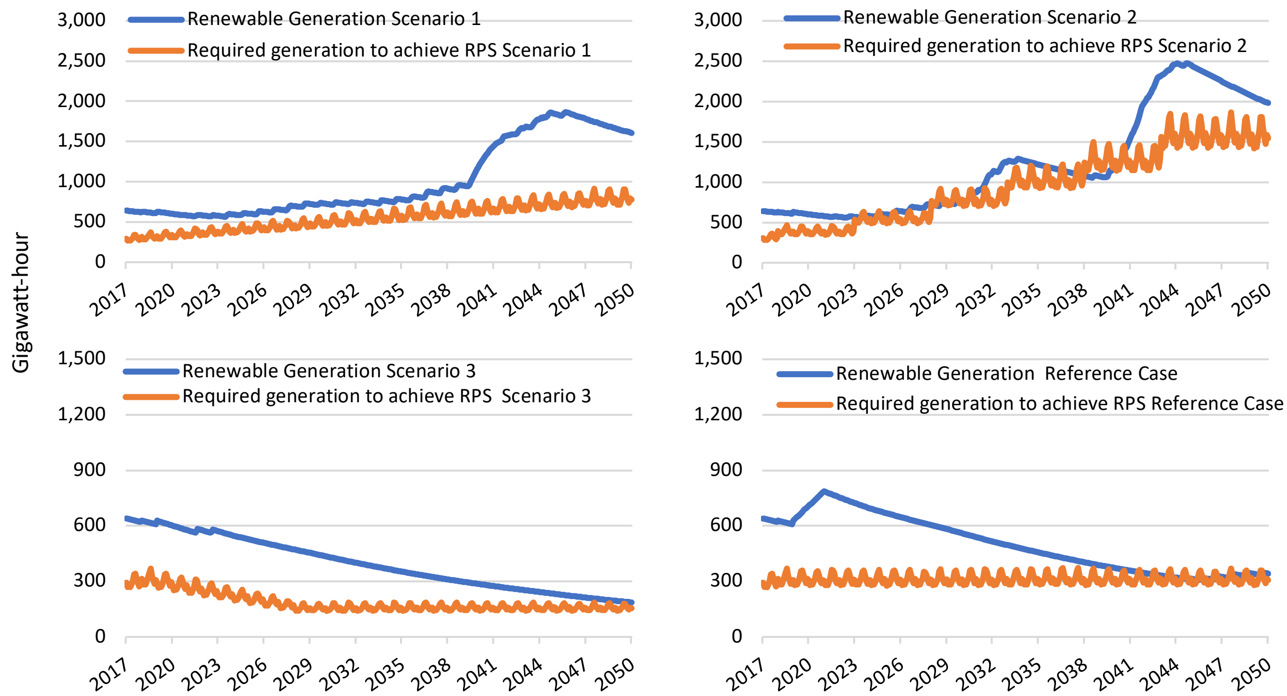

Figure 2-12: Renewable generation versus required generation to meet RPS constraints by the four modeled scenarios.

2.6.2. Economic impacts

Our model is capable of estimating employment and gross economic output by three categories: direct (onsite), indirect, and induced. Total impact is the sum of direct, indirect, and induced impacts. Since direct, indirect, and induced impacts are a fixed fraction of total impact, we only discuss total impacts and state the average of the fraction values. Here, we provide total employment and gross economic output results both state- and county-wide for each of the four modeled scenarios. We then compare results across scenarios and document which scenario yields the largest impact.

In what follows, we first summarize cumulative total employment impact by scenario and rank scenarios from the highest total employment impact to the lowest. We then discuss the years in which the majority of construction of RE and FF power plants occur. Next, we provide cumulative total employment results and briefly discuss the counties that are most affected under each scenario. Lastly, we take a similar approach in explaining gross economic output results.

2.6.2.1. Employment

Figure 2-13 summarizes cumulative total employment impact by the reference case scenario and the three, modeled scenarios. We estimate a total employment impact of 151,857 (42,517 RE and 109,340 FF), 137,393 (99,709 RE and 37,684 FF), 151,284 (112,593 RE and 38,691 FF), and 155,520 (26,271 RE and 129,248 FF) FTE jobs by the reference case and scenarios 1, 2, and 3 respectively to NM during construction and O&M from January 2017 to January 2050. Thus, relative to the reference case scenario, scenarios 1 and 2 (RE intensive scenarios) result in 14,463 and 573 less cumulative (construction and O&M) FTE jobs, while scenario 3 (most FF intensive scenario) yields 3,663 more cumulative jobs. As noted earlier, these results are based on the assumption that all labor is provided locally.

As demonstrated in Figure 2-13, all scenarios estimate a boost in energy employment after 2037. This is because existing coal-fired power plants will retire in 2037 and there will not be any new installation. Depending on scenario, coal generation will be replaced by either RE or NG after 2037, and thus jobs related to coal will be replaced by wind, PV, and/or NG jobs. Although Scenario 2 (100%-RPS) yields less cumulative total jobs than the reference case scenario, its impact fluctuates and is more diverse throughout the timespan of the study. Figure 2-13 and Figure 2-14 depict employment distribution by the four modeled scenarios from 2017 through January 2050.

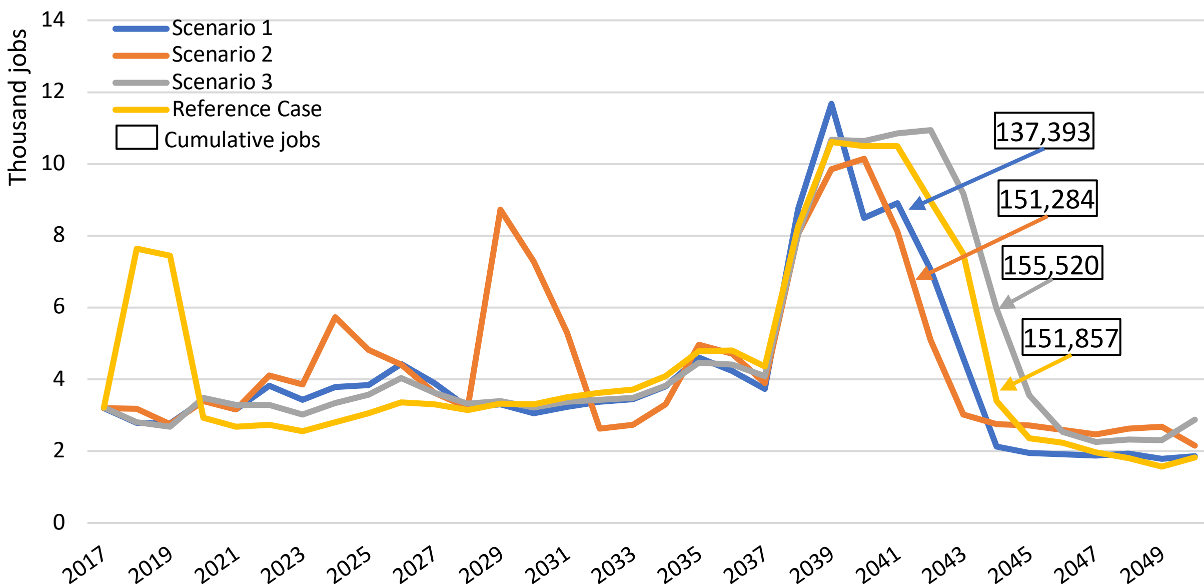

Figure 2-13: Temporal cumulative jobs (construction + O&M) by modeled scenarios from January 2017 to January 2050.

We find higher levels of O&M employment in both energy industries (RE and FF) early on and lower levels as we move forward (see Figure 2-14-b). This is primarily due to changes from new, retired and avoided capacity, along with changes in capacity factor and physical capital degradation rate of power plants over time (EPA, 2015). Overall, it takes less jobs to construct and more jobs to operate FF power plants. The opposite holds true for RE power plants: it takes more jobs to construct and less jobs to operate RE power plants.

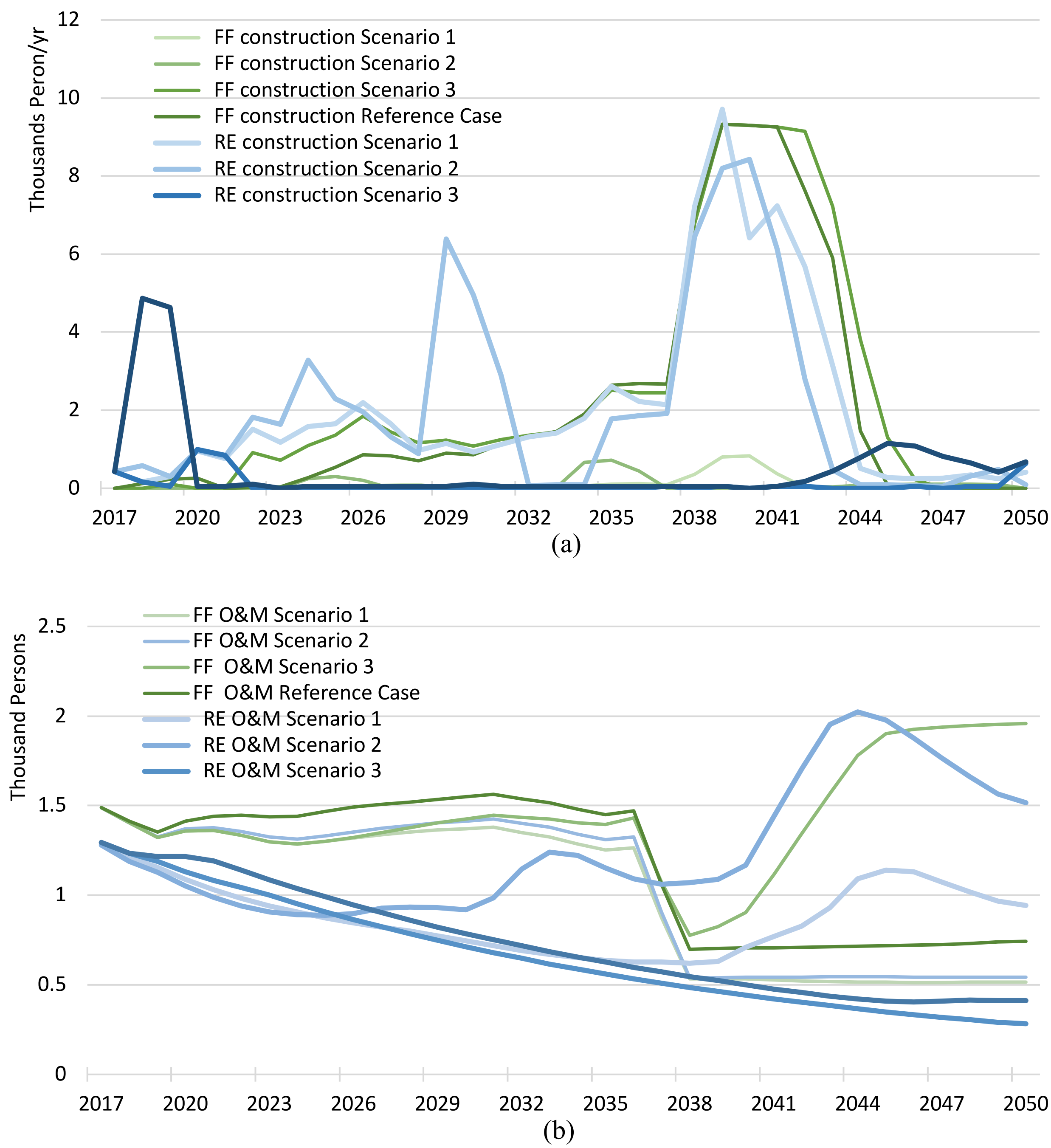

Figure 2-14: Total construction (a) and O&M (b) jobs under four modeled scenarios.

Figure 2-15 summarizes annual average of total employment impact by different energy source and scenario during construction and O&M from 2017 to 2049. On an annum account, the reference case scenario is expected to support on average 750 RE and 1,645 FF O&M FTE jobs. Relative to the reference case scenario, we find that Scenario 1 on average can support 129 more RE and 587 less FF O&M FTE jobs. Similarly, Scenario 2 has the potential to support 494 more RE and 589 less FF O&M FTE jobs on average than the reference case scenario. Lastly, we estimate that Scenario 3 on average supports 82 less RE and 180 less FF O&M FTE jobs than the reference case scenario. Table 2-15 of Appendix summarizes these (annual average employment) impacts by energy type for construction and O&M impacts. Overall, Reference Case Scenario predicts higher annual average of total employment impacts in O&M period than the other three modeled scenarios. It estimates 25%, 5%, and 14% higher number of annual averages of total employment than Scenario 1, Scenario 2, and Scenario 3 respectively during O&M period.

NM had a population of 2,114,333 (see Table 2-9) with unemployment rate of 5.9% in 2017.[52] Every additional 622 number of permanent O&M jobs has the potential to decrease state's unemployment rate by 0.1% (from 5.9% to 5.8%).[53] Thus, all else equal, NM will experience a decrease of 0.26% per year in unemployment rate by adding the permanent O&M jobs into the state's economy under the reference case scenario.[54] Relative to the reference case scenario, unemployment rate will be 0.05%, 0.01%, and %0.03 higher under Scenario 1, Scenario 2, and Scenario 3 respectively. Overall, Reference Case Scenario with the greatest O&M employment impact reduces NM's

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[52] NM's unemployment rate in 2017 and 2018 were 5.9% and 4.9% respectively. Source: Bureau of Labor Statistics at https://data.bls.gov.
[53] Labor force and number of unemployed individuals were 936,287 and 54,927 respectively in 2017. $(54{,}927 - x)/936{,}287 = 5.8\%$, x=622.
[54] Under Reference Case Scenario, number of additional annual average O&M jobs is 2,395. Thus, new unemployment rate is equal to: (54,927 – 2,395) / 936,287 =5.61% yielding a change of -0.26%/year in unemployment rate.

unemployment rate the most, though the difference amongst new unemployment rates under other scenarios compared to the reference case is negligible.

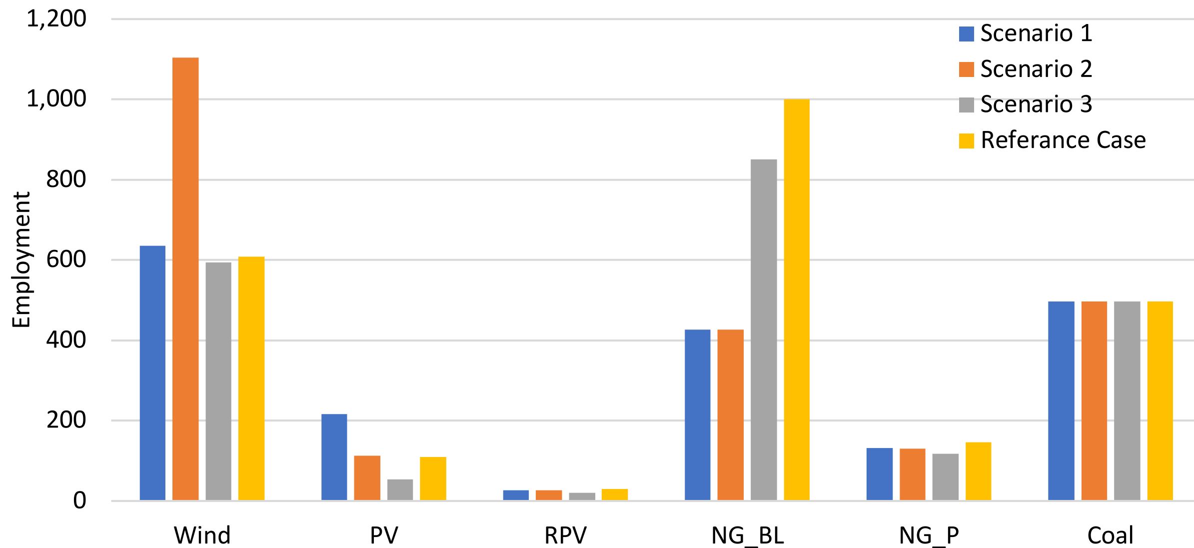


Figure 2-15: Annual average O&M job distribution by modeled scenarios and energy sources from 2017-2049.

Unlike O&M jobs that are permanent, construction jobs are temporal. Hence, presenting construction employment impact on an annual basis ignores its temporal nature. Herein, we summarize employment impact during construction period only for the impacted years. Under Reference Case Scenario, additional wind capacity will be constructed from 2042 to 2049 (3,024 job-years on average), PV from 2018-2019 (4,642 job-years on average) as well as 2042 to 2049 (399 job-years on average), RPV almost annually (88 job-years on average), NG peaker from 2018-2019 (121 job-years on average) as well as 2044 to 2048 (17 job-years on average), NG baseload roughly annually from 2019-2045 (2,560 job-years on average), and there will be no new construction of coal-fired power plants and all the existing ones will retire by 2037 (on average, 780 jobs from 2017 to 2037 and no jobs afterwards). Compared to the reference case scenario, scenarios 1 and 2 will result in higher levels of wind (from 2039 to 2043 (3,024 job-years on average) in Scenario 1 and almost annually (1,234 job-years on average) in Scenario 2), PV (from 2019 to 2050 annually (1,550 job-years on average) in Scenario 1 and almost annually (765 job-years on average) in Scenario 2), RPV (99 annual job-years in Scenario 1 and 119 annual job-years in Scenario 2), and NG peaker (from 2019 to 2050 (207 job-years on average) in Scenario 1 and almost annually (127 job-years on average) in Scenario 2) and lower baseload NG (no construction in scenarios 1 and 2) construction employment. Scenario 3 yields lower number of construction employment in all energy sources, beside NG baseload. Under Scenario 3, wind and NG peaker never are installed, lower number of individuals will be hired for installation of additional PV (from 2020 to 2021 (920 person-years on average)) and RPV (from 2017 to 2019 (218 job-years on average), from 2037 to 2042 (12 job-years on average), and from 2046 to 2050 (160 job-years on average)), and higher construction jobs for baseload NG (almost annually from 2019-2049 (2,689 job-years on average)) than the reference case scenario. Overall, RE installation occurs more often in the RE intensive scenarios than the reference case scenario, while higher level of FF installation takes place in Scenario 3 relative to the reference case.

Now we turn our attention to county-level employment results. Table 2-7 and Table 2-8 summarize construction and O&M cumulative total job-years and jobs respectively. Population in 2017 and 2050, along with unemployment rate in 2017 by county is summarized in Table 2-9. Almost every county will have some sort of RE and FF jobs during the O&M phase, with majority in FF jobs, under the reference case scenario. RE intensive scenarios yield higher number of RE jobs than the reference case scenario, while FF intensive scenario produces higher number of FF jobs. Majority of RE construction job-years in Scenario 1 will be in the solar sector, while wind energy produces the majority of jobs under the second scenario. NG jobs are the main jobs under the third scenario.

*Table 2-7: Construction cumulative total job-years by energy source and county from 2017 to 2050.**

	Scenario 1					Scenario 2					Scenario 3					Reference Case Scenario				
County	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb
Bernalillo	0	0	411	641	0	0	0	587	415	0	0	0	146	0	7,995	0	0	304	31	6,743
Catron	540	1,005	0	0	0	1,532	742	0	0	0	0	78	0	0	0	66	548	0	0	0
Chaves	583	3,765	234	641	0	1,312	1,032	241	415	0	0	0	73	0	0	71	137	169	31	0
Cibola	679	1,367	0	0	0	1,927	977	0	0	0	0	78	0	0	0	83	548	0	0	0
Colfax	679	5,010	0	0	0	1,927	1,271	0	0	0	0	83	0	0	0	83	584	0	0	0
Curry	583	2,801	213	0	0	1,652	1,271	220	0	0	0	83	72	0	0	71	584	158	0	0
De Baca	583	816	0	0	0	1,652	622	0	0	0	0	83	0	0	0	71	584	0	0	0
Dona Ana	0	0	347	641	0	0	0	420	415	0	0	0	104	0	8,005	0	0	231	31	6,834
Eddy	583	1,571	186	36	0	1,652	1,122	193	44	0	0	83	73	0	8,009	71	584	169	22	6,869
Grant	540	1,791	0	0	0	1,532	1,191	0	0	0	0	78	0	0	8,009	66	548	0	0	6,871
Guadalupe	583	2,858	0	0	0	1,652	1,271	0	0	0	0	83	0	0	0	71	584	0	0	0
Harding	583	1,910	0	0	0	1,652	1,271	0	0	0	0	83	0	0	0	71	584	0	0	0
Hidalgo	540	1,029	0	0	0	1,532	755	0	0	0	0	78	0	0	8,010	66	548	0	0	6,878
Lea	583	3,683	181	641	0	923	700	189	415	0	0	0	73	0	8,008	71	137	169	31	6,863
Lincoln	540	81	0	0	0	871	100	0	0	0	0	83	0	0	0	66	129	0	0	0
Los Alamos	357	27	0	0	0	333	29	0	0	0	0	19	0	0	600	83	35	0	0	620
Luna	540	1,421	0	0	0	1,532	1,020	0	0	0	0	78	0	0	8,009	66	548	0	0	6,872
McKinley	0	0	198	641	0	0	0	203	415	0	0	0	69	0	8,008	0	0	158	31	6,860
Mora	679	1,742	0	0	0	1,927	1,232	0	0	0	0	83	0	0	0	83	584	0	0	0
Otero	540	977	219	641	0	1,503	721	224	415	0	0	38	73	0	0	66	137	169	31	0
Quay	583	2,467	0	0	0	1,652	1,271	0	0	0	0	83	0	0	0	71	584	0	0	0
Rio Arriba	679	1,097	0	0	0	1,927	780	0	0	0	0	78	0	0	0	83	548	0	0	0
Roosevelt	583	3,939	0	0	0	1,652	1,271	0	0	0	0	83	0	0	0	71	584	0	0	0
Sandoval	0	0	312	641	0	0	0	288	415	0	0	0	92	0	0	0	0	202	31	0
San Juan	0	0	256	641	0	0	0	575	415	0	0	0	94	0	8,007	0	0	212	31	6,844
San Miguel	540	2,467	0	0	0	1,532	1,271	0	0	0	0	83	0	0	0	66	584	0	0	0
Santa Fe	0	0	318	641	0	0	0	575	415	0	0	0	94	0	0	0	0	216	31	0
Sierra	540	2,051	0	0	0	1,532	1,191	0	0	0	0	78	0	0	0	66	548	0	0	0
Socorro	540	2,156	0	0	0	1,532	1,191	0	0	0	0	78	0	0	0	66	548	0	0	0
Taos	679	436	0	0	0	1,927	359	0	0	0	0	78	0	0	0	83	548	0	0	0
Torrance	679	2,103	0	0	0	1,927	1,191	0	0	0	0	78	0	0	0	83	548	0	0	0
Union	583	2,579	0	0	0	1,652	1,271	0	0	0	0	83	0	0	0	71	584	0	0	0
Valencia	0	0	219	641	0	0	0	223	415	0	0	0	77	0	8,008	0	0	173	31	6,857

*Divide values by 33 (2050 – 2017) to calculate annual average job-years, though not recommended as it ignores the temporal nature of construction phase.

*Table 2-8: O&M cumulative total jobs by energy source and county from 2017 to 2050.**

	Scenario 1					Scenario 2					Scenario 3					Reference Case Scenario				
County	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb
Bernalillo	0	54	198	783	133	0	44	198	778	133	0	72	226	736	1,407	0	72	261	902	1,602
Catron	104	167	0	0	0	751	103	0	0	0	0	18	0	0	0	4	106	0	0	0
Chaves	243	340	44	46	0	738	104	42	42	0	143	8	20	0	0	148	12	44	6	0
Cibola	127	225	0	0	0	917	138	0	0	0	0	40	0	0	0	5	128	0	0	0
Colfax	127	490	0	13	0	917	179	0	13	0	0	90	0	13	0	5	174	0	16	0
Curry	5,559	318	44	0	0	5,826	134	39	0	0	6,010	17	20	0	0	6,015	101	43	0	0
De Baca	113	129	0	0	0	813	83	0	0	0	0	17	0	0	0	5	101	0	0	0
Dona Ana	0	106	110	661	2,732	0	86	118	656	2,732	0	140	100	614	4,009	0	140	130	754	4,960
Eddy	113	228	40	33	0	813	140	34	35	0	0	41	20	27	1,279	5	125	44	38	1,484
Grant	104	255	6	215	0	751	142	5	215	0	0	21	10	215	1,279	4	109	10	262	1,485
Guadalupe	637	411	0	0	0	1,295	206	0	0	0	578	134	0	0	0	583	217	0	0	0
Harding	113	241	0	0	0	813	134	0	0	0	0	17	0	0	0	5	101	0	0	0
Hidalgo	104	169	0	509	0	751	104	0	509	0	0	18	0	509	1,279	4	106	0	620	1,488
Lea	327	341	39	642	6,126	553	115	33	638	6,126	236	96	20	596	7,405	241	100	44	731	9,308
Lincoln	104	14	1	0	0	512	15	0	0	0	0	17	1	0	0	4	27	1	0	0
Los Alamos	75	9	0	0	251	181	8	0	0	251	0	10	0	0	473	5	14	0	0	592
Luna	451	415	3	0	3,790	1,070	291	3	0	3,790	383	282	5	0	5,069	387	370	5	0	6,328
McKinley	0	0	46	56	0	0	0	40	52	0	0	0	21	10	1,279	0	0	46	18	1,480
Mora	127	225	0	0	0	917	132	0	0	0	0	17	0	0	0	5	101	0	0	0
Otero	104	181	49	46	0	736	119	43	42	0	0	54	28	0	0	4	51	52	6	0
Quay	1,625	411	0	0	0	2,205	231	0	0	0	1,669	178	0	0	0	1,674	262	0	0	0
Rio Arriba	127	178	0	0	0	917	106	0	0	0	0	18	0	0	0	5	106	0	0	0
Roosevelt	3,526	401	0	0	0	3,954	134	0	0	0	3,766	17	0	0	0	3,771	101	0	0	0
Sandoval	819	39	91	46	0	754	32	83	42	0	904	52	76	0	0	904	52	104	6	0
San Juan	0	155	55	46	1,060	0	121	90	42	1,060	0	212	24	0	2,338	0	212	53	6	2,828
San Miguel	104	303	1	0	0	751	144	0	0	0	0	33	1	0	0	4	117	1	0	0
Santa Fe	0	21	101	46	0	0	17	126	42	0	0	27	92	0	0	0	27	121	6	0
Sierra	104	285	0	0	0	751	146	0	0	0	0	27	0	0	0	4	114	0	0	0
Socorro	104	289	0	0	0	751	140	0	0	0	0	18	0	0	0	4	106	0	0	0
Taos	127	89	0	0	0	917	62	0	0	0	0	27	0	0	0	5	115	0	0	0
Torrance	4,095	284	0	0	0	4,568	140	0	0	0	4,378	18	0	0	0	4,383	106	0	0	0
Union	1,831	300	0	0	0	2,394	134	0	0	0	1,896	17	0	0	0	1,900	101	0	0	0
Valencia	0	50	49	1,218	0	0	41	43	1,214	0	0	66	22	1,172	1,279	0	66	48	1,432	1,479

Note: Only two counties have coal-fired power plants. San Juan = 15,020 jobs and McKinley=1,398 jobs.
*Divide values by 33 (2050 – 2017) to calculate annual average jobs for each county.

Table 2-9: Population in 2017 and 2050, along with unemployment rate in 2017.

County	Population in 2017	Population in 2050*	Unemployment Rate 2017**
Bernalillo	669,296	783,957	5.5%
Catron	3,532	3,286	6.9%
Chaves	65,640	74,917	6.4%
Cibola	27,442	31,628	7.9%
Colfax	13,409	14,076	6.0%
Curry	49,192	58,709	4.8%
De Baca	1,943	1,967	4.5%
Dona Ana	212,457	252,482	6.9%
Eddy	53,731	60,712	5.3%
Grant	28,722	30,138	6.2%
Guadalupe	4,679	5,279	6.4%
Harding	643	589	6.6%
Hidalgo	4,833	5,270	5.2%
Lea	65,744	77,646	6.6%
Lincoln	19,888	20,130	5.5%
Los Alamos	17,585	18,401	3.8%
Luna	24,709	26,865	14.1%
McKinley	72,873	86,244	8.7%
Mora	4,773	4,984	7.9%
Otero	64,044	73,421	6.1%
Quay	8,809	9,184	6.2%
Rio Arriba	40,218	44,983	6.4%
Roosevelt	20,270	24,778	5.3%
Sandoval	141,542	207,314	6.2%
San Juan	142,718	221,595	7.2%
San Miguel	31,724	47,440	7.4%
Santa Fe	152,987	216,704	5.1%
Sierra	11,863	14,243	7.9%
Socorro	19,497	30,078	6.5%
Taos	34,522	47,312	7.9%
Torrance	17,462	24,896	8.6%
Union	4,858	7,206	3.8%
Valencia	82,728	122,762	6.7%
Total	**2,114,333**	**2,649,196**	**5.90%**

Note: Population in 2050 changes by scenario. *Population in 2050 under the reference case scenario.
**Unemployment data are from Bureau of Labor Statistics.

Since construction jobs, unlike O&M jobs, are temporal, we report cumulative employment impacts for impacted counties. Under the reference case scenario, there will be additional job-years by all the energy sources, with PV and NG holding the majority of jobs for RE and FF sources respectively. Depending on existing labor force and unemployed individuals in a county, an additional 100 job-years can translate into different changes in corresponding unemployment rate. For example, under the reference case scenario Bernalillo and Torrance counties will experience 214 (7,078/33) and 14 (631/33) annual job-years respectively. Although construction job-years in Bernalillo County is more than 15 times higher than that of Torrance County, corresponding job-year figures have the potential to decrease these counties' unemployment rates by 0.1% and 0.2% respectively.

Under Scenario 1, Colfax, Roosevelt, and Cibola counties will experience the highest total employment impact during the construction of additional PVs. This scenario also estimates that all counties, beside seven of the state's most populous counties, will experience 540 to 680 (16 to 21 annual job-years) additional cumulative construction job-years in wind energy. As mentioned earlier, these values can impact county unemployment rates differently depending on labor force and number of unemployed workforces in a corresponding county. For instance, 18 annual job-years in Guadalupe and Quay counties can decrease corresponding unemployment rates by 1.1% and 0.6% respectively (see Table 2-10). RE jobs behave the opposite in the second scenario: wind has the highest impact and PV the second highest. Under Scenario 2, wind energy is capable of creating more than 1,532 cumulative job-years in the impacted counties. PV industry will produce roughly more than 1,000 cumulative job-years on average in the impacted counties. Scenario 3, on the other hand, hardly supports any RE jobs. Majority of the jobs will be in constructing additional NG power plants in the counties with existing infrastructure. Each of these counties will have more than 8,000 new construction job-years cumulatively. Overall, relative to the reference case scenario, rural counties will experience more employment under the RE intensive scenarios, while urban counties (more populous counties) with existing NG infrastructure will see higher level employments under the FF intensive scenario (scenario 3).

O&M county-level employment impacts are more consistent than construction impacts (see Table 2-9). Under all three modeled scenarios and the reference case scenario, Curry, Torrance, and Roosevelt counties will have more than 100 O&M jobs per year in the wind sector, while Colfax, Luna, and Guadalupe counties will enjoy the greatest employment impact from PV installation. Bernalillo, Dona Ana, and Santa Fe are the counties with the highest potential for RPV diffusion and thus employment impact. Lea, Luna, Dona Ana, Valencia, Bernalillo, and Hidalgo counties will also contain the highest number of NG jobs across all four scenarios. Lastly, as the main coal-fired power plants of the state are located in San Juan county, it will experience the greatest employment impact from coal generation. Once again, RE and FF intensive scenarios are proven to yield higher level of O&M employment in the counties with potential for the corresponding energy source.

To put construction and O&M employment impact into perspective, Table 2-10 presents percent change in annual unemployment rate by county after incorporating additional construction and O&M jobs in each scenario. For example, Luna County with 10,454 and 1,475 labor force and number of unemployed individuals respectively has the highest unemployment rate in the state (14.1%). Under the status quo scenario, this county will experience 215 annual permanent O&M jobs and 227 annual construction job-years, which are mainly by NG (see Table 2-7 and Table 2-8). Thus, the O&M jobs alone has the potential to decline Luna County's unemployment rate by 2.1%, once coupled with construction jobs, they can drive unemployment down to 9.9%. Scenario 1 is able to decrease Luna County's unemployment rate by 0.7% (1.4%-2.1%) less than the reference case scenario when only O&M jobs are taken into account, and 2.3% (1.9-4.2%) less than the reference case scenario when both construction and O&M employment are considered. Hence, the reference case scenario can lower unemployment rate in Luna County more than any other scenario. Take Torrance County as another example, this county will experience a decrease of 2.5% in its unemployment rate (from 8.6% to 6.1%) mainly due to operating wind power plants under the reference case scenario, while Scenario 2 has the potential to decrease unemployment rate by 0.1% more than the reference case scenario. Taking construction job-years into account, the reference case scenario can lead to a new unemployment rate of 5.8% (8.6%-2.8%), while Scenario 2 can halve the current unemployment rate (from 8.6% to 4.3%). Thus, Scenario 2 has the potential to lower the unemployment rate in Torrance County more than the reference case scenario.

Table 2-10: Percent change in annual unemployment rate by county

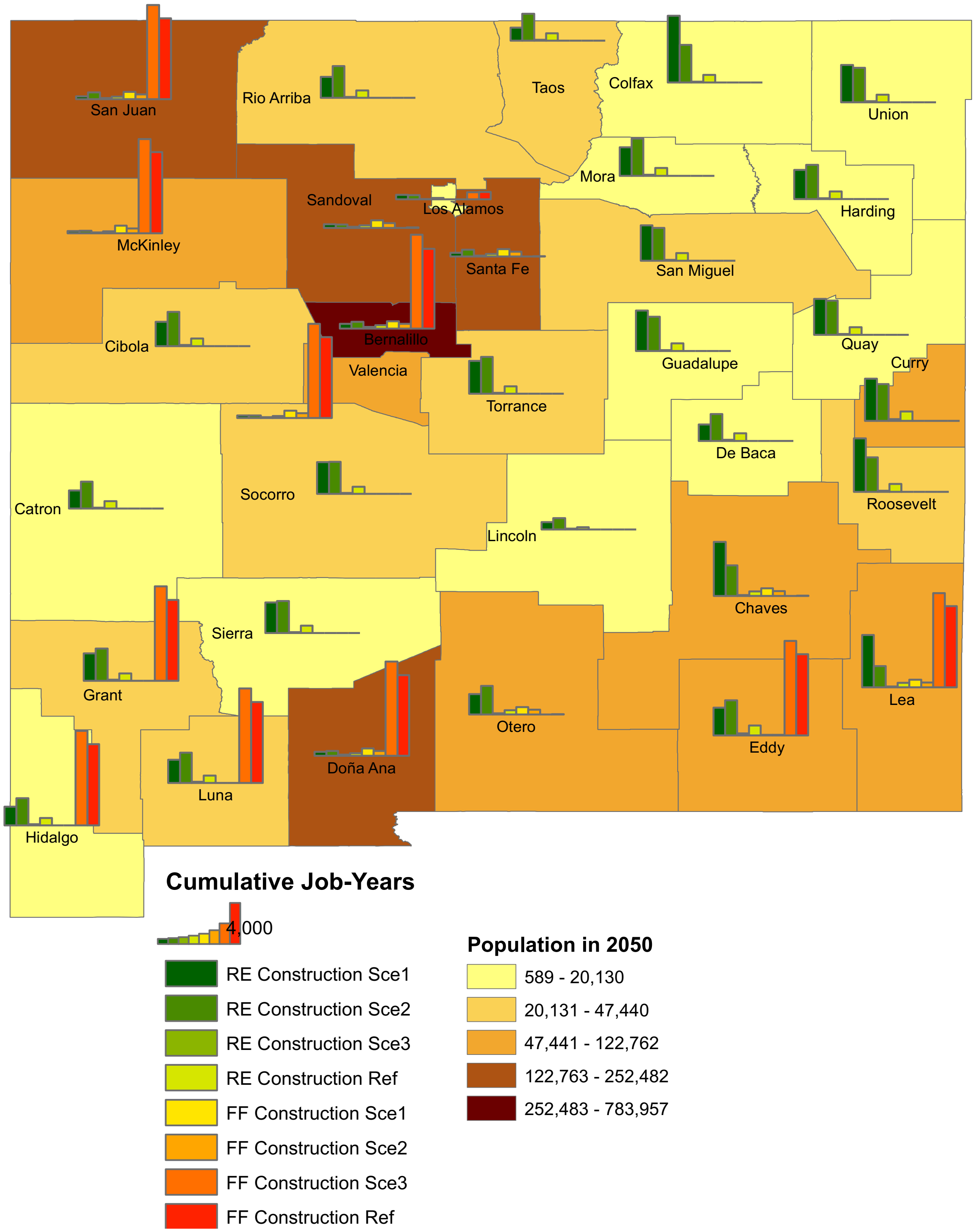
				Only O&M				***Construction + O&M***			
County	**BLS – UR***	labor force	Unemployed	%Δ UR Sce. 1	%Δ UR Sce. 2	%Δ UR Sce. 3	**%Δ UR Ref.**	%Δ UR Sce. 1	%Δ UR Sce. 2	%Δ UR Sce. 3	**%Δ UR Ref.**
Bernalillo	**5.5%**	326,340	17,866	0.0%	0.0%	0.0%	**0.0%**	0.0%	0.0%	-0.1%	**-0.1%**
Catron	**6.9%**	1,154	80	-0.7%	-2.2%	0.0%	**-0.3%**	-4.8%	-8.2%	-0.3%	**-1.9%**
Chaves	**6.4%**	27,274	1,757	-0.1%	-0.1%	0.0%	**0.0%**	-0.7%	-0.4%	0.0%	**-0.1%**
Cibola	**7.9%**	9,081	713	-0.1%	-0.4%	0.0%	**0.0%**	-0.8%	-1.3%	0.0%	**-0.3%**
Colfax	**6.0%**	5,663	342	-0.3%	-0.6%	-0.1%	**-0.1%**	-3.4%	-2.3%	-0.1%	**-0.5%**
Curry	**4.8%**	22,018	1,066	-0.8%	-0.8%	-0.8%	**-0.8%**	-1.3%	-1.3%	-0.9%	**-1.0%**
De Baca	**4.5%**	840	38	-0.9%	-3.2%	-0.1%	**-0.4%**	-5.9%	-11.4%	-0.4%	**-2.7%**
Dona Ana	**6.9%**	93,805	6,445	-0.1%	-0.1%	-0.2%	**-0.2%**	-0.1%	-0.1%	-0.4%	**-0.4%**
Eddy	**5.3%**	28,871	1,523	0.0%	-0.1%	-0.1%	**-0.2%**	-0.3%	-0.4%	-1.0%	**-1.0%**
Grant	**6.2%**	12,154	749	-0.1%	-0.3%	-0.4%	**-0.5%**	-0.7%	-1.0%	-2.4%	**-2.3%**
Guadalupe	**6.4%**	1,636	105	-1.9%	-2.8%	-1.3%	**-1.5%**	-8.3%	-8.2%	-1.5%	**-2.7%**
Harding	**6.5%**	275	18	-3.9%	-10.4%	-0.2%	**-1.2%**	-31.4%	-42.6%	-1.1%	**-8.4%**
Hidalgo	**5.2%**	2,107	109	-1.1%	-2.0%	-2.6%	**-3.2%**	-3.4%	-5.3%	-14.2%	**-14.0%**
Lea	**6.6%**	27,554	1,810	-0.8%	-0.8%	-0.9%	**-1.1%**	-1.4%	-1.1%	-1.8%	**-1.9%**
Lincoln	**5.5%**	8,657	478	0.0%	-0.2%	0.0%	**0.0%**	-0.3%	-0.5%	0.0%	**-0.1%**
Los Alamos	**3.8%**	9,056	341	-0.1%	-0.1%	-0.2%	**-0.2%**	-0.2%	-0.3%	-0.4%	**-0.5%**
Luna	**14.1%**	10,454	1,475	-1.4%	-1.5%	-1.7%	**-2.1%**	-1.9%	-2.2%	-4.0%	**-4.2%**
McKinley	**8.7%**	24,237	2,107	0.0%	0.0%	-0.2%	**-0.2%**	-0.1%	-0.1%	-1.2%	**-1.1%**
Mora	**7.9%**	2,184	172	-0.5%	-1.5%	0.0%	**-0.1%**	-3.8%	-5.8%	-0.1%	**-1.1%**
Otero	**6.1%**	24,778	1,513	0.0%	-0.1%	0.0%	**0.0%**	-0.3%	-0.5%	0.0%	**-0.1%**
Quay	**6.2%**	3,211	200	-1.9%	-2.3%	-1.7%	**-1.8%**	-4.8%	-5.1%	-1.8%	**-2.4%**
Rio Arriba	**6.4%**	16,708	1,076	-0.1%	-0.2%	0.0%	**0.0%**	-0.4%	-0.7%	0.0%	**-0.1%**
Roosevelt	**5.3%**	7,937	419	-1.5%	-1.6%	-1.4%	**-1.5%**	-3.2%	-2.7%	-1.5%	**-1.7%**
Sandoval	**6.2%**	63,918	3,946	0.0%	0.0%	0.0%	**-0.1%**	-0.1%	-0.1%	-0.1%	**-0.1%**
San Juan	**7.2%**	53,194	3,845	-0.1%	-0.1%	-0.1%	**-0.2%**	-0.1%	-0.1%	-0.6%	**-0.6%**
San Miguel	**7.4%**	10,852	807	-0.1%	-0.2%	0.0%	**0.0%**	-1.0%	-1.0%	0.0%	**-0.2%**
Santa Fe	**5.1%**	72,851	3,718	0.0%	0.0%	0.0%	**0.0%**	0.0%	0.0%	0.0%	**0.0%**
Sierra	**7.9%**	4,094	324	-0.3%	-0.7%	0.0%	**-0.1%**	-2.2%	-2.7%	-0.1%	**-0.5%**
Socorro	**6.5%**	6,490	424	-0.2%	-0.4%	0.0%	**-0.1%**	-1.4%	-1.7%	0.0%	**-0.3%**
Taos	**7.9%**	14,979	1,189	0.0%	-0.2%	0.0%	**0.0%**	-0.3%	-0.7%	0.0%	**-0.2%**
Torrance	**8.6%**	5,484	474	-2.4%	-2.6%	-2.4%	**-2.5%**	-4.0%	-4.3%	-2.5%	**-2.8%**
Union	**3.8%**	1,870	71	-3.5%	-4.1%	-3.1%	**-3.2%**	-8.6%	-8.8%	-3.2%	**-4.3%**
Valencia	**6.7%**	29,846	1,989	-0.1%	-0.1%	-0.3%	**-0.3%**	-0.2%	-0.2%	-1.1%	**-1.0%**

Note: UR=unemployment rate; %Δ= Percent change; Sce.= Scenario; Ref.= Reference Case Scenario.

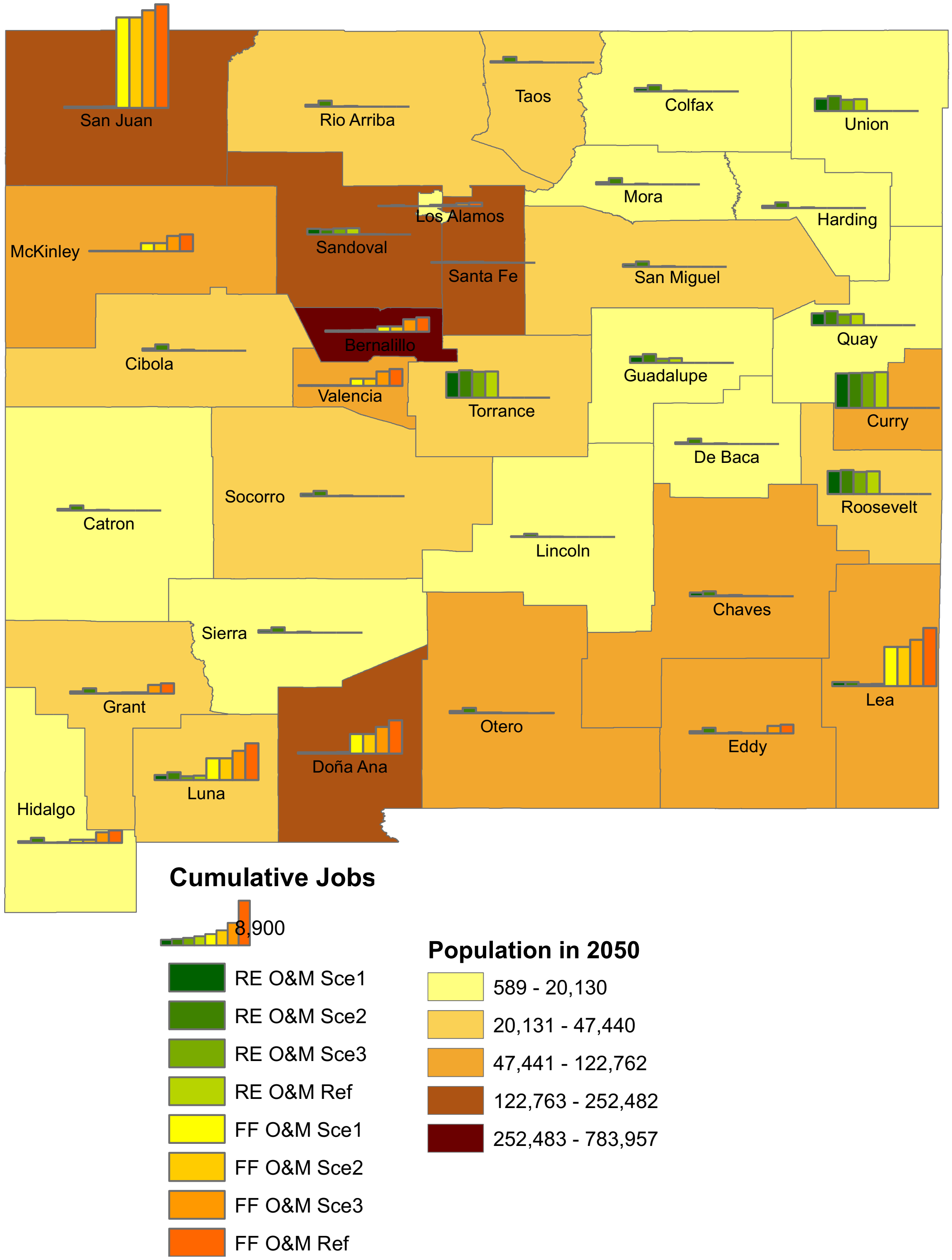
* Unemployment rate, labor force, and number of unemployed are from Bureau of Labor Statistics (BLS).

Map 2-1 and Map 2-2 depict cumulative employment impact by RE and FF during construction and O&M respectively, while Map 2-8 and Map 2-9 of Appendix visualize these impacts by different energy types. Table 2-16 – Table 2-48 of the Appendix summarize construction and O&M decade average employments by county and by impact (direct, indirect, and induced) from 2017 to 2050. To preserve some of the temporality, we divided the timespan into three different time periods (decades): 2017–

2030, 2031–2040, and 2041–2050. Figure 2-23 – Figure 2-25 in the appendix depict regional and temporal total employment impact by PV, Wind, and baseload NG by scenario during construction and O&M from 2004 to January 2050. The purpose of these overlapped graphs is to show how different scenarios yield different impacts in different timespans.



Map 2-1: Cumulative total construction employment impact by modeled scenarios and energy sources from 2017 to 2050 against 2050 population density.



Map 2-2: Cumulative O&M total employment impact by modeled scenarios and energy sources from 2017 to 2050 against 2050 population density.

As mentioned above, direct, indirect, and induced impacts are a fixed fraction of total impact. On average, 78%, 8%, and 14% (65%, 20%, and 15%) of total employment impact of wind power plant during construction (O&M) is direct, indirect, and induced impacts respectively. Similarly, 72%, 9%, and 19% (61%, 18%, and 22%) of total employment impact of solar energy installation is direct, indirect, and induced impacts respectively. Lastly, on average, 67%, 10%, and 22% (53%, 24%, and 23%) of total employment impact of fossil fuel power plant during construction (O&M) is direct, indirect, and induced impacts respectively. One can apply these percentages to arrive at employment results by category. Overall, the majority of employment impact occurs onsite.

2.6.2.2. Gross economic output

Economic output closely follows the employment results: when there is employment impact, there is economic output impact as well. Construction and O&M employees, depending on type of energy source, earn an average annual salary (with benefit) of $35,000 to $58,000 (2017$) and $56,000 to $76,000 (2017$) per year respectively (Mamkhezri et al., 2017). Under Reference Case Scenario, these employments result in cumulative (sum of construction and O&M) total economic output of $24 billion (2017$) (18% RE and 49% O&M) per year from 2017 to 2050. Scenario 1, Scenario 2, and Scenario 3 respectively leads to roughly $3 ($19: 90% RE and 50% O&M), $4 ($20: 94% RE and 54% O&M), and $2 ($22: 4% RE and 45% O&M) billion (2017$) per year less than the reference case scenario. In other words, the reference case scenario yields 25%, 20%, and 9% higher cumulative economic output than Scenario 1, Scenario 2, and Scenario 3 respectively. Figure 2-16 imparts the latter information by energy source and modeled scenarios from 2017 through January 2050. PV and wind construction yield their highest economic output impact in Scenario 1 and Scenario 2 respectively, while NG peaker and NG baseload in Scenario 1 and Scenario 3 respectively. During O&M, beside NG baseload that has its highest economic output under the reference case scenario, all the other energy sources yield their highest impact in the corresponding scenario with the highest impact during construction. Lastly, on an annum account, the reference case scenario yields $355 million ($2017) per year during O&M period, while scenarios 1, 2, and 3 yield $63, $32, and $53 million ($2017) per year less than the reference case scenario respectively.

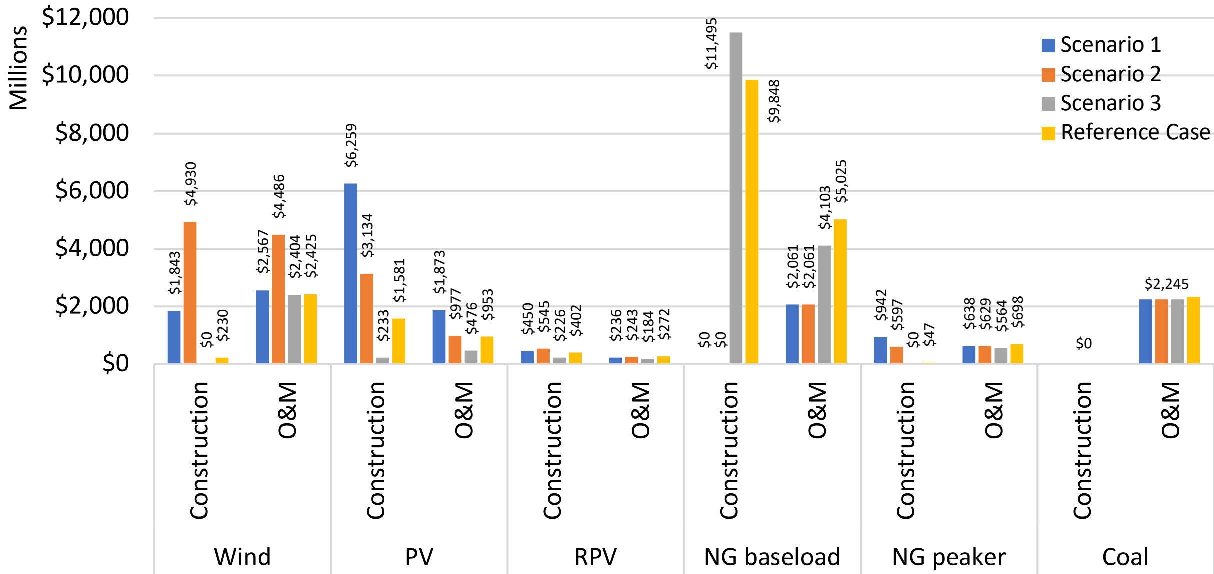
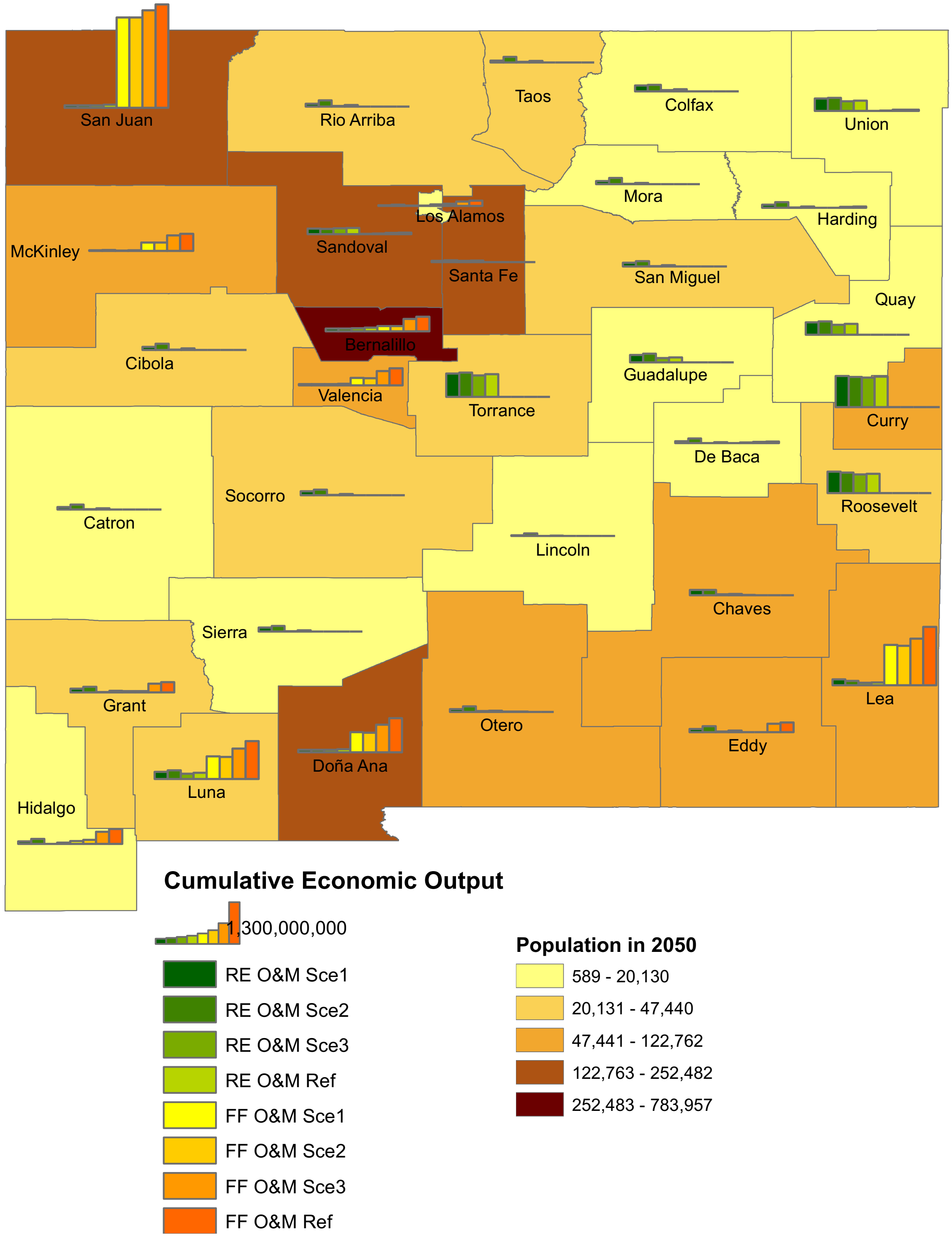


Figure 2-16: Cumulative gross economic output by energy source and modeled scenarios from January 2017 to January 2050. Note: Divide O&M figures by 33 to calculate annual average values.

County-level cumulative economic output during construction and O&M from 2017 to January 2050 are summarized in Table 2-11 and Table 2-12 respectively. Rural counties will benefit under RE intensive scenarios and counties with FF infrastructure in place will benefit from FF intensive scenarios (which are more populous counties). For the same reason discussed above, annual average output of construction does not convey useful information as construction, unlike O&M, does not occur annually. Thus, we only discuss cumulative economic output values during construction phase. Under the reference case scenario, counties with appropriate infrastructure for NG baseload installation will experience 81 million dollars cumulatively over the time period of the study. Scenario 3 generates 14 million dollars more than the reference case scenario in counties with appropriate infrastructure for NG baseload (see Table 2-11). Compared to the reference case scenario, scenarios 1 and 2 produce no economic output from NG baseload as there will be no installation, however, they result in higher economic output from wind and PV installation. Under scenario 1, Colfax, Roosevelt, Chaves, and Lea counties will experience approximately 40 million dollars in cumulative total economic impact from PV installation. Under the second scenario, the majority of counties will experience more than 16 million dollars in cumulative total economic impact from wind plant installation.

Similar to employment impact we observe an emerging pattern during the O&M phase (see Table 2-12). Regardless of scenario, Curry, Torrance, and Roosevelt counties will have the highest economic output (with different magnitudes) from developing wind energy, while Colfax, Luna, and Guadalupe counties are better off with PV installation. This is because these counties meet our siting criteria: not only are they rural, but they also have higher potential for solar or wind energy. Bernalillo, Dona Ana, and Santa Fe are the counties most suitable for RPV diffusion with the highest economic impact.

Developing NG peaker in Valencia, Bernalillo, Dona Ana, Lea, and Hidalgo counties, and NG baseload diffusion in Lea, Luna, and Dona Ana counties will lead to the highest economic output regardless of scenario. Lastly, San Juan county will experience the greatest economic output from its coal-fired generation power plants. Map 2-3 and



Map 2-4 visualize county-level gross economic output results by RE and FF during construction and O&M respectively against reference case population in 2050, and

Map 2-10 and Map 2-11 of Appendix summarize these impacts (results provided in Table 2-11 and Table 2-12) by energy type.

*Table 2-11: Cumulative construction economic output by energy source and county from 2017 to 2050.**

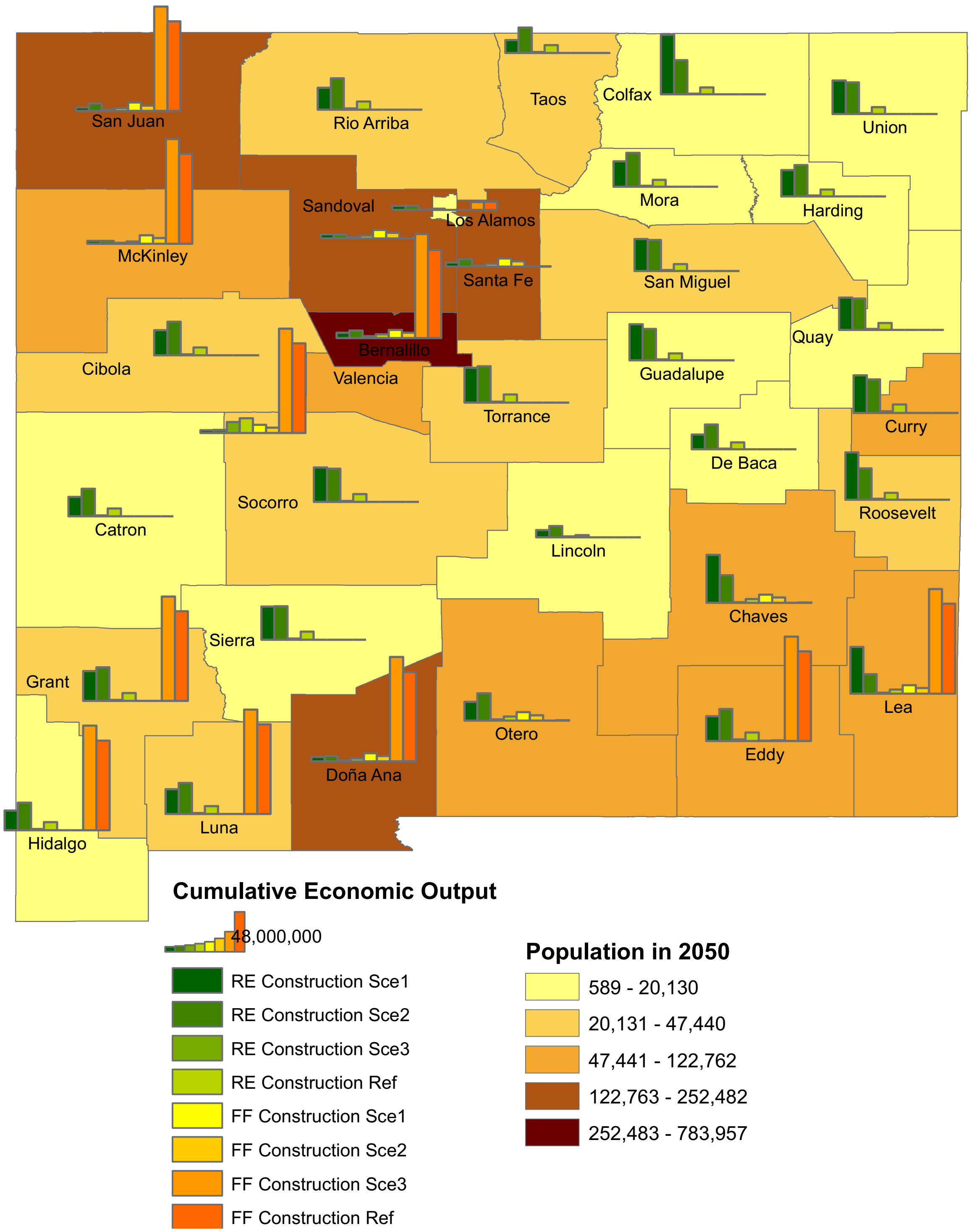
County	Scenario 1 (*$100,000)					Scenario 2 (*$100,000)					Scenario 3 (*$100,000)					Reference Case Scenario (*$100,000)				
	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb
Bernalillo	0	0	49	76	0	0	0	70	49	0	0	0	17	0	949	0	0	36	4	801
Catron	57	120	0	0	0	162	88	0	0	0	0	9	0	0	0	7	65	0	0	0
Chaves	59	357	22	76	0	132	98	23	49	0	0	0	7	0	0	7	13	16	4	0
Cibola	67	163	0	0	0	190	116	0	0	0	0	9	0	0	0	8	65	0	0	0
Colfax	67	475	0	0	0	190	121	0	0	0	0	8	0	0	0	8	55	0	0	0
Curry	59	266	20	0	0	166	121	21	0	0	0	8	7	0	0	7	55	15	0	0
De Baca	59	77	0	0	0	166	59	0	0	0	0	8	0	0	0	7	55	0	0	0
Dona Ana	0	0	41	76	0	0	0	50	49	0	0	0	12	0	951	0	0	28	4	812
Eddy	59	149	18	4	0	166	106	18	5	0	0	8	7	0	951	7	55	16	3	816
Grant	57	213	0	0	0	162	142	0	0	0	0	9	0	0	951	7	65	0	0	816
Guadalupe	59	271	0	0	0	166	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Harding	59	181	0	0	0	166	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Hidalgo	57	123	0	0	0	162	90	0	0	0	0	9	0	0	951	7	65	0	0	817
Lea	59	349	17	76	0	93	66	18	49	0	0	0	7	0	951	7	13	16	4	815
Lincoln	57	8	0	0	0	92	10	0	0	0	0	8	0	0	0	7	12	0	0	0
Los Alamos	35	3	0	0	0	33	3	0	0	0	0	2	0	0	71	8	4	0	0	74
Luna	57	169	0	0	0	162	122	0	0	0	0	9	0	0	951	7	65	0	0	816
McKinley	0	0	24	76	0	0	0	24	49	0	0	0	8	0	951	0	0	19	4	815
Mora	67	165	0	0	0	190	117	0	0	0	0	8	0	0	0	8	55	0	0	0
Otero	57	93	21	76	0	159	68	21	49	0	0	4	7	0	0	7	13	16	4	0
Quay	59	234	0	0	0	166	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Rio Arriba	67	131	0	0	0	190	93	0	0	0	0	9	0	0	0	8	65	0	0	0
Roosevelt	59	374	0	0	0	166	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Sandoval	0	0	37	76	0	0	0	34	49	0	0	0	11	0	0	0	0	24	4	0
San Juan	0	0	31	76	0	0	0	69	49	0	0	0	11	0	951	0	0	25	4	813
San Miguel	57	234	0	0	0	162	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Santa Fe	0	0	38	76	0	0	0	69	49	0	0	0	11	0	0	0	0	26	4	0
Sierra	57	244	0	0	0	162	142	0	0	0	0	9	0	0	0	7	65	0	0	0
Socorro	57	257	0	0	0	162	142	0	0	0	0	9	0	0	0	7	65	0	0	0
Taos	67	52	0	0	0	190	43	0	0	0	0	9	0	0	0	8	65	0	0	0
Torrance	67	251	0	0	0	190	142	0	0	0	0	9	0	0	0	8	65	0	0	0
Union	59	245	0	0	0	166	121	0	0	0	0	8	0	0	0	7	55	0	0	0
Valencia	0	0	26	76	0	0	0	29	49	0	0	0	101	0	951	0	0	135	4	814

*Values are in hundred thousand 2017 USD. Divide values by 33 (2050 – 2017) to calculate annual average economic output for each county though not recommended as it ignores the temporal nature of construction phase..

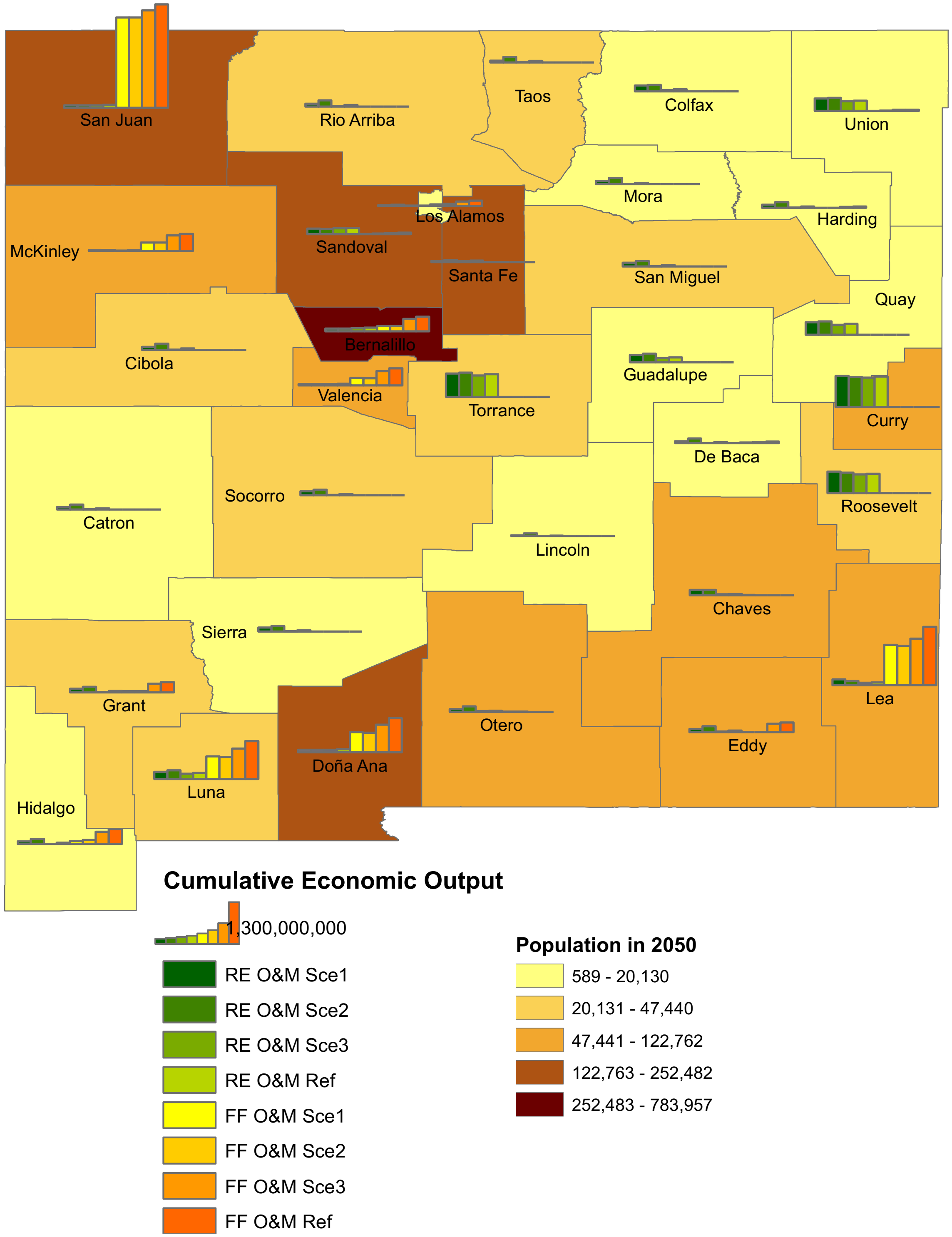
*Table 2-12: Cumulative O&M economic output by energy source and county from 2017 to 2050.**

	Scenario 1 (million $)					Scenario 2 (million $)					Scenario 3 (million $)					Reference Case Scenario (million$)				
County	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb	Wind	PV	RPV	NGp	NGb
Bernalillo	0	15	55	114	19	5	13	53	110	19	0	19	61	105	200	0	20	70	128	227
Catron	14	46	0	0	0	95	29	0	0	0	0	5	0	0	0	1	29	0	0	0
Chaves	31	88	11	7	0	94	26	10	6	0	17	2	5	0	0	18	4	11	1	0
Cibola	17	63	0	0	0	116	39	0	0	0	0	11	0	0	0	1	36	0	0	0
Colfax	17	126	0	2	0	120	44	0	2	0	9	22	0	2	0	9	42	0	2	0
Curry	670	80	11	0	0	699	33	9	0	0	715	4	5	0	0	716	25	10	0	0
De Baca	15	32	0	0	0	97	20	1	2	12	0	5	1	2	31	1	25	1	3	42
Dona Ana	0	29	31	96	399	6	25	32	93	388	0	38	27	87	589	0	39	35	107	729
Eddy	15	57	10	5	0	102	35	8	6	0	0	10	5	4	201	1	31	11	6	235
Grant	14	72	2	31	0	96	40	1	31	0	1	6	3	31	182	2	30	3	37	211
Guadalupe	78	103	0	0	0	160	51	0	0	0	69	32	0	0	0	70	53	0	0	0
Harding	15	60	0	0	0	102	33	0	2	0	0	4	0	2	20	1	25	0	2	25
Hidalgo	14	47	0	74	0	94	29	0	75	26	0	5	0	74	227	1	29	0	90	274
Lea	41	89	10	94	896	68	28	8	91	870	28	23	5	85	1,051	29	24	11	104	1,321
Lincoln	14	3	0	0	0	62	4	0	0	1	0	4	0	0	2	1	7	0	0	4
Los Alamos	10	3	0	0	37	27	4	0	0	52	1	4	0	0	103	1	6	0	0	132
Luna	56	115	1	0	554	128	78	1	0	538	46	76	2	0	739	46	100	2	0	923
McKinley	0	0	13	9	0	7	2	11	7	0	0	0	6	1	181	0	1	12	3	210
Mora	17	56	0	0	0	114	32	0	0	0	0	4	0	0	0	1	25	0	0	0
Otero	14	44	12	7	0	96	30	10	6	0	2	14	7	0	0	3	13	12	1	0
Quay	197	102	0	0	0	269	56	0	0	0	199	43	0	0	0	199	63	0	0	0
Rio Arriba	17	49	0	0	0	118	30	0	0	0	5	5	0	0	0	6	29	0	0	0
Roosevelt	425	103	0	0	0	471	32	0	0	0	449	4	0	0	0	450	24	1	0	0
Sandoval	98	11	25	7	0	90	9	24	6	5	107	15	21	0	24	107	15	29	1	31
San Juan	0	42	15	7	155	5	34	24	6	150	0	57	6	0	332	0	58	14	1	401
San Miguel	14	76	0	0	0	90	34	2	0	0	0	8	1	0	0	1	28	1	0	0
Santa Fe	0	6	28	7	0	5	6	34	6	0	0	7	25	0	0	0	8	33	1	0
Sierra	14	81	0	0	0	95	41	0	0	0	0	7	0	0	0	1	32	0	0	0
Socorro	14	82	0	0	0	96	38	0	0	0	0	5	0	0	0	1	29	0	0	0
Taos	17	25	0	0	0	120	19	0	0	0	6	7	0	0	0	7	32	0	0	0
Torrance	494	80	0	0	0	551	39	0	0	0	523	5	0	0	0	524	29	0	0	0
Union	222	76	0	0	0	285	32	0	4	0	226	4	0	4	20	226	24	0	5	25
Valencia	0	14	14	177	0	0	13	12	172	0	0	19	6	167	182	0	20	13	204	210

Note: Only two counties have coal-fired power plants. San Juan 2,053 and McKinley 192 million (2017$).
* Values are in million 2017 USD. Divide values by 33 (2050 – 2017) to calculate annual average economic output for each county.



Map 2-3: Cumulative economic output during construction from 2017 to January 2050 against 2050 population.



Map 2-4:Cumulative economic output during O&M from 2017 to January 2050 against 2050 population.

During construction (O&M) phase, on average, 77%, 9%, and 14% (63%, 21%, and 15%) of total gross economic output impact of wind power plant is direct, indirect, and induced impacts respectively. These figures for solar energy are 71%, 11%, and 19% (54%, 21%, and 24%) of total employment impact respectively. Lastly, on average, 67%, 13%, and 21% (46%, 33%, and 21%) of total gross economic output impact of fossil fuel power plant during construction (O&M) is direct, indirect, and induced impacts respectively. One can apply these percentages to arrive at gross economic output results by category. Overall, similar to employment impact, majority of the economic output impact is due to direct impacts (onsite). Table 2-49 – Table 2-81 of the Appendix summarize construction and O&M decade average gross economic output by county and by impact (direct, indirect, and induced) from 2017 to 2050. We break down the duration into three segments, 2017–2030, 2031–2040, and 2041–2050, to preserve some of the temporality.

2.6.3. Environmental impacts

Based on all of the three modeled scenarios and the reference case scenario, coal-fired power plants will retire after 2037. This is mainly due to the fact that existing coal-fired power plants are aging (>40 years), fuel contracts with coal mines are ending, and more importantly, coal will not be cost-competitive. As such there will be no new coal-fired power plant constructed in the future (see Figure 2-11). Note that these power plants are the most water-intense and polluting technologies in our set of energy sources (see Table 2-5). Eliminating coal from NM's energy mix will result in fewer negative externalities (GHG, ambient pollutions, and water usage) from FF overall. Different technology costs along with RPS requirements drive the energy source that will replace coal. The more RE replacing coal, the fewer negative externalities and the higher the social benefit from the replacement.

2.6.3.1. Water usage

Figure 2-17 shows the cumulative water withdrawal and consumption by the electric sector under the four modeled scenarios from 2017-2050. The reference case scenario suggests a cumulative 3,481 and 290 billion gallons of water withdrawal and consumption throughout the study timeline. The first two scenarios each use 50 and 32 billion gallons of water withdrawal and consumption less than the reference case scenario respectively. The third scenario, with the most FF infusion in the energy mix, estimates 11 and 7 billion gallons of water withdrawal and consumption respectively higher than the reference case scenario. To put this into perspective, Bernalillo County residents consumed 127 gallons of water per person per day in 2017.[55] Thus, one-billion-gallon water is equivalent to enough water for the entire population of Bernalillo County for approximately 12 days ($\frac{10^9}{127\times 669{,}296}$). Considering a rate of 0.00182 USD/gallon for water consumption by each energy source (Cohen, 2014, p. 37), the reference case scenario will result in a total cost of $527 million ($2017) in water consumption for electricity generation. Scenarios 1 and 2 each lead to saving $58 million in water consumption, while Scenario 3 results in $13 million more cost in water consumption than Reference Case Scenario. Relative to Reference Case Scenario, Scenario 1 and Scenario 2 will each

[55] Source: http://www.abcwua.org/education/pdfs/WaterUseGraph.pdf (accessed 04/08/2019)

result in saving $58 million dollars from using less water, while Scenario 3 will cost $12.6 million dollars more as it is more water intense. Figure 2-18 depicts the temporal water withdrawal and consumption from 2017 to 2050.

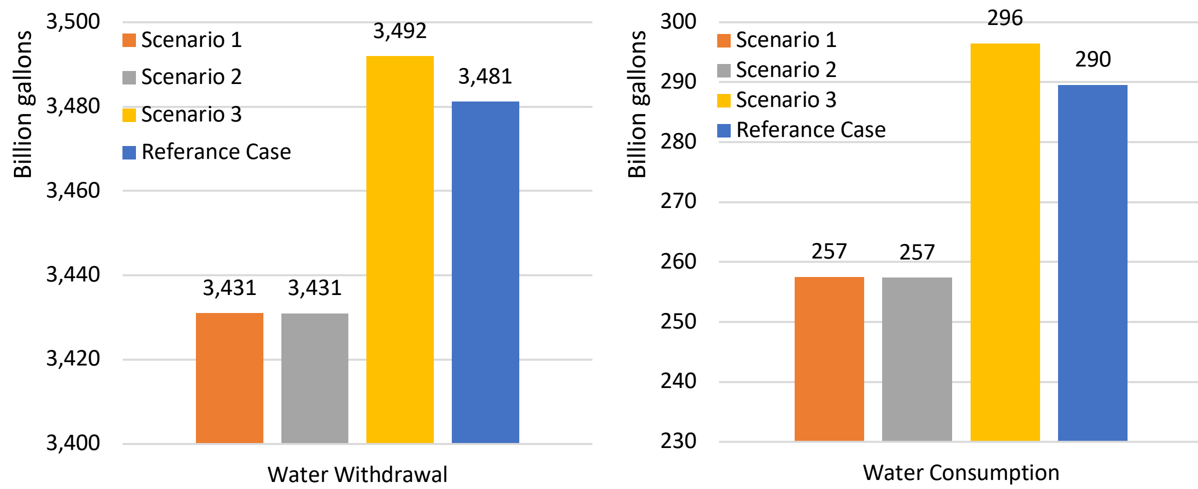


Figure 2-17: Cumulative (2017-2050) water withdrawal and consumption by electric sector under the four modeled scenarios.

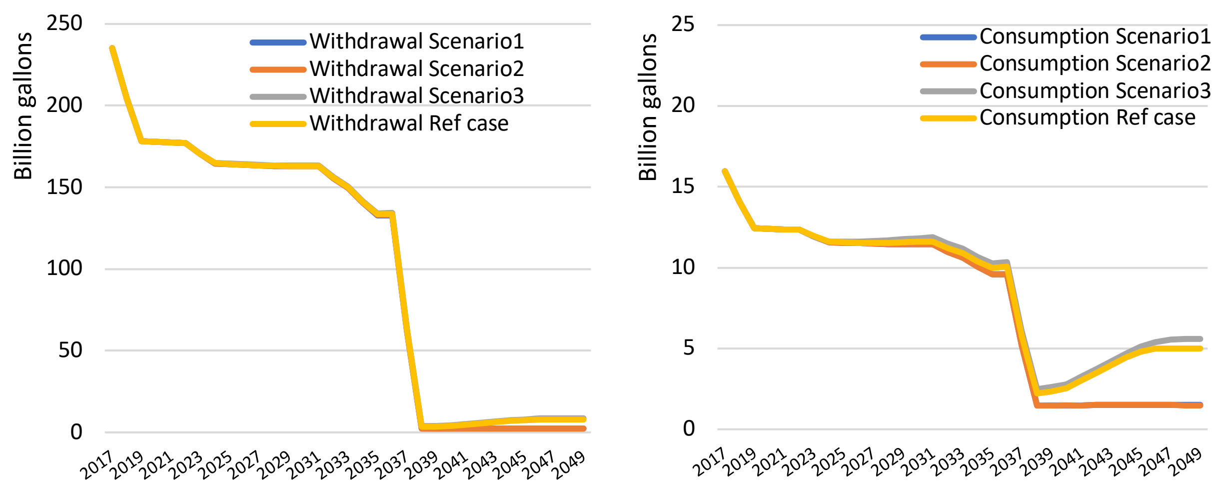
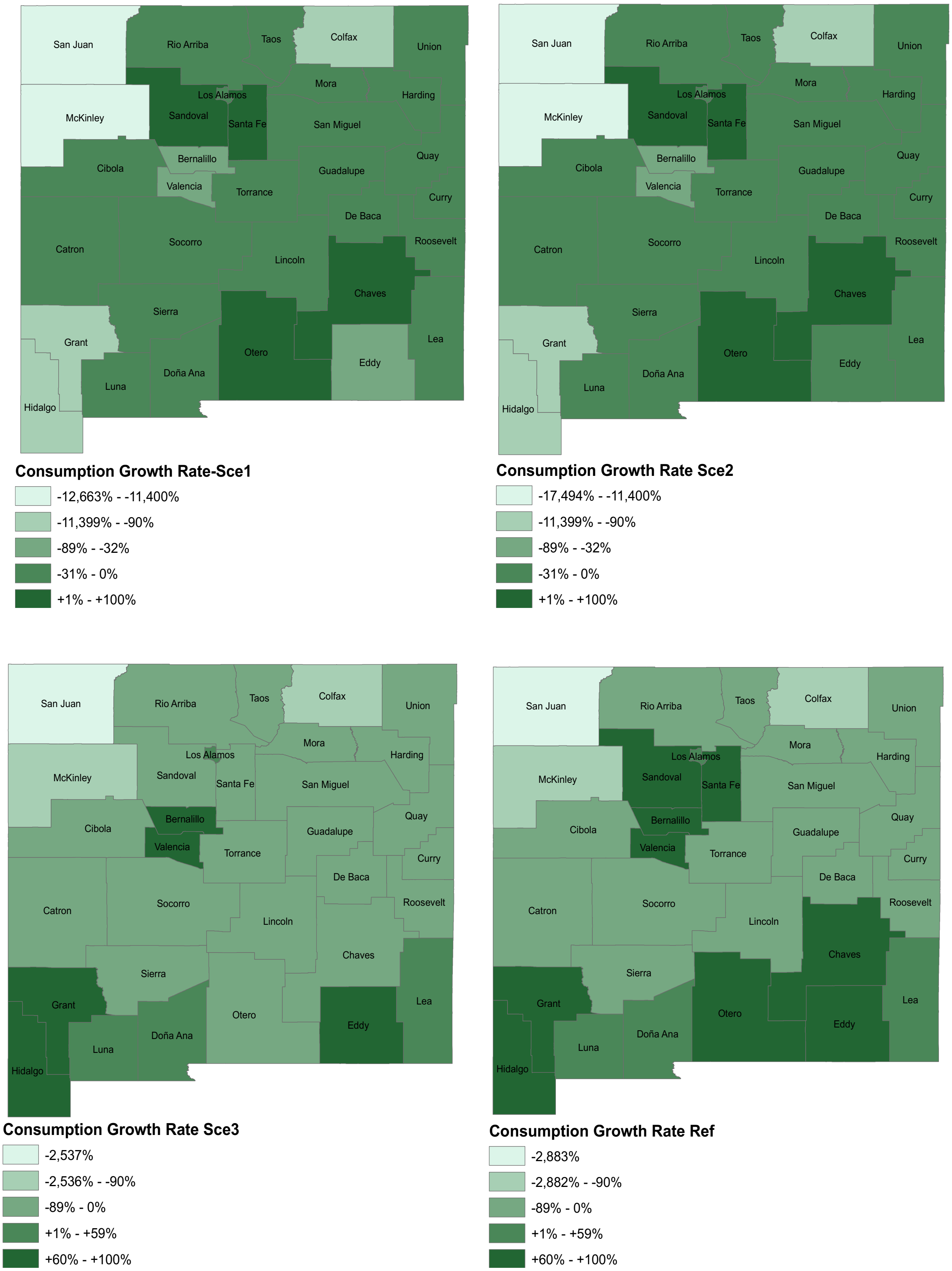


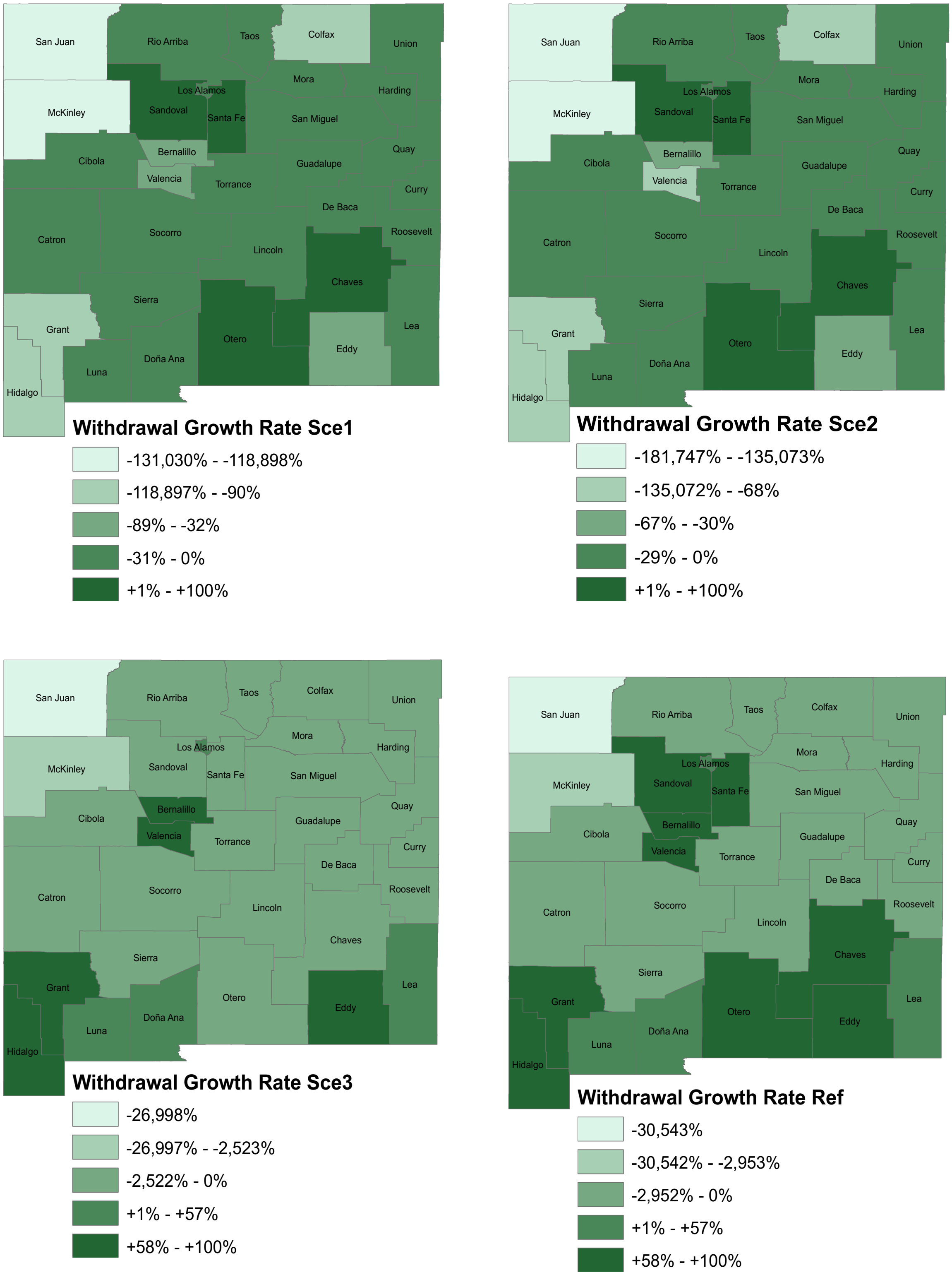
Figure 2-18: Water withdrawal (left) and consumption (right) over time by electric sector under the four modeled scenarios.

Map 2-5 and Map 2-6 highlight regional percentage changes in water withdrawal and consumption in 2050 relative to 2017 for the four modeled scenarios respectively. Negative percentage change means reduction, 0 means no change, and positive percentage change means increase in water consumption/withdrawal. Reference Case Scenario estimates that water consumption decreases by 2050 in 3 counties, increases in 13 counties, and stays unchanged in the remaining counties. Scenario 1 suggests reduction in 8 counties, increase in 4 counties, and no change in water consumption in the remaining counties. Similarly, Scenario 2 estimates water consumption decreases in 10 counties, increases in 4 counties, and stays the same in the remaining counties. Lastly, the third scenario recommends reduction in 3 counties, increase in 9 counties, and no change in water consumption by 2050 in the remaining counties.

Besides scenario 1 that estimates water reduction in 10 counties by 2050, water withdrawal change direction (reduction, increase, or no change) is the same as water consumption with the only difference in the magnitude of the change (Map 2-6).



Map 2-5: Percentage change in water consumption in 2050 compared to 2017 for the four modeled scenarios.



Map 2-6: Percentage change in water withdrawal in 2050 compared to 2017 for the four modeled scenarios.

2.6.3.2. Air pollution and greenhouse-gas emissions

As mentioned above, most scientists agree that air pollution and GHG emissions are threats to not only human and animal health, but also to the ecosystem due to climate change (EPA, 2016b). Consequently, reducing them results in considerable social benefit. Social benefit accounts for dollar value of avoiding premature mortality and morbidity incidences associated with corresponding emissions (PM, SO2, NOx, and CO2). When available, morbidity coefficients come from nonmarket valuation studies (willingness-to-pay to avoid a morbidity caused by an emission). When not available, EPA uses actual cost of treating/mitigating illness (cost-of-illness). To quantify social benefit of avoiding premature mortality, EPA utilizes value of statistical life, which is $7.97 million (2010$) (EPA, 2016a, p. 183). To calculate premature mortality counts, EPA (2016a) utilizes estimated coefficients from the American Cancer Society 4-17 cohort (Krewski et al., 2009) and the Harvard Six Cities cohort (Lepeule et al., 2012), two of the most credible epidemiology studies examining two large population cohorts. These two studies have been consistently used across EPA's regulatory impact analysis and similar academic studies examining the effect of primary and secondary PM's effect on human health (EPA, 2016a; Heo et al., 2016a, 2016b; Wiser et al., 2016; Millstein et al., 2017). Below, we first summarize air pollution and GHG emission impact and their social benefit to the state and counties, and then present avoided premature mortality and morbidity incidences associated with each scenario.

Figure 2-19 and Figure 2-20 depict cumulative impact of air pollution and GHG emissions, along with consecutive social benefit to the state from 2017 to 2050. Cumulatively, the first two scenarios emit roughly 100 million tons GHG less than the reference case scenario throughout the study timeline each leading to more than $6.8 billion (2010$) in cumulative climate benefit. The third case scenario, on the other hand, emits 3% (21 million tons) higher GHG than the reference case scenario, which causes more than $1,400 million (2010$) social cost relative to the reference case scenario. Each one million tons of GHG emissions is equivalent to GHG emissions by approximately 2,500 million miles driven by an average passenger vehicle.[56] Since coal is the only energy source that emits mercury and it stays unchanged throughout our study period, mercury is the same in all four scenarios: 3 tons. Scenario 1 and 2 will result in roughly 500[57] tons less SO2 emission ($3 million (2010$) in social benefit) relative to the reference case scenario, while the third scenario will yield more than 100 tons more SO2 ($1 million (2010$) in social cost) cumulatively from 2017 to 2050. NOx emission in the first two scenarios will reduce by 6,638 and 7,329 tons resulting in $6 and $7 million (2010$) in social benefit compared with the reference case scenario, while the third scenario yield 2,193 tons more and thus $2 million (2010$) in social cost. Lastly, PM emission in scenario 1 and 2 will reduce by 6,163 and 6,186 tons resulting in $122 and $123 million (2010$) in social benefit relative to the status quo scenario, while the third scenario yield 1,339 tons more and hence $27 million (2010$) in social cost.[58]

[56] GHG conversion to miles driven source: https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator (accessed 01/10/2019)
[57] Recognize that NM's RPS does not require utility companies to shut down existing FF power plants and/or terminate existing power purchase agreements with FF power plants, rather to produce a portion of their electricity from RE sources. Thus, polluters (NG and coal) keep polluting until they retire. Once an FF power plant is retired or there is a gap in electricity generation, additional capacity will be driven by scenarios in our model. In other words, we are not "replacing" FF with RE, rather we "add" RE to meet RPS requirements when necessary.
[58] Note that EASIUR model contains two estimates for damages, differing by epidemiological study: the numbers presented here are the low estimate (Krewski et al., 2009), and multiplying those numbers by 2.2 will lead to the high estimate (Lepeule et al., 2012). EASIUR is a fairly strong, and relatively central, choice of model (Millstein et al., 2017).

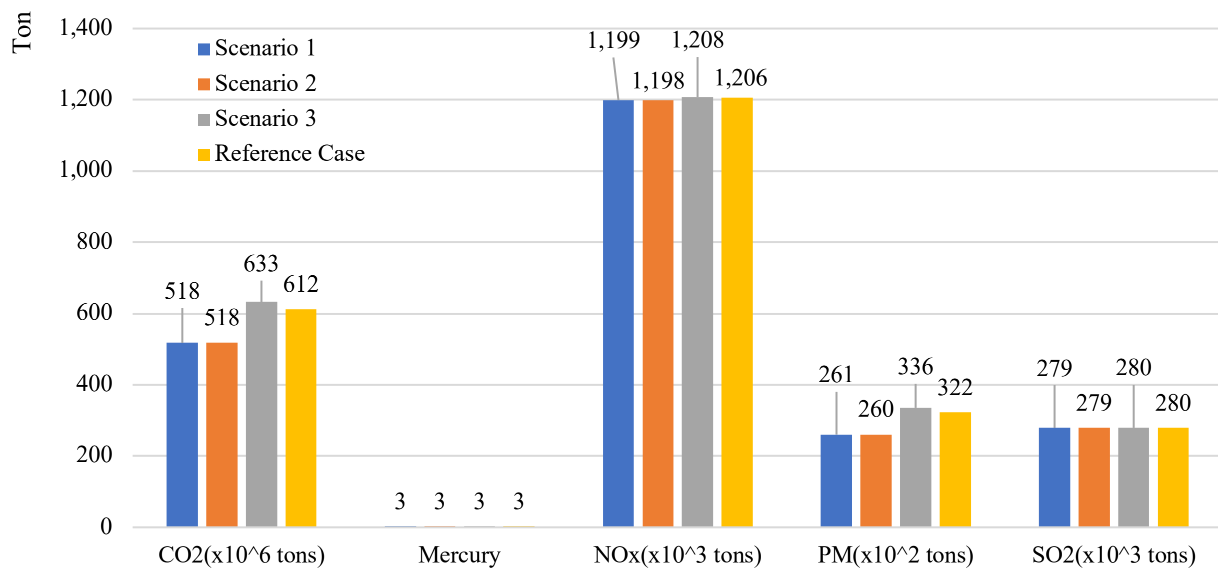


Figure 2-19: State-level cumulative tons of GHG and air emission under four modeled scenarios from 2017 to 2050.

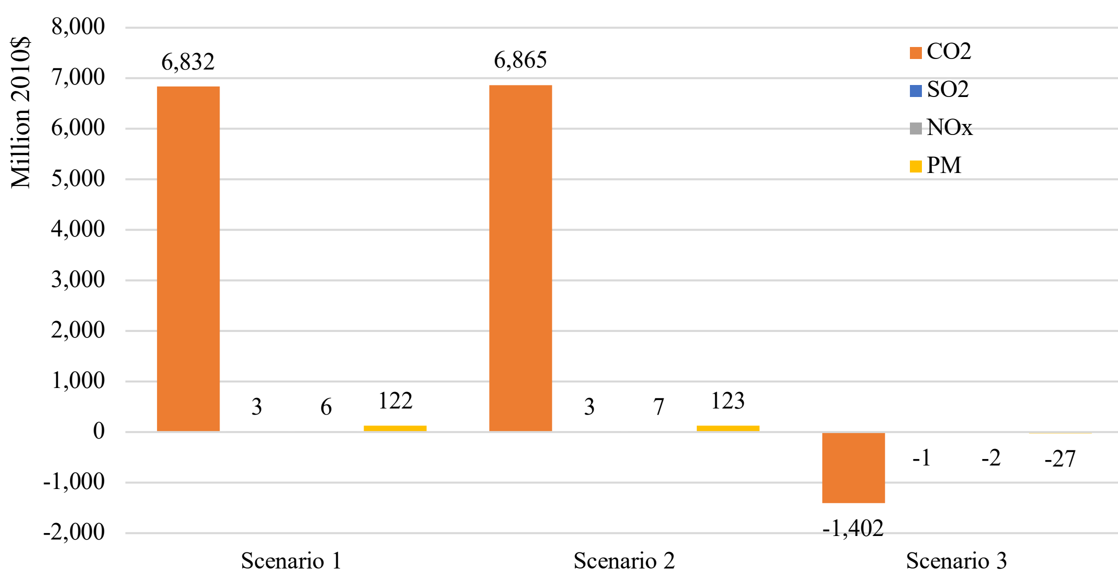
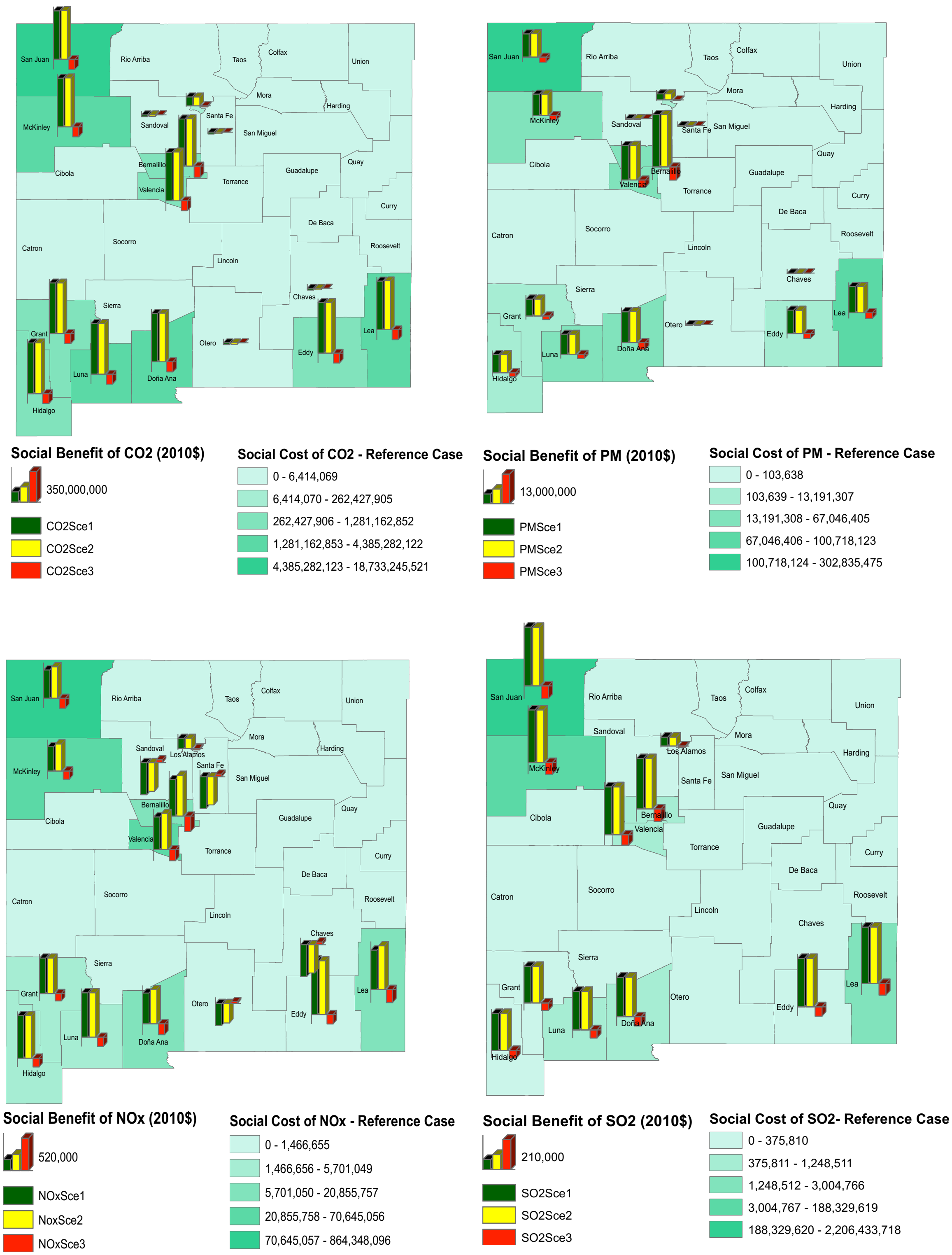


Figure 2-20: Social benefit of air pollution and GHG emission reduction relative to the reference case scenario from 2017 to 2050.

Map 2-7 depicts county-level social benefit of air pollution and GHG emission reduction against corresponding pollutant's social cost in the reference case scenario under the modeled scenarios. For instance, San Juan county, which hosts the main state's coal-fired power plants (main CO_2 emitter), provides the highest social cost of carbon in the reference case scenario ($18,700 million). Carbon reduction from San Juan County in scenarios 1 and 2 relative to the status quo scenario provide global benefits of $670 and $673 million respectively, whereas scenario 3 estimates a $140 million social cost. The question of whether residents of San Juan receive the social benefits/costs of carbon depends on the ideas about reciprocity (e.g., altruism, paternalism, etc.) and is outside of the scope of the current research.



Map 2-7: Social benefit of air pollution and GHG emission reduction against corresponding pollutant's social cost in the reference case scenario under the modeled scenarios.

Table 2-13 summarizes accumulated avoided air pollution, social benefit, and premature mortality and morbidity impact of air pollution under scenarios 1, 2, and 3 from 2017 to 2050 relative to the reference case scenario. Reference case scenario estimates 408 to 924 adult fatality caused by a combination of SO2, NOx, and PM pollutants. Scenarios 1 and 2 each has the potential to avoid 23 to 52 premature mortality incidences, while scenario 3 adds 5 to 11 fatality counts due to exposure to ambient pollution compared to the status quo scenario. While the majority (>90%) of social benefit of each scenario comes from avoiding premature mortality (EPA, 2016a, p. 184), we also estimate a number of additional morbidity benefits, from avoiding nonfatal heart attacks, hospital visits for asthma or other cardiopulmonary conditions, to fewer lost work or school days. For example, the second scenario is estimated to result in avoiding 19 visits to the emergency department or hospital for cardiopulmonary conditions as well as approximately 3,000 less lost work or school days from 2017 to 2050.

*Table 2-13: Accumulated emission, social benefit, and mortality and morbidity incidence reduction relative to reference case scenario by SO2, NOx, and PM reduction via RE installation from 2017 – 2050.**

	Scenario 1			Scenario 2			Scenario 3			*Reference Case*		
	SO2	NOx	PM	SO2	NOx	PM	SO2	NOx	PM	*SO2*	*NOx*	*PM*
Emission Reductions (thousand tons)												
	0.49	6.69	6.22	0.50	7.41	6.24	- .11	-2.21	-1.35	*280*	*1206*	*32*
Social Benefits (2010 million $)												
	3.4	5.9	122.4	3.4	6.6	122.8	-0.7	-2.0	-26.6	*1928*	*1078*	*640*
Premature Mortality Incidences												
Krewski et al. (2009)	0	1	22	0	1	22	0	0	-5	*207*	*95*	*107*
Lepeule et al. (2012)	1	1	50	1	2	50	0	0	-11	*464*	*219*	*241*
Morbidity Incidences												
Emergency department visits for asthma	0	0	7	0	0	7	0	0	-1	*81*	*37*	*36*
Acute bronchitis	1	1	36	1	2	36	0	0	-8	*372*	*251*	*181*
Lower respiratory symptoms	9	19	462	9	20	464	-2	-6	-100	*4,699*	*3,178*	*2,312*
Upper respiratory symptoms	13	26	677	13	29	679	-3	-9	-146	*6,735*	*4540*	*3,334*
Minor restricted-activity days	318	582	16,619	319	643	16,682	-69	-193	-3,586	*169,722*	*99,043*	*82,791*
Lost work days	54	99	2,771	54	110	2,782	-12	-33	-600	*28,485*	*16,673*	*13,975*
Asthma exacerbation	5	1,699	628	5	1,892	630	-2	-522	-156	*5,900*	*226,256*	*3,938*
Hospital Admissions, Respiratory	0	0	5	0	0	5	0	0	-1	*48*	*20*	*24*
Hospital Admissions, Cardiovascular	0	0	6	0	0	6	0	0	-1	*61*	*26*	*30*
Non-fatal Heart Attacks Incidences (age>18)												
Peters et al. (2001)	0	1	22	0	1	22	0	0	-5	*202*	*85*	*105*
Pooled estimate of 4 studies	0	0	2	0	0	2	0	0	-1	*22*	*9*	*11*

*Note: Positive means reduction, whereas negative value indicates addition.

FF and RE power plants also cause avian mortality. FF power plants induce fatality throughout their life-cycle: plant operation, acid rain, mercury, and climate change, while bird fatality associated with wind and PV power plants is mainly due to bird colliding with turbine blades and panels respectively (McCubbin & Sovacool, 2013; Sovacool, 2009; Walston et al., 2016). Figure 2-21 summarizes avian mortality caused by different energy sources (i.e., coal, NG, wind, and PV) under different scenarios. Reference Case Scenario leads to 5,131 thousand avian fatalities, of which FF is responsible for approximately 99% of the overall number of deaths. Relative to the reference case scenario, scenarios 1 and 2 have the potential to save 485 and 441 thousand deaths respectively, while Scenario 3 leads to 106 thousand more avian fatality. Lastly, RE intensive scenarios (scenarios 1 and 2) lead to more than 4,600 thousand bird deaths, which RE is responsible only for 2–3-percent of the overall number. Based on Ebird

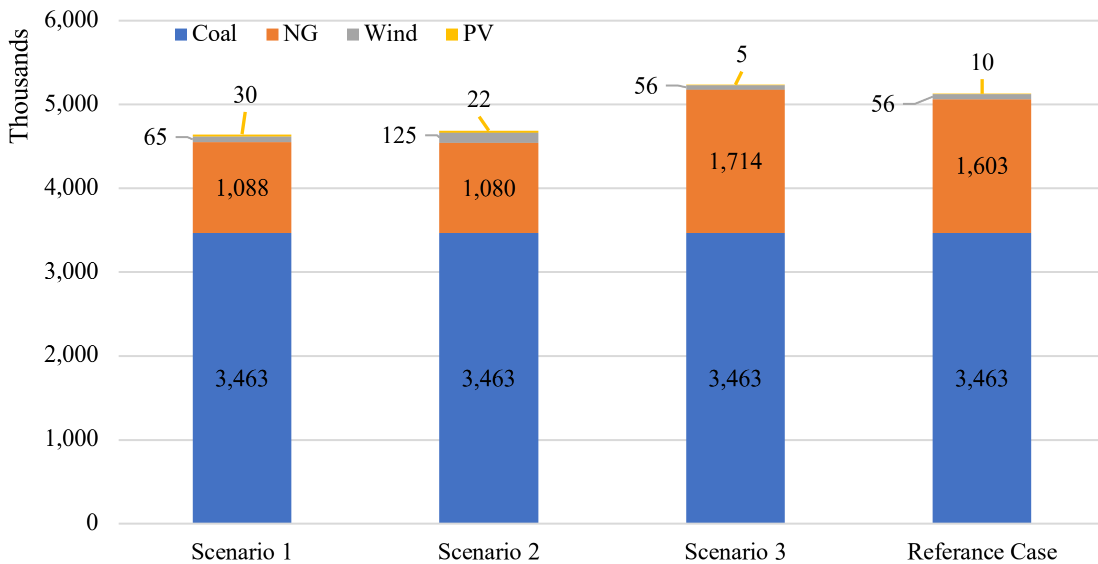


Figure 2-21: Avian mortality caused by coal, NG, wind, and PV power plants under the four modeled scenarios from 2017 to 2050.

Dissanayake and Ando (2014, p.251) conducted a choice experiment survey in Illinois and found that their respondents are willing to pay between $1.11 and $1.13 for each extra bird per year, and between $7.72 and $10.22 for each endangered species annually. Since we are unable to discern different types of birds (generic versus endangered species) in our analysis, we utilize the mean value of the upper level estimates ($\frac{1.13+10.22}{2} = \$5.68$) as how much each bird death worth. We estimate that 100%-RPS scenario is capable of saving $3 million in bird mortality, while 10%-RPS costs the state 1 million dollar more in avian mortality compared with the 20%-RPS scenario.

2.6.4. Summary of cumulative results

Our analysis seeks to investigate the economic and environmental impacts of the status quo scenario, along with three future scenarios. Without considering environmental impacts such as water usage, air pollution, GHG, and bird mortality, our results suggest that the reference case and FF intensive scenarios lead to higher economic output and total employment impacts than the RE intensive scenarios. However, once the environmental impacts are taken into consideration, these results no longer hold true. Compared to the reference case scenario, cumulatively, Scenario 2 and Scenario 1 result in $3,095 and $2,327 million (2017$) higher benefit respectively, and Scenario 3 in $3,325 million (2017$) more cost to the state. This makes Scenario 2 the best scenario, Scenario 1 the second best, Scenario 3 the worst-case scenario, when both environmental and economic impacts are taken into account. Thus, the higher the RPS level, the higher the overall benefit to the state. Table 2-14 summarizes cumulative results relative to the reference case scenario.

Table 2-14: Summary of cumulative results relative to Reference Case Scenario.

	Scenario 1	Scenario 2	Scenario 3
Output	-$4,694,840,852	-$3,961,521,342	-$1,880,920,616
Water benefit	$58,407,646	$58,551,858	-$12,587,753
CO2	$6,831,509,860	$6,865,064,757	-$1,402,017,596
SO2	$3,377,202	$3,390,385	-$734,440
NOx	$5,933,583	$6,550,912	-$1,960,415
PM2.5	$122,373,439	$122,836,438	-$26,595,991
Total Monetary Value	$2,326,760,878	$3,094,873,008	-$3,324,816,811
Employment	-14,464	-573	3,663
Bird Mortality	-485,468	-441,226	105,970

2.7. Conclusion

Legislators across the globe are supporting policies that move toward electricity generation from renewable resources. To this end, some jurisdictions in the U.S. have enacted regulations, such as the RPS. These provide a mechanism that can result in not only GHG emission reduction, but also water preservation. This is especially prudent in geographic locations with limited water resources. Moreover, RPS can support jobs, although the primary policy target of RPS is not focused squarely on job creation. We provide a roadmap of how to quantify the economic and environmental impacts of four scenarios, in which not only RPS level varies, but also technological cost and price of energy. Specifically, we model scenarios of NM's possible future RPS such that RPS will increase either to 50% or 100% or decrease to 10% by 2050. We also include the current level RPS as our baseline. In so doing, we combine results from input-output (JEDI and IMPLAN), econometrics (Stata), and GIS (ArcGIS) and create a unique SD model (Powersim) that enables us to assess regional economic and environmental impacts of different scenarios. Our contribution to the current body of literature is twofold: not only do we assess different RPS scenarios by considering the underlying dynamics within the energy sector, but we also assess these impacts at a lower granular level (i.e., county-level).

Under the status quo scenario, our model estimates 152 thousand cumulative FTE jobs, \$24 billion in economic output, \$3,648 million in air quality cost, \$36 billion in climatic cost, \$527 million worth of water use, 5 million avian mortality, and 409 – 924 premature mortality. Compared with the status quo scenario, our analysis suggests that RE intensive scenarios (Scenario 1 and Scenario 2) lead to less cumulative employment and economic output, but much higher social benefits relative to the reference case scenario: 500 – 15,000 less cumulative jobs, \$3 – \$4 billion less cumulative economic output, \$132 million less air quality cost, \$7 billion less climatic cost, \$58 million less worth of water use (or 32 billion gallons equivalent to enough water for the entire population of Bernalillo County for roughly 376 days), 441 – 485 thousands less avian mortality, and 23 – 53 less premature mortality. The third scenario (10% RPS by 2050) leads to approximately 4,000 more employment, \$2 billion less cumulative economic output, \$29 million more air quality cost, \$1 billion more climatic cost, \$13 million more worth of water use, 100 thousand more avian mortalities, and 5 – 11 more premature mortality than the reference case scenario. Considering the environmental impacts, our analysis finds that the Senate Bill RPS scenario (Scenario 2) is the best scenario followed by the first scenario, while the third scenario is the worst case scenario relative to the reference case scenario. Scenario 2 aligns with support from New Mexicans. In a separate paper by co-authors (Mamkhezri et al., 2018), we estimate that a sample of NM residents are willing to pay $5.4/year on top of their annual electricity bill[59] for each 1% increase in the current level of RPS (20%).[60] To achieve 100%-RPS-by-2050, we extrapolate that NM residents are willing to pay $58, $180, $373, $581, $803, $1,144 million (2017$) in 2020, 2025, 2030, 2035, 2040, and 2050 respectively. Figure 2-22 depicts this transition, all else equal. Note that the wide range of willingness to pay is due to the way the 80%-RPS-by-2040 bill requirements were designed. Under this bill, electric utility companies were required to increase current RPS level to 25% by 2020, 35% by 2025, 50% by 2030, 65% by 2035, and 80% by 2040. The higher the percentage, the higher residents are willing to pay.

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[59] Annual average electricity bill in NM is $900. Source: https://www.electricitylocal.com/states/new-mexico/ (accessed 01/17/2019)
[60] This is an extrapolation out of sample.

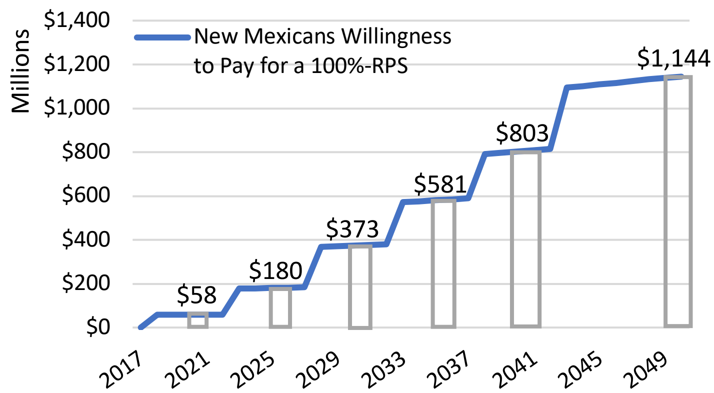

Figure 2-22: NM resident's willingness to pay to help with transitioning to a 100%-RPS, all else equal.

Although scenarios with a lower level of RPS might result in supporting a higher number in employment (in FF sector), these scenarios lead to much higher social cost of GHG and ambient pollution (i.e., premature mortality and morbidity) and water usage. This suggests that coming up with an overarching policy that benefits both the environment and economy is not an easy task. Policymakers seeking to promote energy policies may not only consider economic benefit associated with energy development, but also social welfare. In other words, RPS policies are more desirable when internalizing external costs and hence correcting for market failure (Change, 2015; IPCC, 2011; Wiser et al., 2017).

Further, the most decisive conclusion that can be drawn from job comparison across different scenarios is that the higher the RE development level, the more disperse and rural the employment impact. On the contrary, the higher the level of FF deployment, the less diverse and rural the job impact. San Juan County among all will experience a net negative (loss) in O&M jobs: it will lose 780 jobs from coal-fired power plant retirements after 2037 and will gain, depending on scenario, an annual average of 67 (Scenario 1) to 324 (Scenario 3) jobs. Losing 780 jobs and gaining 67 to 324 jobs would mean rising unemployment rate from 7.2% to 8.1% to 8.6% for San Juan County. Concurrently, the state will experience $683 (Scenario 1) to $686 (Scenario 2) billion in social benefits, particularly from the coal power plants retirement. The disparity in job and economic output distribution across counties and energy sources suggest that counties with varying energy potential and population density will experience variation in impacts.

The most vital determinant in the relationship between local communities and positive economic impacts is largely based on local communities and their ability to participate within energy industries (RE and FF). More directly, local communities with labor forces who can work in energy industries broadly is key to local communities benefiting from development of new sites. Thus, policymakers pursuing strategies to increase local economic benefits might gain from development of workforce readiness programs to ensure that local labor is capable and competitive in the near future. For example, programs could include: a) free or low-cost training and certification courses; b) financial/tax incentives for RE companies, which could facilitate absorption of unemployed populations as a result of transitioning to greater utilization of RE; c) and lastly, development for support within community colleges and technical schools that offer specialized training and certification programs in RE; all of which could lead to a viable pipeline of future RE employees (Kammen, 2008). Development of workforce training programs, and their associated costs, should be considered alongside the results we presented here within. Not highlighted within our study is how the state could grapple with considering tradeoffs in supporting local communities who may be adversely impacted by the development of RE sources. While we have demonstrated the positive economic yields of increasing RPS level, there are other policy implications to be considered. In the literature, it has been demonstrated that localities with greater capacity to produce/provide major material components (i.e., turbines, panels, etc.) see a greater return on investment and number of jobs. Particularly, Lantz et al. (2008) showed that economic output from wind energy investments in the construction period increase by more than a factor of three when they increase the share of major material components supplied by local, or state, manufacturers. Lantz and Tegen (2009) also demonstrated that local ownership component in RE projects has also been shown to increase construction and operation period jobs impacts by a factor of 1–3 times. This suggests that NM decisionmakers can increase the benefit from RE infusion by attracting new manufacturing to the state. Given the rural nature of NM and variable economic outlook across its counties, higher RE diffusion may become an economic tool to stimulate growth in economically-depressed areas.

Our results are broadly consistent with what has been found in the literature (e.g., Barbose et al., 2016; Lantz et al., 2008; Lantz & Tegen, 2009; Sastresa et al., 2010; Millstein et al., 2017; Slattery et al., 2011; Wiser et al., 2016, 2015, 2017). We do recognize that the majority of these studies had explicit research questions only on wind energy. For example, some studies sought to measure the actual economic impact of a particular wind installation at county level (e.g., Slattery et al., 2011), while others estimated a wind vision for the U.S. (e.g., Wiser et al. (2015, 2016)) or the environmental and economic impact of RPS policies nationwide for solely one year (i.e., Barbose et al. (2016)). Similar to Barbose et al. (2016), Millstein et al. (2017), and Wiser et al. (2017), our model suggest that RPS policies have the potential to yield billions of dollars in climatic and air-quality benefits as well as economic benefits.

The tools and theories integrated for the analysis in this research are broadly transferable across a wide range of topics and/or regions. For example, a similar approach can be taken to evaluate RPS policies in each one of the other 28 states with such regulations. Our model can be modified and used for states with existing 100% RPS policies (Hawaii, California, and Washington), and those with promises for 100% clean electricity (Colorado, Connecticut, Massachusetts, Illinois, Oregon, Maine, and Puerto Rico). Additionally, our state-of-the-art modeling and set of methods are applicable to other topics, such as the impact of decarbonization (through a battery smart grid (e.g., smart meter), transportation (e.g., electric vehicle), and energy-efficient buildings), 100%-all-sector-RE (i.e., electricity, heating/cooling, transportation, and industry), oil and NG extraction, or agriculture sector on regional economies. Another expansion of this analysis could include developing nations, as well as other developed countries with similar regulatory mandates. One potential limitation of this work is its monthly time-step. This model cannot be used to estimate minute by minute electricity generation. However, monthly time-step suffices here as the main focus of this research is assessing the regional economic and environmental impacts of electricity. Another caveat is that our model does not calculate electricity rates for each scenario. More expensive scenarios will potentially result in higher electricity rates, which can impact economic activity. This is also important as it has the potential to impact customers' perspective and willingness to pay towards higher level of RE diffusion. Lastly, we assume that employment impacts will be provided 100% by local residents, which is not typically the case in real-world settings; though the model is capable of varying this assumption, we chose not to include herein for the purpose of brevity. Our results provide improved information for state policymakers seeking to alter RPS policies and can also be extrapolated to states with similar energy policies.

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2.8. Appendix

Abbreviation	Definition
AEO	Annual Energy Outlook
EASIUR	Estimating Air Pollution Social Impact Using Regression
eGRID	Emissions and Generation Resource Integrated Database
EIA	Energy Information Administration
EPA	Environmental Protection Agency
FF	Fossil Fuel
FTE	Full-Time Equivalent
GHG	Greenhouse-gas
IMPLAN	Impact Analysis for Planning
JEDI	Jobs and Economic Development Impact
MWh	Megawatt-hour
NG	Natural Gas
NM	New Mexico
NREL	National Renewable Energy Laboratory
O&M	Operating and Maintenance
PV	Utility-Scale Photovoltaic Solar
RE	Renewable Energy
RPS	Renewable Portfolio Standards
RPV	Residential Photovoltaic Solar
SD	System Dynamics

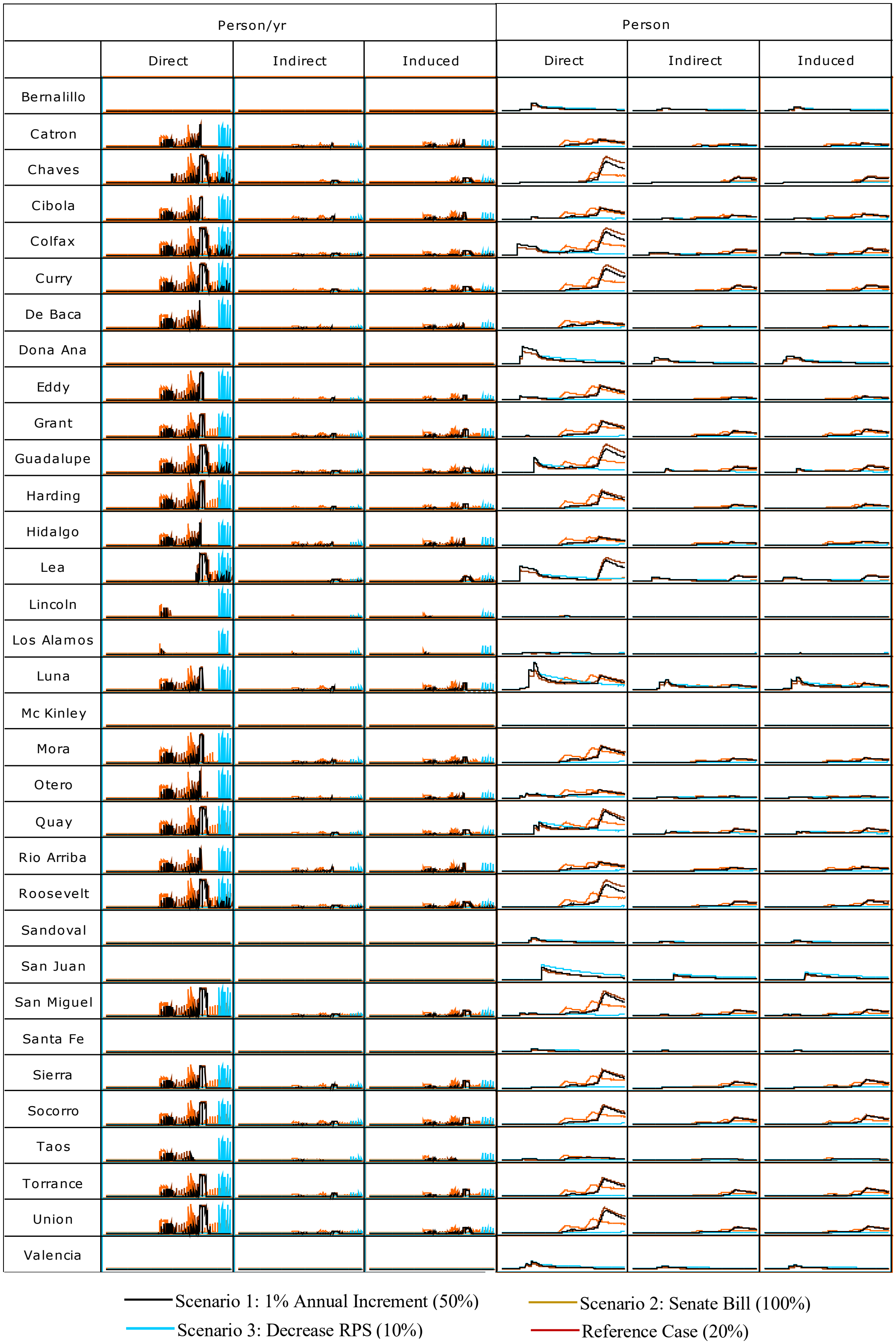


Figure 2-23: PV construction (person/year) and O&M (person) employment under four modeled scenarios.

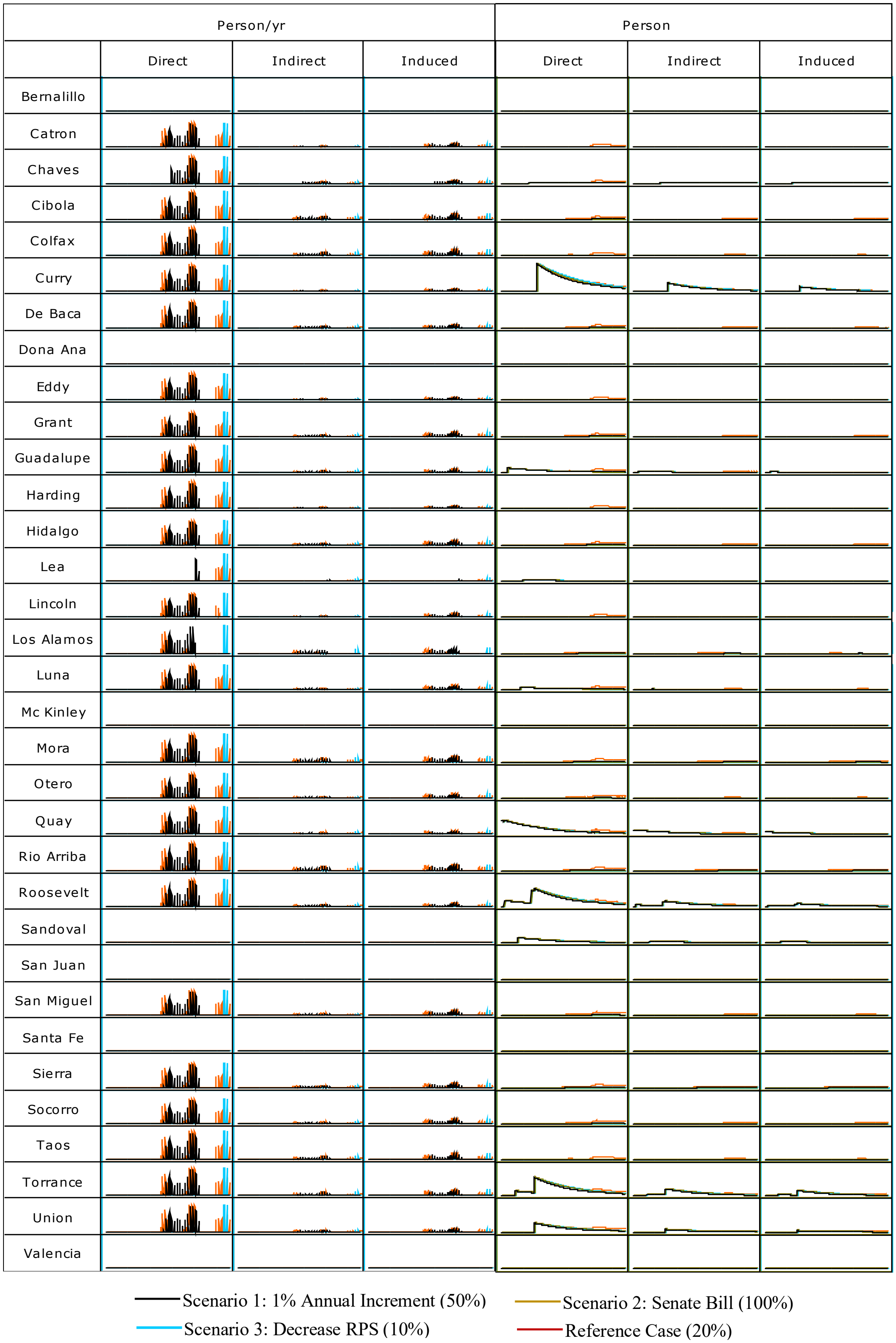


Figure 2-24: Wind construction (person/year) and O&M (person) employment under four modeled scenarios.

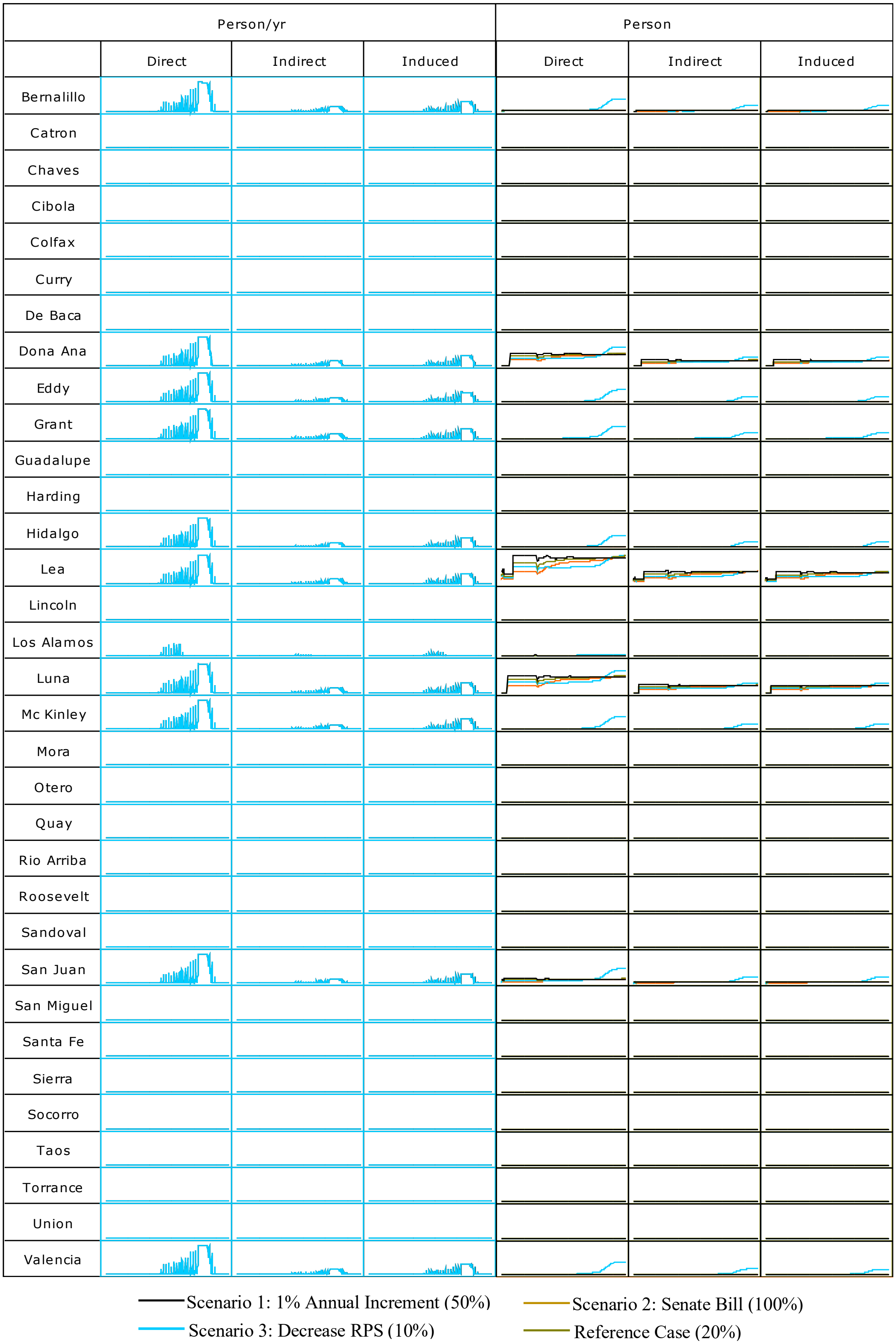
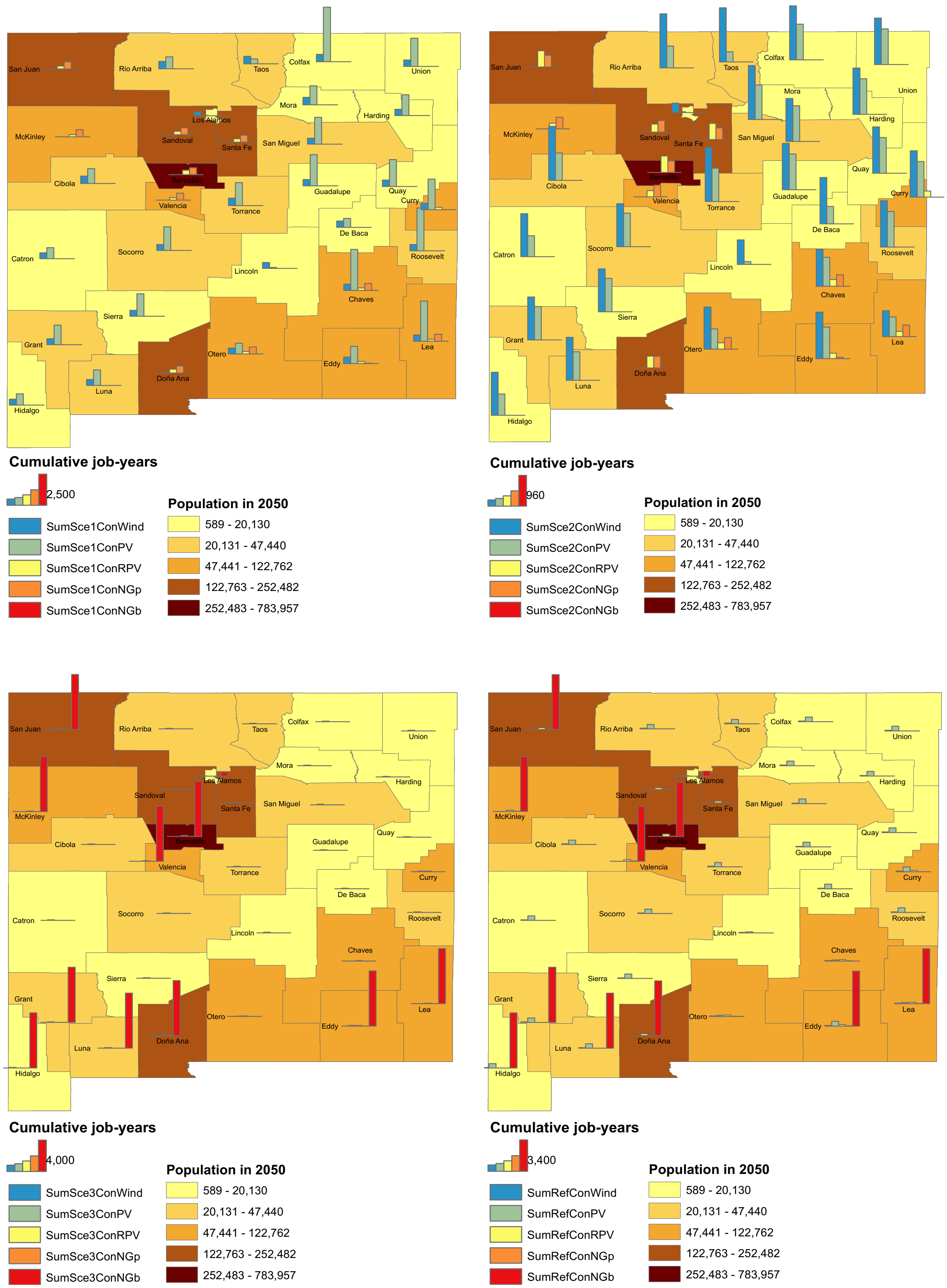
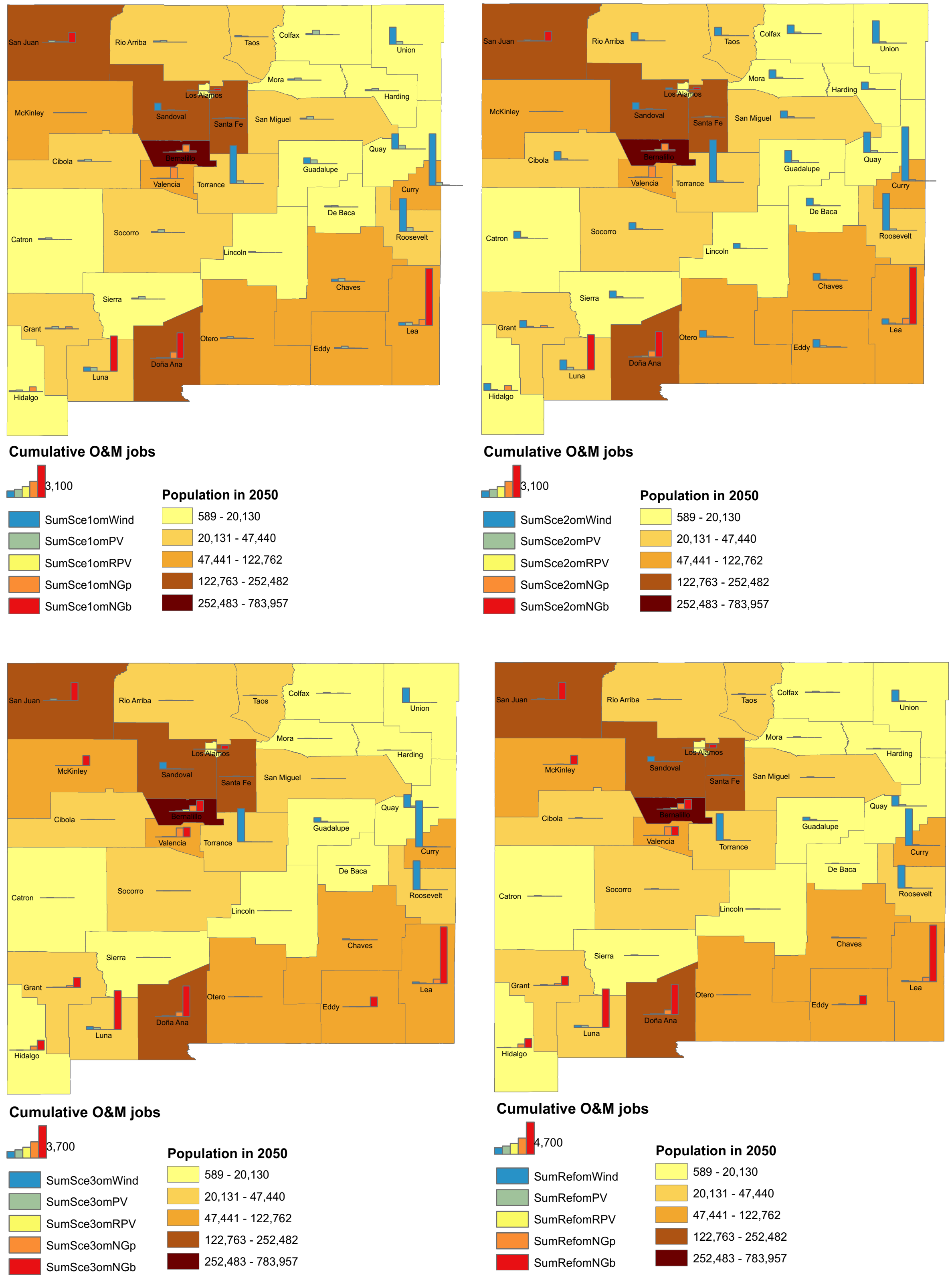


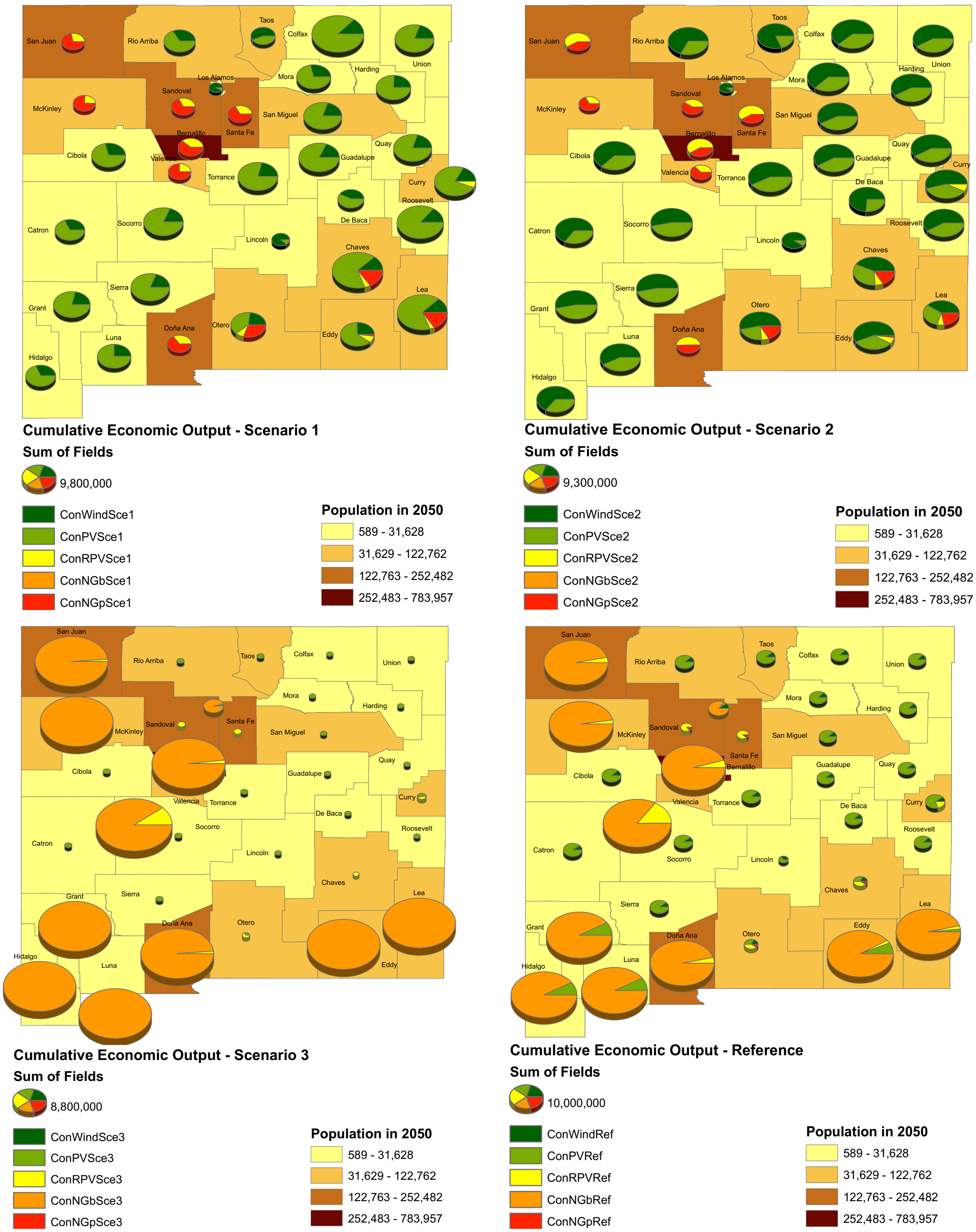
Figure 2-25: NG-BL construction (person/year) and O&M (person) employment under four modeled scenarios.



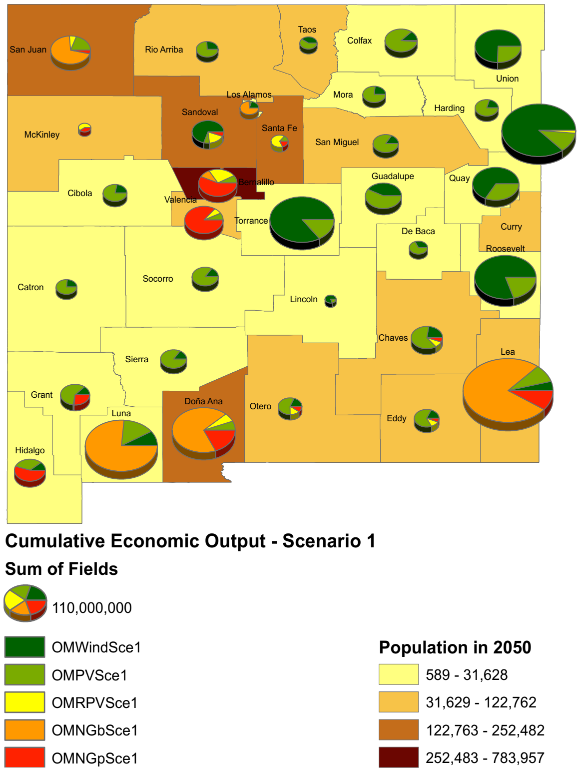
Map 2-8: Cumulative employment impact by energy source during construction from 2017 to January 2050 against 2050 population

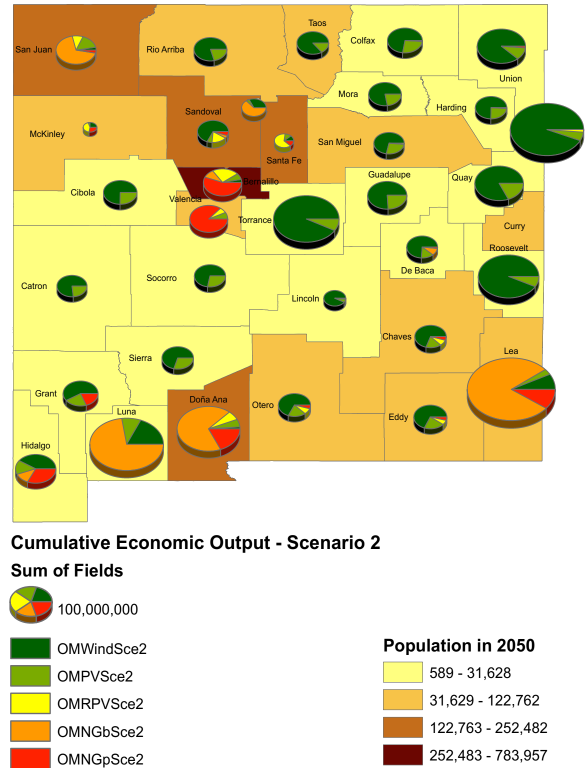


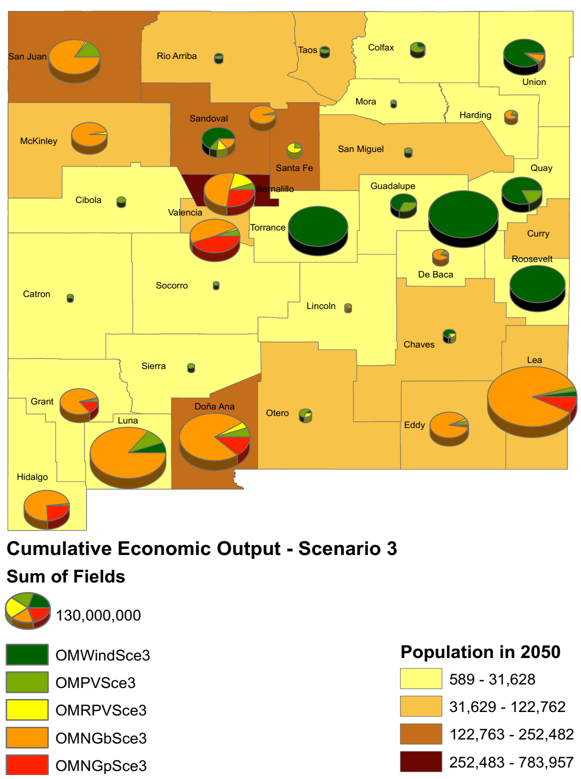
Map 2-9: Cumulative employment impact by energy source during O&M from 2017 to January 2050 against 2050 population

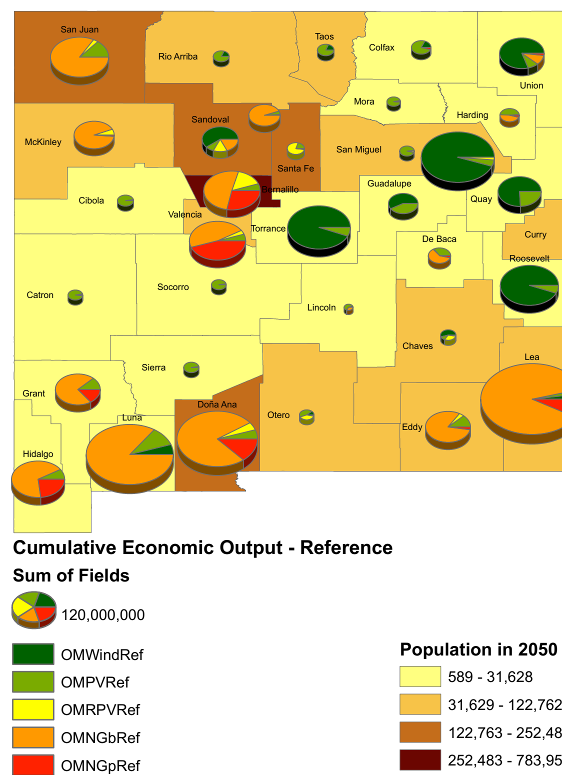


Map 2-10: Cumulative economic output by energy source during construction from 2017 to January 2050 against 2050 population









NOTE: McKinley and San Juan are the only two counties with coal generation. McKinley= 191,651,087 – San Juan = $2,053,135,954.

Map 2-11: Cumulative economic output by energy source during O&M from 2017 to January 2050 against 2050 population

Table 2-15: Annual average employment by energy type and scenario from 2017 to 2050.

	Construction (job-years)			
	Scenario 1	Scenario 2	Scenario 3	Reference Case
Wind	458	1234	0	57
PV	1550	765	56	378
RPV	94	119	32	71
Baseload NG	0	0	2445	2094
Peaker NG	195	127	0	10
	O&M (jobs)			
Wind	636	1,104	594	609
PV	216	113	54	110
RPV	27	27	20	31
Baseload NG	427	427	850	1,001
Peaker NG	132	131	117	146
Coal	498	498	498	498

Table 2-16: Average direct (on-site) construction employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	36	0	0	11	64	0	0	36	10	0	7
Chaves	0	21	0	0	12	71	0	0	40	11	0	7
Cibola	0	42	0	0	12	73	0	0	42	11	0	8
Colfax	0	42	0	0	12	73	0	0	42	11	0	8
Curry	0	41	0	0	12	71	0	0	40	11	0	7
De Baca	0	41	0	0	12	71	0	0	40	11	0	7
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	41	0	0	12	71	0	0	40	11	0	7
Grant	0	36	0	0	11	64	0	0	36	10	0	7
Guadalupe	0	41	0	0	12	71	0	0	40	11	0	7
Harding	0	41	0	0	12	71	0	0	40	11	0	7
Hidalgo	0	36	0	0	11	64	0	0	36	10	0	7
Lea	0	0	0	0	12	67	0	0	40	11	0	7
Lincoln	0	36	0	0	11	18	0	0	36	0	0	7
Los Alamos	0	17	0	0	12	0	0	0	15	0	0	8
Luna	0	36	0	0	11	64	0	0	36	10	0	7
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	42	0	0	12	73	0	0	42	11	0	8
Otero	0	35	0	0	11	64	0	0	36	10	0	7
Quay	0	41	0	0	12	71	0	0	40	11	0	7
Rio Arriba	0	42	0	0	12	73	0	0	42	11	0	8
Roosevelt	0	41	0	0	12	71	0	0	40	11	0	7
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	36	0	0	11	64	0	0	36	10	0	7
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	36	0	0	11	64	0	0	36	10	0	7
Socorro	0	36	0	0	11	64	0	0	36	10	0	7
Taos	0	42	0	0	12	73	0	0	42	11	0	8
Torrance	0	42	0	0	12	73	0	0	42	11	0	8
Union	0	41	0	0	12	71	0	0	40	11	0	7
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-17: Average indirect construction employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	3	0	0	1	4	0	0	2	1	0	0
Chaves	0	2	0	0	1	6	0	0	3	1	0	1
Cibola	0	6	0	0	2	11	0	0	6	2	0	1
Colfax	0	6	0	0	2	11	0	0	6	2	0	1
Curry	0	3	0	0	1	6	0	0	3	1	0	1
De Baca	0	3	0	0	1	6	0	0	3	1	0	1
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	3	0	0	1	6	0	0	3	1	0	1
Grant	0	3	0	0	1	4	0	0	2	1	0	0
Guadalupe	0	3	0	0	1	6	0	0	3	1	0	1
Harding	0	3	0	0	1	6	0	0	3	1	0	1
Hidalgo	0	3	0	0	1	4	0	0	2	1	0	0
Lea	0	0	0	0	1	6	0	0	3	1	0	1
Lincoln	0	3	0	0	1	1	0	0	2	0	0	0
Los Alamos	0	3	0	0	2	0	0	0	2	0	0	1
Luna	0	3	0	0	1	4	0	0	2	1	0	0
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	6	0	0	2	11	0	0	6	2	0	1
Otero	0	2	0	0	1	4	0	0	2	1	0	0
Quay	0	3	0	0	1	6	0	0	3	1	0	1
Rio Arriba	0	6	0	0	2	11	0	0	6	2	0	1
Roosevelt	0	3	0	0	1	6	0	0	3	1	0	1
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	3	0	0	1	4	0	0	2	1	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	3	0	0	1	4	0	0	2	1	0	0
Socorro	0	3	0	0	1	4	0	0	2	1	0	0
Taos	0	6	0	0	2	11	0	0	6	2	0	1
Torrance	0	6	0	0	2	11	0	0	6	2	0	1
Union	0	3	0	0	1	6	0	0	3	1	0	1
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-18: Average induced construction employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	7	0	0	2	12	0	0	7	2	0	1
Chaves	0	3	0	0	2	9	0	0	5	1	0	1
Cibola	0	9	0	0	3	16	0	0	9	2	0	2
Colfax	0	9	0	0	3	16	0	0	9	2	0	2
Curry	0	5	0	0	2	9	0	0	5	1	0	1
De Baca	0	5	0	0	2	9	0	0	5	1	0	1
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	5	0	0	2	9	0	0	5	1	0	1
Grant	0	7	0	0	2	12	0	0	7	2	0	1
Guadalupe	0	5	0	0	2	9	0	0	5	1	0	1
Harding	0	5	0	0	2	9	0	0	5	1	0	1
Hidalgo	0	7	0	0	2	12	0	0	7	2	0	1
Lea	0	0	0	0	2	9	0	0	5	1	0	1
Lincoln	0	7	0	0	2	3	0	0	7	0	0	1
Los Alamos	0	4	0	0	3	0	0	0	3	0	0	2
Luna	0	7	0	0	2	12	0	0	7	2	0	1
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	9	0	0	3	16	0	0	9	2	0	2
Otero	0	6	0	0	2	12	0	0	7	2	0	1
Quay	0	5	0	0	2	9	0	0	5	1	0	1
Rio Arriba	0	9	0	0	3	16	0	0	9	2	0	2
Roosevelt	0	5	0	0	2	9	0	0	5	1	0	1
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	7	0	0	2	12	0	0	7	2	0	1
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	7	0	0	2	12	0	0	7	2	0	1
Socorro	0	7	0	0	2	12	0	0	7	2	0	1
Taos	0	9	0	0	3	16	0	0	9	2	0	2
Torrance	0	9	0	0	3	16	0	0	9	2	0	2
Union	0	5	0	0	2	9	0	0	5	1	0	1
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-19: Average direct (on-site) O&M employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	3	0	0	0	17	0	0	8	36	0	0
Chaves	4	4	4	4	2	15	2	2	10	37	1	2
Cibola	0	4	0	0	0	18	0	0	8	39	0	0
Colfax	0	4	0	0	0	18	0	0	8	39	0	0
Curry	171	156	172	172	85	89	94	94	57	80	60	60
De Baca	0	4	0	0	0	19	0	0	8	39	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	4	0	0	0	19	0	0	8	39	0	0
Grant	0	3	0	0	0	17	0	0	8	36	0	0
Guadalupe	16	18	17	17	8	25	9	9	13	43	6	6
Harding	0	4	0	0	0	19	0	0	8	39	0	0
Hidalgo	0	3	0	0	0	17	0	0	8	36	0	0
Lea	7	6	7	7	3	4	4	4	10	30	2	3
Lincoln	0	3	0	0	0	17	0	0	8	16	0	0
Los Alamos	0	3	0	0	0	4	0	0	5	3	0	0
Luna	11	13	11	11	5	22	6	6	11	39	4	4
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	4	0	0	0	18	0	0	8	39	0	0
Otero	0	3	0	0	0	17	0	0	8	36	0	0
Quay	48	46	48	48	24	38	26	26	22	51	17	17
Rio Arriba	0	4	0	0	0	18	0	0	8	39	0	0
Roosevelt	107	99	108	108	53	63	59	59	39	65	38	38
Sandoval	23	20	23	23	11	9	12	12	6	5	8	8
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	3	0	0	0	17	0	0	8	36	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	3	0	0	0	17	0	0	8	36	0	0
Socorro	0	3	0	0	0	17	0	0	8	36	0	0
Taos	0	4	0	0	0	18	0	0	8	39	0	0
Torrance	110	101	110	110	54	63	60	60	40	65	38	39
Union	54	52	54	54	27	41	30	30	24	52	19	19
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-20: Average indirect O&M employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	1	0	0	0	4	0	0	2	9	0	0
Chaves	1	1	1	1	1	4	1	1	3	11	0	1
Cibola	0	1	0	0	0	7	0	0	3	15	0	0
Colfax	0	1	0	0	0	7	0	0	3	15	0	0
Curry	52	47	52	52	26	27	29	29	17	24	18	18
De Baca	0	1	0	0	0	6	0	0	3	12	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	1	0	0	0	6	0	0	3	12	0	0
Grant	0	1	0	0	0	4	0	0	2	9	0	0
Guadalupe	5	6	5	5	2	8	3	3	4	13	2	2
Harding	0	1	0	0	0	6	0	0	3	12	0	0
Hidalgo	0	1	0	0	0	4	0	0	2	9	0	0
Lea	2	2	2	2	1	1	1	1	3	9	1	1
Lincoln	0	1	0	0	0	4	0	0	2	4	0	0
Los Alamos	0	1	0	0	0	2	0	0	2	1	0	0
Luna	3	3	3	3	1	5	2	2	3	10	1	1
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	1	0	0	0	7	0	0	3	15	0	0
Otero	0	1	0	0	0	4	0	0	2	9	0	0
Quay	14	14	14	14	7	12	8	8	7	15	5	5
Rio Arriba	0	1	0	0	0	7	0	0	3	15	0	0
Roosevelt	33	30	33	33	16	19	18	18	12	20	11	12
Sandoval	9	8	9	9	4	4	5	5	2	2	3	3
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	1	0	0	0	4	0	0	2	9	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	1	0	0	0	4	0	0	2	9	0	0
Socorro	0	1	0	0	0	4	0	0	2	9	0	0
Taos	0	1	0	0	0	7	0	0	3	15	0	0
Torrance	42	39	42	42	21	24	23	23	15	25	15	15
Union	16	16	16	16	8	12	9	9	7	16	6	6
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-21: Average induced O&M employment impact of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	1	0	0	0	4	0	0	2	8	0	0
Chaves	1	1	1	1	0	3	0	0	2	6	0	0
Cibola	0	1	0	0	0	5	0	0	3	12	0	0
Colfax	0	1	0	0	0	5	0	0	3	12	0	0
Curry	30	27	30	30	15	15	16	16	10	14	10	10
De Baca	0	1	0	0	0	3	0	0	1	7	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	1	0	0	0	3	0	0	1	7	0	0
Grant	0	1	0	0	0	4	0	0	2	8	0	0
Guadalupe	3	3	3	3	1	4	2	2	2	7	1	1
Harding	0	1	0	0	0	3	0	0	1	7	0	0
Hidalgo	0	1	0	0	0	4	0	0	2	8	0	0
Lea	1	1	1	1	1	1	1	1	2	5	0	0
Lincoln	0	1	0	0	0	4	0	0	2	4	0	0
Los Alamos	0	1	0	0	0	1	0	0	1	1	0	0
Luna	2	3	2	2	1	5	1	1	2	9	1	1
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	1	0	0	0	5	0	0	3	12	0	0
Otero	0	1	0	0	0	4	0	0	2	8	0	0
Quay	8	8	8	8	4	7	5	5	4	9	3	3
Rio Arriba	0	1	0	0	0	5	0	0	3	12	0	0
Roosevelt	19	17	19	19	9	11	10	10	7	11	7	7
Sandoval	7	6	7	7	3	3	4	4	2	2	2	2
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	1	0	0	0	4	0	0	2	8	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	1	0	0	0	4	0	0	2	8	0	0
Socorro	0	1	0	0	0	4	0	0	2	8	0	0
Taos	0	1	0	0	0	5	0	0	3	12	0	0
Torrance	33	30	33	33	16	19	18	18	12	19	11	12
Union	9	9	9	9	5	7	5	5	4	9	3	3
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-22: Average direct (on-site) construction employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	29	24	4	20	27	16	0	0	0	0	0	11
Chaves	7	17	0	0	184	51	0	0	108	7	0	13
Cibola	29	24	4	20	51	31	0	0	0	0	0	11
Colfax	36	30	5	25	184	51	0	0	171	7	0	13
Curry	36	30	5	25	167	51	0	0	0	7	0	13
De Baca	36	30	5	25	13	6	0	0	0	0	0	13
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	36	30	5	25	72	45	0	0	0	0	0	13
Grant	29	24	4	20	79	41	0	0	0	6	0	11
Guadalupe	36	30	5	25	172	51	0	0	0	7	0	13
Harding	36	30	5	25	98	51	0	0	0	7	0	13
Hidalgo	29	24	4	20	28	17	0	0	0	0	0	11
Lea	0	0	0	0	146	49	0	0	155	7	0	13
Lincoln	4	6	5	7	0	0	0	0	0	0	0	0
Los Alamos	1	1	1	2	0	0	0	0	0	0	0	0
Luna	29	24	4	20	54	34	0	0	0	0	0	11
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	36	30	5	25	85	51	0	0	0	3	0	13
Otero	33	29	2	0	30	16	0	0	0	0	0	13
Quay	36	30	5	25	141	51	0	0	0	7	0	13
Rio Arriba	29	24	4	20	33	18	0	0	0	0	0	11
Roosevelt	36	30	5	25	184	51	0	0	79	7	0	13
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	36	30	5	25	141	51	0	0	0	7	0	13
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	29	24	4	20	96	41	0	0	0	6	0	11
Socorro	29	24	4	20	103	41	0	0	0	6	0	11
Taos	21	17	4	20	0	0	0	0	0	0	0	11
Torrance	29	24	4	20	100	41	0	0	0	6	0	11
Union	36	30	5	25	150	51	0	0	0	7	0	13
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-23: Average indirect construction employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	5	4	1	3	5	3	0	0	0	0	0	2
Chaves	1	2	0	0	17	5	0	0	10	1	0	1
Cibola	5	4	1	3	9	5	0	0	0	0	0	2
Colfax	3	3	0	2	17	5	0	0	16	1	0	1
Curry	3	3	0	2	16	5	0	0	0	1	0	1
De Baca	3	3	0	2	1	1	0	0	0	0	0	1
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	3	3	0	2	7	4	0	0	0	0	0	1
Grant	5	4	1	3	13	7	0	0	0	1	0	2
Guadalupe	3	3	0	2	16	5	0	0	0	1	0	1
Harding	3	3	0	2	9	5	0	0	0	1	0	1
Hidalgo	5	4	1	3	5	3	0	0	0	0	0	2
Lea	0	0	0	0	14	5	0	0	15	1	0	1
Lincoln	0	1	0	1	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	5	4	1	3	9	6	0	0	0	0	0	2
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	3	3	0	2	8	5	0	0	0	0	0	1
Otero	3	3	0	0	3	1	0	0	0	0	0	1
Quay	3	3	0	2	13	5	0	0	0	1	0	1
Rio Arriba	5	4	1	3	6	3	0	0	0	0	0	2
Roosevelt	3	3	0	2	17	5	0	0	7	1	0	1
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	3	3	0	2	13	5	0	0	0	1	0	1
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	5	4	1	3	16	7	0	0	0	1	0	2
Socorro	5	4	1	3	17	7	0	0	0	1	0	2
Taos	3	3	1	3	0	0	0	0	0	0	0	2
Torrance	5	4	1	3	17	7	0	0	0	1	0	2
Union	3	3	0	2	14	5	0	0	0	1	0	1
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-24: Average induced construction employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	10	8	1	7	9	5	0	0	0	0	0	4
Chaves	1	3	0	0	36	10	0	0	21	1	0	3
Cibola	10	8	1	7	17	11	0	0	0	0	0	4
Colfax	7	6	1	5	36	10	0	0	34	1	0	3
Curry	7	6	1	5	33	10	0	0	0	1	0	3
De Baca	7	6	1	5	3	1	0	0	0	0	0	3
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	7	6	1	5	14	9	0	0	0	0	0	3
Grant	10	8	1	7	27	14	0	0	0	2	0	4
Guadalupe	7	6	1	5	34	10	0	0	0	1	0	3
Harding	7	6	1	5	19	10	0	0	0	1	0	3
Hidalgo	10	8	1	7	9	6	0	0	0	0	0	4
Lea	0	0	0	0	29	10	0	0	30	1	0	3
Lincoln	1	1	1	1	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	1	0	0	0	0	0	0	0	0
Luna	10	8	1	7	18	12	0	0	0	0	0	4
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	7	6	1	5	17	10	0	0	0	1	0	3
Otero	6	6	0	0	6	3	0	0	0	0	0	3
Quay	7	6	1	5	28	10	0	0	0	1	0	3
Rio Arriba	10	8	1	7	11	6	0	0	0	0	0	4
Roosevelt	7	6	1	5	36	10	0	0	16	1	0	3
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	7	6	1	5	28	10	0	0	0	1	0	3
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	10	8	1	7	32	14	0	0	0	2	0	4
Socorro	10	8	1	7	35	14	0	0	0	2	0	4
Taos	7	6	1	7	0	0	0	0	0	0	0	4
Torrance	10	8	1	7	34	14	0	0	0	2	0	4
Union	7	6	1	5	29	10	0	0	0	1	0	3
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-25: Average direct (on-site) O&M employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	1	2	2	1	0	1	1	0	0	1	1
Catron	1	1	0	2	4	3	0	2	4	2	0	1
Chaves	0	0	0	0	4	2	0	0	21	5	0	0
Cibola	2	1	1	3	5	3	1	2	6	4	0	2
Colfax	3	2	2	4	7	4	2	3	24	6	1	3
Curry	1	1	0	2	6	3	0	2	15	6	0	2
De Baca	1	1	0	2	4	3	0	2	3	2	0	2
Dona Ana	3	2	3	3	1	1	2	2	1	1	1	1
Eddy	2	1	1	3	6	3	1	2	7	5	1	2
Grant	1	1	0	2	5	3	0	2	8	5	0	1
Guadalupe	4	3	3	6	7	4	2	4	16	6	2	3
Harding	1	1	0	2	6	3	0	2	9	6	0	2
Hidalgo	1	1	0	2	4	3	0	2	4	3	0	1
Lea	2	2	3	3	2	1	2	2	20	4	1	1
Lincoln	0	0	0	1	0	0	0	1	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	6	5	6	8	7	5	4	5	7	5	3	4
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	1	1	0	2	6	3	0	2	8	5	0	2
Otero	2	2	1	1	5	3	1	1	4	3	1	1
Quay	5	4	5	7	8	5	3	5	14	6	2	4
Rio Arriba	1	1	0	2	4	3	0	2	4	3	0	1
Roosevelt	1	1	0	2	6	3	0	2	21	6	0	2
Sandoval	1	1	1	1	0	0	1	1	0	0	0	0
San Juan	3	3	5	5	2	2	3	3	1	1	2	2
San Miguel	2	1	1	3	6	3	1	2	13	6	0	2
Santa Fe	1	0	1	1	0	0	0	0	0	0	0	0
Sierra	1	1	1	2	5	3	0	2	10	5	0	2
Socorro	1	1	0	2	5	3	0	2	10	5	0	1
Taos	1	1	1	2	2	2	0	2	1	1	0	2
Torrance	1	1	0	2	5	3	0	2	10	5	0	1
Union	1	1	0	2	6	3	0	2	13	6	0	2
Valencia	1	1	1	1	1	0	1	1	0	0	1	1

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-26: Average indirect O&M employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	1	1	0	0	0	0	0	0	0	0
Catron	0	0	0	1	2	1	0	1	1	1	0	1
Chaves	0	0	0	0	1	1	0	0	5	1	0	0
Cibola	1	0	0	1	2	1	0	1	2	1	0	1
Colfax	1	1	1	1	2	1	0	1	6	1	0	1
Curry	0	0	0	1	1	1	0	0	4	1	0	0
De Baca	0	0	0	1	1	1	0	0	1	0	0	0
Dona Ana	1	1	1	1	0	0	1	1	0	0	0	0
Eddy	0	0	0	1	1	1	0	1	2	1	0	0
Grant	0	0	0	1	2	1	0	1	3	2	0	1
Guadalupe	1	1	1	1	2	1	1	1	4	1	0	1
Harding	0	0	0	1	1	1	0	0	2	1	0	0
Hidalgo	0	0	0	1	2	1	0	1	1	1	0	1
Lea	1	0	1	1	0	0	0	0	5	1	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	2	2	2	3	3	2	1	2	3	2	1	1
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	0	0	1	1	1	0	0	2	1	0	0
Otero	1	0	0	0	1	1	0	0	1	1	0	0
Quay	1	1	1	2	2	1	1	1	3	2	1	1
Rio Arriba	0	0	0	1	2	1	0	1	1	1	0	1
Roosevelt	0	0	0	1	1	1	0	0	5	1	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	1	1	2	2	1	1	1	1	1	0	1	1
San Miguel	0	0	0	1	1	1	0	1	3	1	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	1	2	1	0	1	3	2	0	1
Socorro	0	0	0	1	2	1	0	1	4	2	0	1
Taos	0	0	0	1	1	1	0	1	0	0	0	1
Torrance	0	0	0	1	2	1	0	1	4	2	0	1
Union	0	0	0	1	1	1	0	0	3	1	0	0
Valencia	0	0	1	1	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-27: Average induced O&M employment impact of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	0	1	1	0	0	0	0	0	0	0	0
Catron	1	0	0	1	2	1	0	1	2	1	0	1
Chaves	0	0	0	0	1	1	0	0	6	1	0	0
Cibola	1	0	0	1	2	1	0	1	3	2	0	1
Colfax	1	1	1	1	2	1	0	1	6	2	0	1
Curry	0	0	0	1	2	1	0	1	4	1	0	0
De Baca	0	0	0	1	1	1	0	1	1	1	0	0
Dona Ana	1	1	1	1	1	0	1	1	0	0	1	1
Eddy	1	0	0	1	2	1	0	1	2	1	0	1
Grant	1	0	0	1	2	1	0	1	4	2	0	1
Guadalupe	1	1	1	1	2	1	1	1	4	2	0	1
Harding	0	0	0	1	2	1	0	1	2	1	0	0
Hidalgo	1	0	0	1	2	1	0	1	2	1	0	1
Lea	1	0	1	1	1	0	0	0	5	1	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	3	2	3	4	3	2	2	2	3	2	1	2
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	0	0	1	2	1	0	1	2	1	0	0
Otero	1	0	0	0	1	1	0	0	1	1	0	0
Quay	1	1	1	2	2	1	1	1	4	2	1	1
Rio Arriba	1	0	0	1	2	1	0	1	2	1	0	1
Roosevelt	0	0	0	1	2	1	0	1	6	1	0	0
Sandoval	0	0	1	1	0	0	0	0	0	0	0	0
San Juan	2	1	2	2	1	1	2	2	1	0	1	1
San Miguel	0	0	0	1	2	1	0	1	3	2	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	1	0	0	1	2	1	0	1	4	2	0	1
Socorro	1	0	0	1	2	1	0	1	5	2	0	1
Taos	1	0	0	1	1	1	0	1	1	0	0	1
Torrance	1	0	0	1	2	1	0	1	5	2	0	1
Union	0	0	0	1	2	1	0	1	4	1	0	0
Valencia	1	0	1	1	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-28: Average direct (on-site) construction employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	7	8	1	4	8	14	3	6	11	14	4	9
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	8	10	1	5	4	2	1	2	3	0	1	2
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	8	10	1	5	4	0	1	2	2	0	1	1
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	7	8	1	4	6	14	2	4	9	1	2	5
Eddy	8	9	1	5	3	0	1	2	0	0	1	2
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	8	8	1	5	3	0	1	2	0	0	1	2
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	7	8	1	4	3	0	0	2	1	0	1	1
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	8	10	1	5	4	0	1	2	2	0	1	2
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	7	8	1	4	5	5	1	3	7	0	2	4
San Juan	7	8	1	4	5	13	1	3	3	14	2	4
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	7	8	1	4	5	13	1	3	8	14	2	4
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	7	8	1	4	3	1	1	2	2	0	1	2

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-29: Average indirect construction employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	1	0	1	1	2	0	1	2	2	1	2
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	1	1	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	1	1	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1	1	0	1	1	2	0	1	2	0	0	1
Eddy	1	1	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	1	1	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	1	1	0	1	1	0	0	0	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	1	1	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	1	1	0	1	1	1	0	1	1	0	0	1
San Juan	1	1	0	1	1	2	0	1	1	2	0	1
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	1	1	0	1	1	2	0	1	1	2	0	1
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	1	1	0	1	1	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-30: Average induced construction employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	2	3	0	1	3	5	1	2	4	5	1	3
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	2	2	0	1	1	0	0	0	1	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	2	2	0	1	1	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	2	3	0	1	2	5	1	1	3	0	1	2
Eddy	2	2	0	1	1	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	2	2	0	1	1	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	2	3	0	1	1	0	0	1	0	0	0	1
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	2	2	0	1	1	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	2	3	0	1	2	2	0	1	2	0	1	1
San Juan	2	3	0	1	2	4	0	1	1	5	1	2
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	2	3	0	1	2	4	0	1	3	5	1	2
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	2	3	0	1	1	0	0	1	1	0	0	1

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-31: Average direct (on-site) O&M employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	4	4	5	5	2	2	3	4	3	3	2	3
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	1	1	1	1	1	1	0	1	1	0	0	1
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	1	1	1	1	1	1	0	1	1	0	0	1
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	2	2	2	2	2	2	1	2	2	2	1	2
Eddy	1	1	1	1	1	1	0	1	1	0	0	1
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	1	1	1	1	1	1	0	1	1	0	0	1
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	1	1	0	1	1	1	0	1	1	0	0	1
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	1	1	1	1	1	1	0	1	1	0	0	1
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	2	2	2	2	1	1	1	2	2	1	1	2
San Juan	1	1	0	1	1	2	0	1	1	3	0	1
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	2	2	2	2	1	2	1	2	2	3	1	2
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	1	1	0	1	1	1	0	1	1	0	0	1

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-32: Average indirect O&M employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	2	1	2	2	1	1	1	1	1	1	1	1
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1	1	1	1	1	1	0	1	1	1	0	1
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	1	1	1	1	0	0	0	1	1	0	0	1
San Juan	0	0	0	0	0	1	0	0	0	1	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	1	1	1	1	1	1	0	1	1	1	0	1
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-33: Average induced O&M employment impact of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	2	2	2	2	1	1	1	2	1	1	1	2
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1	1	1	1	1	1	1	1	1	1	1	1
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	1	1	1	1	1	1	0	1	1	0	0	1
San Juan	0	0	0	0	0	1	0	0	1	1	0	1
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	1	1	1	1	1	1	1	1	1	1	0	1
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-34: Average direct (on-site) construction employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	3	7	0	1	21	17	0	0	21	2	0	1
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	3	7	0	1	21	17	0	0	21	2	0	1
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	3	7	0	1	21	17	0	0	21	2	0	1
Eddy	2	2	0	1	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	3	7	0	1	21	17	0	0	21	2	0	1
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	3	7	0	1	21	17	0	0	21	2	0	1
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	3	7	0	1	21	17	0	0	21	2	0	1
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	3	7	0	1	21	17	0	0	21	2	0	1
San Juan	3	7	0	1	21	17	0	0	21	2	0	1
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	3	7	0	1	21	17	0	0	21	2	0	1
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	3	7	0	1	21	17	0	0	21	2	0	1

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-35: Average indirect construction employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	1	0	0	3	3	0	0	3	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	1	0	0	3	3	0	0	3	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	1	0	0	3	3	0	0	3	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	1	0	0	3	3	0	0	3	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	1	0	0	3	3	0	0	3	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	1	0	0	3	3	0	0	3	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	1	0	0	3	3	0	0	3	0	0	0
San Juan	0	1	0	0	3	3	0	0	3	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	1	0	0	3	3	0	0	3	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	1	0	0	3	3	0	0	3	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-36: Average induced construction employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	2	0	0	7	6	0	0	7	1	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	1	2	0	0	7	6	0	0	7	1	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1	2	0	0	7	6	0	0	7	1	0	0
Eddy	1	1	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	1	2	0	0	7	6	0	0	7	1	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	1	2	0	0	7	6	0	0	7	1	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	1	2	0	0	7	6	0	0	7	1	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	1	2	0	0	7	6	0	0	7	1	0	0
San Juan	1	2	0	0	7	6	0	0	7	1	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	1	2	0	0	7	6	0	0	7	1	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	1	2	0	0	7	6	0	0	7	1	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-37: Average direct (on-site) O&M employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	14	14	14	16	11	11	11	14	11	11	9	12
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	1	0	0	2	2	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	12	12	12	14	10	10	9	12	10	9	7	10
Eddy	1	1	1	1	1	1	0	1	0	0	0	1
Grant	4	4	4	5	3	3	3	4	3	3	3	4
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	10	10	10	11	8	7	7	9	6	6	6	8
Lea	11	11	11	13	9	9	9	11	10	9	7	10
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	0	0	0	1	1	0	0	2	2	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	1	0	0	2	2	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	1	0	0	2	2	0	0
San Juan	0	0	0	0	0	1	0	0	2	2	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	1	0	0	2	2	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	23	22	22	26	18	18	17	22	17	16	14	19

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-38: Average indirect O&M employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	6	6	6	7	5	5	5	6	5	5	4	6
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	1	1	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	5	5	5	6	4	4	4	5	4	4	3	5
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	2	2	2	2	1	1	1	2	1	1	1	2
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	4	4	4	5	3	3	3	4	3	3	3	4
Lea	5	5	5	6	4	4	4	5	4	4	3	5
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	0	0	0	0	0	0	0	1	1	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	1	1	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	1	1	0	0
San Juan	0	0	0	0	0	0	0	0	1	1	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	1	1	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	10	10	10	12	8	8	8	10	8	7	6	9

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-39: Average induced O&M employment impact of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	6	6	6	7	5	5	5	6	5	5	4	5
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	1	1	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	5	5	5	6	4	4	4	5	4	4	3	4
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	2	2	2	2	1	1	1	2	1	1	1	2
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	4	4	4	5	3	3	3	4	3	3	3	4
Lea	5	5	5	6	4	4	4	5	4	4	3	4
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	0	0	0	0	0	0	0	0	1	1	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	1	1	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	1	1	0	0
San Juan	0	0	0	0	0	0	0	0	1	1	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	1	1	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	10	10	10	11	8	8	8	10	7	7	6	8

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-40: Average direct (on-site) construction employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	56	23	0	0	315	321	0	0	183	127
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	56	28	0	0	315	321	0	0	183	127
Eddy	0	0	56	30	0	0	315	321	0	0	183	127
Grant	0	0	56	30	0	0	315	321	0	0	183	127
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	56	30	0	0	315	321	0	0	183	127
Lea	0	0	56	29	0	0	315	321	0	0	183	127
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	29	30	0	0	0	0	0	0	0	0
Luna	0	0	56	30	0	0	315	321	0	0	183	127
Mc Kinley	0	0	56	29	0	0	315	321	0	0	183	127
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	56	28	0	0	315	321	0	0	183	127
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	56	29	0	0	315	321	0	0	183	127

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-41: Average indirect construction employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	8	4	0	0	47	48	0	0	28	19
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	8	4	0	0	47	48	0	0	28	19
Eddy	0	0	8	4	0	0	47	48	0	0	28	19
Grant	0	0	8	4	0	0	47	48	0	0	28	19
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	8	5	0	0	47	48	0	0	28	19
Lea	0	0	8	4	0	0	47	48	0	0	28	19
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	4	4	0	0	0	0	0	0	0	0
Luna	0	0	8	4	0	0	47	48	0	0	28	19
Mc Kinley	0	0	8	4	0	0	47	48	0	0	28	19
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	8	4	0	0	47	48	0	0	28	19
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	8	4	0	0	47	48	0	0	28	19

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-42: Average induced construction employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	18	8	0	0	104	106	0	0	61	42
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	19	9	0	0	104	106	0	0	61	42
Eddy	0	0	19	10	0	0	104	106	0	0	61	42
Grant	0	0	19	10	0	0	104	106	0	0	61	42
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	19	10	0	0	104	106	0	0	61	42
Lea	0	0	19	10	0	0	104	106	0	0	61	42
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	10	10	0	0	0	0	0	0	0	0
Luna	0	0	19	10	0	0	104	106	0	0	61	42
Mc Kinley	0	0	19	10	0	0	104	106	0	0	61	42
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	19	9	0	0	104	106	0	0	61	42
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	19	10	0	0	104	106	0	0	61	42

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-43: Average direct (on-site) O&M employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	2	2	4	3	2	2	18	17	2	2	63	79
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	44	44	46	54	44	44	60	72	43	43	104	139
Eddy	0	0	2	1	0	0	16	15	0	0	61	77
Grant	0	0	2	1	0	0	16	15	0	0	61	77
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	2	1	0	0	16	15	0	0	61	78
Lea	99	100	102	119	98	98	114	144	97	97	158	215
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	4	4	6	6	4	4	9	12	4	4	9	13
Luna	61	62	64	74	61	61	77	95	60	60	121	163
Mc Kinley	0	0	2	1	0	0	16	15	0	0	61	77
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	17	17	19	21	17	17	33	37	17	17	78	101
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	2	1	0	0	16	15	0	0	61	77

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-44: Average indirect O&M employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	1	2	2	1	1	8	8	1	1	29	36
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	20	20	21	24	20	20	27	33	20	20	47	63
Eddy	0	0	1	0	0	0	7	7	0	0	28	35
Grant	0	0	1	0	0	0	7	7	0	0	28	35
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	1	0	0	0	7	7	0	0	28	35
Lea	45	45	46	54	45	45	52	65	44	44	72	98
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	2	2	3	3	2	2	4	6	2	2	4	6
Luna	28	28	29	34	28	28	35	43	27	27	55	74
Mc Kinley	0	0	1	0	0	0	7	7	0	0	28	35
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	8	8	9	10	8	8	15	17	8	8	35	46
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	1	0	0	0	7	7	0	0	28	35

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-45: Average induced O&M employment impact of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1	1	2	2	1	1	8	7	1	1	27	34
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	19	19	20	23	19	19	26	32	19	19	45	60
Eddy	0	0	1	0	0	0	7	7	0	0	27	34
Grant	0	0	1	0	0	0	7	7	0	0	27	34
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	1	0	0	0	7	7	0	0	27	34
Lea	43	43	44	52	43	43	50	63	42	42	69	94
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	2	2	3	3	2	2	4	5	2	2	4	6
Luna	27	27	28	32	27	26	33	41	26	26	53	71
Mc Kinley	0	0	1	0	0	0	7	7	0	0	27	34
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	7	8	8	9	7	7	14	16	7	7	34	44
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	1	0	0	0	7	7	0	0	27	34

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-46: Average direct (on-site) O&M employment impact of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	40	40	40	42	16	11	11	12	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	372	367	367	379	244	205	205	218	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-47: Average indirect O&M employment impact of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	18	18	18	19	7	5	5	5	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	169	167	167	172	111	93	93	99	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-48: Average induced O&M employment impact of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*				2031–2040*				2041–2050*			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	17	18	18	18	7	5	5	5	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	162	160	160	165	106	90	90	95	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and Ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-49: Average direct (on-site) gross economic output impact during construction of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	349	0	0	115	619	0	0	390	239	0	63
Chaves	0	155	0	0	115	619	0	0	390	239	0	63
Cibola	0	349	0	0	115	619	0	0	390	239	0	63
Colfax	0	349	0	0	115	619	0	0	390	239	0	63
Curry	0	349	0	0	115	619	0	0	390	239	0	63
De Baca	0	349	0	0	115	619	0	0	390	239	0	63
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	349	0	0	115	619	0	0	390	239	0	63
Grant	0	349	0	0	115	619	0	0	390	239	0	63
Guadalupe	0	349	0	0	115	619	0	0	390	239	0	63
Harding	0	349	0	0	115	619	0	0	390	239	0	63
Hidalgo	0	349	0	0	115	619	0	0	390	239	0	63
Lea	0	0	0	0	115	524	0	0	390	239	0	63
Lincoln	0	349	0	0	115	261	0	0	390	2	0	63
Los Alamos	0	162	0	0	115	2	0	0	145	0	0	63
Luna	0	349	0	0	115	619	0	0	390	239	0	63
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	349	0	0	115	619	0	0	390	239	0	63
Otero	0	332	0	0	115	619	0	0	390	239	0	63
Quay	0	349	0	0	115	619	0	0	390	239	0	63
Rio Arriba	0	349	0	0	115	619	0	0	390	239	0	63
Roosevelt	0	349	0	0	115	619	0	0	390	239	0	63
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	349	0	0	115	619	0	0	390	239	0	63
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	349	0	0	115	619	0	0	390	239	0	63
Socorro	0	349	0	0	115	619	0	0	390	239	0	63
Taos	0	349	0	0	115	619	0	0	390	239	0	63
Torrance	0	349	0	0	115	619	0	0	390	239	0	63
Union	0	349	0	0	115	619	0	0	390	239	0	63
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-50: Average indirect gross economic output impact during construction of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	23	0	0	8	41	0	0	26	16	0	4
Chaves	0	16	0	0	12	65	0	0	41	25	0	7
Cibola	0	62	0	0	20	110	0	0	70	42	0	11
Colfax	0	62	0	0	20	110	0	0	70	42	0	11
Curry	0	37	0	0	12	65	0	0	41	25	0	7
De Baca	0	37	0	0	12	65	0	0	41	25	0	7
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	37	0	0	12	65	0	0	41	25	0	7
Grant	0	23	0	0	8	41	0	0	26	16	0	4
Guadalupe	0	37	0	0	12	65	0	0	41	25	0	7
Harding	0	37	0	0	12	65	0	0	41	25	0	7
Hidalgo	0	23	0	0	8	41	0	0	26	16	0	4
Lea	0	0	0	0	12	55	0	0	41	25	0	7
Lincoln	0	23	0	0	8	17	0	0	26	0	0	4
Los Alamos	0	29	0	0	20	0	0	0	26	0	0	11
Luna	0	23	0	0	8	41	0	0	26	16	0	4
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	62	0	0	20	110	0	0	70	42	0	11
Otero	0	22	0	0	8	41	0	0	26	16	0	4
Quay	0	37	0	0	12	65	0	0	41	25	0	7
Rio Arriba	0	62	0	0	20	110	0	0	70	42	0	11
Roosevelt	0	37	0	0	12	65	0	0	41	25	0	7
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	23	0	0	8	41	0	0	26	16	0	4
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	23	0	0	8	41	0	0	26	16	0	4
Socorro	0	23	0	0	8	41	0	0	26	16	0	4
Taos	0	62	0	0	20	110	0	0	70	42	0	11
Torrance	0	62	0	0	20	110	0	0	70	42	0	11
Union	0	37	0	0	12	65	0	0	41	25	0	7
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-51: Average induced gross economic output impact during construction of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	55	0	0	18	97	0	0	61	37	0	10
Chaves	0	23	0	0	17	93	0	0	59	36	0	9
Cibola	0	91	0	0	30	161	0	0	101	62	0	16
Colfax	0	91	0	0	30	161	0	0	101	62	0	16
Curry	0	52	0	0	17	93	0	0	59	36	0	9
De Baca	0	52	0	0	17	93	0	0	59	36	0	9
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	52	0	0	17	93	0	0	59	36	0	9
Grant	0	55	0	0	18	97	0	0	61	37	0	10
Guadalupe	0	52	0	0	17	93	0	0	59	36	0	9
Harding	0	52	0	0	17	93	0	0	59	36	0	9
Hidalgo	0	55	0	0	18	97	0	0	61	37	0	10
Lea	0	0	0	0	17	79	0	0	59	36	0	9
Lincoln	0	55	0	0	18	41	0	0	61	0	0	10
Los Alamos	0	42	0	0	30	0	0	0	38	0	0	16
Luna	0	55	0	0	18	97	0	0	61	37	0	10
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	91	0	0	30	161	0	0	101	62	0	16
Otero	0	52	0	0	18	97	0	0	61	37	0	10
Quay	0	52	0	0	17	93	0	0	59	36	0	9
Rio Arriba	0	91	0	0	30	161	0	0	101	62	0	16
Roosevelt	0	52	0	0	17	93	0	0	59	36	0	9
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	55	0	0	18	97	0	0	61	37	0	10
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	55	0	0	18	97	0	0	61	37	0	10
Socorro	0	55	0	0	18	97	0	0	61	37	0	10
Taos	0	91	0	0	30	161	0	0	101	62	0	16
Torrance	0	91	0	0	30	161	0	0	101	62	0	16
Union	0	52	0	0	17	93	0	0	59	36	0	9
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-52: Average direct (on-site) gross economic output impact during O&M of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	321	0	0	0	1905	0	0	975	4210	0	51
Chaves	459	436	483	483	228	1420	265	265	1103	3942	162	213
Cibola	0	321	0	0	0	1905	0	0	975	4210	0	51
Colfax	0	321	0	0	0	1905	0	0	975	4210	0	51
Curry	19270	18561	20301	0301	9561	10276	11113	1113	6334	8841	6791	6842
De Baca	0	321	0	0	0	1905	0	0	975	4210	0	51
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	321	0	0	0	1905	0	0	975	4210	0	51
Grant	0	321	0	0	0	1905	0	0	975	4210	0	51
Guadalupe	1854	2076	1953	1953	920	2710	1069	069	1490	4656	653	704
Harding	0	321	0	0	0	1905	0	0	975	4210	0	51
Hidalgo	0	321	0	0	0	1905	0	0	975	4210	0	51
Lea	756	716	797	797	375	373	436	436	1185	3123	267	318
Lincoln	0	321	0	0	0	1905	0	0	975	2023	0	51
Los Alamos	0	293	0	0	0	537	0	0	565	302	0	51
Luna	1329	1579	1400	1400	659	2483	766	766	1345	4530	468	519
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	321	0	0	0	1905	0	0	975	4210	0	51
Otero	0	278	0	0	0	1865	0	0	975	4188	0	51
Quay	5352	5387	5638	5638	2655	4230	3086	086	2463	5496	1886	1937
Rio Arriba	0	321	0	0	0	1905	0	0	975	4210	0	51
Roosevelt	12075	11751	12721	2721	5991	7150	6963	963	4333	7112	4255	4306
Sandoval	2570	2433	2708	2708	1275	1116	1482	482	715	618	906	906
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	321	0	0	0	1905	0	0	975	4210	0	51
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	321	0	0	0	1905	0	0	975	4210	0	51
Socorro	0	321	0	0	0	1905	0	0	975	4210	0	51
Taos	0	321	0	0	0	1905	0	0	975	4210	0	51
Torrance	12451	12107	13117	3117	6178	7314	7180	180	4437	7203	4388	4439
Union	6078	6074	6403	6403	3016	4545	3505	505	2665	5671	2142	2193
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-53: Average indirect gross economic output impact during O&M of wind power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	81	0	0	0	480	0	0	246	1061	0	13
Chaves	165	157	174	174	82	512	95	95	398	1422	58	77
Cibola	0	136	0	0	0	804	0	0	411	1777	0	22
Colfax	0	136	0	0	0	804	0	0	411	1777	0	22
Curry	6951	6695	7322	322	3449	3706	4008	008	2285	3189	2449	468
De Baca	0	116	0	0	0	687	0	0	352	1519	0	18
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	116	0	0	0	687	0	0	352	1519	0	18
Grant	0	81	0	0	0	480	0	0	246	1061	0	13
Guadalupe	669	749	704	704	332	978	386	386	538	1679	236	254
Harding	0	116	0	0	0	687	0	0	352	1519	0	18
Hidalgo	0	81	0	0	0	480	0	0	246	1061	0	13
Lea	273	258	287	287	135	134	157	157	428	1127	96	115
Lincoln	0	81	0	0	0	480	0	0	246	510	0	13
Los Alamos	0	124	0	0	0	227	0	0	238	127	0	22
Luna	335	398	353	353	166	626	193	193	339	1141	118	131
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	136	0	0	0	804	0	0	411	1777	0	22
Otero	0	70	0	0	0	470	0	0	246	1055	0	13
Quay	1930	1943	2034	034	958	1526	1113	113	888	1983	680	699
Rio Arriba	0	136	0	0	0	804	0	0	411	1777	0	22
Roosevelt	4355	4238	4588	588	2161	2579	2512	512	1563	2565	1535	553
Sandoval	1085	1027	1143	143	538	471	625	625	302	261	382	382
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	81	0	0	0	480	0	0	246	1061	0	13
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	81	0	0	0	480	0	0	246	1061	0	13
Socorro	0	81	0	0	0	480	0	0	246	1061	0	13
Taos	0	136	0	0	0	804	0	0	411	1777	0	22
Torrance	5254	5109	5535	535	2607	3086	3030	030	1873	3039	1852	873
Union	2192	2191	2309	309	1088	1639	1264	264	961	2045	773	791
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-54: Average induced gross economic output impact during O&M of wind power plants by county and scenario from 2017 – 2050.

	2017–2030* (x$1,000)				2031–2040* (x$1,000)				2041–2050* (x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	64	0	0	0	381	0	0	195	842	0	10
Chaves	92	88	97	97	46	286	53	53	222	795	33	43
Cibola	0	109	0	0	0	645	0	0	330	1426	0	17
Colfax	0	109	0	0	0	645	0	0	330	1426	0	17
Curry	3884	3742	4092	092	1927	2071	2240	240	1277	1782	1369	379
De Baca	0	65	0	0	0	384	0	0	197	849	0	10
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	65	0	0	0	384	0	0	197	849	0	10
Grant	0	64	0	0	0	381	0	0	195	842	0	10
Guadalupe	374	418	394	394	185	546	215	215	300	939	132	142
Harding	0	65	0	0	0	384	0	0	197	849	0	10
Hidalgo	0	64	0	0	0	381	0	0	195	842	0	10
Lea	152	144	161	161	76	75	88	88	239	630	54	64
Lincoln	0	64	0	0	0	381	0	0	195	404	0	10
Los Alamos	0	99	0	0	0	182	0	0	191	102	0	17
Luna	266	316	280	280	132	496	153	153	269	905	94	104
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	0	109	0	0	0	645	0	0	330	1426	0	17
Otero	0	55	0	0	0	373	0	0	195	837	0	10
Quay	1079	1086	1136	136	535	853	622	622	497	1108	380	390
Rio Arriba	0	109	0	0	0	645	0	0	330	1426	0	17
Roosevelt	2434	2369	2564	564	1208	1441	1404	404	873	1434	858	868
Sandoval	870	824	917	917	432	378	502	502	242	209	307	307
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	0	64	0	0	0	381	0	0	195	842	0	10
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	64	0	0	0	381	0	0	195	842	0	10
Socorro	0	64	0	0	0	381	0	0	195	842	0	10
Taos	0	109	0	0	0	645	0	0	330	1426	0	17
Torrance	4216	4099	4441	441	2092	2476	2431	431	1503	2439	1486	503
Union	1225	1224	1291	291	608	916	707	707	537	1143	432	442
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-55: Average direct (on-site) gross economic output impact during construction of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	333	243	43	232	312	234	0	0	0	0	0	110
Chaves	68	119	0	0	1729	441	0	0	1011	157	0	110
Cibola	333	243	43	232	593	415	0	0	0	1	0	110
Colfax	333	243	43	232	1729	441	0	0	1604	157	0	110
Curry	333	243	43	232	1568	441	0	0	0	157	0	110
De Baca	333	243	43	232	126	111	0	0	0	0	0	110
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	333	243	43	232	675	441	0	0	0	37	0	110
Grant	333	243	43	232	920	441	0	0	2	157	0	110
Guadalupe	333	243	43	232	1608	441	0	0	2	157	0	110
Harding	333	243	43	232	920	441	0	0	2	157	0	110
Hidalgo	333	243	43	232	327	245	0	0	4	0	0	110
Lea	0	0	0	0	1370	367	0	0	1450	157	0	110
Lincoln	42	52	43	67	1	0	0	0	0	0	0	0
Los Alamos	14	16	11	19	1	0	0	0	0	0	0	0
Luna	333	243	43	232	634	441	0	0	2	10	0	110
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	333	243	43	232	797	441	0	0	2	126	0	110
Otero	308	233	20	0	279	198	0	0	0	0	0	110
Quay	333	243	43	232	1326	441	0	0	0	157	0	110
Rio Arriba	333	243	43	232	380	264	0	0	4	0	0	110
Roosevelt	333	243	43	232	1729	441	0	0	740	157	0	110
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	333	243	43	232	1326	441	0	0	0	157	0	110
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	333	243	43	232	1123	441	0	0	0	157	0	110
Socorro	333	243	43	232	1204	441	0	0	0	157	0	110
Taos	241	198	43	232	1	1	0	0	0	0	0	110
Torrance	333	243	43	232	1164	441	0	0	0	157	0	110
Union	333	243	43	232	1407	441	0	0	0	157	0	110
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-56: Average indirect gross economic output impact during construction of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	68	50	9	47	64	48	0	0	0	0	0	22
Chaves	7	13	0	0	181	46	0	0	106	17	0	12
Cibola	68	50	9	47	121	85	0	0	0	0	0	22
Colfax	35	26	5	24	181	46	0	0	168	17	0	12
Curry	35	26	5	24	165	46	0	0	0	17	0	12
De Baca	35	26	5	24	13	12	0	0	0	0	0	12
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	35	26	5	24	71	46	0	0	0	4	0	12
Grant	68	50	9	47	188	90	0	0	0	32	0	22
Guadalupe	35	26	5	24	169	46	0	0	0	17	0	12
Harding	35	26	5	24	97	46	0	0	0	17	0	12
Hidalgo	68	50	9	47	67	50	0	0	1	0	0	22
Lea	0	0	0	0	144	39	0	0	152	17	0	12
Lincoln	4	5	5	7	0	0	0	0	0	0	0	0
Los Alamos	3	3	2	4	0	0	0	0	0	0	0	0
Luna	68	50	9	47	129	90	0	0	0	2	0	22
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	35	26	5	24	84	46	0	0	0	13	0	12
Otero	32	24	2	0	29	21	0	0	0	0	0	12
Quay	35	26	5	24	139	46	0	0	0	17	0	12
Rio Arriba	68	50	9	47	78	54	0	0	1	0	0	22
Roosevelt	35	26	5	24	181	46	0	0	78	17	0	12
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	35	26	5	24	139	46	0	0	0	17	0	12
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	68	50	9	47	229	90	0	0	0	32	0	22
Socorro	68	50	9	47	246	90	0	0	0	32	0	22
Taos	49	40	9	47	0	0	0	0	0	0	0	22
Torrance	68	50	9	47	237	90	0	0	0	32	0	22
Union	35	26	5	24	148	46	0	0	0	17	0	12
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-57: Average induced gross economic output impact during construction of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	111	81	14	77	104	78	0	0	0	0	0	37
Chaves	14	24	0	0	347	89	0	0	203	32	0	22
Cibola	111	81	14	77	198	138	0	0	0	0	0	37
Colfax	67	49	9	47	347	89	0	0	322	32	0	22
Curry	67	49	9	47	315	89	0	0	0	32	0	22
De Baca	67	49	9	47	25	22	0	0	0	0	0	22
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	67	49	9	47	135	89	0	0	0	7	0	22
Grant	111	81	14	77	307	147	0	0	1	52	0	37
Guadalupe	67	49	9	47	323	89	0	0	0	32	0	22
Harding	67	49	9	47	185	89	0	0	0	32	0	22
Hidalgo	111	81	14	77	109	82	0	0	1	0	0	37
Lea	0	0	0	0	275	74	0	0	291	32	0	22
Lincoln	8	10	9	13	0	0	0	0	0	0	0	0
Los Alamos	5	5	4	6	0	0	0	0	0	0	0	0
Luna	111	81	14	77	211	147	0	0	1	3	0	37
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	67	49	9	47	160	89	0	0	0	25	0	22
Otero	62	47	4	0	56	40	0	0	0	0	0	22
Quay	67	49	9	47	266	89	0	0	0	32	0	22
Rio Arriba	111	81	14	77	127	88	0	0	1	0	0	37
Roosevelt	67	49	9	47	347	89	0	0	149	32	0	22
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	0	0	0	0	0	0	0	0	0	0
San Miguel	67	49	9	47	266	89	0	0	0	32	0	22
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	111	81	14	77	374	147	0	0	0	52	0	37
Socorro	111	81	14	77	401	147	0	0	0	52	0	37
Taos	80	66	14	77	0	0	0	0	0	0	0	37
Torrance	111	81	14	77	388	147	0	0	0	52	0	37
Union	67	49	9	47	282	89	0	0	0	32	0	22
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-58: Average direct (on-site) gross economic output impact during O&M of PV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040**(x$1,000)				2041–2050**(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	142	125	171	171	72	52	105	105	45	28	72	72
Catron	121	56	33	209	444	267	36	179	372	262	24	154
Chaves	20	17	19	19	323	188	12	12	1869	451	8	40
Cibola	166	95	86	263	520	286	68	212	585	403	47	177
Colfax	273	190	216	392	614	325	148	291	2171	526	101	231
Curry	121	56	33	209	537	270	36	179	1314	496	24	154
De Baca	121	56	33	209	370	256	36	179	254	176	24	154
Dona Ana	278	245	335	335	140	101	205	205	87	55	140	140
Eddy	172	101	94	270	533	288	73	216	648	444	50	180
Grant	127	61	39	216	531	272	40	183	819	497	27	157
Guadalupe	364	270	325	501	660	358	215	358	1420	544	146	276
Harding	121	56	33	209	528	270	36	179	817	496	24	154
Hidalgo	121	56	33	209	448	268	36	179	384	270	24	154
Lea	201	177	241	241	180	94	148	148	1783	384	101	133
Lincoln	28	29	33	61	28	32	36	48	17	17	24	33
Los Alamos	22	20	22	31	15	13	17	22	10	7	12	15
Luna	647	520	665	842	768	461	424	567	767	521	289	419
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	121	56	33	209	519	270	36	179	725	485	24	154
Otero	201	135	131	117	467	295	88	72	370	253	60	81
Quay	443	337	425	602	713	396	292	436	1239	564	200	330
Rio Arriba	121	56	33	209	463	269	36	179	420	283	24	154
Roosevelt	121	56	33	209	537	270	36	179	1871	496	24	154
Sandoval	103	91	124	124	52	37	76	76	32	20	52	52
San Juan	364	310	461	461	240	173	351	351	149	94	240	240
San Miguel	155	86	73	249	554	282	60	204	1141	502	41	171
Santa Fe	54	48	65	65	27	20	40	40	17	11	27	27
Sierra	138	71	53	230	545	276	48	192	978	499	33	163
Socorro	121	56	33	209	537	270	36	179	1036	496	24	154
Taos	131	73	55	232	209	170	49	193	130	93	34	164
Torrance	121	56	33	209	537	270	36	179	1004	496	24	154
Union	121	56	33	209	537	270	36	179	1193	496	24	154
Valencia	132	116	159	159	67	48	97	97	41	26	66	66

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-59: Average indirect gross economic output impact during O&M of PV power plants by county and scenario from 2017 – 2050.

	2017–2030** (x$1,000)				2031–2040** (x$1,000)				2041–2050** (x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	86	76	103	103	43	31	63	63	27	17	43	43
Catron	73	34	20	126	268	161	22	108	224	158	15	93
Chaves	7	6	6	6	106	62	4	4	615	149	3	13
Cibola	100	58	52	158	314	173	41	128	353	243	28	107
Colfax	90	63	71	129	202	107	49	96	715	173	33	76
Curry	40	19	11	69	177	89	12	59	432	163	8	51
De Baca	40	19	11	69	122	84	12	59	84	58	8	51
Dona Ana	168	148	202	202	85	61	124	124	53	33	85	85
Eddy	57	33	31	89	175	95	24	71	213	146	16	59
Grant	77	37	24	130	320	164	24	110	494	300	16	95
Guadalupe	120	89	107	165	217	118	71	118	467	179	48	91
Harding	40	19	11	69	174	89	12	59	269	163	8	51
Hidalgo	73	34	20	126	270	162	22	108	232	163	15	93
Lea	66	58	79	79	59	31	49	49	587	126	33	44
Lincoln	9	9	11	20	9	11	12	16	6	6	8	11
Los Alamos	13	12	14	19	9	8	10	13	6	4	7	9
Luna	390	314	402	508	463	278	256	342	463	315	174	253
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	40	19	11	69	171	89	12	59	239	160	8	51
Otero	66	44	43	38	154	97	29	24	122	83	20	27
Quay	146	111	140	198	235	130	96	143	408	186	66	108
Rio Arriba	73	34	20	126	279	162	22	108	253	171	15	93
Roosevelt	40	19	11	69	177	89	12	59	616	163	8	51
Sandoval	62	55	75	75	31	23	46	46	19	12	31	31
San Juan	220	187	278	278	145	104	212	212	90	57	145	145
San Miguel	51	28	24	82	182	93	20	67	376	165	14	56
Santa Fe	33	29	39	39	17	12	24	24	10	6	16	16
Sierra	83	43	32	139	329	167	29	116	590	301	20	98
Socorro	73	34	20	126	324	163	22	108	625	299	15	93
Taos	79	44	33	140	126	102	30	116	78	56	20	99
Torrance	73	34	20	126	324	163	22	108	606	299	15	93
Union	40	19	11	69	177	89	12	59	393	163	8	51
Valencia	80	70	96	96	40	29	59	59	25	16	40	40

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-60: Average induced gross economic output impact during O&M of PV power plants by county and scenario from 2017 – 2050.

	2017–2030**(x$1,000)				2031–2040**(x$1,000)				2041–2050**(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	440	388	529	529	222	160	324	324	138	87	221	221
Catron	375	174	101	547	1373	825	111	553	1149	811	75	477
Chaves	53	46	51	51	855	498	31	31	4949	1195	21	107
Cibola	512	295	266	311	1608	884	212	554	1809	1246	144	546
Colfax	724	504	571	038	1626	861	392	771	5749	1392	267	611
Curry	321	149	87	554	1423	715	95	474	3478	1313	65	409
De Baca	321	149	87	554	981	677	95	474	672	465	65	409
Dona Ana	860	759	1036	036	434	313	635	535	269	170	433	433
Eddy	455	267	248	715	1411	763	193	573	1716	1176	132	476
Grant	392	189	121	567	1641	840	123	566	2531	1536	84	486
Guadalupe	963	715	859	327	1747	948	568	948	3760	1440	388	732
Harding	321	149	87	554	1398	715	95	474	2164	1313	65	409
Hidalgo	375	174	101	547	1385	828	111	553	1186	833	75	477
Lea	531	468	639	539	477	250	392	392	4721	1016	267	353
Lincoln	75	76	87	162	74	85	95	128	46	46	65	87
Los Alamos	67	61	69	97	47	41	53	68	30	22	36	46
Luna	1999	1606	2056	602	2373	1424	1309	752	2370	1611	893	295
Mc Kinley	0	0	0	0	0	0	0	0	0	0	0	0
Mora	321	149	87	554	1375	715	95	474	1919	1283	65	409
Otero	532	357	346	309	1236	780	233	190	979	669	159	215
Quay	1173	892	1126	593	1888	1049	774	154	3282	1495	528	873
Rio Arriba	375	174	101	547	1430	830	111	553	1297	876	75	477
Roosevelt	321	149	87	554	1423	715	95	474	4954	1313	65	409
Sandoval	318	280	382	382	160	115	234	234	99	63	160	160
San Juan	1126	959	1423	423	742	535	1086	086	460	290	741	741
San Miguel	410	227	193	561	1468	747	160	539	3022	1331	109	453
Santa Fe	168	148	202	202	85	61	124	124	52	33	84	84
Sierra	427	220	164	710	1684	853	149	592	3023	1543	102	504
Socorro	375	174	101	547	1661	834	111	553	3202	1532	75	477
Taos	405	225	170	715	645	524	153	596	401	286	104	506
Torrance	375	174	101	547	1660	834	111	553	3104	1532	75	477
Union	321	149	87	554	1423	715	95	474	3158	1313	65	409
Valencia	408	360	491	491	206	148	301	301	128	80	205	205

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-61: Average direct (on-site) gross economic output impact during construction of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	77	111	29	59	94	160	21	59	130	154	57	104
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	77	111	29	59	35	19	3	24	31	0	10	17
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	77	111	29	59	35	4	3	24	14	0	9	9
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	77	111	29	59	68	157	12	42	104	14	31	61
Eddy	77	100	29	59	28	0	3	24	0	0	10	17
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	77	98	29	59	24	0	3	24	0	0	10	17
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	77	111	29	59	38	1	3	24	9	0	10	17
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	77	111	29	59	35	7	3	24	19	0	10	17
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	77	111	29	59	58	67	9	35	85	0	24	43
San Juan	77	111	29	59	58	151	9	35	37	154	26	52
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	77	111	29	59	58	151	10	38	89	154	24	52
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	77	111	29	59	41	17	5	28	24	0	14	26

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-62: Average indirect gross economic output impact during construction of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	16	23	6	12	19	33	4	12	27	31	12	21
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	8	12	3	6	4	2	0	3	3	0	1	2
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	8	12	3	6	4	0	0	3	1	0	1	1
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	16	23	6	12	14	32	2	8	21	3	6	12
Eddy	8	11	3	6	3	0	0	3	0	0	1	2
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	8	10	3	6	3	0	0	3	0	0	1	2
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	16	23	6	12	8	0	1	5	2	0	2	4
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	8	12	3	6	4	1	0	3	2	0	1	2
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	16	23	6	12	12	14	2	7	17	0	5	9
San Juan	16	23	6	12	12	31	2	7	8	31	5	11
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	16	23	6	12	12	31	2	8	18	31	5	11
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	16	23	6	12	8	3	1	6	5	0	3	5

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-63: Average induced gross economic output impact during construction of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	26	37	10	20	31	53	7	20	43	51	19	35
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	15	22	6	12	7	4	1	5	6	0	2	3
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	15	22	6	12	7	1	1	5	3	0	2	2
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	26	37	10	20	23	52	4	14	35	5	10	20
Eddy	15	20	6	12	6	0	1	5	0	0	2	3
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	15	20	6	12	5	0	1	5	0	0	2	3
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	26	37	10	20	13	0	1	8	3	0	3	6
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	15	22	6	12	7	1	1	5	4	0	2	3
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	26	37	10	20	19	22	3	12	28	0	8	14
San Juan	26	37	10	20	19	50	3	12	12	51	9	17
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	26	37	10	20	19	50	3	13	30	51	8	17
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	26	37	10	20	13	6	2	9	8	0	5	9

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-64: Average direct (on-site) gross economic output impact during O&M of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	437	431	534	556	254	246	316	390	303	321	258	364
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	66	87	45	67	95	93	30	95	88	42	29	84
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	66	87	45	67	95	79	30	95	82	33	29	78
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	207	218	231	253	159	189	140	209	203	200	121	203
Eddy	66	85	45	67	93	61	30	95	60	25	29	84
Grant	19	17	24	24	7	4	14	14	4	2	9	9
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	66	85	45	67	91	58	30	95	57	24	29	84
Lincoln	2	2	2	2	1	0	1	1	0	0	1	1
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	10	9	13	13	4	2	7	7	2	1	5	5
Mc Kinley	66	87	45	67	96	77	30	95	82	32	29	84
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	82	101	65	87	100	86	42	107	87	36	36	92
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	165	179	175	197	139	150	106	174	169	85	91	162
San Juan	66	87	45	67	103	150	33	100	130	277	45	121
San Miguel	2	1	2	2	1	0	1	1	0	0	1	1
Santa Fe	194	206	213	236	151	181	129	198	178	289	108	186
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	1	1	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	66	87	45	67	97	91	31	97	98	40	34	94

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-65: Average indirect gross economic output impact during O&M of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	263	260	322	335	153	149	191	235	183	194	156	220
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	22	29	15	22	31	30	10	31	29	14	9	28
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	22	29	15	22	31	26	10	31	27	11	9	26
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	125	132	139	153	96	114	84	126	122	121	73	123
Eddy	22	28	15	22	31	20	10	31	20	8	9	28
Grant	11	10	15	15	4	3	8	8	2	1	5	5
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	22	28	15	22	30	19	10	31	19	8	9	28
Lincoln	1	0	1	1	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	6	5	8	8	2	1	4	4	1	1	3	3
Mc Kinley	40	53	27	40	58	46	18	57	50	19	17	51
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	27	33	21	29	33	28	14	35	29	12	12	30
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	99	108	105	119	84	90	64	105	102	52	55	98
San Juan	40	53	27	40	62	91	20	60	78	167	27	73
San Miguel	1	0	1	1	0	0	0	0	0	0	0	0
Santa Fe	117	124	129	142	91	109	78	119	108	175	65	113
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	40	53	27	40	59	55	19	58	59	24	20	57

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-66: Average induced gross economic output impact during O&M of RPV power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1349	1333	1649	1718	784	761	976	1204	937	992	798	1126
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	176	231	118	177	251	245	80	252	233	110	76	223
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	176	231	118	177	251	210	80	252	216	88	76	207
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	641	674	713	782	491	583	432	647	627	619	375	628
Eddy	176	226	118	177	246	161	80	252	160	67	76	223
Grant	57	53	76	76	21	14	43	43	12	6	27	27
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	1	1	1	1	0	0	1	1	0	0	0	0
Lea	176	224	118	177	241	153	80	252	151	64	76	223
Lincoln	4	4	6	6	2	1	3	3	1	0	2	2
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	30	28	39	39	11	7	22	22	6	3	14	14
Mc Kinley	205	269	138	207	295	237	93	294	254	99	89	260
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	217	269	172	231	266	227	111	282	231	96	96	243
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	509	552	539	608	431	463	329	537	521	264	283	501
San Juan	205	269	138	207	319	465	101	309	401	855	138	375
San Miguel	4	4	6	6	2	1	3	3	1	0	2	2
Santa Fe	600	636	659	728	466	560	399	611	551	894	332	576
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	1	1	2	2	0	0	1	1	0	0	1	1
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	205	269	138	207	300	280	96	299	301	124	105	292

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-67: Average direct (on-site) gross economic output impact during construction of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	32	67	0	12	241	176	0	0	246	65	0	7
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	32	67	0	12	241	176	0	0	246	65	0	7
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	32	67	0	12	241	176	0	0	246	65	0	7
Eddy	20	25	0	12	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	32	67	0	12	241	176	0	0	246	65	0	7
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	32	67	0	12	241	176	0	0	246	65	0	7
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	32	67	0	12	241	176	0	0	246	65	0	7
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	32	67	0	12	241	176	0	0	246	65	0	7
San Juan	32	67	0	12	241	176	0	0	246	65	0	7
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	32	67	0	12	241	176	0	0	246	65	0	7
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	32	67	0	12	241	176	0	0	246	65	0	7

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-68: Average indirect gross economic output impact during construction of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	6	13	0	2	46	33	0	0	47	12	0	1
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	6	13	0	2	46	33	0	0	47	12	0	1
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	6	13	0	2	46	33	0	0	47	12	0	1
Eddy	4	5	0	2	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	6	13	0	2	46	33	0	0	47	12	0	1
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	6	13	0	2	46	33	0	0	47	12	0	1
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	6	13	0	2	46	33	0	0	47	12	0	1
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	6	13	0	2	46	33	0	0	47	12	0	1
San Juan	6	13	0	2	46	33	0	0	47	12	0	1
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	6	13	0	2	46	33	0	0	47	12	0	1
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	6	13	0	2	46	33	0	0	47	12	0	1

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-69: Average induced gross economic output impact during construction of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	10	21	0	4	75	55	0	0	77	20	0	2
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	10	21	0	4	75	55	0	0	77	20	0	2
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	10	21	0	4	75	55	0	0	77	20	0	2
Eddy	6	8	0	4	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	10	21	0	4	75	55	0	0	77	20	0	2
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	10	21	0	4	75	55	0	0	77	20	0	2
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	10	21	0	4	75	55	0	0	77	20	0	2
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	10	21	0	4	75	55	0	0	77	20	0	2
San Juan	10	21	0	4	75	55	0	0	77	20	0	2
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	10	21	0	4	75	55	0	0	77	20	0	2
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	10	21	0	4	75	55	0	0	77	20	0	2

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-70: Average direct (on-site) gross economic output impact during O&M of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1747	1749	1739	1991	1407	1437	1361	1725	1382	1308	1102	1509
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	8	9	0	10	45	75	0	13	280	206	0	13
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	31	31	31	35	24	24	24	30	19	19	19	26
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1459	1461	1452	1663	1181	1211	1136	1441	1200	1126	920	1262
Eddy	71	72	64	83	68	72	50	75	55	59	40	66
Grant	509	509	509	579	398	398	398	501	322	322	322	437
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	1203	1203	1203	1369	941	941	941	1184	762	762	762	1034
Lea	1415	1417	1408	1613	1147	1177	1102	1398	1172	1098	892	1224
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	31	32	23	37	63	93	18	35	294	220	15	33
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	8	9	0	10	45	75	0	13	280	206	0	13
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	8	9	0	10	45	75	0	13	280	206	0	13
San Juan	8	9	0	10	45	75	0	13	280	206	0	13
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	8	9	0	10	45	75	0	13	280	206	0	13
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	2777	2778	2769	3163	2212	2242	2167	2738	2034	1960	1755	2395

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-71: Average indirect gross economic output impact during O&M of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	1257	1258	1251	1432	1012	1033	979	1241	994	941	793	1086
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	6	7	0	7	32	54	0	9	201	148	0	9
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	22	22	22	25	17	17	17	22	14	14	14	19
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	1050	1051	1044	1197	850	871	817	1037	863	810	662	908
Eddy	51	52	46	60	49	52	36	54	40	42	29	47
Grant	366	366	366	417	286	286	286	360	232	232	232	315
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	865	865	865	985	677	677	677	852	548	548	548	744
Lea	1018	1019	1013	1161	825	847	793	1006	843	790	642	880
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	22	23	17	26	45	67	13	25	212	158	10	23
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	6	7	0	7	32	54	0	9	201	148	0	9
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	6	7	0	7	32	54	0	9	201	148	0	9
San Juan	6	7	0	7	32	54	0	9	201	148	0	9
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	6	7	0	7	32	54	0	9	201	148	0	9
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	1998	1999	1992	2276	1592	1613	1559	1970	1464	1410	1262	1723

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-72: Average induced gross economic output impact during O&M of NG peaker power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	802	803	799	914	646	660	625	792	634	600	506	693
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	4	4	0	5	21	34	0	6	128	94	0	6
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	14	14	14	16	11	11	11	14	9	9	9	12
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	670	671	667	764	542	556	522	662	551	517	422	579
Eddy	32	33	29	38	31	33	23	34	25	27	18	30
Grant	234	234	234	266	183	183	183	230	148	148	148	201
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	552	552	552	629	432	432	432	543	350	350	350	475
Lea	650	651	646	741	527	540	506	642	538	504	410	562
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	14	15	11	17	29	43	8	16	135	101	7	15
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	4	4	0	5	21	34	0	6	128	94	0	6
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	4	4	0	5	21	34	0	6	128	94	0	6
San Juan	4	4	0	5	21	34	0	6	128	94	0	6
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	4	4	0	5	21	34	0	6	128	94	0	6
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	1275	1276	1271	1452	1016	1030	995	1257	934	900	806	1099

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-73: Average direct (on-site) gross economic output impact during construction of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	579	232	0	0	3058	3083	0	0	2720	2133
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	585	270	0	0	3058	3101	0	0	2720	2133
Eddy	0	0	587	285	0	0	3058	3108	0	0	2720	2133
Grant	0	0	587	286	0	0	3058	3108	0	0	2720	2133
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	588	289	0	0	3058	3110	0	0	2720	2133
Lea	0	0	587	283	0	0	3058	3106	0	0	2720	2133
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	338	288	0	0	0	86	0	0	0	0
Luna	0	0	587	286	0	0	3058	3108	0	0	2720	2133
Mc Kinley	0	0	587	281	0	0	3058	3106	0	0	2720	2133
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	586	275	0	0	3058	3103	0	0	2720	2133
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	587	280	0	0	3058	3106	0	0	2720	2133

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-74: Average indirect gross economic output impact during construction of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$10,000)				2031–2040*(x$10,000)				2041–2050*(x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	110	44	0	0	580	585	0	0	516	405
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	111	51	0	0	580	588	0	0	516	405
Eddy	0	0	111	54	0	0	580	590	0	0	516	405
Grant	0	0	111	54	0	0	580	590	0	0	516	405
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	111	55	0	0	580	590	0	0	516	405
Lea	0	0	111	54	0	0	580	589	0	0	516	405
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	64	55	0	0	0	16	0	0	0	0
Luna	0	0	111	54	0	0	580	590	0	0	516	405
Mc Kinley	0	0	111	53	0	0	580	589	0	0	516	405
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	111	52	0	0	580	589	0	0	516	405
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	111	53	0	0	580	589	0	0	516	405

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-75: Average induced gross economic output impact during construction of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030* (x$10,000)				2031–2040* (x$10,000)				2041–2050* (x$10,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	181	73	0	0	958	965	0	0	852	668
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	183	85	0	0	958	971	0	0	852	668
Eddy	0	0	184	89	0	0	958	973	0	0	852	668
Grant	0	0	184	90	0	0	958	973	0	0	852	668
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	184	90	0	0	958	974	0	0	852	668
Lea	0	0	184	89	0	0	958	973	0	0	852	668
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	106	90	0	0	0	27	0	0	0	0
Luna	0	0	184	90	0	0	958	973	0	0	852	668
Mc Kinley	0	0	184	88	0	0	958	973	0	0	852	668
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	0	0	183	86	0	0	958	972	0	0	852	668
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	184	88	0	0	958	973	0	0	852	668

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-76: Average direct (on-site) gross economic output impact during O&M of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030* (x$1,000)				2031–2040* (x$1,000)				2041–2050* (x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	264	264	452	393	263	263	1921	1653	259	259	7534	9382
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	5430	5430	5619	6440	5403	5403	7072	8474	5332	5332	12616	16738
Eddy	0	0	189	88	0	0	1673	1469	0	0	7289	9205
Grant	0	0	189	88	0	0	1673	1471	0	0	7289	9207
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	189	88	0	0	1674	1480	0	0	7290	9218
Lea	12177	12177	12366	14335	12117	12117	13789	17267	11956	11956	19244	26207
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	498	498	675	671	496	496	1133	1452	489	489	1118	1635
Luna	7534	7534	7723	8903	7497	7497	9170	11251	7397	7397	14686	19734
Mc Kinley	0	0	189	88	0	0	1672	1458	0	0	7288	9191
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	2107	2107	2296	2552	2097	2097	3767	4173	2069	2069	9355	12111
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	189	87	0	0	1672	1454	0	0	7288	9187

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-77: Average indirect gross economic output impact during O&M of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	190	190	325	283	189	189	1382	1189	187	187	5420	6750
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	3907	3907	4042	4633	3887	3887	5088	6096	3836	3836	9077	12042
Eddy	0	0	136	63	0	0	1204	1057	0	0	5244	6622
Grant	0	0	136	63	0	0	1204	1058	0	0	5244	6624
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	136	63	0	0	1205	1065	0	0	5245	6632
Lea	8761	8761	8896	10313	8717	8717	9920	12423	8602	8602	13845	18855
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	359	359	485	483	357	357	815	1045	352	352	804	1177
Luna	5420	5420	5556	6405	5393	5393	6597	8095	5322	5322	10566	14198
Mc Kinley	0	0	136	63	0	0	1203	1049	0	0	5244	6612
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	1516	1516	1652	1836	1508	1508	2710	3002	1488	1488	6731	8713
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	136	63	0	0	1203	1046	0	0	5244	6610

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-78: Average induced gross economic output impact during O&M of NG baseload power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	121	121	207	180	121	121	882	759	119	119	3459	4307
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	2493	2493	2580	2957	2481	2481	3247	3890	2448	2448	5792	7685
Eddy	0	0	87	40	0	0	768	674	0	0	3347	4226
Grant	0	0	87	40	0	0	768	675	0	0	3347	4227
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	87	40	0	0	769	679	0	0	3347	4232
Lea	5591	5591	5677	6582	5563	5563	6331	7928	5489	5489	8835	12032
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	229	229	310	308	228	228	520	667	225	225	513	751
Luna	3459	3459	3546	4087	3442	3442	4210	5166	3396	3396	6743	9060
Mc Kinley	0	0	87	40	0	0	768	669	0	0	3346	4220
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	967	967	1054	1172	963	963	1730	1916	950	950	4295	5560
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	87	40	0	0	768	667	0	0	3346	4218

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-79: Average direct (on-site) gross economic output impact during O&M of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	4902	4902	4902	5046	1934	1934	1934	2044	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	45833	45833	45833	47108	30076	30076	30076	31906	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-80: Average indirect gross economic output impact during O&M of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	3527	3527	3527	3630	1391	1391	1391	1470	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	32974	32974	32974	33892	21638	21638	21638	22955	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Table 2-81: Average induced gross economic output impact during O&M of coal power plants by county and scenario from 2017 – 2050.

	2017–2030*(x$1,000)				2031–2040*(x$1,000)				2041–2050*(x$1,000)			
	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref	Sce. 1	Sce. 2	Sce. 3	Ref
Bernalillo	0	0	0	0	0	0	0	0	0	0	0	0
Catron	0	0	0	0	0	0	0	0	0	0	0	0
Chaves	0	0	0	0	0	0	0	0	0	0	0	0
Cibola	0	0	0	0	0	0	0	0	0	0	0	0
Colfax	0	0	0	0	0	0	0	0	0	0	0	0
Curry	0	0	0	0	0	0	0	0	0	0	0	0
De Baca	0	0	0	0	0	0	0	0	0	0	0	0
Dona Ana	0	0	0	0	0	0	0	0	0	0	0	0
Eddy	0	0	0	0	0	0	0	0	0	0	0	0
Grant	0	0	0	0	0	0	0	0	0	0	0	0
Guadalupe	0	0	0	0	0	0	0	0	0	0	0	0
Harding	0	0	0	0	0	0	0	0	0	0	0	0
Hidalgo	0	0	0	0	0	0	0	0	0	0	0	0
Lea	0	0	0	0	0	0	0	0	0	0	0	0
Lincoln	0	0	0	0	0	0	0	0	0	0	0	0
Los Alamos	0	0	0	0	0	0	0	0	0	0	0	0
Luna	0	0	0	0	0	0	0	0	0	0	0	0
Mc Kinley	2251	2251	2251	2317	888	888	888	938	0	0	0	0
Mora	0	0	0	0	0	0	0	0	0	0	0	0
Otero	0	0	0	0	0	0	0	0	0	0	0	0
Quay	0	0	0	0	0	0	0	0	0	0	0	0
Rio Arriba	0	0	0	0	0	0	0	0	0	0	0	0
Roosevelt	0	0	0	0	0	0	0	0	0	0	0	0
Sandoval	0	0	0	0	0	0	0	0	0	0	0	0
San Juan	21043	21043	21043	21628	13809	13809	13809	14649	0	0	0	0
San Miguel	0	0	0	0	0	0	0	0	0	0	0	0
Santa Fe	0	0	0	0	0	0	0	0	0	0	0	0
Sierra	0	0	0	0	0	0	0	0	0	0	0	0
Socorro	0	0	0	0	0	0	0	0	0	0	0	0
Taos	0	0	0	0	0	0	0	0	0	0	0	0
Torrance	0	0	0	0	0	0	0	0	0	0	0	0
Union	0	0	0	0	0	0	0	0	0	0	0	0
Valencia	0	0	0	0	0	0	0	0	0	0	0	0

Note: Sce. is Scenario and Ref. is Reference Case Scenario. *Values are the average impact throughout the time period.

Chapter 3: Consumer Preferences for Solar Energy: A Choice Experiment Study

3.1. Introduction

As the urgency of climate change rises, electricity generation in the U.S. is rapidly moving away from coal-fired generation to more environmentally-friendly fossil fuels and, increasingly, towards renewables. The move toward renewables is due to several factors including cost competitiveness, consumer preferences, and state and federal policies, such as federal tax incentives, renewable portfolio standards (RPSs), and state level subsidies for behind-the-meter solar. There are costs associated with these subsidies and RPS, which will eventually trickle down to taxpayers and consumers. As such, these costs might affect residents' preferences toward integrating more RE into the system in the future. The question then becomes how much customers are willing to pay for renewable energy (RE). Lastly, consumer preferences may be a key factor in the type of RE that is installed.

Studies generally do not assess preferences and willingness to pay (WTP) toward a specific RPS goal, but rather evaluate either a generic RE term or its different types (i.e., wind, solar, etc.). Researchers generally find citizens around the globe have a statistically significant and positive WTP for cleaner electricity. Further, they identify and link heterogeneity in preferences for RE to a number of factors, including energy type, respondents' exposure or proximity to RE, respondents' place of place of residence (urban/rural), and people's attitudes towards the environment.

Multiple factors can affect customers' opinions and WTP for RE. There are a plethora of policies and programs currently in place, with high variability in their designs, levels of renewables required, and the number of changes to current standards considered in different locations. However, there is still a lack of understanding of consumer preferences for the level and/or types of renewables, particularly solar energy.

To fulfill the aforementioned gaps, we conducted a choice experiment survey focusing on preferences for different types of solar energy, an area of investigation that is largely missing within the nonmarket valuation literature. The survey is conducted in NM, a state with an RPS and great potential for renewables, particularly in solar, where it ranks third in the U.S. Focusing on the state's major utility consumer base, our choice experiment considers an increase in the RPS and, specifically, preferences for different types of solar. In addition to gauging households' WTP for higher level of RPS, we assess households' attitudes towards smart meters (defined below) in NM. Our evaluation considers factors that are expected to be responsible for variation in preferences: distance to the closest solar installation (solar farm and rooftop solar), location (rural versus urban), and environmental worldview. We find that, on average, respondents are supportive of increasing the RPS level, prefer the extra RPS to come from solar farms, and are supportive of smart meter installation. Additionally, rural respondents are significantly more supportive of solar farm improvement than urban respondents. We observe that distance to nearest solar installation (solar farm and/or rooftop solar) affects preferences toward different types of solar energy. Lastly, we find greater commitment to environmental conservation, as measured by a modified New Ecological Paradigm instrument, leads to higher support for environmental attributes.

3.2. Background

In 2016, the U.S. contributed approximately 15% of global carbon dioxide emissions (Boden, Andres, & Marland, 2017). The electric sector is responsible for the largest share of U.S. emissions (28%) (EPA, 2016). Electricity generation in the U.S. is rapidly moving towards integrating more renewables into the system. Twenty-three percent of electricity generation in the U.S. was from renewable resources in April 2018.[61] The move toward renewables may in part be due to renewable portfolio standards (RPS), which are currently required by 29 states (Barbose, 2017).

RPS policies mandate electric providers to generate a portion of their generation or sale from RE within a certain time frame. The main goal of RPSs policies is to reduce greenhouse-gas emissions and air pollution by reducing use of fossil fuels, particularly within the electric sector. Subsequently, RPS also may help with reducing water

[61] Source: https://www.eia.gov/electricity/monthly/ (accessed 01/22/2019)

consumption and have impacts on state economies through job creation (Barbose et al., 2016). RPS designs are unique to each state and mainly focus on wind and solar energy. Some RPS have distinct goals solely for solar energy: among the 29 states with RPS requirements, 18 states have mandated that electric providers within respective states include a minimum amount (carve-out) from solar energy.[62]

There is a lack of consensus on whether RPSs have a statistically significant and positive effect on RE generation (Carley, 2009; Shrimali et al., 2015; Upton and Snyder, 2017; Wiser et al., 2017; Yin and Powers, 2010), as well as economy and the environment (e.g., Wei and Rose, 2014; Yi, 2015; Wiser et al., 2016; Mamkhezri et al., 2017; Divounguy et al. 2017).[63] Nevertheless, researchers agree RPSs are costly and might directly (e.g., electricity price) or indirectly (e.g., tax) impact citizens (Upton and Snyder, 2017; Palmer and Burtraw, 2005). This may influence taxpayers' opinion on RE in the long-run. Thus, in this research we assess consumers' preferences towards RE, with a focus on solar energy.

We are interested in estimating MWTP for two different types of solar generation scales (solar farm and rooftop) for the following reasons. Electric utility companies with required residential solar carve-outs provide subsidies for rooftop solar to encourage their installation, which may impact all customers' monthly electricity bill. Similarly, utility

[62] For example, New Mexico's RPS has mandated that by 2020, 20% of energy production derive from renewables, including a 23% solar carve-out. Similarly, Nevada's RPS has mandated that by 2025 25% of energy production result from renewables, with a 5% solar carve-out. For more information on the RPS carve-outs, see: http://ncsolarcen-prod.s3.amazonaws.com/wp-content/uploads/2015/01/2014-Daniel-In-State-RPS-Requirements.pdf (accessed 07/23/2018)

[63] For instance, Carley (2009) and Yin and Powers (2010) find that RPSs have a positive impact on RE generation, while Upton and Snyder (2017) find the opposite. Similarly, Wiser et al. (2016) find a RE has positive impact on U.S.'s economy, while Divounguy et al. (2017) suggest the opposite. More recently, Wiser et al. (2017) conclude that RPSs policies are cost-effective when market failure (externalities such as air pollution and climate change) is taken into account.

companies with required utility-scale solar carve-outs own and purchase electricity from solar farms, which is also reflected in customers' monthly rates. Further, beyond the cost variable, there might be factors in the actual solar energy generation that customers value. For example, consumers might prefer decentralized solar panels (rooftop solar) over centralized ones (solar farm) due to the belief that solar farms give utilities a monopoly power over solar energy and take away the user's independence associated with owning rooftop solar. Further, they look unpleasant, occupy a large amount of land, kill birds, and interrupt deer migratory paths. On the other hand, rooftop solar requires individual households to make investment decisions, and is less efficient and cost-effective than solar farms. Since customers might be paying higher rates on their monthly electricity bill due to solar energy development and might perceive different types of solar generation scales differently, it becomes relevant to assess whether there is a difference in preferences toward different types of solar energy.

3.2.1. Review of literature

Nonmarket valuation studies, the focus of this research, usually do not specify an exclusive RPS goal to gauge respondents' WTP, but instead assess respondents' opinion and WTP towards requiring more RE in the energy mix. Of those that do specify an RPS level, they find that respondents are willing to pay a positive premium for RPS (Mozumder et al., 2011; Nkansah & Collins, 2018). Numerous empirical studies have commonly found electricity consumers have positive WTP for the move to RE around the globe (e.g., Soon and Ahmad, 2015).[64] Previous research has also found and linked

[64] For instance, Soon and Ahmad (2015) conducted a meta-analysis of thirty studies from all continents from 2000 and beyond and found a mean WTP of $7.16/month to increase electricity from RE. Among

heterogeneity in preferences for RE to several factors including, but not limited to: energy type (e.g., Gracia et al., 2012; Nkansah & Collins, 2018), respondents' exposure or proximity to RE (e.g., Vecchiato and Tempesta, 2015; Möllendorff & Welsch, 2017), respondents' geographic location (urban/rural) (e.g., Bergmann et al., 2008; Yoo, 2011), and people's attitudes towards the environment (e.g., Strazzera et al., 2012; Yoo & Ready, 2014).

Wind power is currently the most studied energy source within the RE acceptance literature. Researchers find positive WTP the majority of the time (e.g., Nkansah & Collins, 2018; Rehdanz et al., 2017), though sometimes find negative WTP (e.g., Groothuis et al., 2008; Lutzeyer et al., 2018). Scholars link the negative WTP for wind energy to multiple factors, including distance decay effect, which refers to lower WTP the farther away respondents live from a RE development, and vice versa.[65] As noted by Welsch (2016), WTP towards solar energy is one of the most under-studied topics in the field of RE acceptance. Borchers et al. (2007) found that solar energy is the most favored RE technology in comparison to wind, farm methane, biomass, and a generic "green" energy. Likewise, Gracia et al. (2012) showed that solar generated electricity is preferred over wind and biomass. This research is the first to distinguish preferences toward photovoltaic solar (also known as solar farm or utility-scale solar) from residential photovoltaic (also known as rooftop solar) or a combination of the two.

Consumer WTP for wind energy has been studied the most, particularly with respect to exposure or proximity to RE (e.g., Knapp & Ladenburg, 2015; Gudding et al.,

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others see Sundt & Rehdanz (2015), Ma et al. (2015), and Soon and Ahmad (2015) for meta-analysis on WTP for RE.

[65] Other factors include the "NIMBY" (not-in-my-backyard) effect and wind turbine externalities (Rehdanz et al., 2017; Nkansah & Collins, 2018).

2018).[66] To our knowledge there are only three peer-reviewed papers that investigate proximity to solar energy. Using a hedonic regression approach, Dastrup et al. (2012) found that rooftop solar add 3.6% to the sale price of a house in California. They related this to financial and moral benefits to the rooftop solar owner, known as "warm glow." Möllendorff & Welsch (2017) measured exposure to solar farm effect on German consumers' well-being and found a statistically significantly negative effect when a solar farm is located in a neighboring postcode district and no significant effect when a solar facility is located within the same postcode district of a respondent. In an attempt to explain why they found no effect within the same postcode district, the authors also refer to "warm glow" which may counterbalance solar farm's negative externalities. Finally, using an random parameter logit model, Vecchiato and Tempesta (2015)[67] assessed the impact of proximity to solar farms on Italians' preferences for them. The authors found that Italians prefer smaller solar farms that are located within 3 km of their place of residence and exhibit no statistically significant preference if located more than 10 km away from them. These findings are utilized to further investigate the relationship between respondents' exposure to solar farm and rooftop solar[68] and their WTP for solar energy (both solar farm and rooftop solar) development; wherein, we hypothesize that

[66] For an overview of the existing literature on distance to wind energy's impact on WTP, See Table 1 of either Knapp & Ladenburg, 2015 or Gudding et al., 2018.

[67] Vecchiato and Tempesta (2015) investigated Italian consumers' preferences for hypothetical policies that were distinguished by price, the source of energy (solar farm versus biomass), distance to energy facility, the size of energy facility, and the certification of the origin (only for biomass). Unlike Möllendorff & Welsch (2017) where they used a vague "postcode" to indicate distance, Vecchiato and Tempesta (2015) provided an explicit distance range at which their respondents would no longer support solar farm development.

[68] In our survey, solar farms were defined as facilities that provide large-scale generation of solar energy. We noted that, "A large solar farm can generate enough electricity for a community." Rooftop solar was defined as solar panels that are installed on top of building roofs or mounted on the ground. We indicated that, "A rooftop solar unit can generate enough electricity for one household."

distance to rooftop solar and/or solar farm is associated with decreased WTP for corresponding solar energy improvement ($\mathbf{H}_{Distance}$). If there is a statistically significant distance impact on respondents' support, then perhaps respondents' exposure to solar energy may be a factor in shaping their WTP.

In regard to residential location, Bergmann et al. (2008) showed that there is heterogeneity in preferences for RE improvement in urban versus rural place of residence in Scotland. They found that rural citizens support RE projects more than their urban counterparts as majority of RE construction will occur in rural areas. Similarly, Yoo (2011) found that rural residents in Pennsylvania are more supportive of solar farm development than urban residents, though not statistically significant. Further, Brown et al. (2017) noted that a majority of utility-scale RE development to comply with RPS will be located primarily in rural areas of the U.S. As such, we hypothesize that respondents who live in rural areas are distinctly more supportive of both solar farms ($\mathbf{H}_{Rural\text{–}solar\ farm}$) and RPS ($\mathbf{H}_{Rural\text{–}RPS}$).

Previous research indicates that environmental attitudes captured by the New Environmental Paradigm (NEP) scale has been *strongly* correlated with high levels of pro-environmental behaviors (e.g., Dunlap et al., 2000; Whitmarsh, 2009; Kennedy et al., 2015). The NEP scale is designed to capture the relationship between humans and the environment. The higher the NEP scores the greater the commitment to the conservation of natural resources, and vice versa. Over 300 articles have used some version of the NEP to measure environmental attitudes. (Hawcroft and Milfont, 2010). As noted by Faccioli et al. (2018), within stated preference valuation literature, the NEP scale has been given little attention. A majority of the peer-reviewed articles that use the NEP use the contingent valuation technique (e.g., Aldrich et al., 2007; Meldrum, 2015; Halkos & Matsiori, 2017). We hypothesize ($\mathbf{H}_{NEP}$) that a higher (modified) NEP score is associated with higher support for our environmental variables, RPS, rooftop solar, lower water usage, and smart meter installation.

Smart meters are electrical meters that can directly transfer electricity consumption information two ways, to both the customer and the corresponding utility company. This real-time communication will allow utility companies to dictate different time-of-use prices on electricity, which may encourage some customers to switch their use from peak hours (expensive) to low-use hours (less expensive) to save money. Further, smart meters facilitate the use of RE in the grid and minimizes the need for additional power plants to accommodate peak-hour times (peaking natural gas power plants), thus lowering carbon emissions (Ida et al., 2012) and water usage. In the last decade, several studies have assessed consumers' opinion and WTP towards adopting smart meters in Europe (e.g., Kaufmann et al., 2013; Durmaz et al., 2017) and Asia (e.g., Ida et al., 2012; Shim et al., 2018). An important contribution of our paper is that we focus on how use information is delivered to the customer in the U.S. We then estimate MWTP for the competing methods by which smart meters can provide the use information.

This research extends the literature by differentiating solar energy types, employing a modified NEP scale in primary research of RE valuation in a choice experiment setting, and assessing preferences on smart meter and RPS. We test the impact of the actual distance to the nearest solar location (both solar farm and rooftop solar) post-survey, rather than including an ex-ante distance attribute within the survey.

The rest of this paper is organized into four main sections. Section 3.3 presents the study area. Section 3.4 gives a description of the choice experiment design, the survey structure and administration, spatial heterogeneity, theory and the econometrics model, and finally the hypotheses that our paper seeks to test. In Section 3.5, we discuss the regression results. A discussion of results and conclusion will follow in the last section, Section 3.6.

3.3. Study Area: New Mexico

NM possesses substantial renewable resources. NM's available geo-physiological landmass is vast, which can be beneficial for achieving greater uptake of RE sources. The vast areas of NM with non-arable land that receives high wind and sunlight levels, is optimal for increasing RE usage. There are more than 310 days of sunshine with suitable temperature for solar power in NM (AED, 2018). Based on the sun index level developed by the National Renewable Energy Laboratory, NM is ranked 3rd amongst the states with the greatest energy potential from solar energy (NEO, 2010). NM was one of the top 10 states in solar electric capacity on a per-capita basis in both 2014 and 2015 (Weissman and Sargent, 2016) and ranked 15th in the nation in installed solar capacity in 2016 (EIA, 2018a).

NM has a poor economy, ranked 48th in the U.S. with a poverty rate of 19.8%[69], and is highly dependent on the energy industry. NM's budget is volatile as it is mainly driven by oil and natural gas prices: according to the Legislative Finance Committee 2016 report, respectively, a 1-dollar and a 10-cent increase in unit prices of oil and

[69] Source: https://www.usnews.com/news/best-states (accessed 8.23.18)

natural gas translate into $9.5 million in general fund and $6.5 million in additional revenue for NM.[70] NM has three active coal mines that provide two percent of the nation's coal output. NM's coal is either burned in its coal-fired power plants or exported to Arizona's power plant (EIA, 2018a). Although conventional energy's contribution to NM's economy is remarkable, they have the highest contribution to climate change in the state. In 2015, NM's energy industry was responsible for 50.2 million metric tons of carbon dioxide with coal being the main (40.6%) polluter, followed by oil (31.9%) and natural gas (27.5%). The potential economic impact of business-as-usual climate change to NM is considerable. Amongst other costs, increased energy-related costs[71] alone is estimated to be $248 million to NM in 2020 (McCALLY, 2015, p14). As such, NM has joined the move toward RE.

In March 2004, NM adopted an RPS (Senate Bill 43). Under NM's RPS, all large electric utilities are required to produce 20% of total electricity sale in-state from renewable sources by 2020.[72] Of this 20%, at least 20% and 3% are mandated to come from solar farm and rooftop solar respectively.[73] In the 53rd legislative session in 2017, a new bill was introduced that would require all large utilities to generate 80% of their total sales from renewables by 2040 (80% RPS by 2040) (Stewart and Small, 2017). A

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[70] Source: https://www.nmlegis.gov/Entity/LFC/Documents/Finance_Facts/finance%20facts%20oil%20and%20gas%20revenue.pdf For more information on NM's legislations including historical NM's general fund revenue see https://www.nmlegis.gov/ (accessed 8.23.18)

[71] Energy-related costs include products and services with significant energy inputs (e.g., gasoline, electricity, food, mass transit, and etc.).

[72] RPS requires NM's rural electric cooperatives to generate 10% of total electricity sold in-state from renewable sources by 2020.

[73] Public Regulation Commission set RE diversity targets to create a diversified RPS for NM. Based on this portfolio, utility companies are to comprise at least 30% sourcing from wind, 20% from solar, 3% from rooftop solar, and 5% from other resources (other than solar and wind) by 2020. More information about NM's RPS can be found at: http://programs.dsireusa.org/system/program/detail/720 (accessed 5.31.18).

modified version of this bill was passed in March 2019 that mandates a 100% RPS by 2045. Although RPS policies are designed to mitigate emissions, they also help with saving water consumed by fossil fuel generation. Any source of water (surface or groundwater) is scarce in NM.[74] Currently, the entire state is faced with some aspect of drought condition, with more than 86% of the state experiencing severe drought conditions, affecting 100% of NM's population.[75] Thus, water preservation that can arise from decreased utilization of fossil fuel and increased utilization of RE can be potentially useful.

There are three large electric utilities in NM: Public Service Company of New Mexico (PNM), El Paso Electric, and Xcel Energy. Of these three, PNM is NM's largest electric utility company with roughly 528,000 residential and business customers (more than 50% of the total NM consumer pool[76]) and serves 13 counties[77] out of 33 total counties. PNM has more than 1 million solar panels (15 solar farms) and currently more than 11,000 rooftop solar installations connected to its grid (PNM, 2018). This company also has purchase power agreements with several solar facilities within NM to comply with its RPS requirements. In 2017, the RE share of PNM electricity sales was about 15% and it is projected to meet its RPS goal of 20% by 2020 (PNM, 2018), which will lead to a net cost of $25,556,639 to the company in 2020 (O'Connell, 2018).

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[74] Source: https://www.env.nm.gov/water/ (accessed 8.23.18)
[75] As of August 21, 2018, 100% population of NM is affected by drought. Source: https://www.drought.gov/drought/states/new-mexico (accessed 8.23.18)
[76] In October 2018, PNM served 527,683 customers, of which roughly 470,000 were residential. At the same time, there were a total of 1,053,292 electricity customers in NM with 905,133 in the residential sector. Source: EIA form 861-monthly.
[77] Thirteen counties are: Bernalillo, Grant, Hidalgo, Lincoln, Luna, Otero, San Miguel, Sandoval, Santa Fe, Socorro, Torrance, Union, and Valencia.

Further, NM is one of the 43 states[78] with a net metering policy in place. This program, offered by all utility companies in NM, allows solar customers to sell/send back their excess electricity. Customers receive RE certificates (known as “REC”) in return that can be credited to their next bill or rolled over. Utility companies need to buy enough certificates in order to comply with RPS requirement on rooftop solar (3% in the case of NM).[79] For example, PNM rooftop solar customers can utilize RE credits saved during spring months (high-production and low-use months) to use during the summer, when electricity is more expensive. There is a discussion of implementing a policy at PNM in the future that rooftop solar owners can only use their credits in the same month that excess electricity is generated.[80] Another change that PNM is considering is smart meter installation. In 2016, PNM proposed implementing a mandatory smart meter program for its residential customers, which was rejected by NM Public Regulation Commission (NMPRC) (2018) in 2018.

[78] Source: https://www.seia.org/research-resources/net-metering-state (accessed 01.22.19).This source contains more information on Net Metering program in NM.
[79] To make this two-way transaction possible, utility companies install a separate production meter (RE certificate meter), which is different than the smart meter in our study. By smart meter, we mean more advanced types with added features that communicate electricity consumption and price information via an in-home display, online, or phone text. The meter installed by utility companies only captures the production of electricity by the panels and not the electricity consumption by customers. The smart meter examined in this study communicates consumption and price information simultaneously to both customer and the corresponding utility company. See https://www.pnm.com/interconnection-process (accessed 01.22.19).
[80] For more information on the current and the future discussion see: https://www.abqjournal.com/518250/rooftop-solar.html (accessed 5.31.18).

3.4. Methodology

3.4.1. Survey structure and administration

The survey was divided into five sections. We sought respondents' opinions on different sources of energy in the first section. In the second section, we provided short descriptions of the attributes used in the DCE, such as rooftop solar and solar farm, and asked about preferences toward each. The third section was dedicated to the Discrete Choice Experiment (DCE) questions. We gave an overview of the attributes involved in the proposed solar energy plan, asked relevant questions on each attribute, and provided respondents with a set of 4 choices over 3 plans. To reduce hypothetical bias, we reminded our respondents about their budget constraint before asking the DCE questions. The fourth section investigated attitudes toward RE, climate change, level of trust for authorities, and asked a shortened version of the NEP questions. The last section was dedicated to demographic questions. We tested the survey by conducting focus groups and debriefings in Summer 2017, and a pre-test to 100 PNM customers in Fall.[81]

We administered a mixed-mode survey, following the Tailored Design Method (Dillman et al., 2014) to 1,300 randomly-selected consumers of the state's largest electricity utility from 13 counties across NM. We purchased our sample from SSI.[82] We sent out up to 5 contacts by first-class mail: a brief pre-notice letter, the survey packet a week later, a follow-up postcard a week later, a replacement survey 2 weeks later, and the

[81] We conducted 2 focus groups and 12 debriefings. The final version of the questionnaire was ready to be sent out after some minor revisions in Winter 2017.
[82] The sample frame came from a general list purchased from SSI and included all zip codes in which PNM offers service.

final contact that contained the last survey 18 days later. We included a one-dollar bill incentive in the first survey packet (contact 2).

Overall, 404 responses were collected, and 211 questionnaires or invitations were returned by postal service. Assuming all survey recipients of unknown eligibility (undelivered) were not eligible to participate in the survey (AAPOR, 2016), we had a response rate of 37.1% (404/1,089), while assuming undelivered questionnaires were eligible will result in a response rate of 31.8% (404/1,300). Our response rate is comparable to other similar studies (e.g., 27% Mozumder et al. (2011); 35% Nkansah and Collins (2018); 28% Walter et al. (2019, working paper)). We received responses from 10 of the 13 counties that PNM offers service. Table 3-1 summarizes the socio-demographics.

Table 3-1: Socio-demographics

Variables	N	Our survey	Survey population*
Age (year)	404	54	39
Female	397	39%	51%
Education (Bachelor's degree or higher)	394	49%	29%
Income	392	$68,000	$45,500
Location (1–Urban)	404	0.82	0.84

* Sources of data: U.S. Census and Bureau of Business and Economic Research (BBER)

On average, our respondents are 54 years old, make an annual household income of $68,000, and are predominantly male (61%). Approximately, half of our respondents have earned a Bachelor's degree or higher. The largest share of our respondents lives in urban areas (82%). Compared to the population our survey represents, our sample is older, wealthier, more educated, and contains less female. In terms of residential location, that is urban/rural, our sample is comparable to the survey population.[83,84]

3.4.2. Choice Experiment Design

In a DCE survey, individuals are asked to make decisions amongst hypothetical plans with a series of attributes subject to their budget constraints and preferences. It is prudent to provide a clear and realistic description of each attribute prior to presenting the DCE questions. Based on the existing literature, two focus groups, and twelve debriefings, we identified six attributes with their corresponding levels to define a solar energy plan. This background work allowed us to develop a DCE survey, wherein we sought to evaluate respondents' utility gained from each solar energy plan; which derived our dependent outcome measure. Below we described the components of the survey that serves as a foundation for our investigation. Figure 3-1 displays a choice question used in our survey.

[83] Data come from Bureau of Business & Economic Research and U.S. Census Bureau.
[84] Demographic characteristics such as income, age, education, and gender were available in our survey. However, their interaction with our main-effect variables did not lead to statistically significant results. This shows that age, education, and gender might not be the main drivers of our sample's preference for renewable energy in general and solar energy in particular. Similar results were found for Pennsylvanians (Yoo, 2011, p. 22) and West Virginians (Nkansah & Collins, 2018, 22). We do find that respondents with higher levels of income exhibit higher WTP for our main attributes.

Consider the following possible PNM solar energy plans. Which plan would you prefer? *Check Plan A, Plan B, or Current Plan.*

	Plan A	Plan B	Current Plan
Percent of electricity from renewable sources by 2040	80%	50%	20%
Percent of solar energy from rooftop by 2040	9%	5%	9%
Credit policy for rooftop solar customers	Yes	No	Yes
Water used to generate electricity by fossil fuel	Medium- High (3 gallons per person per day)	High (4 gallons per person per day)	High (4 gallons per person per day)
Smart meters installation and feedback	View in-home display	Log into online account	No installation
Change in monthly electricity bill	↑ \$10/month	↑ \$5/month	No change
I would choose Plan →	A	B	CP

Figure 3-1: An example choice question used in the survey.

The first attribute, percent of electricity from renewable sources by 2040 (RPS), was intended to capture preferences towards an increase in the RPS level, especially the 80%-RPS-by-2040 bill. As described in the previous section, the current level of RPS by

2020 is 20%. We used a hypothetical 3rd level in between the proposed and current RPS, 50%. Thus, our first attribute had three levels: 20%, 50%, and 80%.

In choosing our second attribute, percent of solar energy from rooftop by 2040 (Rooftop), we were interested in discerning respondents' preference for rooftop solar verses solar farm. In the description of the second attribute, we mentioned that "*Increasing the share of rooftop solar means decreasing the share of solar farms.*" PNM's Procurement Plan for 2016 (the latest plan that included compliance summary) showed that it generated 31.9% of its solar requirement from solar farm and 3% from rooftop solar. In other words, rooftop solar comprised approximately 9% ($\frac{3\%}{31.9\%+3\%}$) of the total solar generation in 2016. Thus, we used 9% rooftop solar as the status quo level for the second attribute. The second attribute had four levels: 5%, 9%, 20%, and 30%. Figure 3-2 provides graphical representation of NM's status quo levels of total percent of RE by 2040 and percent of solar energy from rooftop by 2040. A change in RPS will affect the rooftop to solar farm proportion (see Figure 3-2). To gauge this impact, we include an interaction term between RPS and Rooftop in our analysis.

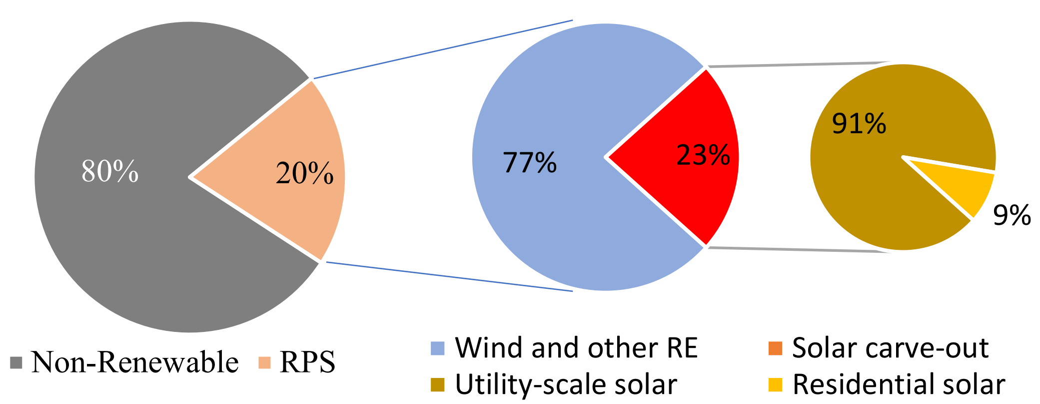

Figure 3-2: Generation Portfolio Mix. Note: Solar requirements are: 20% solar farm and 3% rooftop.

Our third attribute was credit policy for rooftop solar customers (NoCreditBanking), which stem from the current PNM policy toward its rooftop solar customers. This attribute is dichotomous, Yes and No, with Yes being rooftop customers should be allowed to save their RE credits (status quo).

Our fourth attribute, water used to generate electricity by fossil fuel (gallons per person per day) (Water), is capturing the trade-off between fossil fuel generation and RE. The water attribute levels are calculated from Albuquerque-area residents' water use[85], PNM's annual electricity production by source, and the RPS levels proposed in the first attribute. The levels are qualitative, and each are associated with a number of gallons per person per day: Low, Medium-Low, Medium-High, and High with 1, 2, 3, and 4 gallons/person/day respectively (the lower the value, the more water saved). The status quo level is High (4 gallons/person/day). To put this into perspective for our respondents, we provided the average water consumption of Albuquerque residents (127 gallons per person per day) in the survey. We utilized Albuquerque for our calculations as it is the largest metropolitan city in NM, as well as the largest population center serviced by PNM.

Our fifth attribute is smart meter installation and feedback (SmartMeter). The survey considers not only the preference for installation, but if installed, how consumers would access hourly usage and electricity price information. There are three options for how customers could access information: 1- Customers send a phone text message to the utility company and receive information in return ($SmartMeter_{text}$), 2- Customers can

[85] https://www.abqjournal.com/712294/water-use-continues-to-drop.html (accessed 5.31.18).

access information after logging into their online account ($\text{SmartMeter}_{\text{online}}$), and 3- An in-home display will be installed that shows the information ($\text{SmartMeter}_{\text{home}}$) (Gerpott and Paukert, 2013). We also included the status quo scenario (no installation).

Finally, we included a payment vehicle attribute, change in monthly electricity bill (Price), to be able to calculate the marginal price along with MWTP of the attributes. We used $0, $5, $10, $20, $30, and $50 as levels, with no change being the status quo level. Table 3-2 summarizes the attributes and corresponding levels in the current study.

Table 3-2: Attributes, levels, definitions, and expected signs.

Attribute	Attribute Level*	Definition
RPS	**20%**, 50%, 80%	Percent of electricity from renewable sources by 2040.
Rooftop	5%, **9%**, 20%, 30%	Percent of solar energy from rooftop solar by 2040.
NoCreditBanking	**Yes**, No	Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.
Water	Low (1 gal/person/day); Medium-Low (2 gal/person/day); Medium-High (3 gal/person/day); **High (4 gal/person/day)**	Water used to generate electricity by fossil fuel.
SmartMeter	$\text{SmartMeter}_{\text{text}}$, $\text{SmartMeter}_{\text{online}}$, $\text{SmartMeter}_{\text{home}}$, **No installation**	Smart meters installation and usage and price feedback by text, log into online account, or in-home display.
Price	**No change**, $5, $10, $20, $30, $50	Change in monthly electricity bill.

Note: * Levels in bold are status quo levels.

RPS, Rooftop, and Water are assumed to be continuous to have a linear effect on the choice of energy plan. NoCreditBanking is dummy coded and takes a value of 1 if rooftop solar owners can only sell credits in the same month that excess electricity is generated and 0 when they can sell credits any month of the year. The smart meter attribute, however, is divided into its levels (text, online, and in-home display) to reflect the qualitative nature of the levels.

Following the best practice outlined by Kuhfeld (2007), with the attributes and levels summarized in Table 3-2, an orthogonal main effect design that allowed for one interaction term between attributes (RPS and Rooftop) was deployed to develop choice sets in SAS. This resulted in a total of 48 choice sets which were divided into 6 versions. The survey had four choice sets per each version of the six total versions distributed. Each choice set included two alternative plans, along with a current plan alternative. We included the business as usual plan to make our DCE questions more realistic and let our respondents express preferences for or against the status quo. We capture this by incorporating an alternative specific constant (ASC) term in the analysis.

3.4.3. Spatial heterogeneity and NEP scale validity

In order to capture exposure to solar energy, we utilized distance to the closest rooftop solar and solar farm to our respondents, post-survey. Currently, there are 53 solar farms installed in NM (EIA, 2018b). Urban and rural respondents have median distances of about 7 km and 10.5 km respectively to the closest solar farm (as the crow flies).[86] Moreover, PNM has more than 11,000 rooftop solar customers that are connected to its grid.[87] The median urban and rural respondents live 0.15 km and 0.41 km away from the closest rooftop solar respectively. Figure 3-3 depicts our study area, respondents' place of residence, and existing rooftop solar and solar farms. We utilized Geographical

[86] Although urban respondents on average live closer to solar farms, they do not encounter with them as solar farms are usually located in the countryside.
[87] We downloaded the location (lat/long) data of each rooftop from http://www.nmprc.state.nm.us/index.html (accessed 5.31.18).

Information System (GIS) to calculate the distance to the closest rooftop solar and solar farm from respondents' place of residence.[88] Note that respondents were not asked about their awareness of the closest solar installation; we calculated the distance post-survey. Lastly, there are 20 households in our sample who own rooftop solar (their distance to the nearest rooftop solar equal to zero).

[88] To avoid confusion between the second attribute (Rooftop) and the distance variables, we refer to Rooftop (with capital "R") solar only when we talk about the survey attribute.

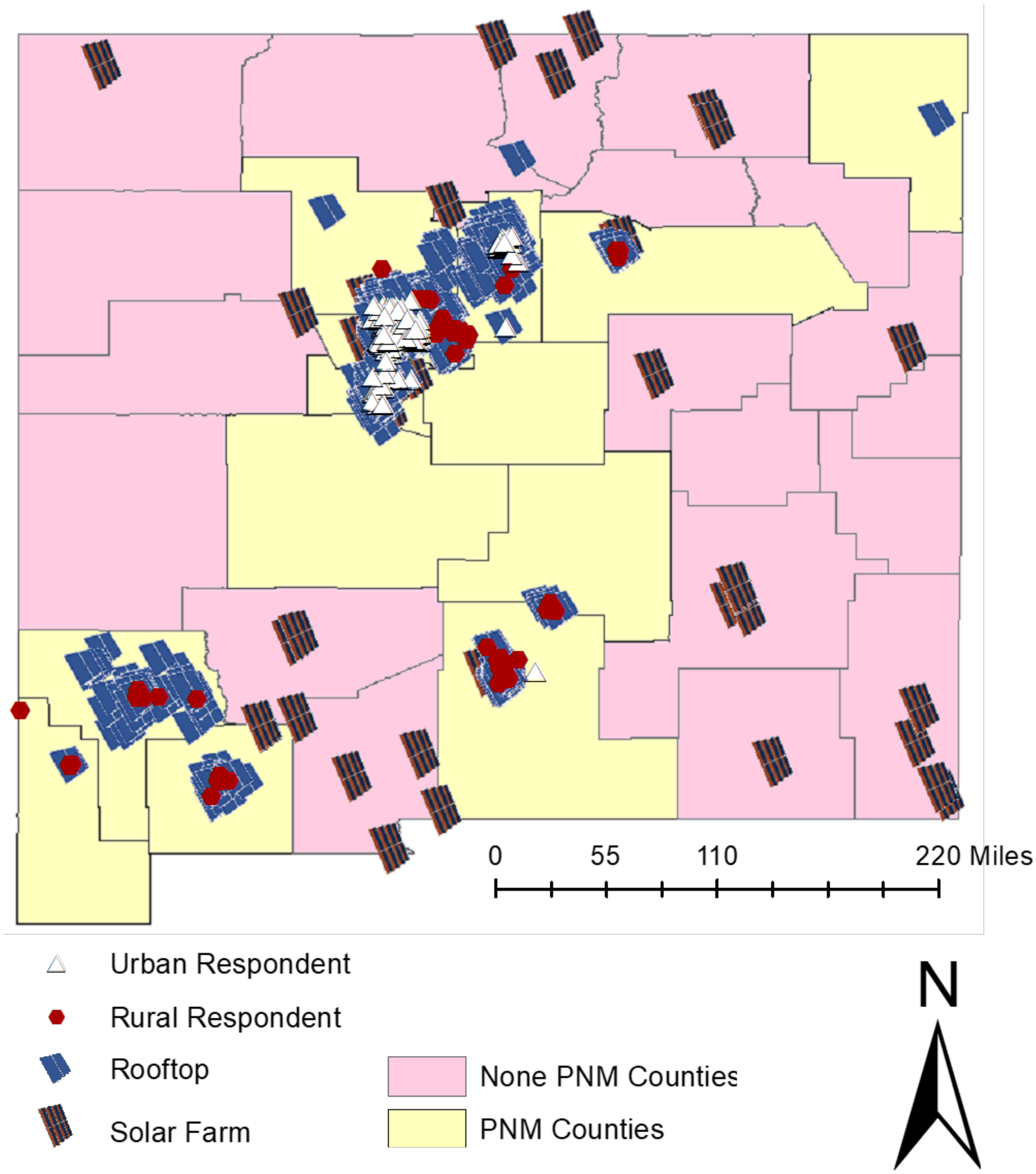

Figure 3-3: Study area

In regard to the NEP scale, we truncated the original NEP questions proposed by Dunlap et al. (2000) and used a reduced (6-item) version following Whitmarsh (2009) and Whitmarsh and O'Neill, (2010).[89] The modified NEP score has reasonably high internal consistency and is thus reliable (Cronbach's alpha 0.7014).

To further validate our NEP score variable, we performed principle component analysis on 18 questions, of which 6 were the NEP questions. This approach identified 3 components. The 6-item NEP formed one of the components. The three components together explain 56.5% variation in the data, of which 33% comes from the NEP component. We consider this as a validation exercise of the use of the modified NEP score in our analysis.

3.4.4. Econometric Model

The DCE methodology is placed within Random Utility Model (RUM) (Luce, 1959; McFadden, 1973) and Lancaster's Consumer theory (Lancaster, 1966). RUM assumes individual utility function contains an observable component (indirect utility) and a stochastic error term. The observable component is captured by the utility individual *j* (j=1, …, 404) gains from the attributes of the m^{th} alternative (m=1, …, 3, including the status quo) in choice set *i* (i=1, …, 4). Equation (9) summarizes the RUM:

$$U_{jmi} = V_{jmi} + \epsilon_{jmi} \tag{9}$$

On the other hand, Lancaster argues that individuals derive their utilities from intrinsic characteristics of goods (e.g., environmental benefits of solar energy) rather than immediate contents of the goods (e.g., solar panels). Assuming a linear in parameter

[89] Statements we included were: "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".

indirect utility function, it is the cumulative utility obtained from each attribute, mathematically:

$$V_{mi} = \beta_0 Price_{mi} + \sum_{a=1}^{A} \beta_i^a X_{mi}^a \tag{10}$$

where *Price* is a continuous variable indicating extra fee that customers will be required to pay for alternative *m* in choice set *i*, X_i' is the a^{th} non-price attribute of the m^{th} alternative in choice set *i,* while β_0 and β_i (a=1, …, A) are the vectors of parameters (including ASC) to be estimated via maximum likelihood estimation approach, representing the contribution of each attribute in the indirect utility V_{mi}. Combining equations (9) and (10) leads to equation (11):

$$U_{jmi} = \beta_0 Price_{jmi} + \sum_{a=1}^{A} \beta_i^a X_{jmi}^a + \epsilon_{jmi} \tag{11}$$

Respondent *j* chooses the alternative *m* in choice set *i* that maximizes her utility, U_{jmi}.

There are numerous modeling methods that can be used to evaluate DCE data. The most common modeling approach is the Multinomial Logit Model (MNL). An MNL model assumes that the stochastic error term in equation 3 is independently identically distributed (i.i.d.) with Generalized Extreme Value type I across respondents. Furthermore, an MNL model posits an unrealistic assumption (Independence from Irrelevant Alternatives (IIA)) that everyone has identical preference for an alternative (i.e., perfect substitution among all alternatives) and hence estimates a utility function for the entire population (McFadden, 1973).[90] Random Parameter Logit model (RPL)[91] is

[90] For more information on the restrictions of MNL, see Train, (2003)
[91] Also known as mixed logit model.

another widely-used modeling approach that does not assume the IIA and captures preference heterogeneity by deriving an individual-level utility function (Train, 2009).[92] We use these two models in our analyses.[93]

In addition, we provide the MWTP for each attribute. The estimated MWTP is the amount of money that a respondent is willing to trade for a marginal (one unit more) change in the level of an attribute. MWTP for attribute *a* can be calculated using equation (12):

$$MWTP = -\left[\frac{\partial U_i/\partial x_a}{\partial U/\partial Price}\right] = -\left(\frac{\beta_a}{\beta_0}\right) \tag{12}$$

where β_a and β_0 are the estimated coefficients on attribute *a* and price parameter in the models respectively.

Empirically, we estimate 4 models: 2 MNL and 2 RPL. Models 1 and 2 are baseline models which estimate main effects for each attribute and an interaction term between RPS and Rooftop solar attributes. Since we are interested in investigating changes from status quo levels of RPS and rooftop/solar farm, we centered the interaction term at their status quo levels. Equation (13) summarizes the global utility specification applied in models 1 and 2:

[92] For a thorough explanation of the econometric modeling, see: Train (2003), Hensher et al. (2005), and Train, (2009).
[93] There are other alternative approaches to model choices in, such as WTP-space and generalized multinomial logit models. WTP-space model directly estimates WTP distributions for each attribute. GMNL model accounts for scale and preference heterogeneities. We utilized the more traditional preference-space approach as WTP-space approach generally led to higher MWTP and also was not a better fit than our preference-space model. Similarly, GMNL models did not lead to significantly better fit and had convergence problem (Gu et al., 2013). Although similar results were derived from both WTP-space and GMNL models. For more information on these models see, Train & Weeks (2005), Scarpa (2012), Scarpa et al. (2008), Hole & Kolstad (2012), Fiebig et al. (2009), and Ben-Akiva et al. (2019) among others.

$$U = ß_0 Price + ß_1 RPS + ß_2 Rooftop + ß_3 NoCreditBanking + ß_4 Water + ß_5 SmartMeter_{text} + ß_6 SmartMeter_{online} + ß_7 SmartMeter_{home} + ß_8 (RPS - 20) \times (Rooftop - 9) + ß_9 ASC + \epsilon \quad (13)$$

where the β's are the estimated coefficients (marginal utility) on price, RPS, Rooftop, no to credit banking, water, smart meter levels, RPS Rooftop interaction term and ASC parameters.

Recall that not only we are interested in capturing unobserved heterogeneity, but also we want to include important observed heterogeneity variables in our modeling. The latter helps with fulfilling the gaps in the literature indicated earlier. In doing so, we estimate models 3 and 4. Equation (14) presents the utility specification of the two models:

$$\begin{aligned} U = ß_0 Price &+ ß_1 RPS + ß_2 Rooftop + ß_3 NoCreditBanking + ß_4 Water \\ &+ ß_5 SmartMeter_{text} + ß_6 SmartMeter_{online} \\ &+ ß_7 SmartMeter_{home} + ß_8 (RPS - 20) \times (Rooftop - 9) + \beta_9 ASC \\ &+ ß_{10} RPS \times rural + ß_{11} Rooftop \times rural \\ &+ ß_{12} RPS \times (Dist\_to\_rooftop) \\ &+ ß_{13} Rooftop \times (Dist\_to\_rooftop) \\ &+ ß_{14} RPS \times (Dist\_to\_solar\ farm) \\ &+ ß_{15} Rooftop \times (Dist\_to\_solar\ farm) + ß_{16} RPS \times NEP \\ &+ ß_{17} Rooftop \times NEP + ß_{18} Water \times NEP \\ &+ ß_{19} SmartMeter_{online} \times NEP + ß_{20} SmartMeter_{home} \times NEP + \epsilon \end{aligned} \quad (14)$$

where the first nine variables ($ß_1$–$ß_9$) are the same as in equation (13). The remaining coefficients capture the observed heterogeneity including location's impact on respondents' attitude towards RPS and solar energy, distance to the closest rooftop solar and solar farm on RPS and Rooftop attributes, and NEP scale on the environmental attributes. We utilize Model 3 to test our hypotheses, $\mathbf{H}_{\text{Rural}}$, $\mathbf{H}_{\text{Distance}}$, and $\mathbf{H}_{\text{NEP}}$. Table 3-3 summarizes the three hypotheses we have developed thus far:

Table 3-3: Hypothesis tested in this study

	Description	**Null Hypotheses***
$\mathbf{H}_{Rural}$	Respondents who live in a rural area are distinctly more supportive of RPS ($\mathbf{H}_{Rural-RPS}$) and solar farm ($\mathbf{H}_{Rural-solar}$ farm).	$H_0{:}\,\beta_{10} \leq 0; H_1{:}\,\beta_{10} > 0$ $H_0{:}\,\beta_{11} \geq 0; H_1{:}\,\beta_{11} < 0$
$\mathbf{H}_{Distance}$	Distance to rooftop and/or solar farm impacts support for solar and RPS improvement.	$H_0{:}\,\beta_{12} \geq 0; H_1{:}\,\beta_{12} < 0$ $H_0{:}\,\beta_{15} \leq 0; H_1{:}\,\beta_{15} > 0$
$\mathbf{H}_{NEP}$	Higher NEP score is associated with higher support for RPS and Rooftop, lower water usage, and smart meter implementation.	$H_0{:}\,\beta_{16} \leq 0; H_1{:}\,\beta_{16} > 0$ $H_0{:}\,\beta_{17} \leq 0; H_1{:}\,\beta_{17} > 0$ $H_0{:}\,\beta_{18} \geq 0; H_1{:}\,\beta_{18} < 0$ $H_0{:}\,\beta_{19} \leq 0; H_1{:}\,\beta_{19} > 0$ $H_0{:}\,\beta_{20} \leq 0; H_1{:}\,\beta_{20} > 0$

* Not only sign but also significance levels of the coefficients tested in these hypotheses matter.

Recall that Bergmann et al. (2008) and Yoo (2011) demonstrate rural residents are more supportive of solar farms, while Brown et al. (2017) shows the majority of utility-scale RE development to comply with RPS will be located in rural areas. These projects might be associated with financial (e.g., jobs, developing local infrastructure) and psychological benefits (pride and prestige in going green) for rural residents. As such, we hypothesized that rural respondents will support solar farm as well as RPS.[94] Thus, statistically significant and positive β_{10} would support the alternative hypothesis of $\mathbf{H}_{Rural-RPS}$ that rural respondents distinctly support RPS. Further, given how the solar energy attribute (Rooftop) is designed, a statistically significant negative Rooftop

[94] The "*rural*" variable captures living in rural areas and not distance to solar locations.

coefficient implies that respondents support solar farm. Thus, the alternative hypothesis of rural respondents distinctly supporting solar farm development ($\mathbf{H}_{Rural\text{–}solar\ farm}$) would be supported by statistically significant negative β_{11}. We examine if a distance decay effect exists on either rooftop solar, solar farm, or both. Recall that Rehdanz et al. (2017) and Nkansah & Collins (2018) demonstrate that the distance decay effect is present in the case of wind energy. Building on this literature, we hypothesized that the distance decay effect holds true in the case of rooftop solar and/or solar farm ($\mathbf{H}_{Distance}$). To investigate this hypothesis, we interact distance to rooftop solar and solar farms with the Rooftop attribute. We are also interested in their impact on RPS (see equation (14)). A negative and statistically significant $ß_{13}$ indicates the closer to rooftop solar a respondent lives the higher utility she gains from rooftop improvement ("warm glow"). Whereas, a positive and statistically significant $ß_{15}$ implies solar farm's distance decay effect (Vecchiato and Tempesta, 2015), that is the farther away a respondent lives from a solar farm the lower utility she derives from solar farm development. Statistically significant and negative β_{13} or positive β_{15} would support the alternative hypotheses on distance hypothesis. Lastly, if the findings on the NEP scale literature persists in our DCE survey setting, one can assert that statistically significant and positive β_{16}, β_{17}, β_{19}, and β_{20} and negative β_{18} would support our five alternative hypotheses of the NEP scale.

Finally, in the RPL models, we assume all the attributes, including price, and the ASC variable are normally distributed and use 400 Halton draw (Train, 1999; Bhat, 2001; Scarpa et al., 2008; Train, 2009; Vecchiato and Tempesta, 2015).[95]

[95] All the analyses are done in Stata using Hole's (2007) clogit(), mixlogit(), and wtp() commands.

3.5. Results

In this section, we highlight results from the valuation analysis. Table 3-4 presents the definition of all the variables utilized in the models and expectations placed on the corresponding variables.

Table 3-4: Definition of variables

Variables	Definition	Expected sign
RPS	Percent of electricity from renewable sources by 2040.	+
Rooftop	Percent of solar energy from rooftop solar by 2040. (Increase in rooftop solar equates with decrease in solar farm)	(?)
NoCreditBanking	Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.	–
Water	Water used to generate electricity by fossil fuel.	–
$SmartMeter_{text}$	Usage and electricity price information via text	(?)
$SmartMeter_{online}$	Usage and electricity price information via online account	(?)
$SmartMeter_{home}$	Usage and electricity price information via an in-home display	(?)
Price	Change in monthly electricity bill.	–
ASC	Alternative specific constant takes a value of 1 for the current plan alternative and 0 otherwise.	–
(RPS-20)*(Rooftop-9)	Interaction between RPS and Rooftop variables, centered on their status quo levels.	(?)
RPS*rural	Interaction between RPS and Rural variable*	+
Rooftop*rural	Interaction between Rooftop and Rural variable	–
Rooftop*Distance to rooftop	Interaction between Rooftop and distance to rooftop solar**	–
RPS*Distance to rooftop	Interaction between RPS and distance to rooftop solar.	–
Rooftop* Distance to solar farm	Interaction between Rooftop and distance to solar farm***.	+
RPS*Distance to solar farm	Interaction between RPS and distance to solar farm.	+
Rooftop*CenteredNEP	Interaction between Rooftop and centered NEP****.	+
RPS*CenteredNEP	Interaction between RPS and centered NEP.	+
Water*CenteredNEP	Interaction between Water and centered NEP.	–
$SmartMeter_{onlline}$*CenteredNEP	Interaction between $SmartMeter_{online}$ and centered NEP.	+
$SmartMeter_{home}$*CenteredNEP	Interaction between $SmartMeter_{home}$ and centered NEP.	+

Notes:
* Rural= Dummy variable that takes a value of 1 if respondent is in a rural area and zero if urban.
** Distance to rooftop solar = Distance to the closest rooftop solar as the crow flies in meter. Distance to Rooftop is divided by 1000 meter.
*** Distance to solar farm = Distance to the closest solar farm as the crow flies in meter. Distance to solar farm is divided by 1000 meter.
**** NEP score is centered at its mean, 23.04.

Based on the existent RE acceptance's literature (i.e., Sundt & Rehdanz, 2015; Ma et al., 2015), we expected that respondents support higher level of RPS. There is no nonmarket valuation study that distinguishes between solar energy types, rooftop solar verses solar farm. Thus, we placed no expectations on the sign of the Rooftop attribute parameter prior to model estimation. Similarly, we placed no expectation on smart meter levels (text, online, in-home display). More than 88% of our respondents chose the statement, "Rooftop solar customers should be allowed to save their credits", thus, we assumed respondents derive a negative utility from not allowing customers to bank credits. We also assumed that NM residents would oppose a policy that increases the use of water consumption by fossil fuel. Lastly, the alternative specific constant and price parameters were expected to be negative. Our hypotheses derived the remaining parameters' expected signs.

For comparison and robustness check, Table 3-5 summarizes results from both the MNL and the RPL models based on choices of 404 respondents.[96] Model 1 and Model 2 specifications include the attributes. In attempting to account for the relationship between RPS and rooftop/solar farm, we included the interaction term between RPS and Rooftop. This interaction term accounts for the relationship as marginal utility gained from a one percent increase in rooftop solar level (1% decrease in solar farm) is not only impacted by rooftop itself (β_2), but also by a change from status quo level of RPS ($\beta_8 \times (RPS - 20)$) (i.e., $\partial U / \partial RPV = \beta_2 + \beta_8 (RPS - 20)$). We centered both attributes at their status quo levels to be able to interpret changes from the current levels of RPS and Rooftop.

[96] 404 respondents returned our questionnaires, each respondent provided us with 4 data points yielding a data set with 1,616 observations.

Further, we included the ASC variable to capture business as usual effect (see equation (13)).

Table 3-5: Regression results of solar energy plans

	MNL	RPL[d]				MNL
	Model 1	Model 2		Model 3		Model 4
VARIABLES	Coef. (SE)	Coef. (SE)	SD	Coef. (SE)	SD	Coef. (SE)
Price[a]	-0.040***	-0.112***	0.092***	-0.103***	0.089***	-0.042***
	(0.003)	(0.019)	(0.017)	(0.013)	(0.014)	(0.003)
RPS[a]	0.022***	0.050***	0.081***	0.044***	0.061***	0.022***
	(0.003)	(0.009)	(0.014)	(0.009)	(0.009)	(0.004)
Rooftop[a]	0.036***	0.085***	-0.039**	0.073***	-0.018	0.031***
	(0.007)	(0.019)	(0.017)	(0.020)	(0.040)	(0.009)
NoCreditBanking[a]	-0.279***	-0.175	-0.747**	-0.109	0.619*	-0.262***
	(0.068)	(0.164)	(0.345)	(0.162)	(0.359)	(0.077)
Water[a]	-0.184***	-0.532***	-0.411**	-0.457***	-0.296	-0.189***
	(0.032)	(0.099)	(0.206)	(0.085)	(0.249)	(0.034)
$\text{SmartMeter}_{\text{text}}$[a]	-0.077	0.262	0.452	0.237	0.644	-0.060
	(0.107)	(0.227)	(0.387)	(0.217)	(0.755)	(0.115)
$\text{SmartMeter}_{\text{online}}$[a]	0.178	0.796***	-0.116	0.873***	0.108	0.312**
	(0.118)	(0.256)	(0.459)	(0.246)	(0.421)	(0.124)
$\text{SmartMeter}_{\text{home}}$[a]	0.230**	0.887***	-1.798***	0.951***	-1.546***	0.301**
	(0.107)	(0.265)	(0.489)	(0.264)	(0.462)	(0.117)
ASC[a]	-0.420***	-1.464***	2.833***	-1.306***	2.306***	-0.530***
	(0.140)	(0.327)	(0.494)	(0.293)	(0.423)	(0.147)
(RPS-20)*(Rooftop-9)	-0.001***	-0.002***		-0.002***		-0.001***
	(0.000)	(0.001)		(0.001)		(0.000)
RPS*rural				0.015		0.009
				(0.013)		(0.006)
Rooftop*rural				-0.069***		-0.027**
				(0.026)		(0.012)
RPS*Distance to rooftop				-0.005***		-0.002**
				(0.002)		(0.001)
Rooftop*Distance to rooftop				0.001		0.000
				(0.002)		(0.001)

(Table 3-5 Cont.)

Table 3-5 (continued)

RPS*Distance to solar farm			0.000	0.000
			(0.001)	(0.000)
Rooftop*Distance to solar farm			0.002*	0.001*
			(0.001)	(0.001)
RPS*CenteredNEP[b]			0.006***	0.003***
			(0.001)	(0.000)
Rooftop*CeneteredNEP[b]			0.004**	0.003***
			(0.002)	(0.001)
Water*CenteredNEP[b]			-0.052***	-0.027***
			(0.015)	(0.008)
$\text{SmartMeter}_{\text{online}}$*Centered NEP[b]			0.126***	0.057**
			(0.042)	(0.022)
$\text{SmartMeter}_{\text{home}}$*Centered NEP[b]			0.078*	0.042*
			(0.046)	(0.023)
Observations[c]	1,599	1,599	1,507	1,507
Log likelihood	-1443	-1181	-1072	-1247
AIC	2907	2399	2205	2537
BIC	2972	2522	2397	2671

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
a: Random parameters assumed normally distributed;
b: NEP score is centered at its mean (23.04);
c: Each of our 404 respondents had 4 choices to make;
d: 400 number of Halton draws were used for the RPL models.

All else being equal (*ceteris paribus*), respondents gain a negative utility by paying an extra monthly fee on top of their current electricity bill in both models. As expected, respondents derive a statistically significant and positive utility from increasing RPS beyond the status quo level (20%) in both models. The statistically significant and positive sign on Rooftop parameter in models 1 and 2 indicates that respondents prefer an increase in rooftop portion of the solar carve-out from its status quo level (9%). As anticipated, respondents do not support a policy that results in consuming more water for electricity generation in both models. NoCreditBanking has negative sign in both models but is only statistically significant in the MNL model.[97] Respondents also derive less utility from the current situation (ASC) than the designed PNM's solar energy alternatives. Lastly, the sign on the interaction term between RPS and Rooftop depends on the level of RPS and Rooftop under question; an increment from status quo level of RPS decreases the utility gained from rooftop diffusion, and vice versa. In other words, marginal utility for rooftop development decreases as RPS increases beyond status quo levels. Thus, increase in rooftop (relative to solar farm) becomes less important if increasing RPS.

Recall that smart meter has three levels: text, online, and in-home display. A statistically significant and positive coefficient estimate on any of those three levels indicates that respondents derive a positive utility from smart meter installation when they access information via the corresponding type of information delivery. With that in mind, our respondents do not support smart meter installation when texting is used as the

[97] This stems from the large degree of preference heterogeneity among respondents. We graphed the kernel density function on Credit_no individual-level coefficients from RPL model. The number of supports and oppositions appear to cancel each other out and hence the insignificancy in RPL model.

type of information delivery in both models. However, both models estimate that respondents derive a positive utility from smart meter installation when they are accessing their usage and electricity price through either online or an in-home display ($\text{SmartMeter}_{\text{online}}$ and $\text{SmartMeter}_{\text{home}}$).[98]

The 4th column of Table 3-5 shows the standard deviations estimated from the RPL model. We assumed all of our parameters, except the RPS and Rooftop interaction term, are normally distributed. All of the standard deviations are statistically significant, except those of SmartMeter_{text} and $\text{SmartMeter}_{online}$. Statistically significant standard deviation indicates that respondents' choice for the corresponding attribute are statistically significantly different and thus preference heterogeneity exists. In other words, heterogeneity results from different respondents placing different values for the potential impact of the attributes. For example, some respondents may oppose RPS because they believe RE facilities look unpleasant (or "*they kill birds*"), while some may support RPS due to RE's positive environmental impact ("*no water and emission*"), which were ideas observed in our focus groups and debriefings. MNL model posits the IIA assumption that everyone has identical preference for an alternative and fails to capture preference heterogeneity. Further, comparing the log likelihood (-1,443 vs. -1,181), the AIC (2,907 vs. 2,399), and the BIC (2,972 vs. 2,522), it is evident that RPL also outperforms MNL from a statistical standpoint. Hence, the focus of the discussion and the analysis of results is solely on the RPL model. For robustness check purposes, we include the MNL models alongside of RPL models.

[98] $\textit{SmartMeter}_{online}$ becomes significant at 95% level after including the spatial heterogeneity and the NEP variables in the MNL model. See Model 4 of Table 3-5.

To further investigate the existence of preference heterogeneity among our respondents, the third model modification additionally includes the variables describing spatial heterogeneity and the NEP scale (see equation (14)). Thus, Model 3 of Table 3-5 accounts for location, that is rural/urban, distance to the nearest solar installation, that is distance to rooftop solar and solar farm, and the NEP scale. Spatial heterogeneity variables are interacted with only RPS and Rooftop attributes, while the NEP score is interacted with other environmental variables (i.e., Water and smart meter – online and in-home display levels only[99]) in addition to RPS and Rooftop. The NEP score is centered at its mean value, 23.04. The additional variables in Model 3 compared to Model 2 are assumed not to be random.

The overall findings of estimated coefficients stay similar in terms of both sign and magnitude across the attributes in the second RPL model with covariates (Model 3). However, two of the nine random parameters (Rooftop and Water) are no longer normally distributed (the 6th column of Table 3-5), which indicates including the spatial heterogeneity and the NEP score variables (observed heterogeneity) in the model capture more of the existing heterogeneity in preference in Model 2.

We find that rural respondents derive statistically lower utility from Rooftop attribute. The interacted variables with the NEP scale are highly statistically significant and have the expected signs. Two out of the four interaction terms defining distance to rooftop and solar farm in Model 3 are statistically significant.[100] The interaction between

[99] We did not consider $\text{SmartMeter}_{\text{text}}$ as it is not statistically significant in Model 2.
[100] We first divided distance not only by solar type (rooftop and solar farm), but also by location (rural and urban), which resulted in 8 variables. We then performed t-tests on all 4-pair related coefficients (e.g., RPS*distance to rooftop*rural and RPS*distance to rooftop*urban) and failed to reject any of the four equality null hypotheses. Further, although the latter model had 4 more parameters than the current Model 3, the model fits were identical. Hence, we went with the current format Model 3.

RPS and distance to the nearest rooftop solar indicates, *ceteris paribus,* the farther away respondents live to rooftop solar, the less supportive of RPS they become. 12 km and 9 km[101] away from rooftop solar will result in no support for RPS from rural and urban citizens respectively. The opposite holds for the interaction term between Rooftop attribute and distance to the closest solar farm. Respondents are weakly more supportive of Rooftop attribute as their distance to the closest solar farm increases. In other words, respondents care less about solar farms as they live farther away from them. However, distance to the closest rooftop solar and solar farm do not affect how respondents feel about Rooftop and RPS respectively. Overall, we observe a decay in support for solar farm with increasing distance from solar farm (distance decay effect), also distance to rooftop solar, and not solar farm, affects respondents' support for RPS. In one hand, the evidence will not support the alternative hypothesis of the farther away one lives from rooftop solar, the less supportive of rooftop solar she is. On the other hand, this evidence will allow us to support the alternative hypothesis of the farther away one lives from solar farm, the less supportive of solar farm one becomes ($\mathbf{H}_{Distance}$).

Now we turn our attention to MWTP. As indicated above, we used equation (12) to derive MWTP. Table 3-6 summarizes the MWTP values. The 2nd column of Table 3-6 reports the MWTP for each parameter in Model 2 and the 3rd column shows the corresponding confidence interval values. We utilized Krinsky and Robb's (1986) bootstrapping approach with 50,000 simulations to estimate the confidence interval. At the status quo levels when RPS is 20% and Rooftop is 9%, the RPL model suggests that our respondents exhibit a MWTP of $.45/month [$0.35–$0.57] and $0.76/month [$0.52–

[101] $Rural = \frac{0.015+0.044}{0.005} = \sim 12\ km; Urban = \frac{0.044}{0.005} = \sim 9\ km$

$1.07] for each 1% increase in the current level of RPS and the share of Rooftop in RPS respectively. Given the MWTP and status quo level of RPS, we can extrapolate that our respondents are willing to pay a premium of $27/month to achieve an 80% RPS. This amount is equivalent to a 36% increase in NM's average current electricity bill.[102]

Table 3-6: Marginal Willingness to Pay Values in USD/month

Variables	Model 2		Model 3	
	MWTP	Krinsky Robb [CI[a]]	MWTP	Krinsky Robb [CI[a]]
Price	--	--	--	--
1% increase in RPS levels by 2040	$0.45***	[$0.35, $0.57]	$0.43***	[$0.3, $0.57]
1% increase in rooftop levels by 2040	$0.76***	[$0.52, $1.07]	$0.71***	[$0.41, $1.03]
No to Credit Banking	-$1.57	[$-4.17, $0.87]	-$1.06	[$-3.83, $1.54]
Water	-$4.77***	[$-6.28, $-3.55]	-$4.44***	[$-5.81, $-3.19]
Smart Meter installation using text	$2.35	[$-1.14, $5.51]	$2.30	[$-1.06, $5.89]
Smart Meter logging to online account	$7.14***	[$3.52, $11.29]	$8.48***	[$4.68, $12.43]
Smart Meter using an in-home display	$7.96***	[$4.31, $12.05]	$9.24***	[$5.43, $13.45]
Business as usual (ASC)	-$13.13***	[$-20.49, $-7.86]	-$12.69***	[$-18.21, $-7.62]
RPS*rural			$0.15	[$-0.05, $0.36]
Rooftop*rural			-$0.67***	[$-1.09, $-0.26]
RPS*Distance to rooftop			-$0.05***	[$-0.08, $-0.03]
Rooftop*Distance to rooftop			$0.01	[$-0.03, $0.04]
RPS*Distance to solar farm			$0.00	[$-0.01, $0.01]
Rooftop*Distance to solar farm			$0.02*	[$0, $0.04]
RPS*Centered NEP			$0.06***	[$0.04, $0.08]
Rooftop* Centered NEP			$0.04**	[$0.02, $0.08]
Water* Centered NEP			-$0.50***	[$-0.78, $-0.28]
$SmartMeter_{online}$* Centered NEP			$1.23***	[$0.41, $1.69]
$SmartMeter_{home}$* Centered NEP			$0.75*	[$0.02, $1.54]

Notes: *** p<0.01, ** p<0.05, * p<0.10;
a: We utilized Krinsky and Robb's (1986) approach to estimate MWTP confidence intervals [CI].

Allowing for RPS and Rooftop levels to vary (i.e., not at the status quo RPS and Rooftop levels) (see Figure 3-2) will result in changing marginal utility magnitudes and

[102] Average electricity bill in NM is $75.00. Source: https://www.electricitylocal.com/states/new-mexico (accessed 5.27.18)

subsequently MWTP values. Note that decreasing rooftop solar equates with increasing solar farm in our analysis. Of interest here is to examine whether RPS and Rooftop parameters change signs (no more support).[103] Overall, *ceteris paribus*, we find that respondents are supportive ($0.07/month) of RPS even at the highest Rooftop level (30%). However, a 62%-RPS can lead to zero support for Rooftop development. The latter could very well happen; an 80%-RPS-by-2040 bill was introduced though did not pass (Stewart and Small, 2017). This indicates that our respondents are supportive of RPS and would prefer it to come from solar farm rather than rooftop, as a zero rooftop solar means 100% solar farm here. As RPS level increases, our respondents' MWTP for rooftop (solar farm) decreases (increases).

For each 1 gallon/person/day (2 million gallons/day[104]) reduction in water consumed by fossil fuel to generate electricity, the RPL model (Model 2) suggests that our respondents are willing to pay $4.77/month [$6.28, $3.55] on top of their current electricity bill. As indicated earlier, New Mexicans are supportive of smart meter as long as the information is communicated either online or via an in-home display and are exhibiting MWTP of $7.14/month [$3.52, $11.29] and $7.96/month [$4.31, $12.05] respectively.[105]

Taking the mean NEP score and zero distance to rooftop and solar farm, along with RPS and Rooftop status quo levels into account in Model 3, there is not a

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[103] $\frac{\partial U}{\partial RPS} = 0.05 - 0.002 \times (RPV - 9) < 0 \Longrightarrow RPV > 34\%$; $\frac{\partial U}{\partial RPV} = 0.085 - 0.002 \times (RPS - 20) < 0 \Longrightarrow RPS > 62.5\%$. Marginal utility values are from Table 3-5. Further, a 9% share of rooftop in a 60% RPS would require many new rooftop solar installations that with the current situation there might not be enough incentives.
[104] Multiplied by NM population.
[105] Rather than a categorical variable, we included a dummy coded smart meter variable that took a value of 1 if agree to smart meter installation and 0 otherwise in Model 2. This variable was significant at a 99% level indicating that our respondents are supportive of smart meter installation. Further, respondents exhibited a MWTP of $5.30/month [$2.50, $8.06].

statistically significant difference between rural verses urban respondents for the RPS attribute, though rural respondents have a higher MWTP (see Table 3-6). Hence, the evidence does not support the alternative hypothesis of $\mathbf{H}_{\text{Rural-RPS}}$ that rural respondents are statistically significantly more supportive of RPS development. However, rural respondents are significantly less in favor of Rooftop solar attribute than urban at zero distance, though overall they support rooftop solar improvement (MWTP=$0.071-$0.67= $0.04/month). This implies that rural respondents are statistically significantly more supportive of solar farm improvement than urban respondents. As solar farms are generally located in the rural area, a decrease in their number might mean less jobs with financial and moral benefits (Dastrup et al., 2012) for the rural citizens. Conversely urban respondents have much higher MWTP ($0.71) for the Rooftop attribute, as they encounter with rooftop more and hence might be associated with the "warm glow" and psychological impact (Möllendorff and Welsch, 2017, p117). Thus, Model 3 provides us with enough reasons to support the alternative hypothesis of rural (urban) residents are more supportive of solar farms (rooftop solar) ($\mathbf{H}_{\text{Rural-solar farm}}$).

In line with other scholars' findings on the NEP scale, Model 3[106] suggests that respondents with positive environmental worldview has positive attitude toward the environment-related variables, namely RPS, Rooftop, water, and online and in-home display smart meter. For each score higher than mean, ceteris paribus, respondents are willing to pay an extra $0.06/month and $0.04/month for 1% increase in RPS and Rooftop respectively. Similarly, for each score higher than the NEP average, respondents are willing to pay $0.50/month, $1.23/month, and $0.75/month to reduce water

[106] Model 4 is the MNL version of Model 3. We included this model for the purpose of comparison and robustness check.

consumption by fossil fuel by 2 million gallons/day[107], install smart meter and access information either online or via an in-home display respectively. Hence, the evidence supports the alternative hypotheses of HNEP that higher NEP is correlated with higher support for the environment-related attributes.

Lastly, letting the interacted variables not be fixed at the status quo levels will allow us to examine different scenarios. Let us assume median distance to rooftop and solar farm for rural and urban respondents and mean NEP score, along with allowing for status quo values of RPS and Rooftop to change.[108] Of interest here is to investigate whether these assumptions lead to further divergent support for RPS and Rooftop by location, that is urban and rural, and how different they are compared to the values we found from Model 2. Similar to model 2, both rural ($0.14/month) and urban ($0.01/month) respondents support RPS even at the highest-level Rooftop. For an RPS level higher than 32.6%, rural respondents are no longer willing to pay a premium to increase share of Rooftop in the RPS. Similarly, 63.4% is the highest RPS level that urban respondents would still accept to support an improvement in the share of Rooftop in RPS. In other words, our respondents, especially those who live in the rural area, want extra RPS to be fulfilled by solar farm rather than rooftop solar. Thus, we can conclude that the higher than the status quo RPS level, the lower the MWTP for rooftop solar and hence the higher the MWTP for solar farm improvements. Worth mentioning, each score higher than the mean NEP score increases the RPS percentages by 2% (34.6% and 65.4%).

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[107] $1\ gallon/person/day \times NM\ population.$

[108] Rural: Distance to rooftop=0.414 km; Distance to solar farm=10.450 km — Urban: Distance to rooftop=0.148 km; Distance to solar farm=6.892 km — Mean NEP score = 23.04.

3.6. Discussion and Conclusion

Renewable electricity generation has increased considerably in the past decade in the U.S. This is due to several factors, including cost competitiveness and state and federal policies, such as production and income tax credits, RPSs, and state level subsidies for solar energy. While these policies have been researched extensively, in this paper we investigate consumer preference and willingness to pay toward renewable energy, with a focus on solar energy. In so doing, we designed a DCE survey focusing on NM's largest electric utility company. In addition to estimating households' WTP, we assessed respondents' attitudes towards advanced smart meter. The survey considers not only the preference for installation (business as usual), but if installed, how consumers would access electricity consumption and price information. We further included spatial and environmental worldview heterogeneity in our analysis. Our results suggest that there is general support for diffusion of the RPS in our sample. However, there is a diminishing return in support for Rooftop solar: after a certain RPS level, our respondents are no more willing to pay for energy plans that persuade rooftop solar improvement. Thus, individuals in our sample want higher RPS to be fulfilled by solar farms rather than rooftop solar. Our respondents are also willing to pay a premium for policies that encourage smart meter installation (especially when they access information through an in-home display or via the internet) and/or reduction in water consumption by fossil fuel for electricity generation.

Using Model 2's findings, we compare our RPS and Rooftop results to those of Mozumder et al. (2011), Borchers et al. (2007), and O'Connell (2018). Mozumder et al. (2011) argue that NM residents are willing to pay $9.27/month on top of their monthly electric charge to increase the share of RE in the energy portfolio mix from 10% to 20%.[109] We carried out a t-test to compare our MWTP calculated from the RPL model ($4.5/month for 10% increase in RPS) with that of Mozumder et al. (2011) with ($10.07)[110] and without ($9.27) inflating the values. The t-test values (t=2.92 p-value<0.002; t=2.56 p-value<0.005) allow us to conclude that our MWTP for an extra 10% RPS is statistically significantly smaller than that of Mozumder et al. (2011) in both cases (inflated and uninflated). Considering the MWTP and status quo level of RPS, *ceteris paribus*, we extrapolated that respondents are willing to pay $27/month to achieve an 80% RPS. This is equivalent to a 36% increase in NM's average current electricity bill. However, Mozumder et al. (2011) found an identical percentage (36%) for a 20% share of electricity to come from RE in their contingent valuation survey. Furthermore, Borchers et al. (2007) found that Delawarean consumers are willing to pay a mean premium of $19.03/month for a voluntary program of 10% solar generation, which is more than 2.5 times more than what our respondents would be willing to pay ($7.10/month) for a similar program. This might be due to either the novelty of RE during those times, the drastic change in government attitudes toward RE, different samples, or more importantly, due to the different economies under question in each survey. During the previous administration, pro-environmental policies were encouraged; the current administration has the opposite view. This might have affected electricity

[109] We compare our results with WTP for the 2nd-10% of Mozumder et al. ($15.04-$5.77=$9.27) (see footnote 13 in Mozumder et al. (2011, p1124)). To justify for the discrepancy in WTP for the first and second 10% increase in the RPS level, they argue that PNM has initiated installation of extra capacity in order to achieve the first 10%. However, no effort had been taken for the second 10% yet and thus the higher WTP for the second 10%. Since PNM is lagging behind in achieving the current RPS level (20%), hence we compare their second 10% with an extra 10% from the current level RPS in our study.

[110] $9.27 \times \frac{CPI_{2017}}{CPI_{2011}} = 9.27 \times \frac{237.46}{218.62} = \$10.07$ CPI data are from BLS

consumers' preferences as well. Lastly, O'Connell (2018, p. 19) estimated that PNM will need to generate 1,340,005 (20% of its total sale of 6,700,025) megawatt-hour RE to comply with its RPS requirement in 2020, which results in a net cost of $25,556,639 to the company. We can extrapolate that an extra 1% (21% RPS) will cost PNM an additional $1,277,827. Dividing this value by PNM's number of customers will result in $2.42 to $2.72 per customer per year. This is roughly half of what our respondents are willing to pay for each 1% increase from the current level of RPS ($5.40/year [$4.20-$6.84]).[111]

Our findings indicate that controlling for spatial and environmental worldview heterogeneity results in a divergence of MWTP values. Consistent with similar studies (Bergmann et al., 2008; Yoo, 2011), as an increase in rooftop solar means a decrease in solar farm deployment in this research, rural respondents are more in favor of RPS and less supportive of Rooftop development. The opposite holds true for urban respondents: more support for Rooftop and less for RPS. This may be a result of the "warm glow" effect, where respondents gain moral and financial benefits from the solar type that surrounds them (Dastrup et al., 2012; Möllendorff & Welsch, 2017). Further, our findings are also consistent with those of Vecchiato and Tempesta, (2015); rural and urban respondents do not exhibit a statistically significantly positive WTP for RPS if they are 12 km and 9 km away from rooftop solar respectively. Moreover, our results suggest that there exists a distance decay effect for only solar farm. Lastly, consistent with the literature (e.g., Hawcroft & Milfont, 2010), we find that respondents with pro-

[111] $1,277,827/470,000= $2.72, where 470,000 is number of PNM's residential customers and $1,277,827/527,638= $2.42, where 527,638 is total PNM's customers as of November 2018. Source of data: EIA-861 form.

environmental behavior are more supportive of policies that are environmentally friendly. This research extends the literature by differentiating solar energy types, assessing preferences on smart meter, and incorporating distance to solar installation through actual distance data rather than an artificially-introduced distance through the survey instrument.

One of the limitations of this study is that we are not able to undertake a cost-benefit analysis of different solar energy types. Future research should include not only the spatial nonmarket component (e.g., externalities, psychological and moral benefits/costs, etc.), but also the market component (e.g., social costs/benefits, rooftop solar and/or solar farm ownership status, etc.). It would be also valuable to include a distance variable within the survey and compare results against actual distance data for different solar energy types. This is important as distance decay effect would be questionable if people generally support solar energy, hence it is unlikely that valuing solar energy is distance dependent.

Our findings suggest that our sample of NM residents are supportive of smart meter installation, however the original PNM smart meter project has been rejected at this time. This provides an opportunity to develop an alternative policy that would incorporate a voluntary smart meter program. Furthermore, to meet the desires of NM residents, our findings suggest that price and usage information provided by smart meter should be conveyed either online or through in-home display. Policies that consider everyone the same are not appropriate, as we find statistically significant differences between rural verses urban perspectives toward RE, especially solar energy. These policies are likely more effective for some groups than others. Efficient energy policy requires technological efficiency and economic viability. It also necessary that public acceptance, spatial and worldview heterogeneity be considered. For NM regulators considering either new RPS policies or altered RPS levels, this research provides improved information with which to develop efficient policy. The results also suggest that regulators in other states considering changes to their own RPS programs may find and improve understanding of consumer heterogeneity valuable.

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Chapter 4: Does the Solemn Oath Lower WTP Responses in a Discrete Choice Experiment Application to Solar Energy?

4.1. Introduction

Resource managers need information about household preferences for quasi-publicly provided non-market goods, such as electricity production from renewable energy. Currently, stated preference methods such as Discrete Choice Experiment (DCE) and the Contingent Valuation Method (CVM) are popular tools to value nonmarketed goods. One concern with the use of these methods is that stated preference surveys may be subject to bias, in particular hypothetical bias – the gap between willingness-to-pay (WTP) response for a hypothetical question and a real incentive. The underlying causes of hypothetical bias are poorly understood, even with extensive current literature on the subject. The issue of hypothetical bias becomes prudent when policymakers are interested in assessing the value of publicly provided non-market goods and stated values are orders of magnitude (for example, by a factor of two) higher than those of real WTP. This leads to challenges in the validity of stated preference results and development of inefficient policies.

To address the issue of hypothetical bias, several *ex ante* design tools and *ex post* calibration approaches have been developed in the stated preference literature. An offered *ex ante* design tool that has emerged more recently in experimental labs that draws upon the social psychology commitment theory is the "solemn oath" script (Jacquemet et al., 2009, 2013), which has respondents sign an oath to provide honest answers. While the effectiveness of the solemn oath approach is still questionable in the ongoing research, the objective of this analysis is to provide an initial field setting test of the solemn oath to a particular DCE (mixed-mode: mail- and online-based) survey application to solar energy. Assuming that the solemn oath will reduce, if not eliminate, the hypothetical bias, we hypothesize that those who took the oath will have a lower marginal WTP (MWTP) for each attribute (defined below) of our survey than those who did not.

Following best practices, we develop and conduct a DCE survey to assess the impact of the solemn oath script on our respondents' behavior in an application to renewable energy with an emphasis on solar energy. The survey was conducted in New Mexico, a state with abundant potential for both renewables and fossil fuel energy, particularly in solar energy. The target of the survey sample was residential customers of New Mexico's major electric utility company. Although we include consequentiality properties (discussed below) set forward by Carson and Groves (2007), our elicitation format is not a dichotomous choice voter referendum with a coercive tax. Thus, our valuation method cannot claim to be incentive compatible (e.g., truth revealing) (ibid).

Thus, we include the solemn oath script to mitigate/eliminate potential hypothetical bias. The sample was divided into two groups: (i) respondents who were asked to sign the solemn script prior to taking the survey, and (ii) respondents who were not presented with the solemn oath script. Our choice questions considered different solar energy plans.

We utilize random parameter logit models in both preference and WTP spaces to assess the effectiveness of the solemn oath script. Hypothesis testing results from marginal WTP distribution across our six attributes show no evidence that the solemn oath lowers valuation measures in this setting. The paper concludes by discussing the implications.

4.2. Background

Survey-based stated preference methods are used to elicit consumer preferences and estimate WTP values for changes in nonmarket (public and private) goods and/or proposed investments in the absence of a market. The two most commonly used techniques are CVM and DCE, are variants on a spectrum of elicitation formats. In the CVM method, respondents are presented with one or more contingent scenarios and asked to make monetary decisions that trade-off income and levels of the non-market good or service, in the form of willingness to pay responses (or willingness to accept compensation responses).[112] With the CVM approach, researchers can estimate WTP for specific increments or decrements in the quantity or quality of a nonmarket good, commonly including large discrete changes or even provision of the non-market good as

[112] There are five different formats that researchers ask CVM questions: 1) open-ended, 2) dichotomous choice, 3) referendum decision, 4) payment cards, and 5) iterative biddings. For a brief definition on each format, for example see (Thacher et al., 2011, p. 21)

a whole. In the DCE approach, the nonmarket good in question, however, is described as a bundle of pre-selected, varying attributes, and respondents are presented with a series of choices among a set of varying bundles. Price/cost is one of the varying attributes across the bundles, enabling researchers to estimate MWTP for each attribute of the nonmarketable good in question. Although the CVM technique was long the predominate stated preference approach, DCE has grown in use over the last several decades in the nonmarket valuation literature, especially in the field of environmental economics.

As the nature of stated preference methods is hypothetical and not real, these techniques are subject to biases, in particular hypothetical bias. Citizens, when asked a hypothetical question, commonly don't think about it as they would when a real expenditure is at issue. Hence, overstating WTP becomes probable, which is referred to as hypothetical bias in the literature. For example, List and Gallet (2001, p. 246) and Little and Berrens (2004, p. 5) in separate meta-analyses find that stated (hypothetical) WTP's are 3 – 3.13 times higher than actual (non-hypothetical) values (known as calibration factor) in their data sets, which only included CVM studies. More recently, Penn and Hu (2018) conducted a meta-analysis with an approximately 4 times larger dataset (132 articles) than those of the previously mentioned meta-analyses (also included choice experiment studies) and found a calibration factor of 1.94.[113] Researchers for decades have been attempting to address the issue of hypothetical bias. With all of the available literature, no theoretical approach can fully justify causes of hypothetical bias in stated preference research (Loomis, 2014; Mitani and Flores, 2014; Penn and Hu, 2018).

[113] They also found that choice experiment studies have significantly (60%) lower calibration factor than dichotomous choice methods. Little et al. (2012) finds similar results, though not statistically significant. For a summary of existing meta-analyses on the topic of hypothetical bias, see Table 1 of Penn and Hu (2018, p.1191).

There are various *ex ante* design tools and *ex post* calibration approaches that can be used to address the issue of hypothetical bias when valuation exercises are not incentive compatible (e.g., truth revelation). Widely-used approaches include cheap talk, consequentiality, certainty follow-up questions, and commitment priming via oath or promise.[114] One common approach that has been extensively used among nonmarket valuation studies is the "cheap talk" script developed by Cummings and Taylor (1999). Cheap talk script educates respondents about the issue of hypothetical bias and simply asks respondents to not overstate their WTP. Regarding the cheap talk effectiveness, the majority of studies find that it either eliminates or reduces the hypothetical bias, while some find either no effect on or over-correction of the bias (Silva et al., 2011; Mahieu et al., 2012; Loomis, 2014).[115] Carson and Groves (2011, p. 305) divide cheap talk scripts used in the literature into two types: "hard" and "soft" cheap talk. Respondents are told that some respondents "lie" in a survey in the hard version, while they are only reminded about their budget constraint in the soft version.[116]

Another tool that has received attention in the recent years is the consequentiality script developed by Carson and Groves (2007). They assert that respondents provide honest answers to a standard dichotomous choice referendum question (for a public good with coercieve tax) if two conditions hold: 1) policy consequentiality and 2) payment consequentialty (Herriges et al., 2010). Under the former condition, survey takers must perceive that results would influence a desirable policy/outcome that they care about, and

[114] For a meta-analysis on various approaches utilized to address the hypothetical bias issue, see for example Penn and Hu (2018).
[115] The valuation method, the characteristics of the good in question, the length of the cheap talk script, or a combination of these can affect the efficacy of the cheap talk script.
[116] For more details on these two types of cheap talk script, see, e.g., Carson and Groves (2011).

under the latter condition they must believe that there is a positive probability that they will pay. So long as these two conditions hold with any positive probability of policy implementation occurrence, the optimal strategy for respondents is to provide honest answers to survey questions. As far as the type of good in question is concerned, binary discrete choice questions are incentive compatible if the good in question is either new public good with coercive payment, choice of which of two new public goods to provide, or change in an existing private or quasi-public good. However, binary choice questions are not incentive compatible if the good in question is either a new public good with donation or a new private or quasi-public good (Carson and Groves, 2007, p. 192). Further, including a third alternative (i.e., status quo alternative) in discrete choice questions results in violating necessary binary condition for incentive compatibility (Carson and Groves, 2007, p. 194). Surveys that don't follow these properties will not be incentive compatible, thus have higher level of potential for hypothetical bias. The efficacy of this approach after employing these properties is encouraging (Carson et al., 2014; Carson and Groves, 2011, 2007; Herriges et al., 2010). This approach can be utilized both as an *ex ante* and/or *ex post* tool to address hypothetical bias by modifying respondents' perceived consequentiality of the valuation questions.

The most popular *ex post* mitigation technique is follow-up certainty questions, where immediately following the valuation questions, respondents are asked to indicate on a scale of usually 1-10 (1 being very uncertain and 10 being very certain), how certain they are of their stated WTP (Champ et al., 1997; Penn and Hu, 2018). Previous studies demonstrate the effectiveness of this approach (Little and Berrens, 2004; Champ et al., 1997, 2009). For example, Champ et al. (2009) conducted a CVM survey to elicit WTP for whooping crane in Madison, Wisconsin. They split their sample into three treatments: actual donation treatment, treatment with follow-up certainty question, and treatment with a cheap talk script. They find that both certainty follow-up question and cheap talk script are capable of eliminating hypothetical bias, though certainty follow-up questions were more consistent. Furthermore, Penn and Hu (2018) attests that certainty follow-up questions and consequentiality approaches both reduce hypothetical bias more than the cheap talk script.

The theory of commitment in social psychology attests that a "promise" can incline people to willingly comply with the promised behavior/action (Pallak et al., 1980; Kulik and Carlino, 1987; Joule et al., 2007; Guéguen et al., 2013). For example, Kulik and Carlino (1987) conducted a commitment manipulation experiment, in which they asked (or not asked) parents of ear-infected children to promise that they would give their children antibiotic medications. Kulik and Carlino found that parents in the promised treatment group complied with medication acquiescence significantly higher than those who were not asked to give a verbal promise. More recently, researchers have designed another *ex-ante* tool that asks respondents to swear upon their honor ("solemn oath") that they will be honest while answering valuation questions (Jacquemet et al., 2009, 2013). Jacquemet et al. draws on the social psychology theory of commitment and hypothesizes that those who sign the oath will remain honest and provide unbiased answer. Along with the solemn oath script (strong oath), researchers have utilized different approaches to prime truth-telling and commitment to answer valuation questions honestly, such as promise script (weak oath) or utilizing honesty priming exercises. In the former approach, respondents sign a promise script, similar to the solemn oath script with much less overtness, while in the later approach, researchers provide scrambled sentences that include truth-telling words (e.g., truth, sincere, honest, candid, factual, etc.) to respondents and ask them to complete tasks (e.g., unscramble and rewrite scrambled sentences).[117] However, the "solemn oath" script is assumed to be the strongest tool amongst other *ex ante* commitment priming tools as it mimics the courtroom oath-taking procedure (Jacquemet et al., 2018, p. 629). Other benefits of using the solemn oath script is that it is simple, short, and easy to comprehend and implement.

Similar to the cheap talk approach efficacy, the literature on oath script is mixed, with some studies finding elimination (Stevens et al., 2013; Jacquemet et al., 2017), some mitigation (de-Magistris and Pascucci, 2014; Jacquemet et al., 2019, 2018), and few no statistically significant effect on hypothetical bias (de-Magistris and Pascucci, 2012; Carlsson et al., 2017). Although this approach is gaining attention in the literature and has been commonly implemented in lab experiments (e.g., Jacquemet et al., 2013; Stevens et al., 2013), its application has yet to be explored in the survey setting. In fact, we can only locate three papers that have utilized an oath script (weak or strong oath) in a survey setting (Carlsson et al., 2013; de-Magistris and Pascucci, 2014; Carlsson et al., 2017), of which two have used DCE approach and only one has utilized the solemn oath script.

Carlsson et al. (2013) conducted a CVM survey and utilized a payment card method to elicit Chinese and Swedish citizens' preferences and WTP for mitigating greenhouse gas emissions (a public good). Carlsson et al. utilized a weak version of the

[117] For example, de-Magistris et al. (2013) primes respondents honesty by providing cues and words related to honesty prior to participating in the DCE question in hope that "priming can unconsciously influence peoples' perception, evaluations, behavior and choice." de-Magistris et al. demonstrate that this honesty priming task, which was completed 24 times by the subjects, mitigate their respondents WTP. In contrast, Howard et al. (2017) utilizes a similar honesty priming approach coupled with the cheap talk script and finds that the honesty prime approach does not reduce hypothetical bias while the cheap talk script does.

oath script and asked their respondents, “Do you feel that you can promise us to answer the questions in the survey as truthfully as possible?” Respondents were then given a dichotomous option to choose from: “Yes, I promise to answer the questions in the survey as truthfully as possible” and “No, I cannot promise this.”[118] They find that their oath script (weak oath) has a statistically significant impact on their respondents’ behavior in responding WTP questions. They conclude that their oath script decreases WTP variance by decreasing the extreme responses (zero WTP and unrealistically high WTP response). They, however, fail to support the hypothesis that their oath script decreases WTP for decreasing greenhouse gas emissions in both countries. They find that oath script decreases WTP in China and not in Sweden. As acknowledged by the authors, the discrepancy in their oath script efficacy might be due to the extremely different cultures in Sweden and China, though no steps have been taken to prove/disprove this point.[119] Further, it might also be due to the different survey administration approaches that were taken in the Chinese versus the Swedish samples. The authors invited respondents to take their survey on laptops in “special rooms” in China, whereas, respondents did not interact with experimenters in Sweden and took the survey online.

de-Magistris and Pascucci (2014) conducted a DCE survey to elicit WTP for two different insect-based sushi (two private, market goods) in the Netherlands. They had three treatment groups: with cheap talk, solemn oath, and no ex ante tool. Their choice experiment valuation questions were not incentive compatible as they contained three

[118] Carlsson et al. use the word “promise” instead of “swear” as swearing upon one’s honor is not customary in neither Swedish nor Chinese courtrooms. Further, they also used a cheap talk script throughout the survey, regardless of treatment groups.

[119] The authors examined the effect of their weak oath on cultural contexts by interacting oath variable with respondents’ socioeconomic characteristics. Socioeconomic variables are not a good proxy to capture cultural difference.

alternatives and failed to follow binary choice question property. They recruited 106 Dutch participants and asked them to answer 8 sushi-related choice questions. de-Magistris and Pascucci find that taking the solemn oath results in Dutch citizens exhibiting lower MWTP for two out of their three attributes of the good in question, while the cheap talk script revealed no impact on lowering MWTP's (bid).[120] Lastly, Carlsson et al. (2017) conducted a DCE survey to elicit Chinese citizen's WTP for private and public transportation (private and quasi-public good) under an oath script (weak oath[121]). They find that their oath script has no statistically significant impact on commuters' choice of transportation in China. In an attempt to explain why they find these results, the authors relate the insignificancy of their MWTP estimates to the "vague" phrasing of their oath script, though a very similar oath script in another paper by the authors (Carlsson et al., 2013) resulted in mitigating hypothetical bias. They also argue that hypothetical bias might not exist in their particular transportation good. Table 4-1 summarizes the findings from the discussed papers that have utilized an oath script in a survey setting. None of these studies' (Carlsson et al., 2013; Carlsson et al., 2017; de-Magistris and Pascucci, 2014) survey designs follow incentive compatibility properties laid out by Carson and Groves (2007).

[120] Note that in their poster that was presented in 2012 (de-Magistris and Pascucci, 2012), the same authors attest that the solemn oath script has no effect on hypothetical bias.
[121] Immediately prior to the DCE questions, the authors asked, "Do you feel you can promise us you will answer the questions that will follow truthfully?" Participants were then given a dichotomous option to choose from: "Yes, I promise to answer the questions in the survey truthfully" and "No, I cannot promise."

Table 4-1: Results of Oath tests of reducing hypothetical bias

Study	Type of good	Elicitation format	Sample pool	*Ex ante/Ex ante* approaches	Survey type	Oath efficacy	IC[a] property
Carlsson et al. (2013)	Public good with compulsory payment	CVM (Payment card)	2,192 none students	Cheap talk (with both versions) & Oath (weak oath)	Internet – Sweden & in-person survey – China[b]	Effective	Not IC
de-Magistris and Pascucci (2014)	Two private goods	DCE: Not dichotomous	106 none students	Cheap talk Oath (solemn oath)	CE Survey	Effective	Not IC
Carlsson et al. (2017)	Private and quasi-public	Dichotomous choice question	1,347 none students	Cheap talk (with both versions) Oath (weak oath)	Field survey	Not Effective	Not IC

a: The authors invited respondents to take their survey on laptops in "special rooms" in China.
b: IC= Incentive Compatible.

The key objective of our paper is to investigate the effect of the solemn oath script in a hypothetical DCE survey application to renewable energy with a focus on solar energy. For the reason of incentive compatibility, we use the solemn oath script to mitigate potential hypothetical bias. We conducted a hypothetical DCE survey to elicit preferences for renewable energy in general and solar energy in particular. We implemented the survey in New Mexico, a state with extensive potential for various energy types. This paper is the first to use the solemn oath script to address potential hypothetical bias in a hypothetical DCE survey setting application to solar energy. This is also the first time that the solemn oath script is utilized in a mail- based survey.

The rest of this paper is organized as follows. Section 4.3 presents the study area. Section 4.4 gives a description of the choice experiment design, the survey structure and administration, theory and the econometrics model, and finally the hypotheses that our paper seeks to test. In Section 3.5, we discuss the regression results. A discussion of results will follow in the last section, Section 3.6.

4.3. Renewable energy in New Mexico

New Mexico has extensive potential for renewable energy, especially solar energy. To take advantage of its renewable energy potential as well as reducing its carbon footprint and decreasing water usage by fossil fuel, New Mexico joined the move towards integrating more renewable energy into its grid by enacting a Renewable Portfolio Standard (RPS)[122] in 2004. New Mexico is one of 29 states with an RPS, which, at the time of survey implementation, required major electric utility companies to source 20% of their in-state electricity sales from renewables by 2020.[123] An 80%-RPS-by-2040 bill (Senate Bill 312) was introduced and rejected in 2017. This bill was re-introduced in January 2019 (House Bill 15).[124] Recently, New Mexico passed a 100% RPS by 2050 bill (Senate Bill 489) in its 54th legislative session and joined Hawaii, California, and Washington for the movement towards carbon free future.[125] New Mexico is also one of 18 states with a diversified RPS, that is, there are different constraints for different types of renewable energy. For example, at least 30%, 20%, and 3% of the 20% RPS needs to be generated from wind, utility-scale solar, and distributed solar energy respectively by 2020.[126]

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[122] RPSs are state-mandated policies that mandate electric utility companies to generate a portion of their electricity from renewables by a certain timeframe.
[123] Based on New Mexico's RPS, rural electric cooperatives are required to source half of what major utility companies are required.
[124] Further details on Senate Bill 312 and House Bill 15 can be found at: https://www.nmlegis.gov/Sessions/17%20Regular/bills/senate/SB0312.pdf and https://www.nmlegis.gov/Sessions/19%20Regular/bills/house/HB0015.pdf respectively (accessed 03.12.2019)
[125] Further details on Senate Bill 489 can be found at: https://www.nmlegis.gov/Sessions/19%20Regular/bills/senate/SB0489.pdf (accessed 04.10.2019)
[126] It is not mentioned as to whether these carve-out percentages will uphold under the new RPS (Senate Bill 489).

More than 310 days of the year is sunny in New Mexico (AED, 2018), ranking the state 3rd best in the nation for its potential in solar energy (NEO, 2010). Further, the price of solar panel technology continues to plummet due to recent innovations in the technology. Compared to 2000, installed price of residential solar has fallen more than threefold (Barbose et al., 2018, p. 18) in 2017 and continues to fall. Hence, in the 54th legislative session in January 2019 (House Bill 210), a Community Solar Act was introduced to make solar energy available for everyone (apartment renters, home owners with inappropriate roofs, middle- and low-income families) in New Mexico.[127]

Amongst three major utility companies in New Mexico, Public Service Company of New Mexico has the largest share of the consumer pool and rooftop solar and utility-scale solar connected to its grid in the state. This utility company also offers a net metering program to all of its solar energy customers, as mandated by the state. For further information on the study area, readers are directed to a related work by coauthors (Mamkhezri et al., 2018).

4.4. Methods and Modeling Consideration

4.4.1. Data and Survey

As discussed above, the survey application was done with NM's largest electric utility company's residential customers. To test solemn oath's effect in the current study, we split our sample into two equally-sized treatment groups. The survey for the first treatment group started with asking respondents to sign and swear upon their honor that

[127] For details on the 210-Bill, see https://www.nmlegis.gov/Sessions/19%20Regular/bills/house/HB0210.pdf (accessed 03.06.2019)

throughout the survey (not only the DCE questions) they will always provide honest answers. The solemn oath script was not included for the second group. Figure 4-1 depicts the solemn oath script utilized in the current study, which closely follows that of Jacquemet et al. (2013). The remaining part of the survey was identical for both groups. To further mitigate hypothetical bias, in both versions of the survey (with and without the solemn oath script), we asked our respondents to give serious consideration to the associated cost of each plan and reminded them about their budget constraints prior to asking the DCE questions.[128] Further, we included the idea of consequentiality, in which we stated the survey responses will be conveyed to policymakers and that the policy could result in universal compulsory payment.[129] For a more detailed description of the survey design and administration, see Mamkhezri et al., (2018).[130]

[128] Although we did not utilize any type of cheap talk script in our survey design, we included the idea of soft cheap talk script in which we reminded respondents about their budget constraint in the survey. The statement we included: "We ask you to pick the plan that you think is best, giving serious consideration to the associated costs; in other words, assume you are paying the mentioned amount. **Choosing a plan implies you are willing to bear the specified additional cost on your monthly electricity bill.**"

[129] The text reads "State policymakers want to know Public Service Company of New Mexico customer opinions. What share of electricity should come from renewable sources and what role should solar energy play?" We then stated that "Decisions about Public Service Company of New Mexico's solar energy future could affect your electricity bill" and that we will "have their opinions heard by state policymakers."

[130] Throughout the survey we stayed neutral and unbiased (energy-wise). For example, we included the statement "Some people find rooftop solar unattractive" when we introduced rooftop solar. Similarly, we mentioned externalities that are associated with utility-scale solar when we defined them, "Some people find solar farms unattractive and believe they change the landscape. Birds can crash into the panels on solar farms, thinking that they're water bodies. Solar farms interrupt deer migratory paths."

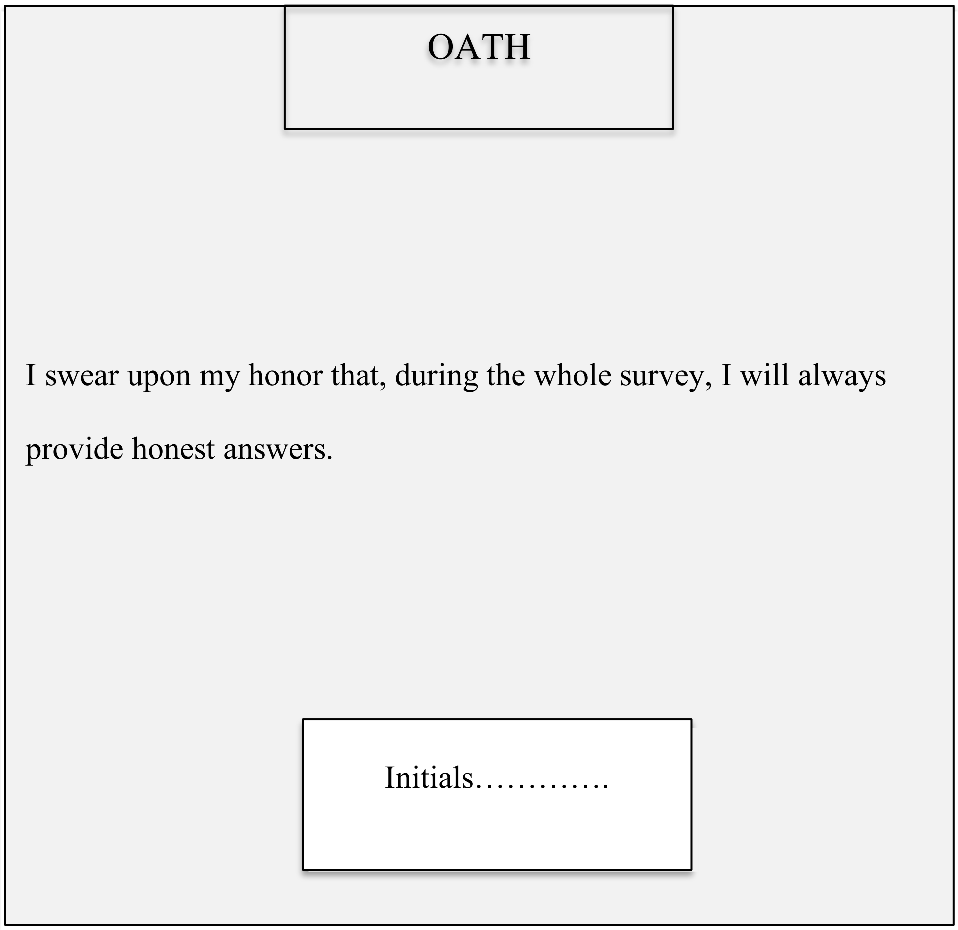

Figure 4-1: The solemn oath script used in this study.

Our DCE survey included 6 attributes that altogether defined various solar energy plans (quasi-public good). These attributes are as follows. The first attribute, *RPS*, was meant to capture preferences towards the re-introduced (then rejected) 80%-RPS-by-2040 bill. This attribute has three levels: 20%, 50%, and 80%, with 20% being the status quo level. The second attribute, *Rooftop*, was meant to distinguish respondents' preferences towards different types of solar energy (rooftop solar and solar farm). This attribute had four levels: 5%, 9%, 20%, and 30%, with 9% being the status quo level. The third attribute, *No Credit Banking*, was meant to capture respondents' Yes (status quo) or No attitudes towards whether rooftop solar owners should be allowed to save and roll-over credits generated from excess electricity generation throughout the year. The fourth attribute, *Water*, was meant to capture the trade-off made by respondents between fossil fuel and renewable energy. This attribute also had four levels: 1, 2, 3, and 4 gallons/person/day, with 4 being the status quo level. The higher the level, the more water is used by fossil fuel generation. The status quo level is High (4 gallons/person/day). The fifth attribute, *Smart Meter*, was advanced smart meters installation. This attribute also had four levels that each level described different ways in which electricity information would be communicated: in-home display, online account, text, and no installation (status quo). Lastly, we included a cost attribute, *Price*, to enable us to estimate MWTP for each attribute. This attribute had six levels: $0, $5, $10, $20, $30, and $50 as levels, with $0 being the status quo level. Each level represents the amount that each respondent would be willing to pay on top of her monthly electricity bill to achieve the corresponding solar energy plan. Table 3-2 present the attributes and their corresponding levels, while Figure 3-1 exhibits a DCE sample used in our survey.

Table 4-2: Attributes, levels, definitions, and expected signs.

Attribute	Attribute Level*	Definition
RPS	**20%**, 50%, 80%	Percent of electricity from renewable sources by 2040.
Rooftop	5%, **9%**, 20%, 30%	Percent of solar energy from rooftop solar by 2040.
NoCreditBanking	**Yes**, No	Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.
Water	Low (1 gal/person/day); Medium-Low (2 gal/person/day); Medium-High (3 gal/person/day); **High (4 gal/person/day)**	Water used to generate electricity by fossil fuel.
SmartMeter	$\text{SmartMeter}_{\text{text}}$, $\text{SmartMeter}_{\text{online}}$, $\text{SmartMeter}_{\text{home}}$, **No installation**	Smart meters installation and usage and price feedback by text, log into online account, or in-home display.
Price	**No change**, \$5, \$10, \$20, \$30, \$50	Change in monthly electricity bill.

Note: * Levels in bold are status quo levels. Source: Mamkhezri et al. (2018, Table 2).

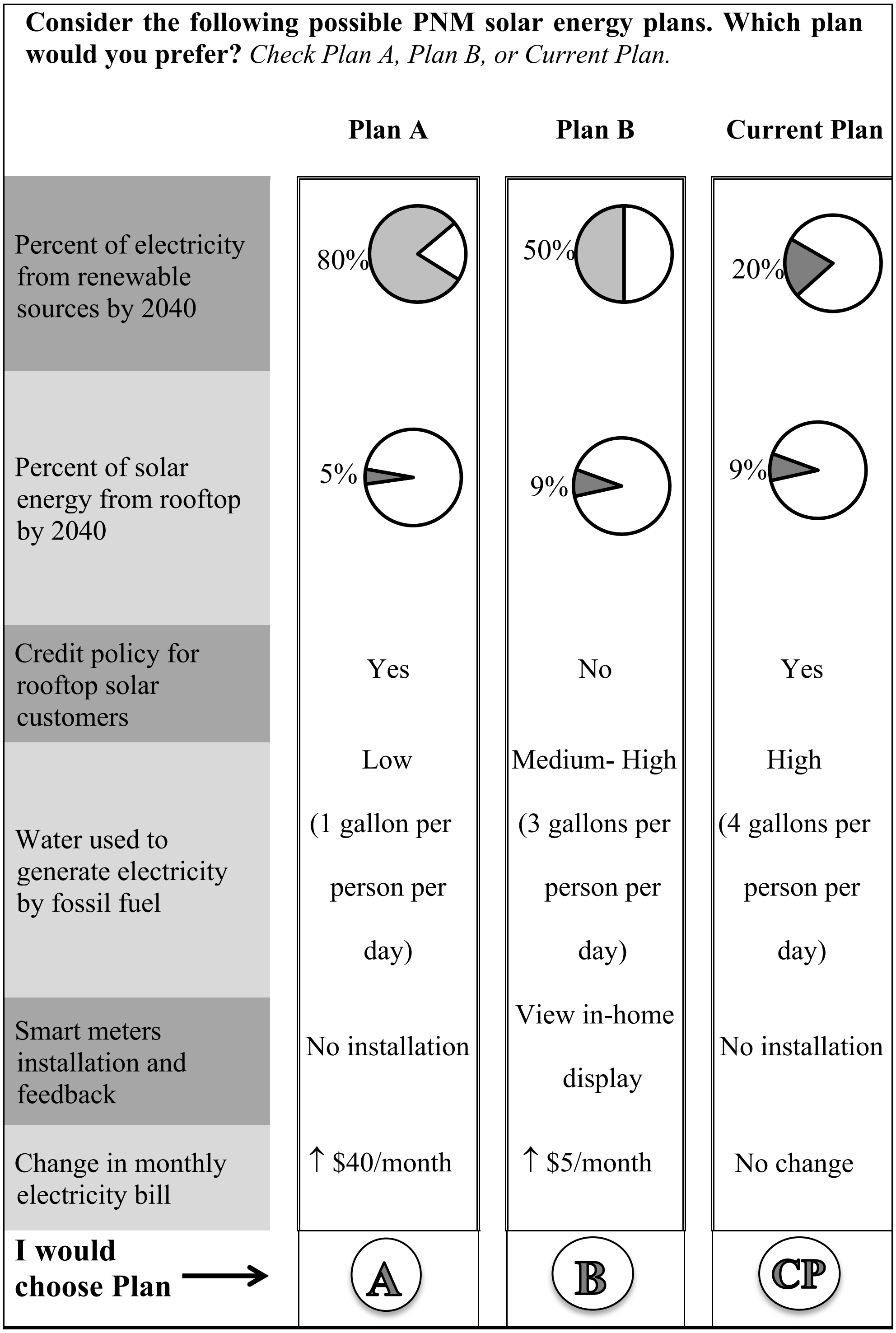

Figure 4-2: An example choice question used in the survey.

Compared to a CVM approach, the objective of DCE studies is not as clear to the survey taker because of the multi-attribute nature of the good. We followed best practices in developing the DCE survey. As is customary in DCE surveys (e.g., van Osch et al. (2019); Lutzeyer et al. (2018); Thacher et al. (2011); Taylor et al. (2010)), respondents are presented with basic information on each attribute and are given the opportunity to provide an opinion about each. This is prudent especially when attributes are not self-explanatory, which was the case in our survey. For example, the majority of our two focus groups and twelve debriefings participants did not know what solar farms, renewable portfolio standards, or advanced smart meters were. As such, we determined that the basic information on each attribute needed to be provided to our respondents in the main questionnaire.

As described in the previous study (Mamkhezri et al., 2018), our design led to 24 choice sets which were divided into 6 versions. Each choice set had three alternatives, of which one was the status quo solar energy plan capturing preference towards the business-as-usual alternative.[131] This was captured by including an alternative specific constant (ASC) term in the analysis. Respondents were given four choices to make per each survey version. Out of 482 responses that we received, 221 were with the solemn oath and 261 were without.[132] We excluded those from the oath group who had completed the survey and refused to sign the oath in our analysis (19 respondents). Overall, we collected 1,852 initial observations as each respondent provided us with four data points.

[131] Including the business-as-usual alternative violates the necessary binary condition for incentive compatibility (Carson and Grove, 2007).
[132] Our data is different than the previous study (Mamkhezri et al., 2018). We collected 78 more responses (34 and 44 with and without the solemn oath) for the current study.

4.4.2. Empirical Model Specification

To evaluate the efficacy of solemn oath script in a DCE survey application to solar energy, we estimate the Random Parameter Logit models (RPL) in both preference-space and WTP- space (Train and Weeks, 2005; Train, 2009). Preference-space model estimates individual's marginal utility for each attribute, whereas WTP-space model estimates individual's MWTP for each attribute. MWTP's are estimated post-estimation in the preference-space model.

Below we summarize model specification under each space. Next, we apply these specifications into our empirical models and develop our hypothesis.

The utility person *n* (*n*=1, …, 463) gains from choosing *m*th alternative (*m*=1, …, 3, including the status quo) in choice set *i* (i=1, …, 4) can be specified as a function of the price attribute, p_{nmi}, and other non-price attributes, x_{nmi}:

$$u_{nmi} = \alpha_n p_{nmi} + \beta_n' x_{nmi} + e_{nmi} \tag{15}$$

where α_n and β_n are individual-specific marginal utility of price and non-monetary attributes respectively. The error term is independently identically distributed (iid) with extreme value across respondents. The variance of e_{nmi} varies across respondents and can be written as: $\nu_n^2 \left(\frac{\pi^2}{6}\right)$, where ν_n is a scale parameter for respondent *n*. Following Train and Weeks (2005), we divide equation (9) by the scale parameter ν_n to obtain a new error term that is iid type I extreme value (Gumbel) with constant variance of $\left(\frac{\pi^2}{6}\right)$:

$$U_{nmi} = \lambda_n p_{nmi} + c_n' x_{nmi} + \epsilon_{nmi} \tag{16}$$

where $U_{nmi} = u_{nmi}/\nu_n$, $\lambda_n = \alpha_n/\nu_n$ and $c_n = \beta_n/\nu_n$. Train and Weeks (2005) calls this utility specification, equation (16), the model in preference-space, as the coefficients (marginal utilities) denote preferences. MWTP for a non-price attribute is the ratio of the attribute's coefficient by the price coefficient: $\psi_n = c_n/\lambda_n$. Thus, one can re-write equation (16) as:

$$U_{nmi} = \lambda_n(p_{nmi} + \psi_n' x_{nmi}) + \epsilon_{nmi} \tag{17}$$

Train and Weeks (2005) calls this utility specification, equation (17), the model in WTP-space. The coefficients under WTP-space can be interpreted as MWTP directly.

Following Hole and Kolstad (2012) and Thiene and Scarpa (2009), we estimate the coefficients of both preference-space and WTP-space models utilizing maximum simulated likelihood. Empirically, we adopt utility equations (16) and (17) and estimate Model 1 and Model 2, equations (18) and (19), for preference-space and WTP-space respectively:

$$\begin{aligned} U = \lambda\, Price\ &+ c_1 RPS + c_2 Rooftop + c_3 NoCreditBanking + c_4 Water \\ &+ c_5 SmartMeter_{text} + c_6 SmartMeter_{online} + c_7 SmartMeter_{home} \\ &+ c_8(RPS - 20) \times (Rooftop - 9) + c_9 ASC + \epsilon \end{aligned} \tag{18}$$

and

$$\begin{aligned} U = \lambda\, (Price\ &+ \psi_1 RPS + \psi_2 Rooftop + \psi_3 NoCreditBanking + \psi_4 Water \\ &+ \psi_5 SmartMeter_{text} + \psi_6 SmartMeter_{online} \\ &+ \psi_7 SmartMeter_{home} + \psi_8(RPS - 20) \times (Rooftop - 9) \\ &+ \psi_9 ASC) + \epsilon \end{aligned} \tag{19}$$

where the *c*'s are marginal utility and ψ's are MWTP of the non-monetary attributes. In order to test the efficacy of the solemn oath script, we multiply each attribute by a dummy coded variable *oath* that takes a value of 1 if respondent has signed the solemn oath script and zero otherwise. Equations (20) and (21) present the utility function specifications under preference-space (Model 3) and WTP-space (Model 4) respectively.

$$\begin{aligned}
U = \lambda\, Price\ &+ c_1 RPS + c_2 Rooftop + c_3 NoCreditBanking + c_4 Water \\
&+ c_5 SmartMeter_{text} + c_6 SmartMeter_{online} + c_7 SmartMeter_{home} \\
&+ c_8 (RPS - 20) \times (Rooftop - 9) + c_9 ASC \\
&+ c_{10} Price \times oath + c_{11} RPS \times oath + c_{12} Rooftop \times oath \\
&+ c_{13} NoCreditBanking \times oath + c_{14} Water \times oath \\
&+ c_{15} SmartMeter_{text} \times oath + c_{16} SmartMeter_{online} \times oath \\
&+ c_{17} SmartMeter_{home} \times oath \\
&+ c_{18} (RPS - 20) \times (Rooftop - 9) \times oath + c_{19} ASC \times oath + \epsilon
\end{aligned} \tag{20}$$

and

$$\begin{aligned}
U = \lambda\, (Price\ &+ \psi_1 RPS + \psi_2 Rooftop + \psi_3 NoCreditBanking + \psi_4 Water \\
&+ \psi_5 SmartMeter_{text} + \psi_6 SmartMeter_{online} \\
&+ \psi_7 SmartMeter_{home} + \psi_8 (RPS - 20) \times (Rooftop - 9) \\
&+ \psi_9 ASC + \psi_{10} Price \times oath + \psi_{11} RPS \times oath \\
&+ \psi_{12} Rooftop \times oath + \psi_{13} NoCreditBanking \times oath \\
&+ \psi_{14} Water \times oath + \psi_{15} SmartMeter_{text} \times oath \\
&+ \psi_{16} SmartMeter_{online} \times oath + \psi_{17} SmartMeter_{home} \times oath \\
&+ \psi_{18} (RPS - 20) \times (Rooftop - 9) \times oath + \psi_{19} ASC \times oath) + \epsilon
\end{aligned} \tag{21}$$

Assuming that the solemn oath will reduce, if not eliminate, the hypothetical bias (Jacquemet et al., 2009, 2013, 2018, 2019; de-Magistris and Pascucci, 2014), we hypothesize that those who took the pledge will have a statistically significantly lower

MWTP for each attribute than those who did not. Thus, for each attribute, our null hypothesis is that MWTP of those who signed the pledge is equal to those who did not.

H_0: $MWTP_{oath} = MWTP_{no-oath}$

H_A: $MWTP_{oath} < MWTP_{no-oath}$

For example, to test the null hypothesis for *RPS* at its status quo level (20%), based on equation (20) we will have: $U = \lambda\, Price\ + c_1 RPS + c_{10} Price \times oath + c_{11} RPS \times oath$; $MWTP_{oath}^{RPS} = -(c_1 + c_{11})/(\ \lambda + c_{10})$ and $MWTP_{no-oath}^{RPS} = -c_1/\ \lambda$. Thus, the null hypothesis under preference-space model becomes: ${H_0}^{RPS}$: $(c_1 + c_{11})/(\ \lambda + c_{10}) = c_1/\ \lambda$. Under the WTP-space specification, equation (21), the null hypothesis becomes: ${H_0}^{RPS}: \psi_1 = \psi_{11}$. The same logic applies to the remaining attribute coefficients (see Table 3-3). In both models, statically significant and negative/positive (depending on attribute)[133] estimated coefficients of the interacted variables with the dummy *oath* ($c_{10} - c_{19}$ & $\psi_{10} - \psi_{19}$) variable will enable us to test the null hypotheses. In so doing, Wald tests can be performed on each attribute's MWTP estimates. If the estimates are statistically significantly different from zero and have the appropriate signs (see Table 4-2), then the evidence support the solemn oath script as effective. Table 4-3 summarizes all the hypotheses that need to be tested in this study.

[133] Based on the result of Model 2 of Mamkhezri et al. (2018): negative when *RPS*, *Rooftop*, and *Smart Meter*, and positive when *No Credit Banking*, *Water*, and *ASC*.

Table 4-3: Hypothesis tested in this study

	Null Hypotheses*	
	Preference-space	**WTP-space**
HRPS[a]	$H_0^{RPS}: (c_1 + c_{11})/(\lambda + c_{10}) = c_1/\lambda$	$H_0^{RPS}: \psi_1 = \psi_{11}$
	$H_A^{RPS}: (c_1 + c_{11})/(\lambda + c_{10}) < c_1/\lambda$	$H_A^{RPS}: \psi_1 < \psi_{11}$
H*Rooftop*[a]	$H_0^{Rooftop}: (c_2 + c_{12})/(\lambda + c_{10}) = c_2/\lambda$	$H_0^{Rooftop}: \psi_2 = \psi_{12}$
	$H_A^{Rooftop}: (c_2 + c_{12})/(\lambda + c_{10}) < c_2/\lambda$	$H_A^{Rooftop}: \psi_2 < \psi_{12}$
H*NoCreditBanking*	$H_0^{Credit}: (c_3 + c_{13})/(\lambda + c_{10}) = c_3/\lambda$	$H_0^{Credit}: \psi_3 = \psi_{13}$
	$H_A^{Credit}: (c_3 + c_{13})/(\lambda + c_{10}) < c_3/\lambda$	$H_A^{Credit}: \psi_3 < \psi_{13}$
H*Water*	$H_0^{Water}: (c_4 + c_{14})/(\lambda + c_{10}) = c_4/\lambda$	$H_0^{Water}: \psi_4 = \psi_{14}$
	$H_A^{Water}: (c_4 + c_{14})/(\lambda + c_{10}) < c_4/\lambda$	$H_A^{Water}: \psi_4 < \psi_{14}$
H*SmartMeter*	$H_0^{Text}: (c_5 + c_{15})/(\lambda + c_{10}) = c_5/\lambda$	$H_0^{Text}: \psi_5 = \psi_{15}$
	$H_A^{Text}: (c_5 + c_{15})/(\lambda + c_{10}) < c_5/\lambda$	$H_A^{Text}: \psi_5 < \psi_{15}$
	$H_0^{Online}: (c_6 + c_{16})/(\lambda + c_{10}) = c_6/\lambda$	$H_0^{Online}: \psi_6 = \psi_{16}$
	$H_A^{Online}: (c_6 + c_{16})/(\lambda + c_{10}) < c_6/\lambda$	$H_A^{Online}: \psi_6 < \psi_{16}$
	$H_0^{Home}: (c_7 + c_{17})/(\lambda + c_{10}) = c_7/\lambda$	$H_0^{Home}: \psi_7 = \psi_{17}$
	$H_A^{Home}: (c_7 + c_{17})/(\lambda + c_{10}) < c_7/\lambda$	$H_A^{Home}: \psi_7 < \psi_{17}$
H*ASC*	$H_0^{ASC}: (c_9 + c_{19})/(\lambda + c_{10}) = c_9/\lambda$	$H_0^{ASC}: \psi_9 = \psi_{19}$
	$H_A^{ASC}: (c_9 + c_{19})/(\lambda + c_{10}) < c_9/\lambda$	$H_A^{ASC}: \psi_9 < \psi_{19}$

*The significance levels along with their signs enable us to reject or not reject the null hypothesis.
a: We test RPS and Rooftop at their status quo levels, 20% and 9% respectively. Thus, c_8 and c_{18} along with ψ_8 and ψ_{18} will not be included in the hypotheses testing.

We assume all the non-monetary attributes, including the ASC variable, have normal distribution, the interacted variables are fixed, and use 400 Halton draws in both preference-space and WTP-space models (Train, 1999; Bhat, 2001; Scarpa et al., 2008; Train, 2009). *Price* is assumed to have normal distribution in the preference-space model and log-normal distribution in the WTP-space.[134] Lastly, all the analyses are done in Stata 14 using Hole's (2007, 2016) user-written commands.[135]

4.5. Results

In the current section, we first define the variables used in the modeling and their expected signs. Next, we illuminate results from preference-space and WTP-space models. Finally, we report hypotheses testing results after performing Wald tests and graphing Kernel density plots.

Table 3-4 summarizes the variables' definitions, as well as our expectations of their signs. Based on the previous study (Mamkhezri et al, 2018), we expect our respondents derive positive utility from increasing *RPS* and *Rooftop* levels and smart meter installation ($Smart\ Meter_{text}$, $Smart\ Meter_{online}$, and $Smart\ Meter_{home}$), while they derive negative utility from the current solar energy plan (*ASC*) and policies that increase water usage by fossil fuel generation (*Water*), stop rooftop owners from banking credits produced from excess electricity generation (*NoCreditBanking*), increase monthly electricity bill (*Price*), and require higher levels of RPS to source from rooftop solar rather than solar farm *((RPS-20)*(Rooftop-9)*). Our original hypothesis that the solemn oath script reduces hypothetical bias leading to lower MWTP for each attribute derives the remaining signs. For instance, if solemn oath script works under our survey setting, it

[134] We also included a log-normally distributed *Price* in the preference-space model. Results were comparable to when Price is normally distributed, and the model with log-normal *Price* variable did not lead to statistically significantly better fit.
[135] We used mixlogit(),wtp(), and mixlogitwtp().

should lower MWTP that respondents place on variables with expected positive signs mentioned above (i.e., RPS, Rooftop, and smart meter). The opposite holds true for parameters with expected negative signs (*Price*, *NoCreditBanking*, *Water*, *ASC*, and *(RPS-20)*(Rooftop-9)*) (see Table 4-3).

Table 4-4: Definition and expected signs of variables

Variables	Definition	Expected sign*
RPS	Percent of electricity from renewable sources by 2040.	+
Rooftop	Percent of solar energy from rooftop solar by 2040. (Increase in rooftop solar equates with decrease in solar farm)	+
NoCreditBanking	Rooftop solar owners can only sell their credits in the same month that excess electricity is generated.	–
Water	Water used to generate electricity by fossil fuel.	–
$SmartMeter_{text}$	Usage and electricity price information via text	+/–
$SmartMeter_{online}$	Usage and electricity price information via online account	+
$SmartMeter_{home}$	Usage and electricity price information via an in-home display	+
Price	Change in monthly electricity bill.	–
ASC	Alternative specific constant takes a value of 1 if the current plan chosen and 0 otherwise.	–
(RPS-20)*(Rooftop-9)	Interaction between *RPS* and *Rooftop* variables, centered on their status quo levels.	–
RPS*oath	Interaction between *RPS* and the oath variable**	–
Rooftop*oath	Interaction between *Rooftop* and the oath variable	–
NoCreditBanking*oath	Interaction between *NoCreditBanking* and the oath variable	+
Water*oath	Interaction between *Water* and the oath variable	+
$SmartMeter_{text}$*oath	Interaction between $SmartMeter_{text}$ and the oath variable	–/+
$SmartMeter_{online}$*oath	Interaction between $SmartMeter_{online}$ and the oath variable	–
$SmartMeter_{home}$*oath	Interaction between $SmartMeter_{home}$ and the oath variable	–
Price*oath	Interaction between *Price* and the oath variable	–
ASC*oath	Interaction between *ASC* and the oath variable	+
(RPS-20)*(Rooftop-9) *oath	Interaction between *(RPS-20)*(Rooftop-9)* and oath variable	+

Notes: This is a modified version of Table 4 in Mamkhezri et al. (2018). *The main attributes' expected signs are based on the previous study's results (Mamkhezri et al., 2018). In order for the solemn oath to mitigate hypothetical bias, the expected signs should hold true for the interacted variables with the oath variable. **Oath is a dummy coded variable that takes a value of 1 if respondent has signed the solemn oath script and zero otherwise.

Table 4-4 presents the main effects and MWTP estimates for each attribute along with an interaction term between RPS and Rooftop attributes at their status quo levels for the preference-space and WTP-space models, models 1 and 2 (equations (18) and (19)).[136] Main effect results, especially preference-space results, are comparable to those of the previous study in terms of signs and significance levels (Mamkhezri et al., 2018). Exceptions are *NoCreditBanking* and $SmartMeter_{home}$ attributes, where *NoCreditBanking* is statistically significant and $SmartMeter_{home}$ is statistically significant at only 5% and 10% levels in preference-space and WTP-space respectively. This discrepancy might stem from the different dataset utilized in the current study, as this study contains more data than the previous study. As expected, respondents are in favor of *RPS*, *Rooftop*, $SmartMeter_{online}$ and $SmartMeter_{home}$, and oppose to *NoCreditBanking, Water, ASC* and *Price* attributes. Statistically significant standard deviation estimates denote the existence of preference heterogeneity for the corresponding attribute; there exists substantial heterogeneity in preferences in all the attributes, except *NoCreditBanking* and $SmartMeter_{text}$ (only in preference-space model) attributes. For a more detailed description of main effect results, readers are directed to Mamkhezri et al. (2018). Log-likelihood along with the information criteria (Akaike information criterion (AIC) and Bayesian information criterion (BIC)) values of each model indicate goodness-of-fit for the corresponding model. Comparing model fit on a statistical standpoint, our results are in line with the literature; our preference-space models generally lead to better fit than WTP-space models (Hensher and Greene, 2011; Hole and Kolstad, 2012; Sonnier et al., 2007; Train and Weeks, 2005). Lastly, preference-space models also result in lower MWTP than WTP-space models.

[136] For comparison and robustness check, we also include results from Multinomial Logit (MNL), RPL with lognormal *Price,* and Generalized Multinomial Logit (GMNL) models in the appendix. Results are comparable across various models in terms of significance level and sign.

Table 4-5: Regression results of solar energy plans without the solemn oath dummy variable

	Preference-Space			WTP-Space	
VARIABLES	Coef.	SD (SE)	MWTP [CI][d]	Coef. (SE)[e]	SD (SE)
Price[a]	-0.080***	0.058***	--	--	--
	(0.013)	(0.012)			
RPS[a]	0.037***	0.056***	$0.47***	0.583***	0.836***
	(0.008)	(0.009)	[$0.36, $0.59]	(0.079)	(0.081)
Rooftop[a]	0.071***	-0.060**	$0.89***	1.103***	0.958***
	(0.018)	(0.024)	[$0.59, $1.2]	(0.202)	(0.227)
NoCreditBanking[a]	-0.367***	0.338	-$4.59***	-6.513***	-3.777
	(0.122)	(0.616)	[$-7.58, $-2.1]	(1.824)	(5.404)
Water[a]	-0.354***	0.510***	-$4.43***	-5.112***	6.354***
	(0.081)	(0.144)	[$-5.9, $-3.07]	(0.993)	(2.119)
$\text{SmartMeter}_{\text{text}}$[a]	0.127	0.023	$1.59	-0.669	-19.207***
	(0.193)	(0.218)	[$-2.73, $5.33]	(3.164)	(6.606)
$\text{SmartMeter}_{\text{online}}$[a]	1.061***	-1.032*	$13.27***	12.755***	-7.498
	(0.244)	(0.530)	[$9.24, $17.46]	(2.763)	(8.215)
$\text{SmartMeter}_{\text{home}}$[a]	0.507**	-1.207***	$6.34**	4.563*	-12.741*
	(0.202)	(0.406)	[$2.43, $10.17]	(2.527)	(6.527)
ASC[a]	-1.658***	2.349***	-$20.73***	-31.405***	48.513***
	(0.273)	(0.385)	[$-31.81, $-13.45]	(5.388)	(6.053)
(RPS-20)*(Rooftop-9)	-0.002***		-$0.03***	-0.035***	
	(0.000)		[$-0.04, $-0.02]	(0.006)	
Price(λ)[b]	--		--	-2.886***	0.032
				(0.081)	(0.156)
Observations[c]	1,901			1,901	
Log likelihood	-1479			-1492	
AIC	2995			3021	
BIC	3122			3148	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. 400 number of Halton draws were used. **a**: Random parameters assumed normally distributed. **b**: *Price* variable in WTP-space is assumed to be lognormally distributed. Post-estimation mean and SD are -0.095*** (0.013) and 0.120 (0.033) respectively. **c**: Each of our 482 respondents had 4 choices to make. **d**: Krinsky and Robb's (1986) approach is used to estimate preference-space MWTP confidence intervals [CI]. **e**: Coefficients of the nonmonetary attributes in the WTP-space model are the mean MWTP.

To facilitate testing the efficacy of the solemn oath script, the 3rd and 4th models' specifications also include interacted variables with the *Oath* variable. These new variables are assumed to be fixed and not random. Table 4-5 reports the estimated means, standard deviation, and MWTP coefficients for these models, equations (20) and (21).[137] The overall findings of main effect coefficients ($c_1 - c_9$ of preference-space model and $\psi_1 - \psi_9$ of WTP-space model) in terms of signs and significance levels stay similar to models 1 and 2.[138] However, none of the interacted variables with the solemn oath scrip dummy variable (*Oath*), beside *(RPS-20)*(Rooftop-9)*Oath* in Model 4[139], are statistically significant. Further, *RPS***Oath*, *Rooftop***Oath*, *NoCreditBanking***Oath,* and *(RPS-20)*(Rooftop-9)*Oath* variables have the opposite signs compared to the expected signs exhibited in Table 3-4.[140] Overall, not only the interacted variables with the solemn oath script are not statistically significant, but also they generally do not have the expected signs to reduce hypothetical bias. Similar to models 1 and 2, WTP-space results are not better fits than preference-space results, and they also commonly result in higher MWTP's, though we include both models for comparison and robustness check as suggested by Hole and Kolstad (2012). Lastly, Hole and Kolstad (2012) find that different model estimations can lead to different significance levels of estimated coefficients. This is the case with *NoCreditBanking* and $SmartMeter_{home}$ attributes in the current study.

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[137] MNL, RPL with lognormal *Price,* and GMNL models' results are included in the appendix for comparison and robustness check. These models' results are comparable to those of the current study's in terms of significance level and sign.

[138] $SmartMeter_{home}$ in WTP-space and *(RPS-20)*(Rooftop-9)*Oath* in preference-space variables are marginally significant at 10% level (p-values are 0.103 and 0.010 respectively).

[139] The only interacted variable with *Oath* that results in statistically significant MWTP in WTP-space is *(RPS-20)*(Rooftop-9)*Oath*. However, it has the opposite sign of what we expected: A negative sign on this variable indicates that respondents who took the solemn oath support higher levels of RPS to source from solar farm rather than rooftop solar even more than those who did not sign the oath script. This variable is statistically significantly different from zero (H0: MWTP=0: chi2=3.71 and p-value=0.054).

[140] We ran models 3 and 4 on the dataset used in Mamkhezri et al. (2018) (prior to collecting 78 more responses) and arrive at similar results: beside, *Rooftop*Oath* and *(RPS-20)*(Rooftop-9)*Oath* variables, none of the other interacted variables with the *Oath* variable were statistically significant (see Table 4-10 of Appendix).. Further, the *Rooftop*Oath* and *(RPS-20)*(Rooftop-9)*Oath* variables have the opposite sign (opposite to assigned signs in Table 3-4) indicating, if anything the solemn oath scripts increase MWTP for higher levels of the *Rooftop* attribute.

Table 4-6: Regression results of solar energy plans with the solemn oath dummy variable

	Preference-Space			WTP-Space	
VARIABLES	Coef. (SE)	SD (SE)	MWTP [CI][d]	Coef. (SE)[e]	SD (SE)
Price[a]	-0.078***	0.060***	--	--	--
	(0.012)	(0.011)			
RPS[a]	0.037***	0.060***	$0.47***	0.614***	0.921***
	(0.008)	(0.009)	[$0.32, $0.66]	(0.110)	(0.103)
Rooftop[a]	0.056***	0.057***	$0.72***	0.927***	1.054***
	(0.017)	(0.021)	[$0.37, $1.12]	(0.278)	(0.250)
NoCreditBanking[a]	-0.308*	0.436	-$3.98*	-5.305**	-4.237
	(0.168)	(0.342)	[$-7.98, $-0.43]	(2.530)	(6.019)
Water[a]	-0.391***	0.486***	-$5.04***	-5.914***	6.387***
	(0.094)	(0.108)	[$-7.06, $-3.25]	(1.379)	(2.376)
$\text{SmartMeter}_{\text{text}}$[a]	0.029	-0.515	$0.37	-2.284	21.965***
	(0.259)	(0.466)	[$-5.65, $5.78]	(4.444)	(8.021)
$\text{SmartMeter}_{\text{online}}$[a]	1.088***	0.827	$14.03***	14.323***	-6.846
	(0.297)	(0.617)	[$8.3, $20.13]	(3.876)	(9.039)
$\text{SmartMeter}_{\text{home}}$[a]	0.532*	-1.356***	$6.86*	5.948[f]	-14.746**
	(0.276)	(0.436)	[$1.08, $12.73]	(3.648)	(6.304)
ASC[a]	-1.867***	2.795***	-$24.06***	-32.892***	-51.534***
	(0.372)	(0.386)	[$-36.38, $-15.23]	(7.352)	(7.284)
(RPS-20)*(Rooftop-9)	-0.002***		-$0.02***	-0.028***	
	(0.001)		[$-0.03, $-0.01]	(0.007)	
Price*Oath	-0.007		-$0.09	-0.090	
	(0.010)		[$-0.35, $0.12]	(0.126)	
RPS*Oath	0.004		$0.05	0.047	
	(0.011)		[$-0.18, $0.29]	(0.157)	
Rooftop*Oath	0.032		$0.41	0.551	
	(0.029)		[$-0.2, $1.05]	(0.417)	
NoCreditBanking*Oath	-0.108		-$1.40	-2.330	
	(0.250)		[$-6.79, $4.12]	(3.764)	
Water*Oath	0.038		$0.48	0.469	
	(0.136)		[$-2.52, $3.43]	(2.103)	
$\text{SmartMeter}_{\text{text}}$*Oath	0.137		$1.76	2.080	
	(0.403)		[$-6.93, $10.85]	(6.576)	
$\text{SmartMeter}_{\text{online}}$*Oath	-0.075		-$0.97	-3.690	
	(0.401)		[$-9.72, $7.92]	(6.052)	
$\text{SmartMeter}_{\text{home}}$*Oath	-0.052		-$0.67	-2.702	
	(0.372)		[$-8.99, $7.37]	(5.438)	
ASC*Oath	0.263		$3.39	1.415	
	(0.507)		[$-7.49, $15]	(9.394)	
(RPS-20)*(Rooftop-9)*Oath	-0.001[f]		-$0.02	-0.022**	
	(0.001)		[$-0.04, $0]	(0.011)	
Price(λ)[b]	--		--	-2.913***	-0.009
				(0.101)	(0.165)
Observations[c]	1,826			1,826	
Log likelihood	-1413			-1426	
AIC	2884			2910	
BIC	3076			3101	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. 400 number of Halton draws were used. **a**: Random parameters assumed normally distributed.
b: *Price* variable in WTP-space is assumed to be lognormally distributed. Mean and SD are -0.054*** (0.005) and 0.000 (0.009) respectively.
c: Each of our 463 respondents had 4 choices to make.
d: Krinsky and Robb's (1986) approach is used to estimate MWTP (USD/month) confidence intervals [CI].
e: Coefficients of the nonmonetary attributes in the WTP-space model are the mean MWTP.
f: Marginally significant at 10% level.

To further investigate the solemn oath effectiveness and test the hypotheses laid out in Table 3-3, we conduct Wald tests under both preference-space and WTP-space models comparing each attribute's MWTP for those who signed the solemn oath and those who did not. Table 4-7 reports chi-squares and p-values for each of the null hypotheses ($MWTP_{Oath}$=$MWTP_{No\ Oath}$) tested in the current study. Hypotheses testing results from MWTP distribution across all attributes show no evidence that the solemn oath script lowers valuation responses in this setting at the precision level of 10%.[141] These results further support the findings of models 3 and 4. Lastly, the only variable that is marginally significant is *Rooftop* in the WTP-space model (Model 4) at the 18.7% level. However, the positive sign of the variable's estimated MWTP (Model 4) reveals that the solemn oath script, if anything, increases MWTP rather than decreasing.

[141] Similar results were attained when utilizing the dataset used in Mamkhezri et al. (2018). See Table 4-11 of Appendix.

Table 4-7: Wald test for each attribute's MWTP in Preference-space and WTP-space

	Preference-Space[a] Chi2 (p-value)	WTP-Space[b, c] Chi2 (p-value)
RPS	0.01	0.09
	(0.942)	(0.765)
Rooftop	0.75	1.74
	(0.387)	(0.187)
NoCreditBanking	0.1	0.38
	(0.756)	(0.536)
Water	0.25	0.05
	(0.615)	(0.823)
$SmartMeter_{text}$	0.11	0.10
	(0.746)	(0.752)
$SmartMeter_{online}$	0.17	0.37
	(0.681)	(0.542)
$SmartMeter_{home}$	0.06	0.25
	(0.803)	(0.619)
ASC	0.54	0.02
	(0.462)	(0.880)

P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
a: Null hypotheses: H0: $MWTP_{oath} = MWTP_{no\text{-}oath}$
b: Null hypotheses: H0: Attribute*oath = 0
c: The only interacted variable with *Oath* that results in statistically significant MWTP is *(RPS-20)*(Rooftop-9)*Oath*. However, it has the opposite sign of what we expected in order to decrease potential hypothetical bias (chi2=3.71, p-value=0.054).

Following Scarpa et al. (2008) and Hole and Kolstad, (2012), we graph Kernel density plots based on 100,000 draws from the estimated individual-specific coefficients and MWTP in preference-space and WTP-space models respectively. Figure 4-3 demonstrates the MWTP distributions for each attribute with and without including the solemn oath script (*Oath* equals 1 and 0 respectively) derived from equations (20) and (21).[142] These figures exhibit that the preference-space models, equation (20), generally have wider distribution with longer tails than WTP-models, equation (21), which is consistent with the literature (Train and Weeks, 2005; Balcombe et al., 2009; Hensher and Greene, 2011; Lanz and Provins, 2013; Scarpa et al., 2008; Sonnier et al., 2007; Thiene and Scarpa, 2009). Further, both with and without *Oath* graphs (straight and dashed lines respectively) overlap, indicating signing the solemn oath script does not lead to a statistically significant difference in distributions, regardless of what space in which models are analyzed (preference or WTP). The latter results provide us with even further evidence to not reject the null hypotheses of equal MWTPs between the two samples, with and without solemn oath script, at any common knowledge precision levels.

[142] See Figure 4-4 of Appendix for Kernel density graphs on Mamkhezri et al.'s (2018) dataset.

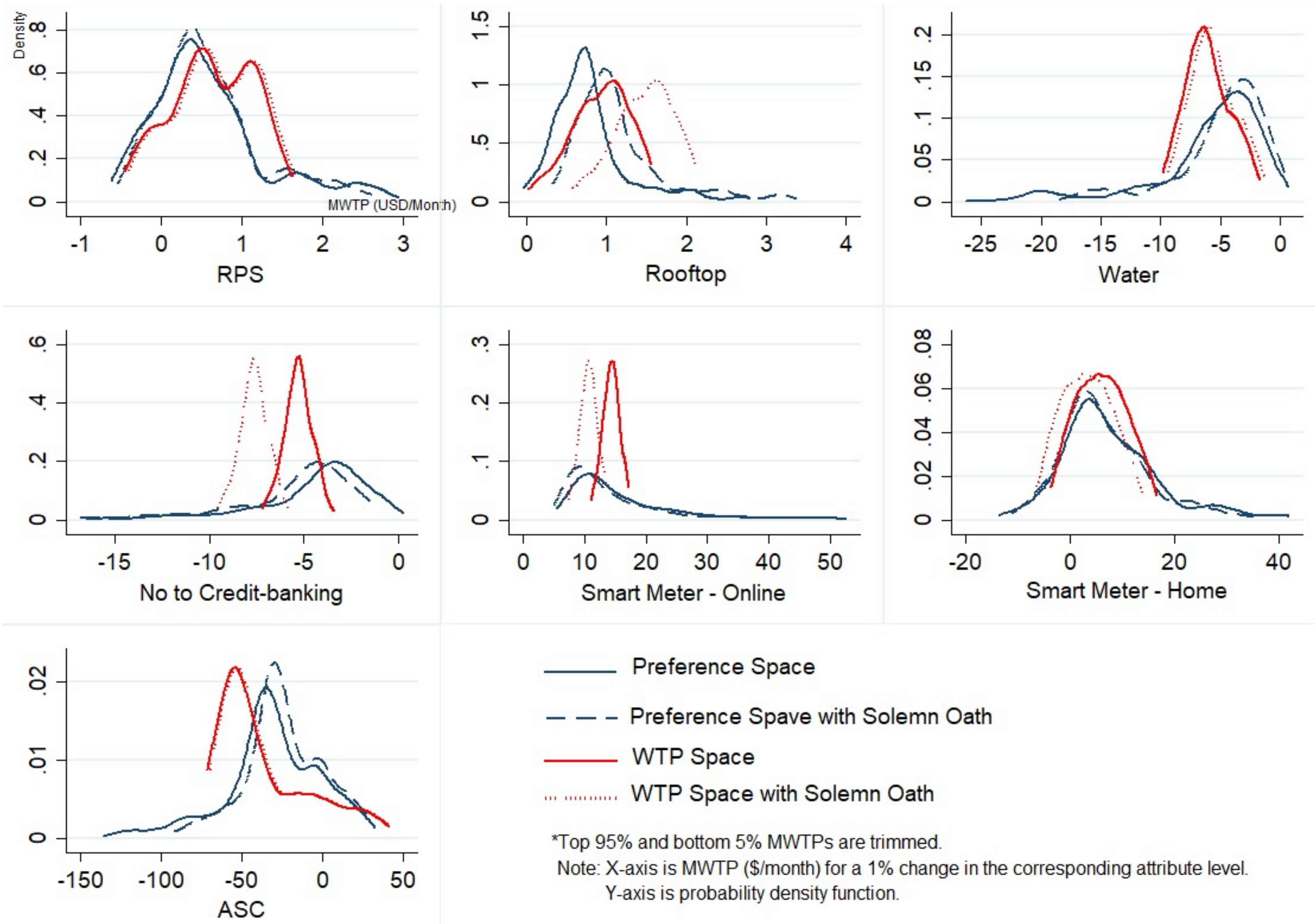

Figure 4-3: MWTP in Preference-Space and WTP-Space With and Without Solemn Oath. Note: Y-axis is Probability Density (not probability), which can exceed one.

4.6. Discussion and Conclusion

The primary objective of this study is to assess the efficacy of solemn oath script on potential hypothetical bias in a particular DCE survey application to solar energy. This study focuses on the impact of response under two alternative mechanisms: with and without having respondents sign the solemn oath script prior to taking a survey. The survey that each group received was distinguished by those including or excluding the solemn oath script. Using preference-space and WTP-space RPL models, we find no evidence that the solemn oath script impacts respondents MWTP behavior in a context of solar energy. Our Wald tests results, along with Kernel density plots of MWTP distribution across all attributes suggest that we cannot reject the null hypothesis of equivalence of MWTPs between those who took the solemn oath and those who did not for any of our attributes at the precision level of 10%. Hence, we are unable to corroborate the solemn oath script's effectiveness, as suggested by the literature (Jacquemet et al., 2009, 2013, 2018, 2019; de-Magistris and Pascucci, 2014), in a particular DCE survey application to solar energy.

There are a variety of interpretations as to why the solemn oath script reveals no effect in the case of our study. Three in particular are as follows.

Since a real payment or expenditure is not at issue in this study, we are not able to estimate actual WTP and compare it with hypothetical WTP (the current results). Hence, we cannot claim that there is or there is not hypothetical bias. Since our elicitation format would not fulfill incentive compatibility criteria set forward by Carson and Groves (2007), thus possibly hampering the external validity of the results through existing potential hypothetical bias. It is, however, conceivable that our survey does not suffer from hypothetical bias. Some previous studies have shown that it is feasible for WTP in a hypothetical situation (survey or laboratory experiment) to be equal to actual WTP (no hypothetical bias) (Cameron et al., 2002; Carlsson and Martinsson, 2001; Hensher, 2010). For instance, Hensher (2010) assessed the difference between hypothetical and real attitudes (i.e., stated and revealed preferences) towards transport mode and ticket type in three various DCE studies in New Zealand and Sydney. Although his choice questions in the stated preference setting would not follow the necessary binary condition for incentive compatibility, Hensher failed to reject the hypothesis of equal MWTP in stated and revealed preferences, and found no evidence of hypothetical bias.

The place in which the solemn oath script was presented to our respondents was not prior to the DCE questions. We asked our respondents to sign the solemn oath script at the beginning of the survey. However, prior to asking the DCE questions, we reminded our respondents about their budget constraint. As stated by Loomis (2014), the solemn oath script is a more effective tool when coupled with the cheap talk script. Although we did not utilize any type of a cheap talk script (short/long or soft/hard) or consequentiality script in our survey design, we included the idea of a soft cheap talk script budget constraint and policy and payment consequentiality in both the with and without the solemn oath script versions of the survey. Thus, it is also possible that the short reminder scripts are responsible for the elimination of hypothetical bias, if there was any. However, we are unable to test this hypothesis as these ex ante tools were included in both versions of the survey.

Lastly, it is challenging to relate our results to the existing literature as majority of the previous studies utilize different methodologies, including laboratory experiments, and investigate different nonmarket goods. Another possibility is that the solemn oath script may have limited application outside of the experimental lab and/or on different nonmarket goods, although it is an intriguing tool. To the best of our knowledge, there is only one unpublished DCE work that finds a similar result to that of the current study (Carlsson et al., 2017) and two peer-reviewed (DCE and CVM) studies that find an oath script (weak and strong oath) has the potential to reduce hypothetical bias (Carlsson et al., 2013; de-Magistris and Pascucci, 2014). Despite the different elicitation approach that one of the peer-reviewed studies has taken, neither one investigates an environmental nonmarket good (their goods are sushi and transport-related). Thus, further investigation in the vein may be valuable.

As for the area of future research, one could conduct a similar DCE study application to solar energy in the laboratory to investigate whether results differ when the survey setting is altered. In doing so, one can test the effectiveness of solemn oath, honesty priming through a promise[143], and cheap talk scripts, along with the presence of hypothetical bias. To facilitate the hypotheses testing, the sample can be divided into 6 treatment groups: (1) hypothetical DCE with the solemn oath script, (2) hypothetical DCE with a promise script, (3) hypothetical DCE with cheap talk, (4) actual DCE with the solemn oath script, (5) actual DCE with a promise script, and (6) actual DCE with cheap talk. One could also alter the monetary incentives provided to participants to test whether stakes matter under this setting (Andersen et al., 2011). Lastly, the effect of the location in which the oath is presented to participants can be investigated by either placing the oath prior to the DCE questions or at the beginning of the experiment.

[143] Similar to the honesty priming script used by Stevens et al., (2013).

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4.7. Appendix

Table 4-8: Supplementary regression results

	MNL	RPL[b]		GMNL	
VARIABLES	Coef.	Coef.	SD	Coef. (SE)	SD
Price[a]	-0.039***	--	--	-0.105***	0.088***
	(0.002)			(0.024)	(0.027)
RPS[a]	0.020***	0.037***	0.056***	0.052***	0.092***
	(0.003)	(0.006)	(0.007)	(0.016)	(0.023)
Rooftop[a]	0.031***	0.071***	0.051***	0.093***	-0.081***
	(0.007)	(0.014)	(0.017)	(0.031)	(0.021)
NoCreditBanking[a]	-0.346***	-0.380***	0.230	-0.548*	-0.345
	(0.061)	(0.119)	(0.242)	(0.303)	(0.564)
Water[a]	-0.145***	-0.355***	0.449***	-0.478***	-0.569
	(0.032)	(0.067)	(0.134)	(0.129)	(0.371)
$\text{SmartMeter}_{\text{text}}$[a]	-0.059	0.129	0.576	0.111	0.488**
	(0.100)	(0.183)	(0.508)	(0.259)	(0.204)
$\text{SmartMeter}_{\text{online}}$[a]	0.335***	0.968***	0.810	1.453***	-1.285**
	(0.107)	(0.202)	(0.577)	(0.400)	(0.516)
$\text{SmartMeter}_{\text{home}}$[a]	0.165*	0.472***	-0.831**	0.599**	2.084***
	(0.094)	(0.168)	(0.413)	(0.290)	(0.711)
ASC[a]	-0.638***	-1.899***	2.616***	-2.315***	3.623***
	(0.127)	(0.289)	(0.430)	(0.729)	(1.076)
(RPS-20)* (Rooftop-9)	-0.001***	-0.002***		-0.003***	
	(0.000)	(0.000)		(0.001)	
Ln(Price)[b]		-2.829***	0.975***		
		(0.114)	(0.112)		
Tau					0.563**
					(0.267)
Gamma					-0.890
					(0.743)
Observations[c]	1,901	1,901		1,901	
Log likelihood	-1715	-1474		-1473	
AIC	3451	2985		2988	
BIC	3517	3111		3128	

Notes: MNL and GMNL are Multinomial Logit and Generalized Multinomial Logit respectively. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
a: Random parameters assumed to be normally distributed.
b: *Price* is assumed to be lognormally distributed under RPL model.
c: Each of our 482 respondents had 4 choices to make.

Table 4-9: Supplementary models

	MNL	RPL[b]		GMNL	
VARIABLES	Coef.	Coef.	SD	Coef. (SE)	SD
Price[a]	-0.036***	--	--	-0.073***	0.057***
	(0.003)			(0.011)	(0.010)
RPS[b]	0.019***	0.038***	0.061***	0.032***	0.053***
	(0.003)	(0.009)	(0.008)	(0.008)	(0.007)
Rooftop[b]	0.023***	0.065***	0.059***	0.050***	0.041*
	(0.008)	(0.020)	(0.021)	(0.017)	(0.025)
NoCreditBanking[b]	-0.301***	-0.331**	-0.313	-0.250	0.130
	(0.086)	(0.168)	(0.437)	(0.170)	(0.616)
Water[b]	-0.164***	-0.404***	0.458***	-0.394***	-0.380***
	(0.043)	(0.103)	(0.151)	(0.105)	(0.147)
$SmartMeter_{text}$[b]	-0.108	0.082	0.742	-0.009	0.022
	(0.133)	(0.269)	(0.613)	(0.253)	(0.522)
$SmartMeter_{online}$[b]	0.336**	0.976***	0.861	0.989***	1.091**
	(0.143)	(0.298)	(0.740)	(0.282)	(0.435)
$SmartMeter_{home}$[b]	0.214[e]	0.505**	-1.067***	0.498**	1.005***
	(0.135)	(0.257)	(0.384)	(0.244)	(0.385)
ASC[b]	-0.625***	-1.913***	-2.604***	-1.602***	-2.748***
	(0.176)	(0.365)	(0.396)	(0.338)	(0.343)
(RPS-20)*(Rooftop-9)	-0.001***	-0.002***		-0.001***	
	(0.000)	(0.001)		(0.001)	
Price*Oath	-0.004	0.001		-0.003	
	(0.005)	(0.010)		(0.010)	
RPS*Oath	0.002	0.002		0.005	
	(0.005)	(0.010)		(0.011)	
Rooftop*Oath	0.017	0.029		0.033	
	(0.014)	(0.027)		(0.028)	
NoCreditBanking*Oath	-0.065	-0.077		-0.092	
	(0.123)	(0.243)		(0.232)	
Water*Oath	0.018	0.008		0.042	
	(0.066)	(0.134)		(0.132)	
$SmartMeter_{text}$*Oath	0.090	0.062		0.186	
	(0.207)	(0.405)		(0.393)	
$SmartMeter_{online}$*Oath	-0.066	-0.015		-0.063	
	(0.218)	(0.387)		(0.401)	
$SmartMeter_{home}$*Oath	-0.097	0.018		-0.007	
	(0.190)	(0.351)		(0.334)	
ASC*Oath	0.071	0.119		0.060	
	(0.263)	(0.519)		(0.511)	
(RPS-20)*(Rooftop-9)*Oath	-0.001*	-0.001*		-0.001[e]	
	(0.000)	(0.001)		(0.001)	
Ln(Price)[a]		-2.772***	0.985***		
		(0.183)	(0.131)		
Tau				0.251	
				(0.200)	
Gamma				1.013	
				(0.648)	
Observations[c]	1,826	1,826		1,826	
Log likelihood	-1655	-1408		-1417	
AIC	3351	2874		2895	
BIC	3483	3065		3100	

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
a: *Price* is lognormally distributed under RPL model and normally distributed under GMNL.
b: Random parameters assumed to be normally distributed.
c: Each of our 463 respondents had 4 choices to make.
e: Marginally significant at 11.3% – 13.9% level.

Table 4-10: Regression Results with the previous data set.

	Preference-Space			WTP-Space	
VARIABLES	Coef. (SE)	SD (SE)	MWTP [CI][d]	Coef. (SE)[e]	SD (SE)
Price[a]	-0.105***	0.100***	--	--	--
	(0.022)	(0.021)			
RPS[a]	0.051***	0.083***	$0.49***	0.785***	1.036***
	(0.013)	(0.016)	[$0.33, $0.67]	(0.125)	(0.118)
Rooftop[a]	0.054**	0.034	$0.51**	1.159***	-0.641
	(0.022)	(0.030)	[$0.19, $0.87]	(0.303)	(0.398)
NoCreditBanking[a]	0.030	0.840*	$0.28	-2.609	8.141
	(0.241)	(0.433)	[$-3.87, $4.14]	(3.022)	(7.906)
Water[a]	-0.538***	-0.358	-$5.12***	-6.276***	4.825
	(0.138)	(0.303)	[$-7.25, $-3.38]	(1.579)	(2.964)
$SmartMeter_{text}$[a]	0.141	0.693	$1.34	-3.237	21.634***
	(0.353)	(1.350)	[$-4.68, $7.08]	(4.404)	(6.920)
$SmartMeter_{online}$[a]	0.535*	0.440	$5.09*	7.288*	2.177
	(0.318)	(0.274)	[$0.1, $11.01]	(4.301)	(7.468)
$SmartMeter_{home}$[a]	1.008**	1.855***	$9.59**	6.216[f]	-20.130***
	(0.408)	(0.601)	[$3.46, $16.75]	(4.516)	(6.164)
ASC[a]	-1.578***	2.926***	-$15.01***	-23.490***	51.958***
	0.001	0.000	[$-26.64, $-7.23]	0.003	0.000
(RPS-20)*(Rooftop-9)	-0.001[f]		-$0.01[f]	-0.029***	
	(0.001)		[$-0.02, $0]	(0.008)	
Price*Oath	-0.022		-$0.21	-0.205	
	(0.015)		[$-0.48, $0.03]	(0.147)	
RPS*Oath	0.002		$0.02	0.013	
	(0.014)		[$-0.23, $0.25]	(0.178)	
Rooftop*Oath	0.072**		$0.68**	0.918*	
	(0.036)		[$0.12, $1.33]	(0.484)	
NoCreditBanking*Oath	-0.447		-$4.26	-7.429*	
	(0.356)		[$-10.27, $1.42]	(4.492)	
Water*Oath	0.021		$0.20	0.076	
	(0.177)		[$-3.02, $2.87]	(2.295)	
$SmartMeter_{text}$*Oath	0.229		$2.18	0.489	
	(0.531)		[$-6.7, $10.94]	(6.521)	
$SmartMeter_{online}$*Oath	0.519		$4.94	-0.995	
	(0.531)		[$-3.62, $13.78]	(6.577)	
$SmartMeter_{home}$*Oath	-0.162		-$1.54	-4.425	
	(0.509)		[$-10.46, $6.58]	(6.498)	
ASC*Oath	0.067		$0.64	-4.182	
	(0.646)		[$-9.73, $11.82]	(10.277)	
(RPS-20)*(Rooftop-9)*Oath	-0.002**		-$0.02**	-0.031**	
	(0.001)		[$-0.04, $-0.01]	(0.013)	
Price(λ)[b]	--		--	-2.837***	-0.127
				(0.128)	(0.242)
Observations[c]	1,563			1,563	
Log likelihood	-1150			-1180	
AIC	2359			2418	
BIC	2546			2605	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. 400 number of Halton draws were used. **a**: Random parameters assumed normally distributed. **b**: *Price* variable in WTP-space is assumed to be lognormally distributed. Mean and SD are -0.059*** (0.008) and 0.008 (0.015) respectively. **c**: Each of our 392 respondents had 4 choices to make. Out of 404 respondents, 186 were given the option to sign the oath script and only 9 respondents refused to do so. **d**: Krinsky and Robb's (1986) approach is used to estimate MWTP (USD/month) confidence intervals [CI]. **e**: Coefficients of the nonmonetary attributes in the WTP-space model are the mean MWTP. **f**: Marginally significant at 13%-17% level.

Table 4-11: Wald test results on the previous data set

	Preference-Space[a]	WTP-Space[b, c]
	Chi2 (p-value)	Chi2 (p-value)
RPS	0.27	0.01
	(0.603)	(0.943)
Rooftop	2.46	3.59*
	(0.117)	(0.058)
NoCreditBanking	1.4	2.73*
	(0.238)	(0.098)
Water	0.44	0
	(0.507)	(0.973)
$SmartMeter_{text}$	0.12	0.01
	(0.726)	(0.94)
$SmartMeter_{online}$	0.51	0.02
	(0.474)	(0.88)
$SmartMeter_{home}$	0.39	0.46
	(0.534)	(0.496)
ASC	0.28	0.17
	(0.598)	(0.684)

P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
a: Null hypotheses: H0: $MWTP_{oath} = MWTP_{no\text{-}oath}$
b: Null hypotheses: H0: Attribute*oath = 0
c: Rooftop and NoCreditBanking are the only two interacted variables with *Oath* that result in marginally significant at 10% level MWTP. However, they both have the opposite sign of what we expected in order to decrease potential hypothetical bias.

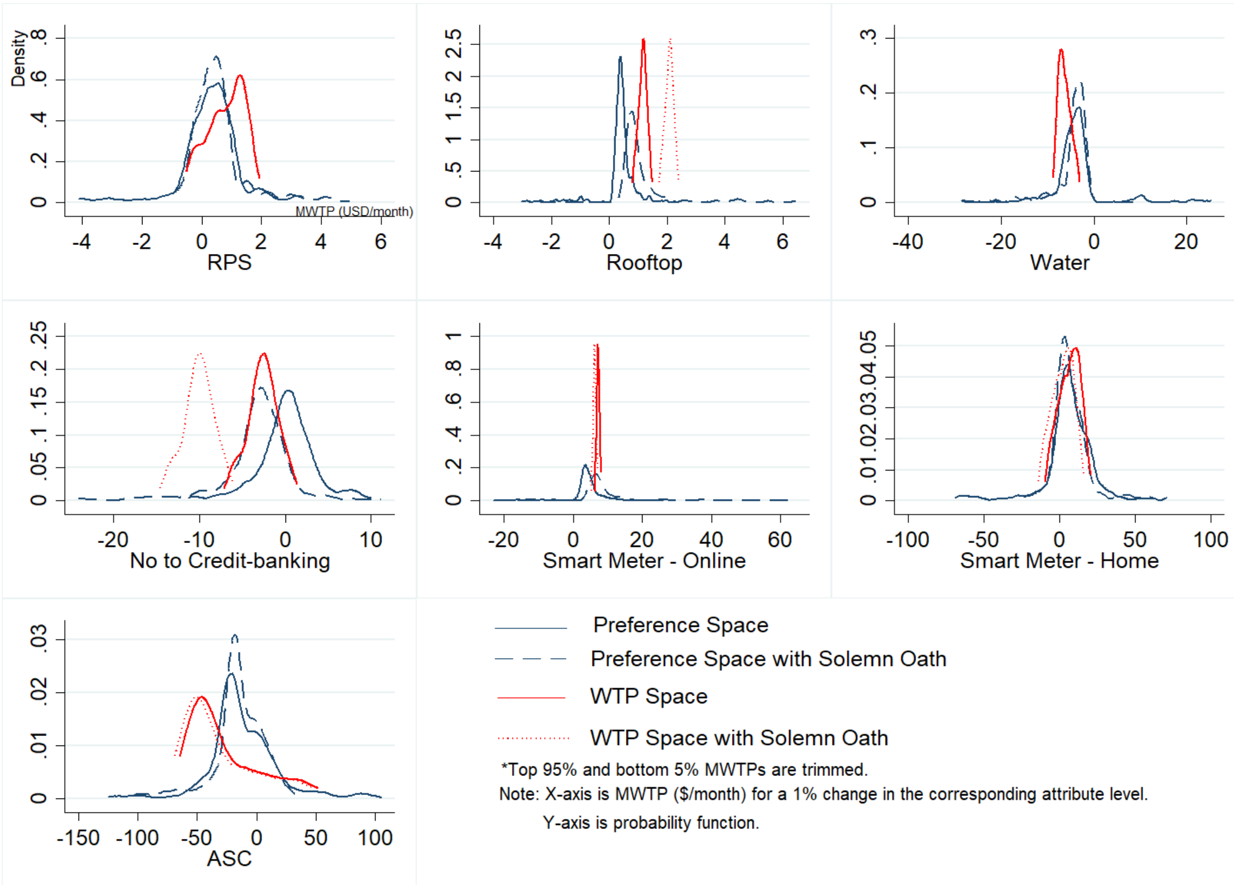

Figure 4-4: MWTP in Preference-Space and WTP-Space With and Without Solemn Oath – Previous dataset.

Chapter 5: Conclusion

5.1. Overview

Renewable energy's (RE) share of electricity generation is rising in the United States. Several factors contribute to this movement, in particular state and federal policies in favor of renewable energy such as renewable portfolio standards (RPSs), declining cost of RE development, and consumer preferences. The body of literature is not keeping pace with assessment of these factors' impact on the diffusion of RE in the United States. This dissertation is an attempt to address identified gaps within the literature.

This dissertation is an assessment of market and non-market valuation of RE, specifically within the electricity sector. It contributes to the ongoing energy economics literature through a series of three chapters. The first chapter assesses the economic (e.g., employment, economic output, explicit costs, etc.) and environmental (e.g., externality, implicit costs such as health impact, water use, greenhouse gases, etc.) impacts of RE. The following two chapters are based on a discrete choice experiment survey we conducted in New Mexico. In this chapter, we investigate respondents' opinion and willingness to pay (WTP) for RE, particularly solar energy. In the final chapter, we assess respondents' attitudes under different settings to investigate whether the hypothetical nature of survey leads to biased results. New Mexico is utilized as a case study in this research as it has abundant potential for different energy sources, particularly for RE. Below, we summarize each chapter and areas for future research briefly.

5.2. Chapter Two

In this chapter, we provide a roadmap of how to measure the economic and environmental impacts of different RE scenarios. In so doing, we combine various methodologies such as econometrics, GIS, input-output, and epidemiology into a unique system dynamics model to estimate the impact of RPS on a state's economy and the environment under four scenarios: 10%, 20%, 50%, and 100% RPS by 2050. We carry out our analysis in New Mexico, a southwestern state in the U.S. with an RPS of 20% by 2020 (reference case scenario) and abundant potential for fossil fuel and renewable energy sources.[144] This research is the first to construct such a multifaceted model in a granular level to estimate economic and environmental impacts of different energy scenarios. Under the former two scenarios, our results suggest that the majority of supported jobs will be in the urban counties with existing infrastructure for fossil fuel power plants, while the latter two scenarios support jobs primarily in the RE sector in rural counties. This suggests that local communities will be positively impacted by renewable energy-intensive scenarios if they are prepared in advance through workforce readiness programs. Although the former two scenarios result in higher economic

[144] At the time of analysis, Renewable Portfolio Standard was still set at 20% by 2020.

impacts, these scenarios also lead to higher social cost of greenhouse-gases and air pollution and water usage. Higher level RPS scenarios are only economically viable when market failure is taken into account. Thus, policymakers seeking to promote energy policies should not only consider economic impact, but also environmental impact. Our results provide improved information for states with or in the process of enacting similar energy policies.

The state-of-the-art modeling approaches utilized in this chapter can be used across topics and regions, as the theories combined for the analysis are not restricted to the electricity sector in New Mexico. Topics could include the impact of decarbonization (through smart grid (e.g., smart meter), transportation (e.g., electric vehicle), and energy-efficient buildings), 100%-all-sector-RE (i.e., electricity, heating/cooling, transportation, and industry), oil and natural gas extraction, or agriculture sector on regional economies. Regions could include granular level such as plant- and county-level to higher special levels such as countries (developed and developing). Our model can be modified and utilized by a layperson without prior knowledge of underlying theories. One possible limitation of this work is that we did not include transportation (i.e., electric vehicle) in our analysis. Once transportation starts moving toward integrating additional electric vehicles into transportation, in-state electricity demand within the transportation sector will increase, thus creating a higher need for capacity additions to fulfill the RPS requirement. Our findings provide prudent information for decisionmakers in the current political environment of the United States, particularly in New Mexico, as the 100% RPS Bill was recently passed in the Senate.

5.3. Chapter Three

In this chapter, we conduct a discrete choice experiment survey to assess citizens' WTP and their preference heterogeneity toward RE, especially different types of solar energy (rooftop solar and solar farm). In addition, we study consumers' attitudes towards advanced smart meter installation and water usage by the fossil fuel sector. Our sample drew from the consumers of New Mexico's major electric utility company. In our analysis, we incorporate factors such as distance, location (urban/rural), and environmental worldview (captured via the New Ecological Paradigm) that are expected to be responsible for variation in preference. This research extends the literature in three ways: 1) differentiates preferences and WTP estimation for different solar energy types, 2) employs the New Ecological Paradigm scale in a primary research of RE valuation in a choice experiment setting, and 3) assesses preferences on advanced smart meter and higher-level RPS. Utilizing different random parameter logit models, we find that respondents are in favor of RPS and rooftop solar and they desire higher level of RPS source from solar farm and advanced smart meter installation (especially if they receive electricity information either online or through an in-home display device). We also find respondents are opposed to a policy that refuses rooftop solar owners to bank their RE credits, a policy that increases the water usage by fossil fuel sector to generate electricity, and the current solar energy plan. Incorporating the observed heterogeneity factors in the analysis led to further divergent results. We find that distance to the closest solar energy installation (rooftop solar and solar farm) as the crow flies, location (rural/urban), and the level of environment conservation impact citizen's preference and WTP toward RE. Our findings provide enriched information for policymakers seeking to promote RE policies and suggest that these policies should consider public acceptance, spatial, and worldview heterogeneity.

Future research may incorporate community solar, along with solar farm and rooftop solar to further disentangle attitudes and WTP for solar energy. One can also include a distance attribute and compare results with respondents' actual distance (acquired post-survey) to different solar types. This can further support (or disprove) the distance decay effect result we find on solar farm in this chapter.

5.4. Chapter Four

This chapter addresses the issue of hypothetical bias through implementing the solemn oath script approach. For the reason of incentive compatibility, we use the solemn oath script to mitigate potential hypothetical bias. This chapter is an attempt to answer the question, "Does the solemn oath lower WTP responses in a discrete choice experiment application to solar energy?" To answer this question, survey sample (the same survey as the previous chapter) was divided into two even treatment groups: one group was asked to sign the solemn oath script before answering the survey and the other was without the script. We utilized random parameter logit models in the willingness to pay space and preference space to estimate marginal WTP for each attribute. We then compared the two groups' marginal WTP distributions using Wald test and kernel density graphs. These results suggest that there is no statistically significant difference at the precision level of 10% in marginal willingness to pay values and distributions between the two groups. There are a variety of explanations as to why solemn oath exhibited no effect in this case. Two in particular are either there was not hypothetical bias in this particular survey (which we are unable to test), or the solemn oath may have limited application outside of the experimental lab. Our findings suggest that the solemn oath script needs further investigation especially in discrete choice experiment settings. The contribution of this chapter is twofold: 1) We are the first to use the solemn oath scrip to address potential hypothetical bias in a DCE survey setting application to solar energy. 2) We are the first to implement the solemn oath script in a mail-based survey.

An expansion of this work is to implement the same discrete choice experiment study in the laboratory to examine whether results vary when the survey setting is changed. One could also assess whether the location in which the oath is presented matter by having participants sign the oath either at the start of the experiment or prior to answering the discrete choice experiment questions. It would also be interesting to examine whether the monetary reward that is provided to participants to participate in the experiment has an effect on results.

5.5. Final Remarks

When it comes to energy policy, it is easy to pass long-term packages that take effect decades into the future without quantifying economic and environment impacts associated with such laws, as is the case with RPSs. Ultimately, these policies have real effects on society through electricity prices, tax rates, and health costs associated with environmental changes. Why do we enact energy policies in the first place? First and foremost, their role is to improve the lives of *people*. We must remember that policies need to include consumers' preferences in addition to the economic and environmental impacts to make positive changes for the future of our society. This dissertation provides improved information within each of these domains to support efficient and sustainable policy development that meet the needs and desires of consumers and society as a whole.