DISSERTATION

TESTING A MULTILEVEL MODEL TO IDENTIFY GEOGRAPHIES OF SUPPORT FOR WIND DEVELOPMENT IN THE UNITED STATES

Submitted by

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ABSTRACT

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To combat climate change, the U.S. electricity sector must transition from the current system, mostly comprised of fossil-based fuels, to a carbon-free system. A transition of this magnitude requires collaboration with local communities and a deep understanding of geographies of support that contextualize conditions conducive to community-supported renewable energy development. A framework proposed by Boudet (2019) presents a multidimensional model of support with four high-level variable categories that influence public responses to new and renewable energy technologies: technology, people, place, and process. Although grounded in previous research, the framework has yet to be tested in tandem and interactions between variables have yet to be explored in the context of utility-scale renewable energy development. This dissertation fills this gap and helps practitioners better understand community interests in wind development by testing a novel multilevel model predicting support for wind energy using Boudet's technology, people, and place categorization scheme and a large set of publicly-available, national datasets that assess variables at varying geospatial levels.

When all categories of Boudet's framework were modeled in tandem, perceptions about the environmental and economic impacts of wind turbines (i.e., the technology category), including perceived job impacts, climate impacts, and property value impacts, significantly predicted support for wind development. Climate change acceptance also significantly predicted support for wind development, but demographic components of the people category did not. Disadvantaged community status was examined as part of the place category because the transition to carbon-free energy affords the opportunity to address legacy environmental injustices in those communities. However, the place category did not

significantly predict support for wind development, with the possible exception of county-level rural designation.

In addition to performing the first test of Boudet's framework in the context of utility-scale wind development, the current work examined geographies of support for wind development in the form of interactions across variable categories, which have not previously been explored in the context of wind development. The belief that turbines create jobs is more strongly related to support for development among those who assert that climate change is not happening than among those who assert that climate change is caused by a combination of human activities and natural patterns. Trends were also uncovered that indicate the potential existence of additional geographies and warrant further investigation. Representative sampling of liberal or progressive individuals and oversampling of individuals from highly rural areas and those with less than high school educational attainment will provide more precise estimates of the potential moderating effect of rural designation on three variables—the belief that turbines create jobs, political views, and educational attainment. Exploration into the impact of the age of historical energy installations on wind support also revealed no significant results but an interesting trend—more recent installations tended to be associated with lower support for wind development, which can be explored further in future research that focuses on data collected in areas with wind installations.

This work can inform first steps in the wind energy siting process by highlighting when and why certain geographies tend to be supportive of wind development. By identifying geographies of support, the current work will help practitioners better align development interests with community interests. Although research shows that those supportive of wind development outnumber those in opposition, working with communities to address the concerns of those opposed to development, even if in the minority, is an important component of energy justice. Moreover, predicting where this opposition is less likely to occur will aid in the pursuit of successful, equitable energy transitions.

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CHAPTER I: INTRODUCTION

Due to human activities, current concentrations of carbon dioxide (CO_2) in the atmosphere are higher than they have been in two million years (Intergovernmental Panel on Climate Change [IPCC], 2023). This has caused temperatures to rise at historically unprecedented rates, with global surface temperature nearly 2°F (1.1°C) higher than it was in the late 19th century. High CO_2 concentrations are causing substantial increases in sea levels, extreme heat events, floods, droughts, extreme storms, and species loss. Millions of people are affected by these events each year, with already vulnerable groups (e.g., Least Developed Countries, Small Island Developing States, Indigenous populations, and low-income households) impacted most severely. These ecological impacts not only harm economic and infrastructural stability, but they also negatively affect human health and well-being by increasing food and water insecurity and making pandemics, such as the COVID-19 pandemic, more likely (IPCC, 2023). In the western United States, for instance, wildfire season is getting longer and more intense due to climate change, which hurts air quality, causes respiratory and cardiovascular disease, and destroys property and human livelihoods (U.S. Global Change Research Program [USGCRP], 2018). Communities in the southeastern United States are also particularly vulnerable—they will continue to suffer from worsening extreme heat, storm surges caused by rising sea levels, and vector-borne diseases.

Limiting temperature rise to 3.6°F (2°C) will require immediate action, and because energy production creates the most greenhouse gas (GHG) emissions, decarbonization of the energy sector is particularly important (IPCC, 2023). To decarbonize the energy sector, renewable energy technologies must be developed enough so that the amount of energy produced from renewable technologies matches or exceeds the amount of energy currently produced by fossil-based technologies. In the U.S., around 60% of electricity is generated using fossil fuels and 21% is generated by renewable energies (U.S. Energy Information Administration [EIA], 2024b). To drive renewable development of this magnitude, sites suitable for renewable technologies must be identified, which requires not only policymaking, but also local community support.

A vast body of research has identified predictors of community support for renewable energy development, but much of it has been siloed within individual fields that use differing levels of analysis (Boudet, 2019; Rand & Hoen, 2017). However, a framework proposed by Boudet (2019) presents four high-level variable categories that have been shown to influence public responses to new and renewable energy technologies: technology, people, place, and process. The framework is unique in that it unites psychological research, which focuses on individual-level variables, and sociological research, which focuses on community-level variables, both of which impact support for development. Moreover, it is amenable to the integration of social science and energy technology variables. Although grounded in previous research, to the author's knowledge, the framework and its variables have yet to be tested in tandem and interactions between variables have yet to be explored in the context of utility-scale renewable technology development (see Min & Ko, 2023, for a partial test of the framework in the context of rooftop solar adoption). The current study fills this gap by developing a model of support for wind energy using Boudet's technology, people, and place categorization scheme. Wind energy is the focus of this work because wind is the most thoroughly researched renewable technology from a social science perspective, allowing this study to test the framework and associated model using well-established predictors and a large, national dataset. This study defines relationships and interactions between individual-level and community-level predictors of support for wind development to establish geographies of support, or "perception geographies" (Boudet, 2019, p. 452), that contextualize conditions conducive to community-supported development. Thus, the study deepens the field's understanding of local infrastructure siting and ultimately aids in executing equitable, community-focused energy transitions.

Energy Use, Climate Change, and Just Energy Transitions

Although the catastrophic effects of climate change are understood and the relationship between fossil fuel combustion and climate change are known (IPCC, 2023; USGCRP, 2018), the U.S. is still largely powered by fossil fuels. In 2022, the electric power sector in the U.S. produced 25% of the country's total emissions, largely because 60% of electricity was produced by natural gas and coal (EIA, 2024b; U.S. Environmental Protection Agency [EPA], 2024).

Renewable energy sources, on the other hand, are less widespread despite emitting far fewer GHGs than their fossil-based counterparts. Solar and wind electricity generation, for instance, emits between 90–98% fewer GHGs than electricity generated from combined cycle gas and between 94–99% fewer GHGs than electricity generated from coal across the technologies' lifecycles (Schlömer et al., 2014). Decarbonizing the electric grid (i.e., transitioning away from a carbon-based energy supply) will thus substantially reduce emissions and help prevent worsening impacts from climate change.

Decarbonization also brings another opportunity—to correct injustices created by the current energy system. A just energy transition is one guided by principles of energy justice, which originated from the environmental justice movement and is defined as "the goal of achieving equity in both the social and economic participation in the energy system, while also remediating social, economic, and health burdens on marginalized communities" (Baker et al., 2019, p. 5). Practitioners focused on energy justice seek to correct historic and continued energy-related injustices by a) identifying communities disproportionately exposed to energy-related hazards and ensuring they receive the benefits of clean energy development (distributive justice) and b) co-developing infrastructure siting plans with communities, or at least meaningfully including impacted communities in decision-making processes for infrastructure siting (procedural justice; Sovacool & Dworkin, 2015).

Distributive Justice

Distributive injustices exist in the current energy system as unequal exposure to energy-related environmental hazards poses serious health risks to underserved communities. Fossil fuel combustion produces air pollutants, including fine particulate matter ($PM_{2.5}$), diesel particulate matter, sulfur oxides, nitrogen oxides, and ozone, which adversely impact human health, particularly respiratory and cardiovascular systems (California Air Resources Board, 2023; Dignon, 1992; Garcia et al., 2023; Liu et al., 2012; Tessum et al., 2019, 2021; EPA, 2023c; Wang et al., 2016). Research has demonstrated the adverse effects of these pollutants, showing that proximity to industrial activities impacts brain development, academic achievement, and mental health (Malin, 2020; Merz et al., 2020; Peek et al., 2009; Zhang et al., 2022). Additionally, proximity to carbon-based power plants has been shown to increase hospitalization rates for respiratory diseases (Liu et al., 2012) and the occurrence of attention deficit hyperactivity disorder and anxiety in children (Zhang et al., 2022).

Exposure to industrial hazards is a distributive injustice because proximity to these hazards varies sociodemographically. Historically and in the present day, low-income individuals and people of color, controlling for income, are more likely to live near environmentally hazardous sites and industrial activities, including power generation facilities (Brender et al., 2011; Clark et al., 2017; Commission for Racial Justice, 1987; Di Fonzo et al., 2022; Epstein & Selber, 2002; Gochfeld & Burger, 2011; Mcrae & LaPuma, 2016; Sovacool & Dworkin, 2015; EPA, 2023b). Consequently, in the U.S., Black and African American individuals and Hispanic and Latinx individuals are exposed to more $PM_{2.5}$ than white individuals, and low-income households are exposed to more $PM_{2.5}$ than higher-income households (M. Bell & Ebisu, 2012; Perlin et al., 2001; Tessum et al., 2019, 2021; EPA, 2019; Wang et al., 2016).

Energy generation from renewable sources creates fewer air pollutants compared to fossil-based energy generation and ultimately improves air quality (Gharbi et al., 2023; Xie et al., 2023); thus, the current energy transition and the reduction of fossil fuel extraction provides an opportunity to mitigate socioeconomic, racial, and ethnic disparities in exposure. However, to achieve just energy transitions, procedural justice must also be addressed.

Procedural Justice

Procedural injustices are pervasive in industrial activities in the United States. The modern environmental justice movement was catalyzed in part by the unsuccessful attempt by the majority African American community in Warren County, North Carolina, to stop the nearby development of a hazardous waste landfill in the early 1980s (Taylor, 2014). Procedural injustices persist today in energy development as developers, government officials, and policy-makers, in the United States and beyond, consistently fail to include key stakeholders meaningfully in decision-making processes (Fry et al., 2015;

Jami & Walsh, 2017; Malin et al., 2019; Malin & DeMaster, 2016; Malin & Ryder, 2023; Sovacool & Dworkin, 2015). For instance, to avoid a state-wide vote, the Colorado government created a task force in 2014 comprised of community members, oil and gas companies and developers, and public officials, which "replaced direct democracy" to make recommendations for the state's oil and gas regulations (Malin & Ryder, 2023, p. 332). The Colorado government asserted that the task force would be impartial and represent community and industrial interests evenly; however, Malin and Ryder found that the task force instead reinforced procedural injustices by failing to include a representative selection of community participants, overrepresenting the oil and gas industry, and failing to be transparent about the participant selection process. The state ultimately failed to enact any regulations to address community members' concerns of distributive and procedural injustices in oil and gas development.

Renewable Energy and Justice

Importantly, renewable energy is not immune to energy injustices, and some past renewable energy development projects have instead contributed to the problem (Elmallah & Rand, 2022; Jami & Walsh, 2017; Mueller & Brooks, 2020; Nilson & Stedman, 2022; Rand & Hoen, 2017; Susskind et al., 2022). Elmallah and Rand (2022), for instance, found that procedural justice in wind farm development in Ohio and Minnesota was unsupported by state regulations, which required only one public meeting be held about proposed wind projects, and by a lack of information and feedback sharing between community members and decision-makers. Without purposeful efforts to plan and implement equitable processes in renewable development, the future decarbonized energy system risks perpetuating historic injustices.

The energy justice movement seeks to remediate distributive and procedural injustices by distributing the harms and benefits of the energy system more equitably across communities, by requiring community-led decision-making or meaningful involvement of stakeholders in decision-making processes (Sovacool & Dworkin, 2015), and by "explicitly centering the concerns of frontline communities to make energy more accessible, affordable, clean, and democratically managed" (Baker et al., 2019, p. 5). Energy justice is important not only for the well-being of individuals harmed by the current energy system but because decarbonization efforts that work towards justice are more likely to be successful—renewable energy projects that include diverse perspectives, incorporate collaborative decision-making processes, and distribute costs and benefits equitably have better outcomes and are more likely to be accepted by community members than those without just processes (Beierle, 2002; Bidwell, 2016b; Chief et al., 2016; Gross, 2007; Jacquet, 2015; Liebe et al., 2017; Perlaviciute & Steg, 2014). Procedural justice is also important because, if communities most exposed to hazardous energy-related activities are left out of decision-making processes, the issues they face are less likely to be addressed (M. Bell & Ebisu, 2012).

Consequentially, energy justice has become central for many practitioners supporting energy transitions at the national and local levels. In the early 2020s, the Biden administration instituted the Justice40 Initiative to support an equitable energy transition (The White House, n.d.). The initiative stated that certain federal agencies, including the U.S. Department of Energy (DOE), had to direct at least 40% of investments to disadvantaged communities (DACs), defined in part by a community's exposure to pollution-, energy-, and climate-related burdens (U.S. Council on Environmental Quality [CEQ], 2022). Although clean energy development is likely to slow in the latter half of the 2020s due to the Trump administration's change in energy priorities (Joselow & Washington, 2025), activity around just energy transitions is still abundant—researchers continue to build knowledge of equitable renewable energy development (e.g., Hermwille et al., 2025; Phillips & Kaschny, 2024; Sovacool et al., 2024), developers continue to pursue renewable energy technologies given their declining costs (e.g., Gelles, 2025), and renewable energy development is still being pursued at the state and local levels (e.g., City of Phoenix, 2025; New York State Energy Research and Development Authority (NYSERDA), 2025; State of California, 2025). Additionally, regardless of national priorities, identifying DACs alongside community conditions more conducive to support for renewable technologies can lead to more productive engagement efforts and faster and more equitable decarbonization by focusing resources in areas more likely to support development (Brewer et al., 2015). The current work seeks to contribute to the literature on just energy transitions and to help address energy injustices in future development activities by helping developers and policymakers identify geographies that could be more supportive of development.

Support for Renewable Energy

Decades of research have documented broad support for grid decarbonization and renewable energy development in the United States. During the energy crisis of the 1970s, a review found that a majority of Americans preferred renewable energy over fossil fuel development and believed that renewable technologies would become more common in the future (Farhar et al., 1980). In the 1990s, support for renewables remained high—a review by Krohn and Damborg (1999) found that there were more Americans who wanted the U.S. to prioritize renewables in energy research and development than those who preferred fossil fuels and nuclear energy. Recent research shows that high levels of support persist today (Boudet, 2019; Carley et al., 2020; Carlisle et al., 2015; Rand & Hoen, 2017; Sharpton et al., 2020), even among Republicans, who tend to be less supportive of energy transitions than Democrats: in a national survey of more than 10,000 Americans, 70% of Republicans supported an increase in solar farms, and 60% of Republicans supported an increase in wind farms (Kennedy et al., 2023b).

Substantial research, however, has revealed a distinction between general support for renewable development and local support for renewable siting, which are not necessarily correlated—although widespread general support is well documented, local support is more varied (Carlisle et al., 2015; Larson & Krannich, 2016; O'Connor et al., 2022; Rand & Hoen, 2017). Initially, this was referred to as the not-in-my-backyard (NIMBY) phenomenon. However, NIMBYism has largely been refuted for several reasons. First, the impact of proximity to renewable facilities on public opinion varies; while some studies have found that closer proximity is associated with lower support, other studies failed to find this relationship, found a weak relationship, or found the opposite relationship (Devine-Wright, 2005). For instance, one study found that public support for renewable development in Utah decreased with closer proximity (Larson & Krannich, 2016), whereas a nationwide assessment found that attitudes toward local and general development of wind energy were correlated ($r = .44$) and that support for wind facilities increased with closer proximity because, as the authors posited, familiarity can lead to positive attitudes (Hoen et al., 2019). NIMBYism also dismisses the concerns of communities impacted by development and discourages dialogue, when in reality, research has documented serious community concerns that practitioners should work to address (Rand & Hoen, 2017). Even when concerns are unfounded, dismissal further hampers support. Researchers have thus rejected the simplistic NIMBY view in favor of more nuanced investigations into the causes of public opposition to renewable energy siting.

These investigations have found, firstly, that local opposition to renewable development exists (Jami & Walsh, 2017; Larson & Krannich, 2016; D. Mulvaney, 2017; Stokes et al., 2023). Stokes et al. (2023) found that, between 2000 and 2016, 17% of wind projects in the United States faced opposition in the form of physical protests, legal action, legislation, and letters to news editors, and Susskind et al. (2022) documented 23 wind and 23 utility-scale solar projects that were delayed or canceled between 2008 and 2021 due to concerns about wildlife (in Nevada and Oregon) and procedural injustices (in Hawai'i). Additionally, although New York State is currently undergoing large-scale preparations for wind and solar expansion, the state is facing opposition from rural communities who feel they are bearing the infrastructural burden to electrify highly urbanized areas (Nilson & Stedman, 2023).

Support for wind development, however, typically far exceeds opposition (Carlisle et al., 2014, 2015, 2016; Crawford et al., 2022; Hoen et al., 2019; Larson & Krannich, 2016; Mayer et al., 2021; K. Mulvaney et al., 2013; Petrova, 2016; Rand & Hoen, 2017). A comprehensive review of public responses to wind development found that 70–90% of respondents living near existing wind facilities had positive or neutral attitudes about the facilities (Rand & Hoen, 2017), and Stokes et al. (2023) found that, although some wind projects have faced opposition, an average of 23 people attended wind development protests between 2000 and 2016.

Even if protests against renewable energy development are attended by small numbers of individuals, these protests can be disruptive, and loud oppositional minorities can obscure majority support and make funders and policy-makers apprehensive to pursue development (D. Bell et al., 2005; Crawford et al., 2022; Jami & Walsh, 2017; K. Mulvaney et al., 2013; Stokes et al., 2023). Additionally, working with communities to address the concerns of those opposed to development, even if in the minority, is an important component of energy justice, and predicting where this opposition is likely to occur will aid in the pursuit of successful, equitable transitions.

Predicting Support: The Technology, People, Place, and Process Framework

A large body of research has explored predictors of support for renewable energy development, especially for onshore, utility-scale wind turbines (Carley et al., 2020; Rand & Hoen, 2017). In their review of research on support for new energy technologies (including wind energy), Boudet (2019) proposed a framework to explain public responses to energy development using technology, people, place, and process categories and outlined the evidence establishing connections between these categories and support for development. Technology and people variables are most relevant at the individual level, whereas place and process variables are contextual and most relevant at the community or project level. Thus, this framework emphasizes the need for energy siting research that combines psychological and sociological perspectives, fields that are complementary but often not examined in tandem.

Although the variables included in Boudet's (2019) framework have been linked in previous research to public responses to energy technologies, to the author's knowledge, research has yet to test the categories explicitly and simultaneously in the context of utility-scale energy development. Additionally, although Boudet highlights the overlapping nature of the categories and the likely existence of interactions, they did not propose relationships between the categories nor suggest specific ways in which the variables might interact. There is growing interest in exploring geographies of support that examine interactions between variables to contextualize responses to energy technologies. For instance, as described previously, proximity to development has a nuanced relationship with support for development, and proximity's impact on support varies depending on local and individual circumstances (Zanocco et al., 2020). Understanding the conditions that foster support for or opposition to energy development, instead of simply identifying the extent of support for energy development, can lead to greater community involvement and satisfaction with the development process, helping with the pursuit of just energy transitions. Thus, the goals of the current research are to use a multilevel linear regression model to 1) test Boudet's framework in the context of a utility-scale wind development and 2) investigate the existence of interactions between the variables included in the model.

In the next several subsections, I will characterize the framework's categories and describe the empirically supported predictors of wind energy in relation to those categories, describing potential interactions when relevant research is available. This information is also presented in summary form in Table 1.

Technology. This category represents perceived technology characteristics, such as sound emissions, aesthetics, and economic impacts. According to Boudet, the perception of technology impacts, and not actual impacts, is most relevant in the development of opinions about energy technologies.

Wind turbines emit sound that modulates as they spin. A comprehensive survey of over 1,200 residents living within 7 miles of wind facilities in Canada found that the average outdoor turbine noise at residences was 35.6 dBA, with a maximum of 46 dBA (Michaud et al., 2016), which is similar to sound levels produced by turbines in the United States and reported by the DOE (2023)[1]. These levels are within or near the World Health Organization's (WHO) recommended limit of 45 dBA for average exposure to wind turbine noise (WHO, 2022), and many studies and reviews have found little to no evidence that noise from wind energy impacts human health (Ellenbogen et al., 2023; Jami & Walsh, 2017; Knopper et al., 2014; Michaud et al., 2016; Radun et al., 2022; Rand & Hoen, 2017).

Nevertheless, wind turbine noise can cause annoyance and opposition to wind development among nearby residents (Bessette & Depew, 2019; Hoen et al., 2019; Hübner et al., 2019; Jami & Walsh, 2017; Karasmanaki, 2022; K. Mulvaney et al., 2013; Radun et al., 2022), especially when sound levels surpass 40 dBA (Knopper et al., 2014). Annoyance can be disruptive, and some research has found that annoyance itself can cause health-related impacts, including sleep disturbance and negative affect, which nearby residents sometimes attribute to the noise itself (Karasmanaki, 2022; Müller et al., 2023; Qu & Tsuchiya, 2021).

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[1] For reference, a jet engine 100 ft away produces 140 dBA, and a nearby refrigerator produces 55 dBA (Yale, n.d.).

Wind turbine annoyance can also be caused by factors unrelated to the noise; thus, some community members can be annoyed with, and experience health impacts from, wind facilities regardless of whether sound and proximity limits are enforced (Haac et al., 2019; Hübner et al., 2019; Jami & Walsh, 2017; Karasmanaki, 2022; Knopper et al., 2014; Müller et al., 2023). Concerns over the visual and landscape impacts of wind turbines, for instance, are common criticisms of wind development and are associated with annoyance and opposition to development among nearby residents (Bessette & Depew, 2019; Boudet, 2019; Carlisle et al., 2015; Crawford et al., 2022; Jami & Walsh, 2017; K. Mulvaney et al., 2013; Nilson & Stedman, 2022; Perlaviciute & Steg, 2014; Rand & Hoen, 2017).

Perceptions of the economic impacts of wind facilities can also impact support for development. While some individuals have negative perceptions of the economic impacts of turbines, including reduced property values and increased electricity rates, many individuals have positive perceptions, including job creation, increased local tax revenue, lower electricity rates, and the preservation of rural livelihoods and agricultural land (Bessette & Depew, 2019; Bidwell, 2013; Biggs et al., 2022; Boudet, 2019; Carlisle et al., 2015; Hoen et al., 2019; Klick & Smith, 2010; K. Mulvaney et al., 2013; Perlaviciute & Steg, 2014; Rand & Hoen, 2017; Slattery et al., 2012; Susskind et al., 2022). Economic impacts seem to be especially important in the formation of opinions of wind turbine siting among individuals with low concern about climate change or environmental issues (Jepson et al., 2012), including in Texas and Iowa, where wind farms are sometimes perceived as “the vehicle that will reverse economic decline” in rural areas (Slattery et al., 2012, p. 3699).

People. People variables are characteristics of the individuals responding to the energy technology, including sociodemographic characteristics, attitudes, values, and knowledge. Although demographic characteristics predict the adoption of certain renewable technologies, including rooftop solar and electric vehicles (G. L. Barbose et al., 2021; Kann & Toth, 2017; Lukanov & Krieger, 2019; Min & Mayfield, 2023; Reames, 2020; Sunter et al., 2019), research on wind energy has generally found little evidence that demographic characteristics predict support (Carlisle et al., 2014, 2015; Nilson & Stedman, 2023; Rand & Hoen, 2017; Roddis et al., 2018; Walker & Baxter, 2017). Exceptions include

Stokes et al. (2023), who found that opposition to wind projects was more likely to occur in areas with a higher proportion of white residents and a lower proportion of Hispanic/Latinx residents.[2] Klick and Smith (2010) also found that race and ethnicity predicted support for development, in addition to gender and religious affiliation, with women having lower support and Christians and Catholics having stronger support. Additionally, although that study failed to find a relationship between educational attainment and support, Bidwell (2013) found that education had a positive relationship with wind caution (i.e., support for renewables generally but a preference for conservation and prioritizing other non-wind renewable technologies).

There is somewhat more evidence that political ideology predicts support for wind energy, but results remain inconsistent. Research has found that, generally speaking, Republicans tend to be less supportive of renewable technologies than Democrats (Hawes & Nowlin, 2022; Kennedy et al., 2023b). Political ideology's association with support for local development, however, is more varied. Klick and Smith (2010) found that political ideology predicted support for local development, with conservatives being less supportive of wind, but they found that party identification was unrelated. Evidence also suggests that political ideology could moderate the relationship between proximity to and support for wind development. Although there have been no previous investigations of this interaction in the context of wind energy, a study of support for oil and gas development in New York and Pennsylvania identified a three-way interaction between proximity to development, political ideology, and state of residence—in Pennsylvania, conservative respondents living further from development were more supportive than those living closer to development, while liberal and moderate respondents showed the opposite pattern; however, this interaction was not found among New York respondents (Zanocco et al., 2020). An

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[2] Stokes et al. (2023) emphasize that this finding does not necessarily mean that Latinx residents were more supportive of development; instead, it could indicate that White residents felt more empowered to protest development projects than Latinx residents.

interaction between political affiliation, proximity, and state in the context of wind energy could explain why the relations between political affiliation, proximity, and support for development are inconsistent.

Pro-environmental attitudes and environmental values also have varying impacts on support for wind energy—environmentalism can predict both support for and opposition to development (Bidwell, 2013; Boudet, 2019; Burch et al., 2020; Crawford et al., 2022; Fergen & B. Jacquet, 2016; Jacquet, 2012; Larson & Krannich, 2016; D. Mulvaney, 2017; Perlaviciute & Steg, 2014; Rand & Hoen, 2017; Slattery et al., 2012; Susskind et al., 2022; Walker & Baxter, 2017). Rand and Hoen (2017) explain that these debates "typically revolve around local environmental harms versus regional or global benefits" (p. 141)—concerns about wildlife, landscape, and noise impacts are often central to the former, whereas concerns about climate change and air pollution are often central to the latter. Given the diverging foci of the environmental benefits of wind energy, pro-environmental attitudes are generally less predictive of support than other variables (Carlisle et al., 2014, 2015; Nilson & Stedman, 2023; Rand & Hoen, 2017).

Concern for climate change, on the other hand, predicts support for wind energy more consistently than broad environmental attitudes (Carlisle et al., 2015; Hawes & Nowlin, 2022; Hoen et al., 2019; Mayer et al., 2021). Climate change acceptance could also explain why the literature reports mixed results on the impact of political views on support for renewable energy development, as one study found that climate change acceptance mediated the relationship between political affiliation and support for renewable development (Hawes & Nowlin, 2022). Another study found that climate change acceptance explained significantly more variance in support for renewable energy policy among Democrats than among Republicans, who instead relied more on the economic impacts of renewable energy policy when forming their opinions (Gustafson et al., 2020), indicating a possible interaction between climate change acceptance and political views.

Knowledge about wind turbines is another people-related variable and pertains to the information deficit model, which posits that increasing an individual's knowledge about a topic will increase support and engagement in desirable behaviors (Bidwell, 2016a). Although much research fails to find evidence of this model and instead demonstrates that supporters and opponents of wind energy have similar levels of knowledge (Fast, 2014; Rand & Hoen, 2017), some research has demonstrated that increasing knowledge can increase support (Bidwell, 2016a).

Lastly, place attachment, which describes an individuals' feelings of connection to the place they reside and a desire for place preservation, has been found to impact support for energy development in Europe (Rand & Hoen, 2017). These studies found that, if wind energy is seen as harmonious and consistent with local culture and residents' perceptions of place, development is more supported (Boudet, 2019). In the U.S., however, there is less research on place attachment, and results are varied—Jacquet and Stedman (2013) found that place attachment had little to no impact on support for development, and Bidwell (2013) found that place attachment predicted wind caution but not wind enthusiasm.

Place. Place variables describe the energy context in which participants live and are characteristics of the location, at varying geospatial resolutions, where energy development could take place (Boudet, 2019; Wolske et al., 2017). Proximity to important local sites, for instance, can impact residents' support for energy development. Development near wildlife and natural areas can face opposition; however, as described previously, perceived local environmental risks have varying impacts on support for development depending on an individual's environmental priorities (i.e., local environmental versus global climate change concern; Boudet, 2019; Rand & Hoen, 2017). Development near population centers can also face opposition, especially for technologies perceived as risky (Boudet, 2019). Conversely, even rural areas, with lower population densities, might be particularly critical of energy development if residents perceive that the energy and economic benefits of development will flow to urban communities, an issue which is also addressed in the process category. This effect is partially counteracted, however, when community economic need is high, which can make residents more willing to host development projects if economic benefits will remain local. Although DAC status has never been tested in predictions of support for energy development, the relationship between community economic need and support for development suggests that DAC status might be related to support.

Support for energy development can also be impacted by a location's energy context, including technology salience, technical potential for energy development, and historical experience with energy development. Place variables might be particularly important for individuals inexperienced with wind turbines (i.e., those living in areas without existing turbines). As Boudet (2019) explains, when a technology is non-salient, opinions about the technology are not developed from experience with the technology itself. Instead, opinions are derived from historical experiences with other energy technologies and cues from political leaders and the media, variables which can be captured in the place category. Therefore, because individuals not living near turbines lack direct experience with the technology, they might rely more heavily on place variables. Technologies become more salient when energy infrastructure is highly observable (Boudet, 2019); therefore, because wind turbines are highly visible, they are more salient to local communities. Residents living near turbines are thus able to form opinions based on experience with the turbines (i.e., technology variables) and with the development process (i.e., process variables). This means that technology and process variables might impact nearby residents' opinions more heavily than other variables, whereas residents not living near turbines might conversely rely more on place variables.

Process. Process variables are characteristics of the energy development siting process and measure the extent to which projects seeking to address distributive and procedural injustices. Perceptions of poor procedural justice in renewable energy projects and low trust in decision-makers are highly impactful on project support and are associated with annoyance, negative attitudes, and opposition to development (Bessette & Depew, 2019; Carlisle et al., 2015, 2016; Crawford et al., 2022; Elmallah & Rand, 2022; Fast & Mabee, 2015; Firestone et al., 2018; Hübner et al., 2019; Huijts et al., 2012; Mills et al., 2019; Müller et al., 2023; Nilson & Stedman, 2023; Perlaviciute & Steg, 2014; Rand & Hoen, 2017; Susskind et al., 2022; Walker & Baxter, 2017). Hoen et al. (2019), for instance, found that perceptions of procedural justice were strongly correlated with attitudes about local wind development ($r = .64$), and some wind research has found that projects' procedural characteristics are more important than aesthetic characteristics in the formation of public opinions of facility development (Hoen et al., 2019; Songsore & Buzzelli, 2015).

Similarly, perceptions of the distributive aspects of wind development projects are also powerful predictors of support for development. As described previously, residents living near wind turbines are often concerned that the economic benefits of facilities will be inequitably distributed and largely flow to non-local entities, especially when the development projects lack mechanisms for allowing community investment or ownership. Consequently, community-owned wind projects tend to face less opposition (Jami & Walsh, 2017; Rand & Hoen, 2017; Stokes et al., 2023).

This exemplifies the importance of energy development that is distributionally and procedurally just. When only certain landowners nearest to wind facilities are compensated financially, it can “create perceptions of ‘winners’ and ‘losers’ and increase intra-community conflict” (Rand & Hoen, 2017, p. 139). Additionally, as described previously, renewable projects that prioritize procedural justice are more likely to be supported by community members (Baxter et al., 2013; Bidwell, 2016b; Liebe et al., 2017), partly because involving residents in the siting decision-making process can reduce the annoyance of nearby residents (Müller et al., 2023).

Summary

A summary of variables related to Boudet’s framework and their relationship to support for wind development is presented in Table 1. According to Boudet’s (2019) framework, predictors of opinions about energy technologies can be categorized into technology, people, place, and process variables.

- **Technology variables** are perceptions of energy technology characteristics (e.g., the extent to which an individual believes wind turbines create noise pollution). There is substantial evidence in the literature that technology variables predict support for development, especially beliefs about a turbine’s impact on noise pollution, visual obstruction, economic conditions, and climate.
- **People variables** are characteristics of the individuals responding to wind energy (e.g., political views). Little evidence generally exists in the literature of a relationship between individual characteristics and support; however, there are a few exceptions. Some research has found evidence that climate change concern and political views impact support for development.

- **Place variables** are characteristics of the location in which wind energy could be developed (e.g., technical potential for wind energy). Some evidence demonstrates a connection between place variables and support for development. For instance, the evidence is mixed on the impact of proximity to energy development on support. More research is needed to understand this relationship more thoroughly, and moderator variables could exist.
- **Process variables** are characteristics of the energy development decision-making process (e.g., the extent to which a wind development project incorporates procedural justice). There is substantial evidence that process variables predict support for development. Meaningful inclusion of community stakeholders in decision-making processes increases support, as does fair compensation and benefits-sharing among nearby residents.

Table 1. **Summary of Variables from Boudet's Framework and Their Relation to Support for Development**

Variable	Current Evidence on the Variable's Relation to Support for Development
Technology	**This category represents perceptions of wind turbine characteristics. There is substantial evidence that technology variables predict support for development.**
🟢 Noise	Substantial evidence demonstrates a negative relationship with support, regardless of whether noise is below recommended limits.
🟢 Visual impacts	Substantial evidence demonstrates a negative relationship with support.
🟢 Economic impacts	Substantial evidence demonstrates a relationship with support, and both positive and negative perceptions of wind energy's economic impacts exist. Economic impacts might be most important for individuals with low concern for climate and environmental issues.
🟢 Climate benefits	Evidence demonstrates a positive relationship with support.
People	**This category represents characteristics of the individuals responding to wind energy. Little evidence generally exists on the relationship between individual characteristics and support; however, there are a few exceptions.**
🟡 Political ideology	Evidence is mixed, but some research demonstrates a relationship with support. Although untested in the context of wind, political ideology might moderate the relationship between proximity and support.
🟡 Environmental values	Evidence is mixed, but some research demonstrates a relationship with support. Local environmental concern is typically associated with lower support, whereas climate change concern is typically associated with higher support.
🔴 Race, gender, & education	Little evidence exists.
🔴 Religion	Little evidence exists.
🔴 Knowledge	Little evidence exists.
Place	**This category represents characteristics of the location in which wind energy could be developed. Some evidence demonstrates a connection between place variables and support for development, and potential interactions exist.**
🟡 Proximity to existing turbines	Evidence is mixed, but some research demonstrates a relationship with support. Proximity to turbines might impact the importance of the other categories that predict support.
🟡 Proximity to other energies	Evidence demonstrates a relationship with support.
🟡 Proximity to natural areas	Evidence demonstrates a negative relationship with support among individuals concerned with local environmental impacts. This effect decreases among those more concerned with global climate change concerns or economic impacts.
🟡 Proximity to populations	Evidence demonstrates a negative relationship with support, especially if the technology is also perceived as risky.
🟡 Economic need	Evidence demonstrates a positive relationship with support.
🟡 Place attachment	Evidence demonstrates a negative relationship with support in European studies, but there is less evidence in North American studies.
🟡 Technical and political context	Evidence demonstrates a relationship with support, especially among individuals inexperienced with living near turbines.
Process	**This category represents characteristics of the development decision-making process and is related to distributive and procedural justice. There is substantial evidence that process variables predict support for development.**
🟢 Procedural characteristics	Substantial evidence demonstrates a relationship with support—meaningful inclusion of all stakeholders in decision-making processes increases support.
🟢 Distributive characteristics	Substantial evidence demonstrates a relationship with support—fair compensation and sharing the benefits of energy development among nearby residents increases support.

Note. Colored dots indicate the extent to which evidence exists of a variable's relation to wind support. Green dots indicate substantial evidence, yellow dots indicate some or mixed evidence, and red dots indicate little evidence.

The Current Research

Previous research has investigated relationships between support for wind energy and many of the technology, people, place, and process variables described in Boudet's (2019) framework. However, several questions remain unanswered. The framework's categories have not been tested in tandem in the context of utility-scale energy development. Additionally, there is evidence that yet-unexplored interactions could exist between the variables included in the framework, which, if uncovered, could help identify geographies of support that expand our understanding of the causes of support for and opposition to wind development. Lastly, to the author's knowledge, the relationship between DAC status and renewable support has never been examined. Given the importance of justice in energy transitions, it is crucial to not only identify DACs but to also understand the impact that DAC status has on support for development. To begin to answer these questions, I developed a multilevel linear regression model that predicted support for wind development in the U.S. using operationalized psychological and contextual variables related to Boudet's framework, as shown in Figure 1.

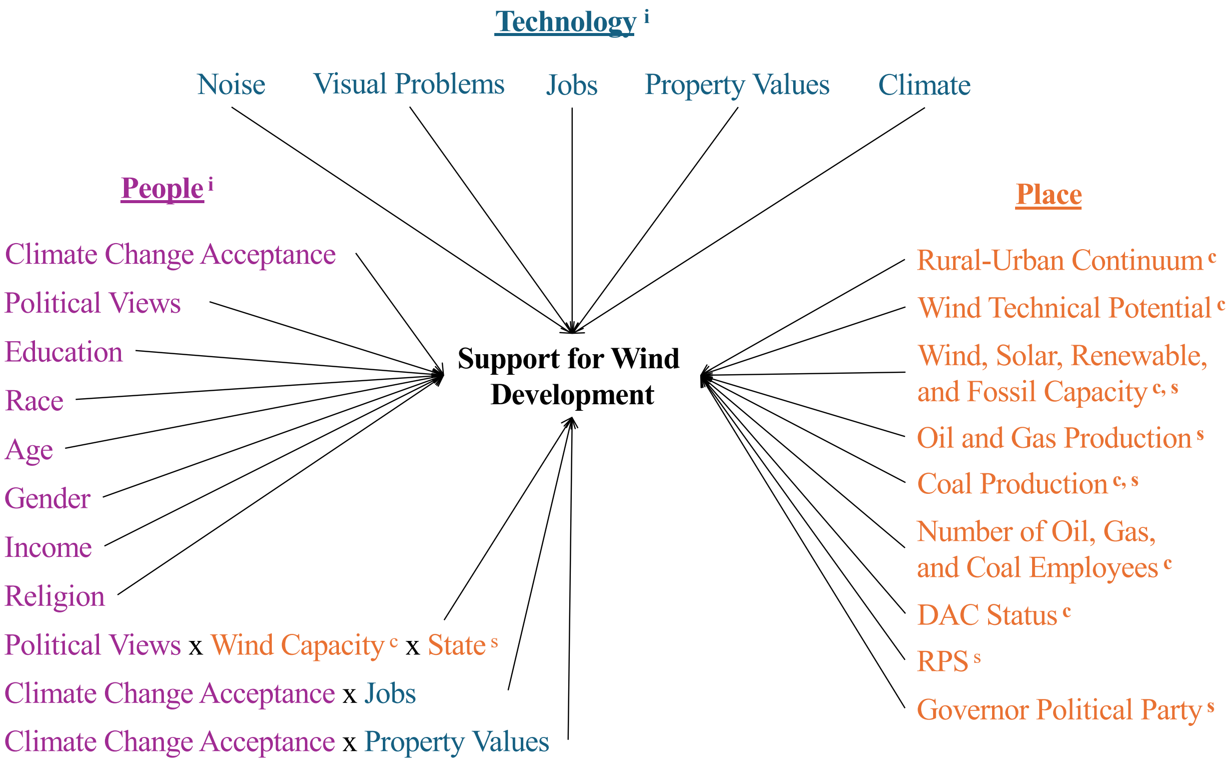

Figure 1. **Multilevel Model to Assess the Technology, People, and Place Categories of Boudet's Framework**
Note. DAC = disadvantaged community; RPS = renewable portfolio standard. Renewable capacity excludes onshore wind and solar capacity.
^{i} Individual-level, ^{c} county-level, and ^{s} state-level variables

Wind development was the focus of this work because, although wind energy is currently the most widespread type of renewable generation (EIA, 2024b), it still has a large amount of growth potential (National Renewable Energy Laboratory [NREL], 2023). Additionally, a large body of literature has established predictors of support for wind energy (Rand & Hoen, 2017), which was leveraged to test Boudet's (2019) framework. Wind energy can be developed at a large-scale (i.e., utility-scale) or a small-scale (i.e., distributed energy resources), but this work focused on utility-scale development for two reasons: 1) utility-scale technologies have far more potential for development and capacity than distributed resources (NREL, 2023) and 2) data on utility-scale power plant capacity is readily available (EIA, 2023), whereas nationwide data on distributed energy resources are not.

Hypotheses and High-Level Analysis Plan

The current study used operationalized people, place, and technology variables to predict support for wind development, as proposed by Boudet (2019). Process variables were not included in the current research because this work examined support for hypothetical wind development rather than support for actual or proposed development. Although process variables are important predictors of support for development, they are measurable only when examining specific proposed or existing wind projects. Instead, this work tests Boudet's technology, people, and place categories by using data drawn from a variety of publicly available, national data sources, including the National Surveys on Energy and Environment (NSEE; Borick et al., 2019), the EIA, and NREL. The research goals were addressed using multilevel regression modeling that included main analyses and exploratory analyses.

Main Analyses. To conduct the main analyses, I developed a multilevel linear regression model predicting support for wind development using the technology, people, and place variables shown in Figure 1. Based on the literature outlined previously, I hypothesized that all technology variables would relate positively to support for wind development. Among the people variables, I expected conservative participants to be less supportive of wind development than liberal participants, and I expected those who accept that climate change is caused by human activities to be more supportive of wind development than those who assert that climate change is not happening. Additionally, I expected climate change acceptance to interact with the belief that turbines impact jobs and property values, such that support for development would be more strongly related to beliefs about job and property value impacts for participants who accept that climate change is caused by human activities than among those who do not accept that climate change is happening. Hypotheses related to the place variables were harder to form because interactions involving these variables are likely to exist, and they are largely untested. For instance, proximity to wind turbines (operationalized as wind capacity), could relate to support for development differently depending on technology perceptions, and living near other types of energy facilities (i.e., oil and gas production or coal production) could similarly relate differently to support for wind depending on the extent to which the previous development was perceived as just. I thus formed no hypotheses related to the place variables.

Exploratory Analyses. I also conducted several exploratory analyses. Evidence is mixed regarding the relationship between proximity and support for development; therefore, I tested several potential moderating variables, including each of the technology and people variables. I also examined whether the technology and people variables moderate the relationship between rural designation and support for development. Lastly, given that a community's historical experience with energy development can impact support for development (which was assessed in the current work through the place variables), it is possible that recency of the historical installations could also matter—more recent impressions could impact perceptions more than development that occurred farther in the past. Therefore, I also explored whether the age of energy installations was related to support for development.

Conclusion

Although "strong public support is not sufficient for the development of wind-power capacity," public support "will contribute favourably to siting policy" (Wolsink, 2000, p. 63). There is substantial research into public opinions of wind energy research; however, that research has largely not been incorporated into decision-making processes among policymakers and developers (Rand & Hoen, 2017). Incorporating public support data, however, is beneficial—it will help developers down-select development sites that are more likely to be supported by community members, at which point public engagement, which can be quite costly, can begin and have a greater likelihood of success (Brewer et al., 2015). Public support data will also help practitioners better align development interests with community interests. Thus, this work leverages public support data to investigate geographies of support for wind energy and contributes to the literatures on wind energy opinions and siting by deepening the field's knowledge of the conditions conductive to support for development. Understanding where and why public support tends to be strongest will inform successful siting processes because those communities will have better conditions for development and could be more receptive to engaging with practitioners on development projects. Furthermore, considerations of public support in wind development projects will have beneficial justice implications—including communities supportive of wind development in decision-making processes can help build trust between government entities, developers, and community members and help expand energy-related community self-determination.

CHAPTER II: METHODOLOGIES

Materials

As described in the previous chapter, many variables at varying geospatial resolutions impact support for wind development, data for which often originate from disparate sources. Thus, I collated data from several sources to conduct the analyses and operationalized technology, people, and place variables as described below.

Technology

To assess the technology variables, which relate to perceptions of the risks and benefits of wind turbines, I used the Fall 2016 wave of the NSEE (Borick et al., 2019), which is a national, public opinion survey on climate change understanding, mitigation policies, and energy technologies (Muhlenberg College, 2020; University of Michigan, 2018). The Center for Local, State, and Urban Policy at the University of Michigan and the Institute of Public Opinion at Muhlenberg College jointly conducted the survey, via both landline telephones and cell phones, biannually from 2008–2018. The authors of the NSEE obtained landline and cell phone numbers from the Marketing Systems Group, chose phone numbers randomly, and obtained a response rate of 11% for the Fall 2016 wave. Since 2020, the survey has been conducted annually and exclusively by the Institute of Public Opinion at Muhlenberg College. The Fall 2016 wave participants came from all 50 states, including respondents from California most frequently ($n = 104$) and from South Dakota ($n = 1$) and Vermont ($n = 1$) least frequently (see Figure 2).

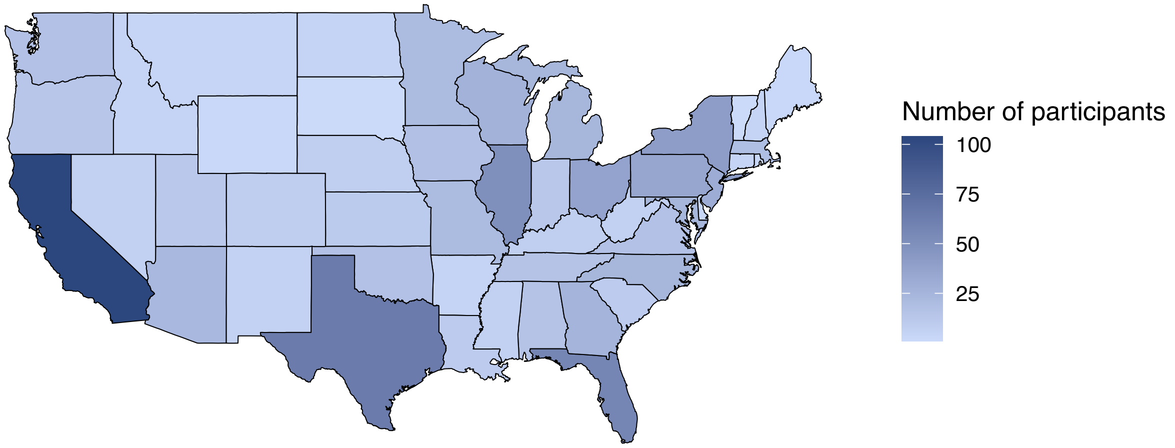

Figure 2. **Map of Participants from the Fall 2016 Wave of the NSEE**

The Fall 2016 wave is the only wave of the NSEE to include participant perceptions of five wind turbine characteristics: noise pollution, visual problems, job creation, property value reduction, and climate change mitigation (see Table 2). Each variable was assessed on a scale from 1 (strongly disagree) to 4 (strongly agree). Noise, property value, and visual impacts were reverse scored so that higher values would be expected to be indicative of more support for wind energy.

Table 2. **Technology Variables (Individual-Level)**

Variable Name	Description	Year	Source
Technology		2016	Borick et al. (2019)
Turbine noise *	Wind turbines create noise pollution		
Visual problems *	Wind turbines produce visual or aesthetic problems		
Jobs	Wind turbines create jobs		
Property values *	Wind turbines reduce nearby property values		
Climate impacts	Wind turbines limit climate change		

*Reverse-scored variables

People

The Fall 2016 wave of the NSEE also contains participants' sociodemographic and certain value-based characteristics. Although I expected most of the people variables to be unrelated to support for wind development, the model includes all people-related variables provided by the NSEE to test the people category of Boudet's (2019) framework: political views, climate change acceptance, education, race/ethnicity, age, gender, income, and religion (see Table 3). Climate change acceptance has six response alternatives. For four of those alternatives, respondents accept that climate change is happening, but they differ on the perceived cause of climate change: 1) human activity, 2) a combination of human activity and natural patterns, 3) natural patterns alone, and 4) not sure of the cause. The fifth alternative includes participants who are not sure whether climate change is happening, and the sixth includes participants who do not accept that climate change is happening.

Table 3. **People Variables (Individual-Level)**

Variable Name	Type	Values or Levels	Year	Source
People			2016	Borick et al. (2019)
Political views	Continuous; self-reported	(1) Very conservative (2) Somewhat conservative (3) Moderate (4) Somewhat liberal (5) Very liberal		
Climate change acceptance	Nominal; self-reported	(1) Not happening (2) Not sure if happening (3) Happening – not sure of cause (4) Happening – natural patterns (5) Happening – a combination (6) Happening – human activity		
Educational attainment	Continuous; self-reported	(1) Less than high school education (2) High school graduate (3) Some college or technical school (4) College graduate (5) Graduate or professional degree		
Race/ethnicity	Nominal; self-reported	(1) White/Caucasian (2) African American (3) Hispanic or Latino (4) Asian (5) Mixed race and other		
Age	Continuous; self-reported	(1) 18–29 years (2) 30–44 years (3) 45–64 years (4) 65 and older		
Gender	Nominal; assessed by the interviewer	(1) Female (2) Male		
Income	Continuous; self-reported	(1) Less than $20,000 (2) $20,000–$40,000 (3) $40,000–$60,000 (4) $60,000–$80,000 (5) $80,000–$100,000 (6) Over $100,000		
Religion	Nominal; self-reported	(1) Protestant (2) Catholic (3) Jewish (4) Muslim (5) Hindu (6) Other (7) Atheist		

Place

The place variables assess the energy context in which participants live. These variables largely come from sources other than the NSEE, but I combined them with the NSEE data using participants' county of residence. County of residence is not included in the publicly available NSEE dataset. However, the Principal Investigator (PI) for the NSEE project made a dataset available for the current analysis that includes participants' county of residence by matching ZIP Codes to county names (C. Borick, personal communication, February 6, 2024). ZIP Codes were then removed from the dataset to protect participant confidentiality. I then matched county names with their associated Federal Information Processing Series (FIPS) codes. Because many of the sources used in the current work include FIPS codes, this process facilitated matching across data sources. As a result, the analyses in the current research include county-level place variables, shown in Table 4.

Table 4. **Place Variables (County- and State-Level)**

Variable Name	Level	Description	Year	Source
Place				
County	County	County of residence, assigned by researcher using self-reported ZIP Codes	2016	Borick et al. (2019)
State	State	State of residence, self-reported	2016	Borick et al. (2019)
Rural-urban code	County	9-level variable based on population size and adjacency to metropolitan areas: (1) Urban, ≥ 1 million people (2) Urban, 250,000 to 1 million people (3) Urban, < 250,000 people (4) Rural, ≥ 20,000 people, adjacent (5) Rural, ≥ 20,000 people, nonadjacent (6) Rural, 5,000 to 20,000 people, adjacent (7) Rural, 5,000 to 20,000 people, nonadjacent (8) Rural, < 5,000 people, adjacent (9) Rural, < 5,000 people, nonadjacent	2013	USDA (2020)
Wind technical potential	County	Modeled theoretical upper-limit for generation potential of onshore, utility-scale wind turbines, considering resource potential and land availability but not market or economic constraints, in millions of MWh	2020[3]	NREL (2023)
Wind capacity	County; State	Nameplate capacity (i.e., capacity at power plants) for onshore wind in thousands of MW	2016	EIA (2023)
Solar capacity	County; State	Nameplate capacity for solar technologies in thousands of MW	2016	EIA (2023)
Renewable capacity	County; State	Nameplate capacity for batteries, hydropower, flywheels, geothermal, and offshore wind in thousands of MW	2016	EIA (2023)
Fossil capacity	County; State	Nameplate capacity for coal, natural gas, and petroleum in thousands of MW	2016	EIA (2023)
Coal production	County; State	Coal production in millions of short tons	2016	EIA (2024c)
Coal employees	County	Number of coal employees in thousands	2016	EIA (2024c)
Oil and gas production	State[4]	Oil and gas production in quadrillion BTU	2016	EIA (2024d)
Oil employees	County	Number of gas employees in thousands	2016	DOE (2017)
Gas employees	County	Number of gas employees in thousands	2016	DOE (2017)
DAC status	County	Proportion of DAC census tracts, defined using eight categories of burden: climate change, energy, health, housing, pollution, transportation, wastewater, and workforce	2010-2022[5]	U.S. CEQ (2022)
RPS	State	Binary indicator of existence of active RPS policies, either yes or no	2016	G. Barbose (2017)
Governor political party	State	Political party of state governor, either Democrat or Republican	2016	Kaplan (2021)

Note: DAC = disadvantaged community; RPS = Renewable portfolio standards.

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[3] Technical potential was modeled in 2020 using data from previous years and is not available for 2016.

Proximity. Previous research has shown that proximity to energy development has varying impacts on support for development, and further, when predicting support for fossil fuel development, proximity to development interacts with political views and state of residence. The current research examined proximity to four types of energy technologies—onshore wind, solar, renewable (excluding onshore wind and solar), and fossil technologies. Because this work examined support for hypothetical wind development and because the finest resolution that the NSEE can provide publicly for participant location is county, I operationalized proximity for the three types of technologies using county- and state-level nameplate capacities in 2016 rather than a measurement of participants' distance from a particular energy facility. Nameplate capacity is a measure of a power plant's potential for energy generation. Specifically, it is the maximum amount of energy a technology can produce in power plants under ideal conditions (EIA, 2024a) and is provided by the EIA for power plants with one megawatt (MW) or greater combined capacity (2023). Thus, in this work, proximity to wind development and its interactions with certain technology, people, and place variables were examined using wind capacity at the county level as a proxy for proximity to development.

Proximity of energy development to population centers can also impact support; thus, the analyses included a county-level rural-urban continuum code that assessed population size and adjacency to metropolitan areas on a scale from 1 (a metropolitan county with 1 million or greater population) to 9 (a rural county with less than 2,500 population, not adjacent to metropolitan area; U.S. Department of Agriculture [USDA], 2020).

Existing Resources and Policies. The model included several additional county- and state-level variables to further contextualize the energy landscape and participants' experiences with the energy

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[4] The model will not include county-level oil and gas production estimates because a nationwide dataset of county-level oil and gas production does not exist for 2016. Some states provide their own historical, county-level production datasets; however, 15 of the 34 oil and gas-producing states do not.

[5] DAC status was published in 2022 using data from 2010 to 2022.

industry: county technical potential for wind development; state oil and gas production; county and state coal production; state renewable portfolio standards (RPS); and political party of the state's governor.

Technical potential is the modeled amount of energy that could be generated in a geographic area given its resource and land availability (NREL, 2012, 2023). For instance, the technical potential for onshore wind is estimated by modeling the strength of wind resources that flow in an area and the land available for utility-scale development, excluding bodies of water and land already developed (NREL, 2023). Technical potential is a theoretical upper bound for generation-—it does not consider market feasibility and assumes all available land is developed with turbines; thus, any given geographic area is unlikely to achieve its full modeled potential. Nevertheless, technical potential is useful for prioritizing technology development in regions with the greatest relative generation potential and, for the purposes of the current study, for contextualizing and comparing development opportunities across counties.

State-level oil and gas production in 2016 was obtained from the EIA (2024d), which provides production estimates for all states in billion BTU. To estimate coal production, I used EIA data that provide short tons of coal production at each mine in the U.S. in 2016 (2024c) and aggregated to the county and state levels by summing the estimates across all mines within each jurisdiction.

RPS policies dictate how much of a state's electricity resource mix must be comprised of renewables (NREL, 2022) and can impact a state's energy landscape (G. Barbose, 2023); therefore, the model included a binary indicator of whether active RPS policies existed in each state in 2016 using data from G. Barbose (2017). The political party of the state's governor can also impact a state's energy landscape (Bonnet & Olper, 2024) and could represent a political cue from which state residents develop opinions about wind energy; thus, the model also included the governor's political party in 2016 (Kaplan, 2021; National Governors Association, 2024).

DAC Status. To assess the potential impact DAC status has on support for development, the model included DAC status designated at the census tract-level by the U.S. CEQ (2022). To aggregate DAC status to the county level, I calculated the proportion of census tracts designated as disadvantaged within a county.

Outcome Measure

Support for wind development was estimated using an item from the NSEE that assessed the extent of participants' support for wind turbines being placed in their community on a scale from 1 (strongly oppose) to 4 (strongly support). Specifically, interviewers asked participants the following: "Assuming there were suitable locations for them, would you strongly support, somewhat support, somewhat oppose, or strongly oppose wind turbines being placed in your community?" The outcome variable was treated as continuous in the model.

Participants

The Fall 2016 wave of the NSEE had data for 940 participants. As described previously, for each participant, the PI matched Zip Codes with county names, and I matched county names with their associated FIPS codes. This process revealed that, when the original researchers conducted the telephone survey, the interviewers likely mis-recorded the state of residence for several participants. I corrected these mistakes, but only when the corrections were obvious. For instance, Howell County, MS, was recorded for one participant, but Howell County is in Missouri (i.e., "MO") instead of Mississippi ("MS"). Because there is only one Howell County in the U.S. and the abbreviation for Missouri could easily be mistaken for "MS," I corrected the participant's state of residence. When the correction was not obvious (e.g., the same county name existed in several states), I removed the participant from the dataset. In total, I made 14 corrections and excluded 15 participants without a correct county and state assignment. Additionally, I excluded 25 participants without any county assignment, and because technical potential estimates for utility-scale wind are only provided for the 48 contiguous states, I excluded participants from counties and county equivalents in Alaska (*n* = 6) and Hawai'i (*n* = 2). This process resulted in a final dataset with 892 participants.

The final sample included participants from the 48 contiguous states, representing 427 counties. The number of participants per state ranged from one to 104; two states had only one participant, and the average number of participants per state was 18.9. The number of participants per county ranged from one to 20; 256 counties had only one participant, and the average number of participants per county 2.1[6]. The sample was comprised of 58% men and is 77% white, 8% African American, 6% Hispanic or Latinx, 3% Asian, and 6% mixed race or other. Participants most often identified as politically moderate (34%) and Protestant (40%). The sample was distributed fairly evenly across age groups, income groups, and education, except for those who obtained less than a high school education, who represented only 3% of the sample. Lastly, most participants reported accepting that climate change is occurring (68%), whereas 19% reported that it is not occurring and 12% were unsure. Descriptive statistics are described in greater detail in the next chapter.

Analysis

All analyses were conducted in RStudio version 2025.05.0+496. I first calculated descriptive statistics for each variable and visually inspected the relationships between each predictor variable and the outcome. I then built the multilevel model using the *lme4* and *lmerTest* packages, beginning with an unconditional model before building the full model with predictors and interaction terms. After building the full model, I tested assumptions, imputed missing data using multiple imputation, and interpreted the model using the imputed datasets.

Model-Building

I built the full model one component at a time, beginning with an unconditional model, then adding main effects and interaction terms (Nezlek, 2012) using the *lme4* package (Bates et al., 2015). The full model includes three levels of observations: individual level (level 1), county level (level 2), and state level (level 3). The unconditional model and the full model were run using restricted maximum likelihood estimation, as opposed to maximum likelihood estimation, because the former produces more accurate estimates for the fixed and random effects, especially for higher-level sample sizes below 50 (McNeish,

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[6] I retained participants from counties and states with only one participant because, although within-cluster variation would not be estimated for those counties and states, the participants' responses could still be used to inform individual-level slopes (Nezlek, 2012).

2017). The full model was interpreted using several statistics, including the intraclass correlation coefficients (ICCs) calculated from the unconditional model, R-squares, the predictors’ beta estimates, and significance testing ($\alpha = .05$).

An Unconditional Multilevel Model. An unconditional model with a random intercept and no predictors was used to calculate ICCs, which describe the proportion of level one variance that can be explained by between group differences and is a type of effect size measure in multilevel modeling (Lorah, 2018). Because the full model included three levels and thus had two group designations (i.e., county and state), I calculated the proportion of variance explained by both between-county and between-state differences using the following equations (Hedges et al., 2012):

$variance(county)/[variance(state) + variance(county) + variance(individual)]$

$variance(state)/[variance(state) + variance(county) + variance(individual)]$

Main Effects and Interactions. I then built several additional models. Model 2 included each main effect from the technology, people, and place categories. Model 3 included the interaction terms for climate change acceptance and perceived job impacts and for climate change acceptance and perceived property value impacts. Lastly, Model 4 included the three-way Wind capacity x Political views x State interaction term. Each model retained all predictors used in the previous model, regardless of whether the predictors were significant because inclusion of subsequent variables can impact the effect and significance of other variables in the model. To determine whether the models needed to include random slopes for any of the predictor variables, I used ANOVA tests to compare simple linear regression models predicting the outcome variable from each of the predictors individually, both with and without random slopes. This process revealed that there would be no benefit to including random slopes for any of the predictors, with p-values greater than .05 in all cases. Therefore, for most variables, Models 2-4 did not include any random slopes. However, failure to include lower-level random slopes in a cross-level interaction is “anti-conservative” and can inflate significance (Heisig & Schaeffer, 2019, p. 260). Therefore, because Model 4 had a cross-level interaction (Wind capacity x Political views x State), Model

4 included a random slope for political views between states and counties and a random slope for wind capacity between states.

Assumptions Testing

Multilevel regression assumes the following conditions: independence of observations within each level, linearity of relationships, homoscedasticity (i.e., equal residual variance at any value of the predictors and fitted values), and normality of residuals (Hox, 2013). I also assessed collinearity among the predictor variables before and during model building, which informed the creation of the final model (Model 5). I then assessed linearity, homoscedasticity, and normality using the final model.

Collinearity. Collinearity (i.e., correlation between predictor variables) can increase standard errors and make the true relationships between the collinear predictors and outcome variable difficult to ascertain (Dormann et al., 2013). I tested collinearity using bivariate correlations (among the continuous, ordinal, and binary variables) and variance inflation factors (VIFs; among all variable types). Collinearity is more likely to be problematic when bivariate correlations are greater than .70, and Dormann et al. found that the simple and commonly used method for dealing with collinearity, called the select method, performed well relative to more complicated methods. Thus, I used the select method, which involves identifying bivariate correlations above a chosen threshold and only including the better predictor of the two in the model. This method has the disadvantage of risking type II errors (i.e., failing to identify an effect that exists); however, the model assessed in the current research is complex with many predictors and several interactions, and thus, removing collinear predictors had the added benefit of helping prevent developing a model that is too complex to be supported by the data. Following guidance from Dormann et al. (2013), I used a threshold of $r > .70$ to remove predictors.

I also examined VIFs to test collinearity among all variable types (including the nominal variables) and to ensure the select method did not miss any highly correlated variables in the model. Researchers recommend different guidelines for identifying problematic VIFs, but many suggest removing or transforming variables with VIFs greater than 10 (O’Brien, 2007). Further, O’Brien cautions against using strict cutoff points and instead suggests considering theoretical importance when removing variables. Thus, I used a VIF threshold of roughly 10 and prioritized theoretical and model importance when removing variables.

Linearity, Homoscedasticity, and Normality. To assess the relationship between the fitted values and the residuals, I examined residual plots using the *performance* package (Lüdecke et al., 2021), and to assess the relationships between the predictors and the residuals, I examined partial residual plots, which account for the other predictors in the model, using the *ggeffects* package (Lüdecke, 2018). Once necessary variable transformations were made, I used a Q-Q plot to assess normality of residuals.

Missing Data

Data were only missing at the individual level. In total, 14 individual-level variables were incomplete (see Table 5), and 58.5% of all cases had at least one missing variable. The data were assumed to be missing completely at random based on Little's Test (*p* = .46; Little, 1988). Regardless, I conducted multiple imputation using the final model with transformed variables so the model was correctly specified before imputation (Slade & Naylor, 2020; Von Hippel, 2009). I generated 20 imputed datasets based on guidance from Graham et al. (2007), who found that 20 imputations were sufficient when the fractions of missing information (FIC) are less than .10, which was true for most of the variables in my model.

Table 5. **Summary of Missingness**

Variable	**Number of Missing Cases**	**Percent of Missing Cases**	**Total Cases**
Income	215	24.1%	892
Property values	191	21.4%	
Turbine noise	185	20.7%	
Climate impacts	174	19.5%	
Religion	103	11.5%	
Visual problems	94	10.5%	
Jobs	88	9.9%	
Political views	85	9.5%	
Wind support	56	6.3%	
Race	29	3.3%	
Education	24	2.7%	
Age	18	2.0%	
CC accept	16	1.8%	
Gender	15	1.7%	

Note. CC Accept = climate change acceptance

I conducted multiple imputation using the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011). The package offers several methods to conduct imputation, each with its own benefits and drawbacks based on the model and the data. I conducted imputation using two methods and used trace, density, and strip plots to compare the methods' convergence and plausibility to determine which method best fit the data. To account for the multilevel structure of the data, I first used a multilevel method; however, the multilevel method does not support imputation of nominal variables, so I imputed the nominal variables using predictive mean matching, which assumed the nominal variables were ordinal. I also conducted imputation using a single-level method, which allowed true nominal imputation using polytomous regression. In both cases, I used predictive mean matching for all continuous and ordinal variables. This is because even the continuous variables in the dataset are range-restricted, and predictive mean matching maintains the variables' data structure and range (Slade & Naylor, 2020). The trace plots for both methods showed that the results converged for each variable, indicated by intermingled trace lines with no trends. Both methods also produced plausible results—the variables were constrained with the correct ranges, and the density plots showed that the imputations matched the shape of the original variables. I ultimately used the multilevel method because, for some variables, the shape of the density plots matched the original data better. Thus, I assessed the final model results by pooling the estimates obtained from 20 multilevel imputed datasets.

Exploratory Analyses

This research includes several exploratory analyses—interactions with proximity to wind development, interactions with rural designation, and the relationship between year of energy infrastructure installation and support for wind development.

Proximity Interactions. As described in the previous chapter, the relationship between proximity to energy development and support for development varies; whereas some studies found that closer proximity is associated with lower support, others found the opposite relationship (Devine-Wright, 2005), which could suggest that a yet-unidentified variable (or variables) moderates the relationship between proximity and support. Therefore, I explored additional interactions between proximity and the technology variables, between proximity and the people variables, and between proximity and the rural-urban designation. I first visualized the potential interactions and then added the interactions as predictors, one at a time, in the final model to assess their significance with the multiply imputed data. As with the main analyses in the current research, proximity was operationalized as county-level wind capacity.

Rural Interactions. I also investigated whether a county's rural designation moderates the relationship between the technology or people variables and support for wind development. I first visualized the potential interactions and then added the interactions as predictors, one at a time, to the final model to assess their significance with the multiply imputed data. Because very few participants lived in counties designated as an 8 or 9 on the rural-urban continuum, I transformed the continuum to a binary variable for all exploratory analyses by assigning scores 1 through 3 as metropolitan and scores 4 through 9 as rural, as defined by the USDA (2020).

Age of Installation. A community's historical experience with energy development can impact perceptions of proposed development, which was assessed in the current work through the place variables. Recency of the historical development could also matter—more recent impressions could impact perceptions more than development that occurred farther in the past. Therefore, I conducted analyses to determine whether the age of energy installations impacts support for wind development. Age of previous installations was operationalized using eight variables—the age of the newest and the oldest wind, solar, renewable, and fossil installations within a given county. I first visualized the relationships between each of the age of installation variables and subsequently added the variables to the final model. This analysis could only be conducted across counties with wind, solar, renewable, or fossil installations because all other counties had missing values for age of installation. In the cases where the model was too complex to be supported by the complete cases, I also examined simple multilevel regression models, with age of installation as the only predictor.

CHAPTER III: THE MULTILEVEL MODEL

In this chapter, I describe the final model, the model's assumptions, and the final model results. I initially built the models and tested assumptions using the subsample of complete cases without imputed data to ensure the correct model was used in the imputation process, but all model interpretations were made using the multiply imputed data.

Building the Models

As described in the previous chapter, the models were defined as follows:

- Model 1 was the unconditional model used to assess ICC.
- Model 2 included each main effect from the technology, people, and place categories.
- Model 3 included the following interaction terms: Climate change acceptance x Perceived job impacts; Climate change acceptance x Perceived property value impacts.
- Model 4 included the Wind capacity x Political views x State three-way interaction term, in addition to a random slope for political views between states and counties and a random slope for wind capacity between states.

During the model-building process, conducted before imputing the missing data, I found that it was not possible to run Model 4 with the random slope for political views between counties, which was necessary to test the three-way interaction between wind capacity, political views, and state. According to the model output, the number of complete observations (*n* = 370) was less than the number of random effects necessary to test the random slope (*n* = 524), and therefore, the random-effects parameters could not be identified[7]. To determine whether exclusion of the three-way interaction would impact model interpretation or fit, I tested the three-way interaction in Model 4 without the problematic random slope

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[7] I also tested Model 5 after imputation and obtained the same error: the number of observations (*n* = 892) was less than the number of random effects necessary to test the random slope (*n* = 1,026).

and found the interaction to be non-significant. Because failure to include random slopes for lower-level variables involved in cross-level interactions can inflate significance (Heisig & Schaeffer, 2019), the interaction would likely not have been significant in either case, even if I had the ability to include the necessary random slope in Model 4. I also found that Model 3 had significantly better fit than Model 4 using an ANOVA test ($p < .05$). Therefore, I proceeded with Model 3, without the three-way interaction, to conduct assumptions testing.

Assumptions Testing

Collinearity. There were no collinear predictors at the individual level—all bivariate correlations were .44 or less, and the VIFs were less than 5.0 for all predictors (see Table 6). Among the county-level predictors, collinearity did exist. The number of coal jobs correlated highly with coal production ($r = .90$), and the VIFs for these variables were 8.5 and 8.4, respectively (see Table 7). I thus removed coal jobs from the model due to its smaller model estimate relative to coal production. For all other county-level predictors, bivariate correlations were under .70, and the VIFs were under 7.2, so they were retained in the model. Collinearity also existed among the state-level predictors—oil and gas production correlated highly with wind capacity ($r = .81$), and the VIFs for these variables were 13.4 and 11.3, respectively (see Table 8). Because wind is the focus of the current research, I removed oil and gas production from the model and retained wind capacity. Although the model subsequently did not test the impact of oil and gas production on support for wind, county-level oil and gas jobs were included. All VIFs in this reduced model were less than 7.2, and because the bivariate correlations for all remaining variables were under .70, I retained each of them in the model (O'Brien, 2007).

Table 6. **Individual-Level Collinearity Tests: Bivariate Correlations and Variance Inflation Factors**

Continuous and Ordinal Predictors

	Turbine Noise	Visual Problem	Jobs	Property Values	Climate Impacts	Political Views	Education	Age	Gender
r									
Visual Problems	.41	–	–	–	–	–	–	–	–
Jobs	.08	.17	–	–	–	–	–	–	–
Property Values	.25	.41	.10	–	–	–	–	–	–
Climate Impacts	.11	.17	.32	.15	–	–	–	–	–
Political Views	< .01	.13	.17	.14	.27	–	–	–	–
Education	.03	.06	.09	-.02	.09	.08	–	–	–
Age	-.15	-.12	-.07	-.08	-.20	-.19	-.05	–	–
Gender	-.03	.00	-.09	-.04	.04	.03	-.02	.16	–
Income	-.02	-.05	.06	-.12	.05	-.04	.44	-.03	-.10
VIF	1.49	1.60	1.41	1.55	1.57	1.42	1.56	1.31	1.18

Nominal Predictors

	Race	Religion	Climate Change Acceptance
VIF	3.00	3.17	2.65

Table 7. **County-Level Collinearity Tests: Bivariate Correlations and Variance Inflation Factors**

	Rural-Urban	Wind Potential	Wind Capacity	Solar Capacity	RE Capacity	Fossil Capacity	Coal Production	Oil Jobs	Gas Jobs	Coal Jobs
r										
Wind Potential	.19	–	–	–	–	–	–	–	–	–
Wind Capacity	.04	.04	–	–	–	–	–	–	–	–
Solar Capacity	-.10	.13	.51	–	–	–	–	–	–	–
RE Capacity	-.06	.11	-.01	.29	–	–	–	–	–	–
Fossil Capacity	-.27	.04	.10	.40	.19	–	–	–	–	–
Coal Production	.04	-.02	-.02	-.02	-.03	.02	–	–	–	–
Oil Jobs	-.10	.00	-.02	.20	.34	.38	-.02	–	–	–
Gas Jobs	-.11	-.02	.00	.04	.01	.37	-.01	.08	–	–
Coal Jobs	.01	-.01	-.02	-.02	-.02	.02	.90	-.02	-.01	–
DAC Status	.32	.10	.04	.06	.02	.02	.10	-.01	.04	.11
VIF	4.92	1.98	1.51	2.93	7.16	4.65	8.40	6.96	1.90	8.46

Note. RE = renewable energy; O&G = oil and gas; DAC = disadvantaged community

Table 8. **State-Level Collinearity Tests: Bivariate Correlations and Variance Inflation Factors**

	Wind Capacity	Solar Capacity	RE Capacity	Fossil Capacity	O&G Production	Coal Production
r						
Solar Capacity	.16	–	–	–	–	–
RE Capacity	.11	.51	–	–	–	–
Fossil Capacity	.64	.29	.06	–	–	–
O&G Production	.81	.03	-.08	.68	–	–
Coal Production	.07	-.09	-.12	.02	.23	–
RPS	.16	.19	.16	.03	.05	-.21
VIF	11.28	6.77	7.10	6.23	13.41	2.23

Note. RE = renewable energy; O&G = oil and gas; RPS = renewable portfolio standard

Linearity, Homoscedasticity, and Normality. The residual plots revealed a linear and homoscedastic relationship between the residuals and the fitted values. Similarly, the partial residual plots revealed linear and homoscedastic relationships between the residuals and each of the individual-level predictors. However, eight predictors in total at the county and state levels had non-linear and heteroscedastic relationships with the residuals: oil jobs, gas jobs, solar capacity, renewable capacity, and coal production at the county level, each of which were non-linear and heteroscedastic; wind capacity at the county level, which was heteroscedastic; and renewable capacity and coal production at the state level, both of which were non-linear. Square root transformations yielded the relationships linear and homoscedastic for each variable, except county-level coal production because very few counties produce coal, and those that do produce coal have little variance in wind support scores. I thus attempted both natural logarithmic and base 10 logarithmic transformations of coal production, but the relationship in both cases was still heteroscedastic. Thus, I removed county-level coal production from the model given that very few counties produced coal, and the variable was not significant nor informative, with a p-value greater than .05 and a very small beta estimate. State-level coal production, however, was retained in the model. After completing the transformations and removing county-level coal production, I tested the normality assumption and found normally distributed residuals using a Q-Q plot.

The Final Model

To summarize, I removed coal jobs and oil and gas production from Model 3 for high correlations (r = .90, .81) and high VIFs (8.5, 13.41), indicating collinearity. I also removed county-level coal production due to its non-linear and heteroscedastic relationship with the residuals but was able to retain state-level coal production. Several other variables that initially had non-linear and heteroscedastic relationships with the residuals were retained in the model after making square root transformations: county-level oil jobs, gas jobs, solar capacity, renewable capacity, and wind capacity and state-level renewable capacity and coal production. This final model (Model 5), shown in Figure 3, was then used to conduct multiple imputation using the multilevel method described in the previous chapter.

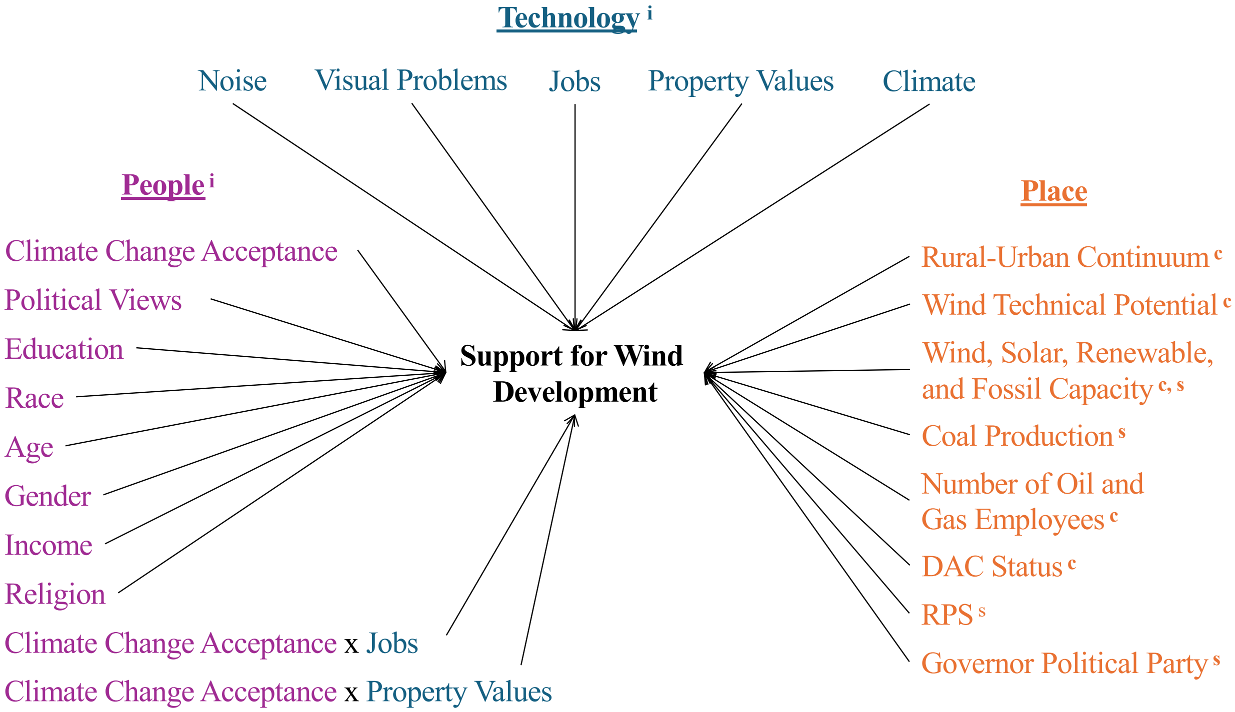

Figure 3. **Final Model to Assess the Technology, People, and Place Categories of Boudet's Framework**
Note. DAC = disadvantaged community; RPS = renewable portfolio standard. Renewable capacity excludes onshore wind and solar capacity.
^{i} Individual-level, ^{c} county-level, and ^{s} state-level variables

Results and Discussion

Descriptive Statistics

Descriptive statistics, calculated across all imputed datasets, can be found in Table 9 (continuous variables) and Table 10 (ordinal and nominal variables). For descriptive statistics by state, see

APPENDIX A. For most variables, the descriptive statistics calculated across the complete cases (i.e., the dataset without imputation) were identical to the statistics calculated across the imputed data. For the few variables that differed between the datasets, the mean and standard deviation for all continuous variables using the complete-case dataset were within ±0.03 units of the multiply imputed dataset, and the percentages calculated for the ordinal and nominal variables using the complete-case dataset were within ±0.62 units of the multiply imputed dataset.

Table 9. **Descriptive Statistics for Continuous Variables**

Variable	**Multiply Imputed Data**		
	m	***SD***	***min, max***
Individual-Level			
Wind support	3.23	0.97	1.00, 4.00
Turbine noise	3.01	1.00	1.00, 4.00
Visual problems	2.88	1.00	1.00, 4.00
Jobs	3.27	0.80	1.00, 4.00
Property values	2.60	0.97	1.00, 4.00
Climate impacts	2.76	1.01	1.00, 4.00
County-Level			
DAC status	0.35	0.26	.00, 1.00
Gas jobs (thousands; sq. rt.)	0.40	0.54	0.07, 7.97
Oil jobs (thousands; sq. rt.)	0.10	0.15	0.00, 2.16
Wind capacity (thousand MW, sq. rt.)	0.04	0.16	0.00, 1.81
Solar capacity (thousand MW; sq. rt.)	0.05	0.15	0.00, 1.50
RE capacity (thousand MW; sq. rt.)	0.08	0.21	0.00, 1.56
Fossil capacity (thousand MW)	0.66	1.33	0.00, 11.10
Wind potential (million MWh)	6.35	16.91	0.00, 208.07
State-Level			
Coal production (million short tons; sq. rt.)	1.93	2.68	0.00, 17.24
Wind capacity (thousand MW)	2.75	4.85	0.00, 20.19
Solar capacity (thousand MW)	0.90	2.34	0.00, 9.86
RE capacity (thousand MW; sq. rt.)	1.30	1.08	0.00, 4.63
Fossil capacity (thousand MW)	26.99	23.21	0.13, 100.01

Note. DAC = disadvantaged community; RE = renewable energy

Table 10. **Descriptive Statistics for Ordinal and Nominal Variables**

Variable	Multiply Imputed Data	Variable	Multiply Imputed Data
Age:	18-29 years: 23.49%	Religion:	Protestant: 40.11%
	30-44 years: 20.36%		Catholic: 26.73%
	45-65 years: 29.48%		Other: 25.23%
	65 and older: 26.67%		Atheist: 4.64%
			Jewish: 1.64%
Education:	Less than high school: 2.64%		Hindu: 1.26%
	High school graduate: 25.32%		Muslim: 0.39%
	Some college or technical school: 29.16%		
	College graduate: 25.05%	CC accept:	Happening (human activity): 28.41%
	Graduate or professional degree: 17.83%		Happening (a combination): 21.79%
			Happening (natural patterns): 14.45%
Income:	Less than \$20,000: 13.51%		Happening (not sure of cause): 3.55%
	\$20,000–\$40,000: 20.32%		Not sure if happening: 12.50%
	\$40,000–\$60,000: 17.55%		Not happening: 19.30%
	\$60,000–\$80,000: 16.11%		
	\$80,000–\$100,000: 11.88%	Rural-urban:	1 (most metro): 52.02%
	Over \$100,000: 20.62%		2 (metro): 19.62%
			3 (metro): 9.75%
Political views:	Very conservative: 21.76%		4 (rural): 6.73%
	Somewhat conservative: 19.51%		5 (rural): 2.24%
	Moderate: 33.82%		6 (rural): 4.15%
	Somewhat liberal: 16.39%		7 (rural): 3.70%
	Very liberal: 8.52%		8 (rural): 0.90%
			9 (most rural): 0.90%
Gender:	Male: 58.13%		
	Female: 41.87%	RPS:	Yes: 71.64%
			No: 28.36%
Race:	White: 77.40%		
	African American: 7.68%	Governor party:	Democrat: 34.42%
	Mixed race and other: 6.05%		Republican: 65.58%
	Hispanic or Latinx: 5.87%		
	Asian: 3.00%		

Note. CC accept = climate change acceptance; RPS = renewable portfolio standards.

Unconditional Model

There was some variance between counties and states, but the vast majority of variance existed within groups (see Table 11). Two percent of the variance in support for wind existed between counties, and 98% existed within counties. State-level variance is even smaller—0.5% of the variance in wind support existed between states, and 99.5% existed within states. Regardless, I maintained the multilevel structure of the model as suggested by Nezlek (2012) to most accurately capture cross-level relationships.

Table 11. **Results for Model 1: The Unconditional Model**

Fixed Effects	***b***	***SE***	***t-value***	***p-value***
Intercept	3.22	0.04	83.63	< .0001
Random Effects	***var***	***ICC***		
States	0.005	.005	-	-
Counties within states	0.017	.018	-	-
Residual	0.918	-	-	-

Final Model

The final model tested using the imputed data had a singular fit because the random effect variances were near-zero. Researchers have found that singular fits are common in multilevel modeling and are typically non-problematic (Bates et al., 2015; DeBruine & Barr, 2021; McNabb & Murayama, 2021). I tested several alternative models to establish that singularity in this case was non-problematic: a two-level model without the state-level random effect, a two-level model without the county-level random effect, a single-level model without any random effects, and a multilevel model generated with the complete cases instead of the multiply imputed data. To determine whether ignoring state and/or county-level clustering in the two- and single-level models would have been acceptable, I assessed the design effects for the state and county clusters, which estimate the extent to which violation of non-independence is problematic (Lai & Kwok, 2015; Peugh, 2010). Design effects less than two indicate that there is minimal bias introduced by clustering; therefore, because the design effects in this case were close to one, the two- and single-level models would have been acceptable. However, the alternative models produced nearly identical results to the final, three-level model tested using imputed data. Thus, to account for the random effect variance that did exist, I chose to proceed with the original and final three-level model.

The R^2 for the final model was .25 and was obtained by pooling the R^2 estimates from each imputed dataset. Estimate results from the final model are presented in Figure 4, Table 12 (intercept, individual-level main effects, and random effects), Table 13 (interaction between climate change acceptance and property values), Table 14 (interaction between climate change acceptance and jobs), Table 15 (county-level main effects), and Table 16 (state-level main effects).

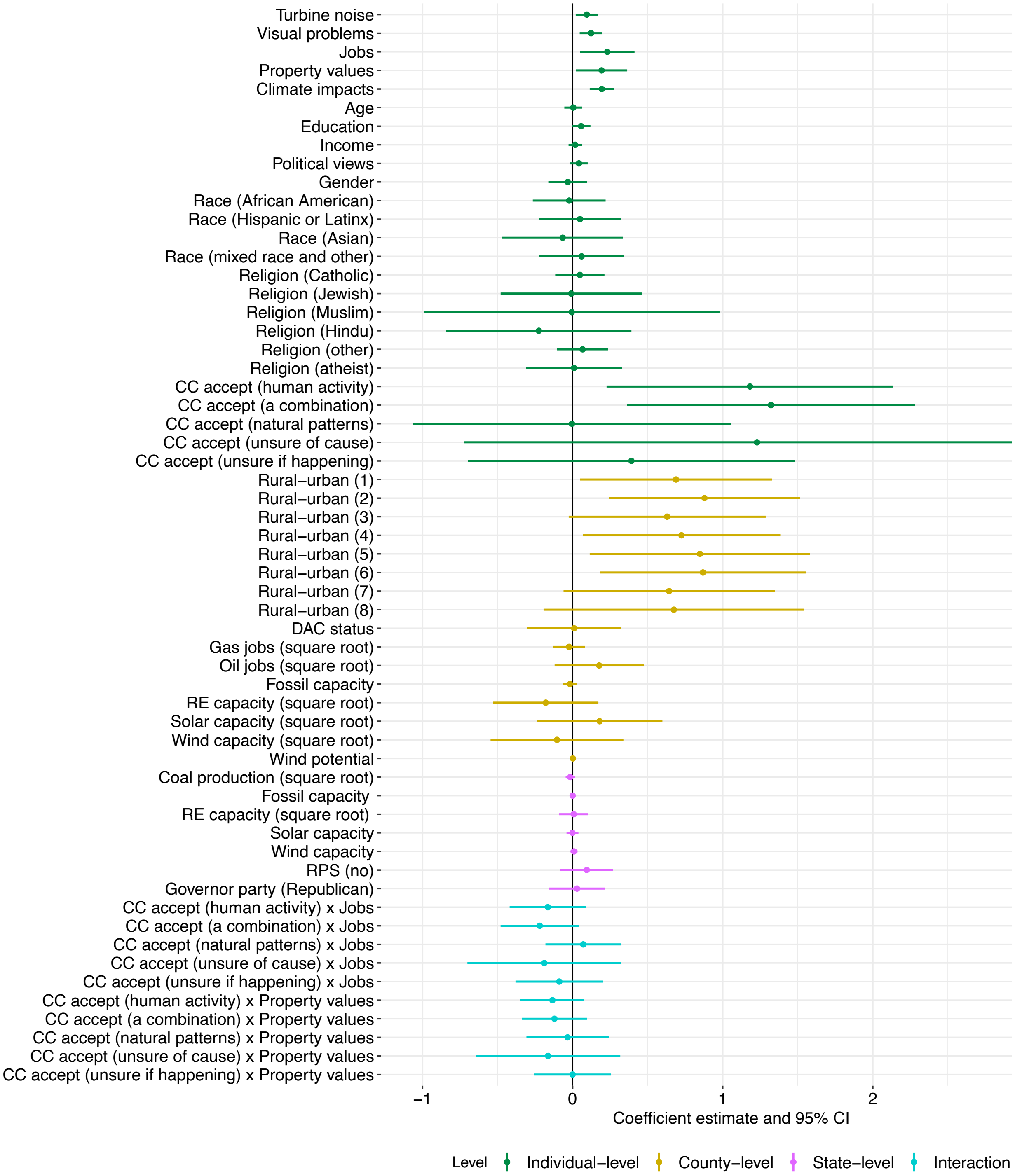

Figure 4. **Coefficient Estimates and Confidence Intervals for the Final Model**
Note. CC accept = climate change acceptance; DAC = disadvantaged community; RE = renewable energy; RPS = renewable portfolio standards. For ease of viewing, the full x-axis is not shown; thus, the upper confidence interval limit for CC accept (unsure if happening) is not visible.

Technology Variables. There were several significant individual-level predictors, including each of the technology variables (see Table 12). The belief that turbines create jobs had the strongest relationship with wind support. A one-unit increase in beliefs about jobs was associated with a 0.23 increase in wind support (*p* < .05), all else equal (see Figure 5). The other technology variables also significantly predicted wind support to varying degrees—a one-unit increase in the belief that turbines help limit climate change and a one-unit decrease in the belief that wind turbines reduce nearby property values were both associated with a 0.19 increase in wind support (*p* < .001; *p* < .05; see Figure 6 and Figure 7), and a one-unit decrease in the belief that wind turbines create visual problems was associated with a 0.12 increase in wind support (*p* < .01; see Figure 8). The technology variable with the weakest relationship with wind support was the belief that turbines create noise pollution, for which a one-unit decrease is associated with a 0.10 increase in wind support (*p* < .05; see Figure 9). This evidence supports the hypotheses I posed for the technology variables—namely, that each variable (after reverse-scoring property value, visual, and noise impacts) would relate positively to support for wind development.

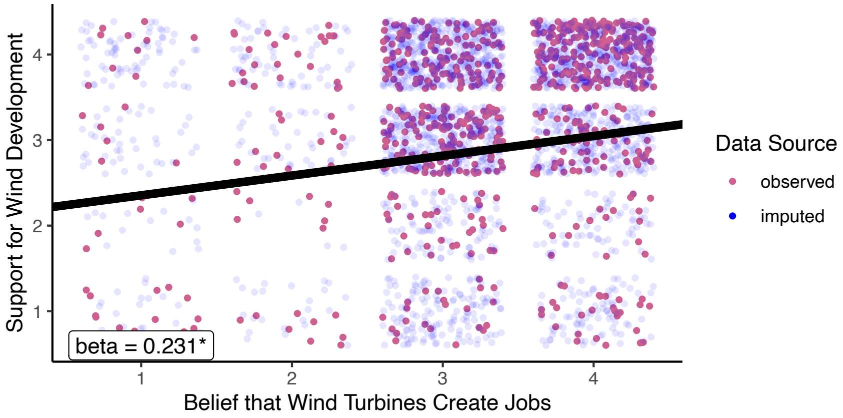

Figure 5. **Wind Jobs and Support for Wind**
* *p* < .05

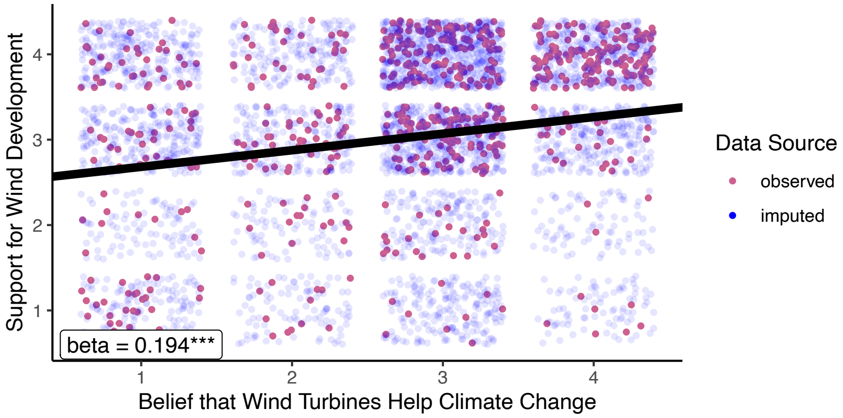

Figure 6. **Climate Impacts and Support for Wind**
*** $p < .001$

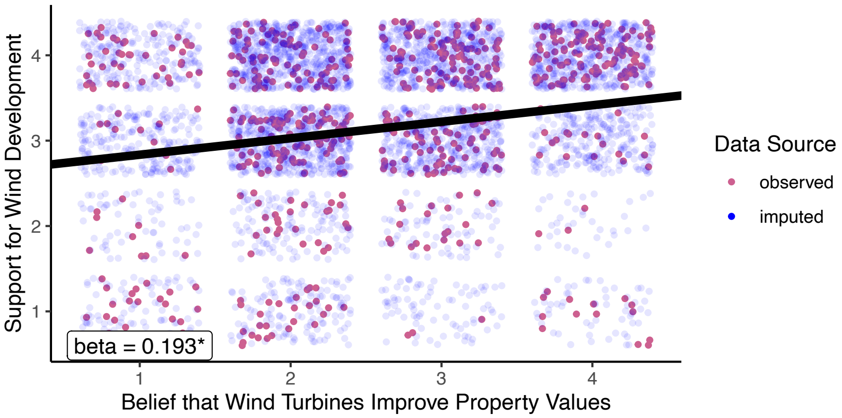

Figure 7. **Property Values and Support for Wind**
* $p < .05$

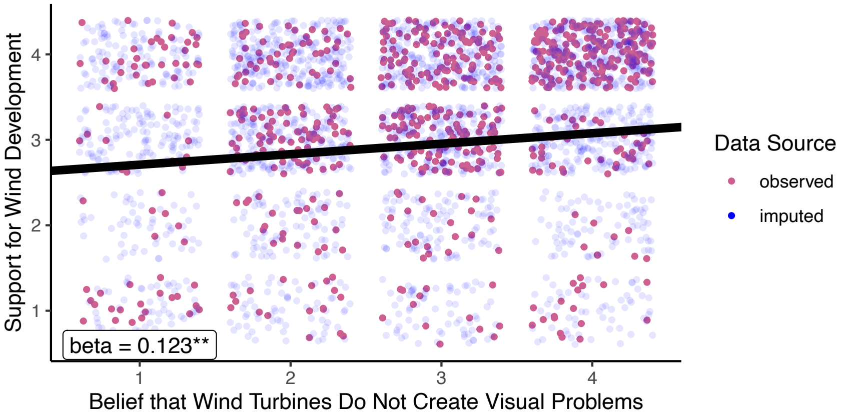

Figure 8. **Visual Problems and Support for Wind**
** $p < .01$

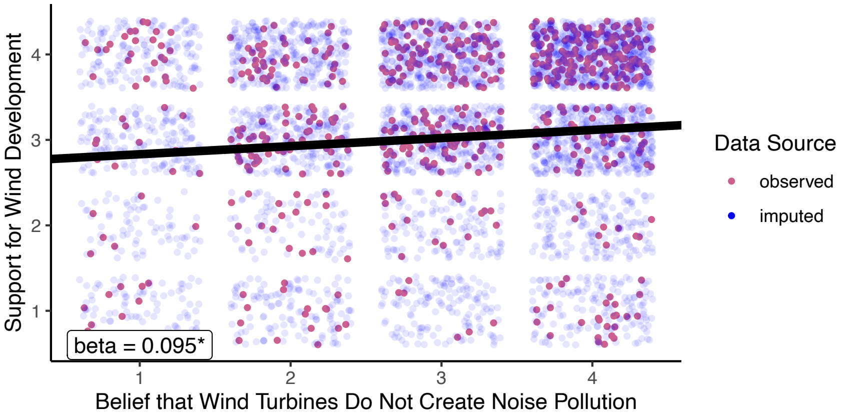

Figure 9. **Turbine Noise and Support for Wind**
* $p < .05$

Table 12. **Individual-Level Main Effect Results**

	Final Model					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Intercept	-0.592	0.546	-1.085	493.0	-1.665	0.481
Technology Variables						
Turbine noise	0.095*	0.038	2.510	228.4	0.020	0.169
Visual problems	0.123**	0.039	3.184	349.2	0.047	0.198
Jobs	0.231*	0.092	2.504	409.4	0.050	0.413
Property values	0.193*	0.087	2.233	185.7	0.023	0.364
Climate impacts	0.194***	0.041	4.753	167.8	0.114	0.275
People Variables						
Age	0.004	0.030	0.138	1,986.6	-0.055	0.063
Education	0.057•	0.032	1.783	863.7	-0.006	0.119
Income	0.017	0.023	0.771	186.0	-0.027	0.062
Political views [a]	0.042	0.030	1.418	430.0	-0.016	0.100
Gender (female)	-0.033	0.066	-0.501	963.4	-0.162	0.096
Race (African American)	-0.023	0.124	-0.186	1,392.8	-0.266	0.220
Race (Hispanic or Latinx)	0.049	0.138	0.356	5,898.7	-0.222	0.321
Race (Asian)	-0.067	0.205	-0.325	580.7	-0.469	0.335
Race (mixed race and other)	0.060	0.144	0.417	418.2	-0.222	0.342
Religion (Catholic)	0.048	0.083	0.579	563.8	-0.116	0.212
Religion (Jewish)	-0.010	0.240	-0.041	17,794.0	-0.480	0.460
Religion (Muslim)	-0.006	0.502	-0.011	3,305.0	-0.990	0.979
Religion (Hindu)	-0.225	0.314	-0.717	560.3	-0.842	0.392
Religion (other)	0.066	0.087	0.765	404.0	-0.104	0.237
Religion (atheist)	0.009	0.162	0.056	562.5	-0.310	0.328
CC accept (human activity)	1.182*	0.486	2.432	376.8	0.226	2.137
CC accept (a combination)	1.322**	0.488	2.707	697.8	0.363	2.280
CC accept (natural patterns)	-0.005	0.538	-0.009	277.2	-1.064	1.055
CC accept (unsure of cause)	1.229	0.986	1.247	120.4	-0.722	3.180
CC accept (unsure if happening)	0.392	0.555	0.707	475.7	-0.698	1.482
Random Effects	***var***					
States	0.021					
Counties within states	< .000					
Residual	0.704					

Note. CC accept = climate change acceptance. The reference cases for the nominal variables were as follows: gender was "male," race was "white/Caucasian," religion was "Protestant," and CC accept was "not happening" (i.e., the participant's assertion that climate change is not happening).

[a] For political views, 1 = *very conservative* and 5 = *very liberal*.

•p < .10; *p < .05; **p < .01; ***p < .001

People Variables. The rest of the individual-level predictors are people variables, which includes demographic characteristics and climate change acceptance. As shown in Table 12, the people variables tended to have small, non-significant estimates in the final model, which largely supports my expectations that most people variables would be unrelated to support for wind development.

Political Views. However, I did expect political views to be significantly related to support for wind, which was not the case ($b = 0.04$, $p = .16$; see Figure 10). Previous research into the effect that political views have on support for renewable energy development have found contrasting results, with many sources not finding evidence of a relationship. Additionally, Hawes and Nowlin (2022) found that climate change acceptance mediated the effect of political affiliation on renewable energy support, which could explain the differential impacts of political affiliation across studies—research that does not include a measure of climate change acceptance would find a relationship between political views and support for renewable energy, whereas research that *does* include climate change acceptance would *not* find a relationship. Therefore, the current study's findings are not especially surprising given that the research included a measure of climate change acceptance. Further, upon closer examination, I found that participants who identified as liberal were underrepresented in the NSEE data. According to Pew Research, in 2015, 22% of Americans identified as somewhat liberal and 13% identified as very liberal, whereas 10% identified as very conservative (Geiger, 2016). In contrast, in the Fall 2016 wave of the NSEE, only 16% of participants identified as somewhat liberal and 9% identified as very liberal, whereas 22% identified as very conservative, yielding very conservative participants overrepresented by more than 10 points (see Figure 11). Because liberal individuals tend to be more supportive of wind energy (Funk & Kennedy, 2016; Kennedy et al., 2023a), the current research might have failed to find a significant effect for political views because liberal individuals are underrepresented in the data. Future research should obtain a sample that is more representative of political views in the U.S., which will yield results that are potentially more pronounced for political views.

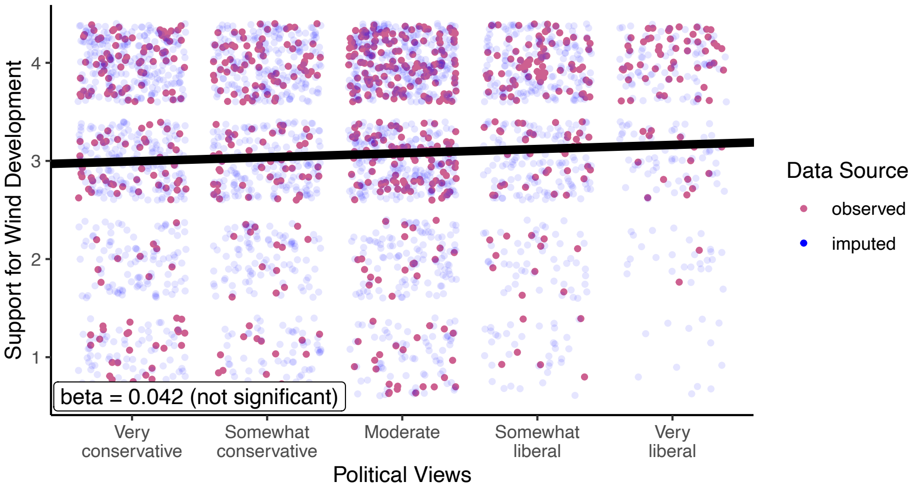

Figure 10. **Political Views and Support for Wind**

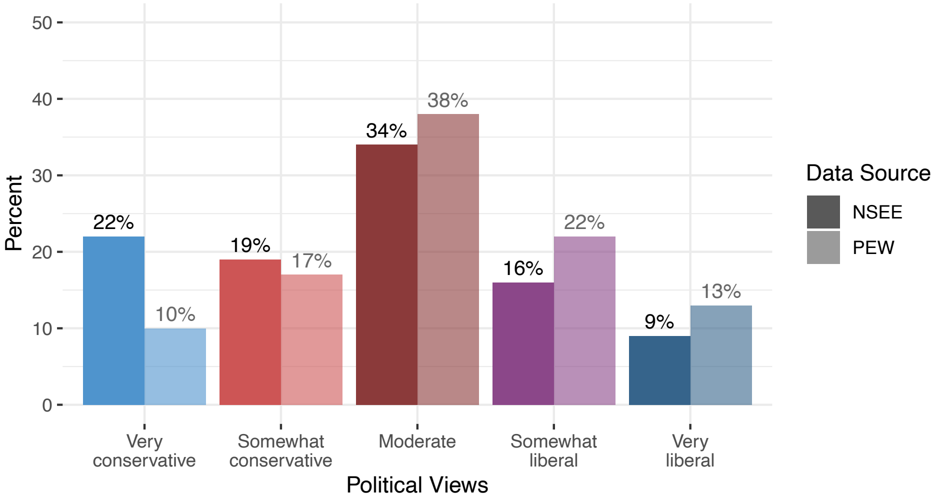

Figure 11. **Political Views: NSEE 2016 vs Pew Research 2015**

Educational Attainment. Additionally, contrary to my expectations, educational attainment was significant at the 90% confidence level, although the estimate was quite small (see Figure 12). For each one-unit increase in educational attainment, support for wind increased by 0.06. As shown in Figure 13, participants with less than a high school education are underrepresented, and participants with a college or graduate degree are overrepresented in the NSEE data. In the Fall 2016 wave of the NSEE, only 3% of participants attained less than a high school education, whereas according to the U.S. Census, 22% of Americans attained that level of education in 2016 (U.S. Census Bureau, 2017). Future research should obtain a representative sample based on educational attainment, which could strengthen the results—if those with less than a high school education are frequently less supportive of wind development, the effect of educational attainment could become more pronounced.

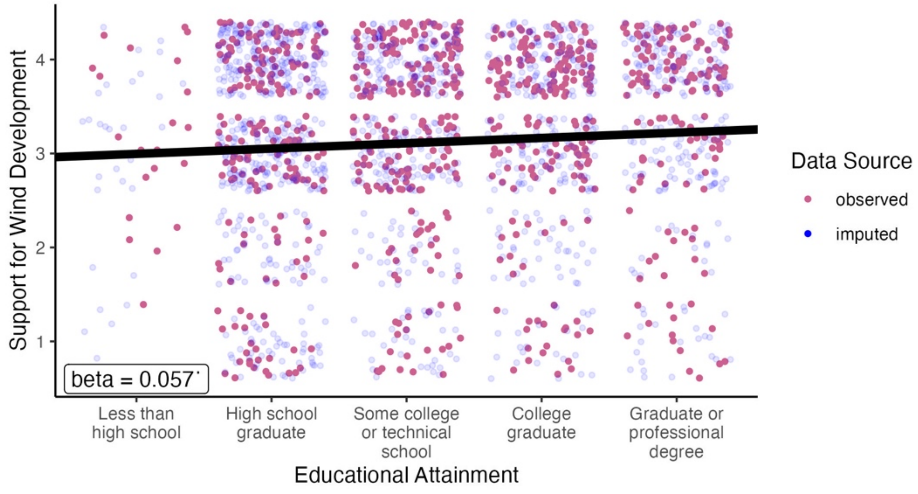

Figure 12. **Educational Attainment and Support for Wind**
• $p < .05$

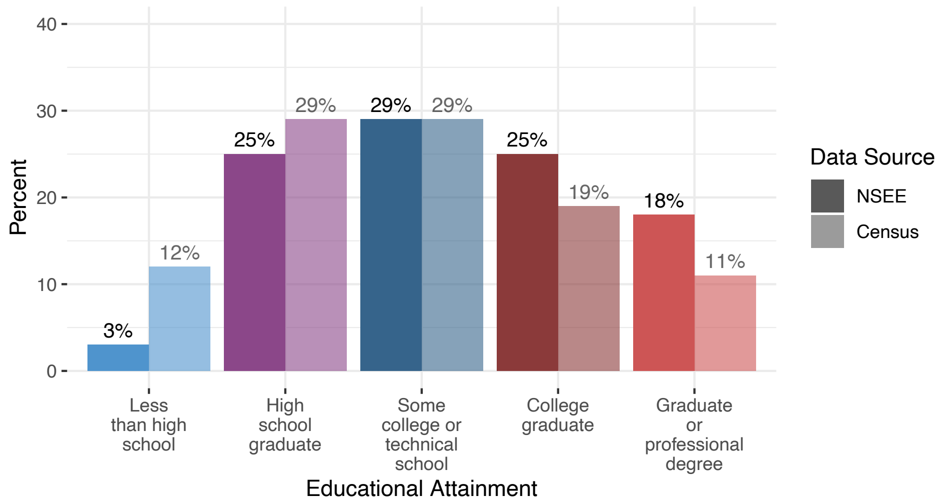

Figure 13. **Educational Attainment: NSEE 2016 vs Census 2016**

Climate Change Acceptance. My hypotheses related to climate change acceptance were partially supported. When using the lowest level of climate change acceptance as the reference case (i.e., the assertion that climate change is not happening), two levels were significant. The model supported my expectation that participants who accept that climate change is caused by human activities would be significantly more supportive of wind development than participants who assert that climate change is not happening (see Figure 14). All else equal, participants who assert that climate change is caused by human activities are predicted to have a wind support score 1.18 units higher than those who assert that climate change is not happening (*p* < .05). Additionally, participants who assert that climate change is caused by both human activities and natural patterns are predicted to have a wind support score 1.32 units higher than those who assert that climate change is not happening (*p* < .01). None of the other levels of climate change acceptance were significantly different than the reference case.

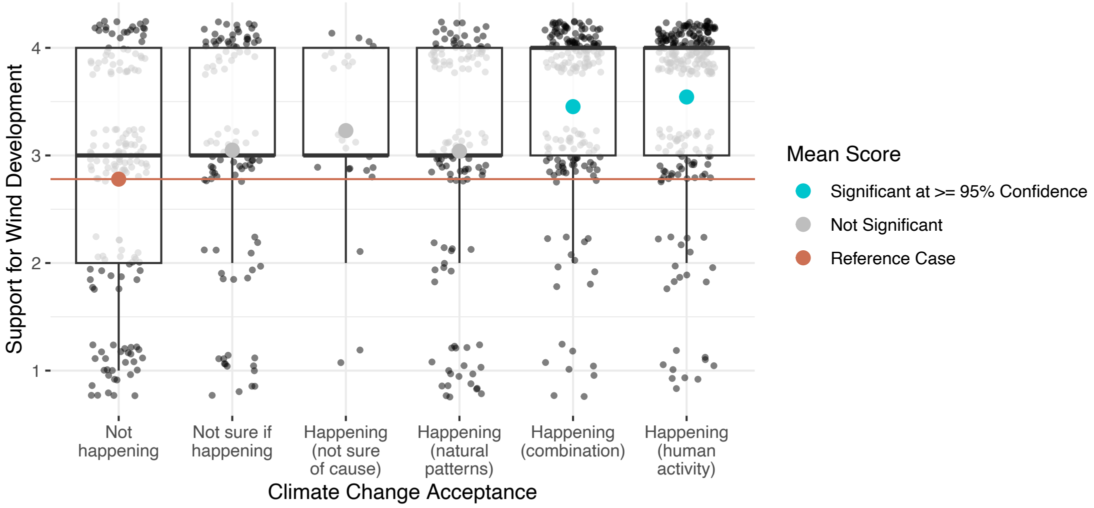

Figure 14. **Climate Change Acceptance and Support for Wind**

I also expected climate change acceptance to moderate the relationship between beliefs about the economic impacts of wind development (i.e., property value impacts and job impacts) and support for wind development. The interaction between property value impacts and climate change acceptance was not significant (see Table 13), even after adjusting the reference case. However, the interaction between job impacts and climate change acceptance was significant for certain reference cases and levels. The predicted change in wind support for a one-unit increase in jobs beliefs was 0.22 units lower for participants who assert that climate change is caused by a combination of factors (i.e., human activities and natural patterns) than those who assert that climate change is not happening, (*p* < .10; see Table 14). I then changed the reference case and found two additional interactions. When compared to participants who assert that climate change is caused by natural patterns, the predicted change in wind support for a one-unit increase in jobs beliefs was 0.24 units lower for participants who assert that climate change is happening ($p < .10$) and 0.29 units lower for participants who assert that climate change is caused by a combination of factors ($p < .05$).

Table 13. **Climate Acceptance by Property Values Interaction Results**

			Final Model			
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
CC accept (human activity) x Property values	-0.135	0.108	-1.245	254.6	-0.347	0.078
CC accept (a combination) x Property values	-0.121	0.110	-1.103	289.3	-0.337	0.095
CC accept (natural patterns) x Property values	-0.033	0.138	-0.242	102.7	-0.308	0.241
CC accept (not sure of cause) x Property values	-0.163	0.243	-0.671	140.4	-0.644	0.318
CC accept (not sure if happening) x Property values	< 0.000	0.130	-0.001	281.3	-0.257	0.257

Note. The reference case for climate change acceptance (CC accept) was “not happening” (i.e., the participant’s assertion that climate change is not happening).

Table 14. **Climate Acceptance by Jobs Interaction Results**

			Final Model			
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Climate change acceptance (CC accept) reference case: “Not happening”						
CC accept (human activity) x Jobs	-0.165	0.129	-1.280	274.9	-0.420	0.089
CC accept (a combination) x Jobs	-0.219•	0.133	-1.649	392.6	-0.480	0.042
CC accept (natural patterns) x Jobs	0.071	0.128	0.551	784.9	-0.181	0.322
CC accept (not sure of cause) x Jobs	-0.188	0.260	-0.724	157.2	-0.701	0.325
CC accept (not sure if happening) x Jobs	-0.089	0.149	-0.596	486.7	-0.381	0.204
CC accept reference case: “Happening – natural patterns”						
CC accept (human activity) x Jobs	-0.236•	0.124	-1.908	906.0	-0.479	0.007
CC accept (a combination) x Jobs	-0.290*	0.129	-2.249	1,085.8	-0.542	-0.037
CC accept (not sure of cause) x Jobs	-0.259	0.254	-1.017	192.6	-0.760	0.243
CC accept (no sure if happening) x Jobs	-0.159	0.151	-1.053	558.0	-0.456	0.138
CC accept (not happening) x Jobs	-0.071	0.128	-0.551	784.9	-0.322	0.181

•$p < .10$; *$p < .05$

Thus, although my hypothesis about the moderating effect of climate change acceptance on property value impacts was not supported, my hypothesis about the moderating effect of climate change acceptance on job impacts was supported. The belief that turbines create jobs predicted support for wind development more strongly among participants who assert that climate change is not happening than among those who assert that climate change is caused by a combination of factors (see Figure 15).

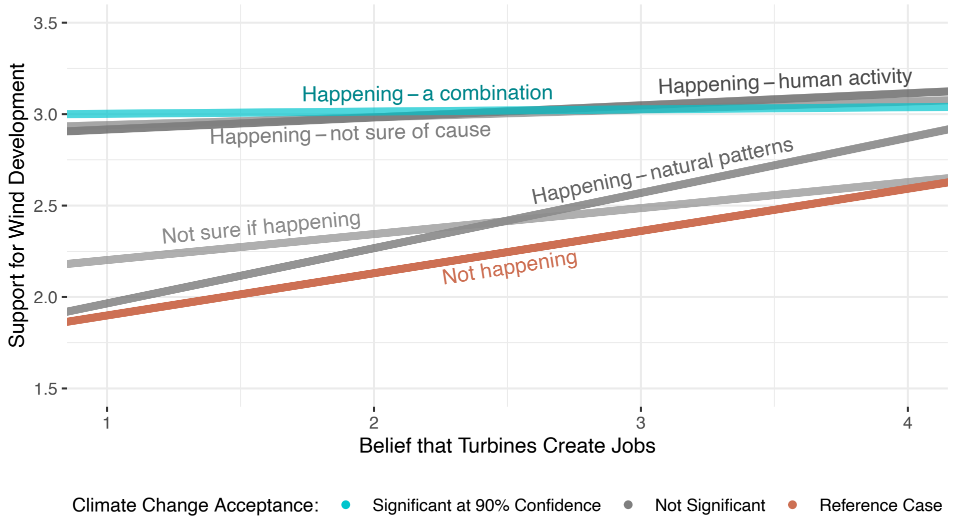

Figure 15. **Job Impacts by Climate Change Acceptance (Reference: 'Not Happening')**

Similarly, the belief that turbines create jobs predicted support for wind development more strongly among participants who assert that climate change is caused by natural patterns than among those who assert that climate change is caused by either human activity or a combination of factors (see Figure 16). These results are consistent with previous qualitative research that demonstrated that perceived economic impacts of wind development are especially important in forming opinions about wind development among individuals with low concern about climate change or environmental issues (Jepson et al., 2012).

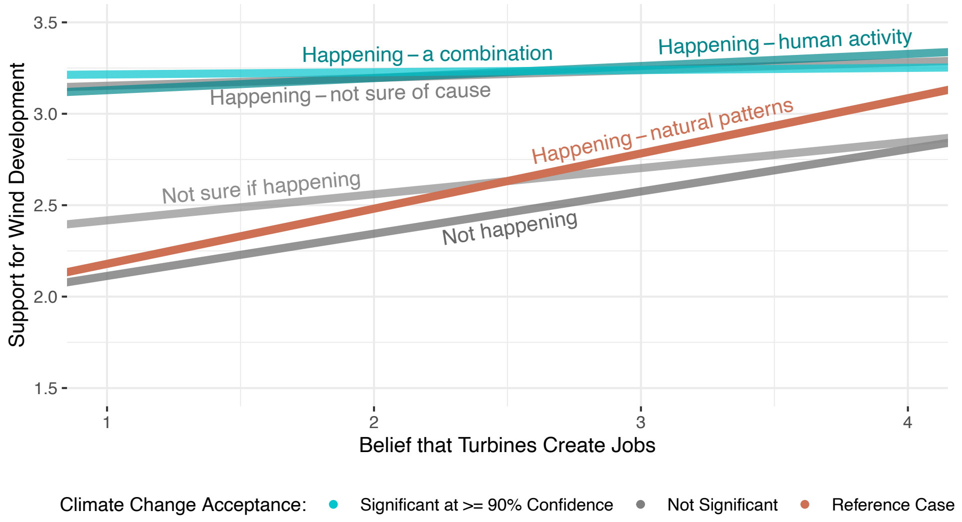

Figure 16. **Job Impacts by Climate Change Acceptance (Reference: 'Happening – Natural Patterns')**

Place Variables. Only one place variable was significant across both the county- and state-level predictors, as shown in Table 15 and Table 16—the rural-urban continuum code. The rural-urban continuum ranges from 1 (most metropolitan) to 9 (most rural). When compared to the most rural counties in the final model, counties with designations 1, 2, 4, 5, and 6 were significant at the 95% confidence level or higher, and counties with designations 3 and 7 were significant at the 90% confidence level (see Figure 17). Importantly, though, these results should be interpreted with caution. Only eight participants were from counties with a designation of 9; therefore, these results might not be representative of people from the most rural counties in the country. To address this issue, I transformed the continuum to a binary variable, with designations 1 through 3 assigned metropolitan and designations 4 through 9 assigned rural, as defined by the USDA (2020). I then compared the mean wind support score among participants from metropolitan counties to the mean score among participants from rural counties and found no significant difference ($t = 0.60$, $df = 681.9$, $p = .55$; see Figure 18). These data provide evidence that rural designation does not predict support for wind development; however, because people from the most rural counties were underrepresented, these results might not generalize to those populations.

Table 15. **County-Level Main Effect Results**

	Full Model					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Place Variables						
Rural-urban (1)	0.689*	0.327	2.110	6,928.6	0.049	1.329
Rural-urban (2)	0.879**	0.325	2.708	9,770.7	0.243	1.515
Rural-urban (3)	0.630•	0.335	1.882	5,024.1	-0.026	1.286
Rural-urban (4)	0.725*	0.336	2.160	11,609.4	0.067	1.384
Rural-urban (5)	0.848*	0.375	2.264	9,498.9	0.114	1.582
Rural-urban (6)	0.868*	0.351	2.474	4,824.5	0.180	1.556
Rural-urban (7)	0.643•	0.359	1.792	3,637.9	-0.061	1.347
Rural-urban (8)	0.674	0.443	1.523	14,031.0	-0.194	1.543
DAC status	0.010	0.158	0.062	738.9	-0.301	0.321
Gas jobs (square root)	-0.023	0.053	-0.437	1,444.9	-0.128	0.081
Oil jobs (square root)	0.177	0.151	1.168	2,174.6	-0.120	0.474
Wind capacity (square root)	-0.104	0.226	-0.462	3,196.5	-0.547	0.338
Solar capacity (square root)	0.180	0.213	0.844	3,960.7	-0.238	0.598
RE capacity (square root)	-0.179	0.179	-1.000	7,148.5	-0.530	0.172
Fossil capacity	-0.018	0.025	-0.727	4,082.2	-0.066	0.030
Wind potential	0.002	0.002	0.747	1,591.5	-0.003	0.006

Note. DAC = disadvantaged community; RE = renewable energy. The reference case for the rural-urban code was a score of 9 (i.e., a rural county with less than 2,500 population, not adjacent to metropolitan area).
•*p* < .10; **p* < .05; ***p* < .01; ****p* < .001

Table 16. **State-Level Main Effect Results**

	Full Model					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Place Variables						
Coal production (square root)	-0.015	0.016	-0.975	276.2	-0.047	0.016
Wind capacity	0.009	0.012	0.748	1,571.5	-0.015	0.033
Solar capacity	-0.001	0.020	-0.046	1,171.1	-0.041	0.039
RE capacity (square root)	0.007	0.049	0.143	1,060.2	-0.090	0.104
Fossil capacity	< 0.000	0.003	0.144	851.1	-0.005	0.005
RPS (no)	0.094	0.090	1.050	477.2	-0.082	0.270
Governor party (Republican)	0.029	0.094	0.310	2,383.4	-0.156	0.215

Note. RE = renewable energy; RPS = renewable portfolio standard. The reference case for RPS was "Yes," and the reference case for governor party was "Democrat."

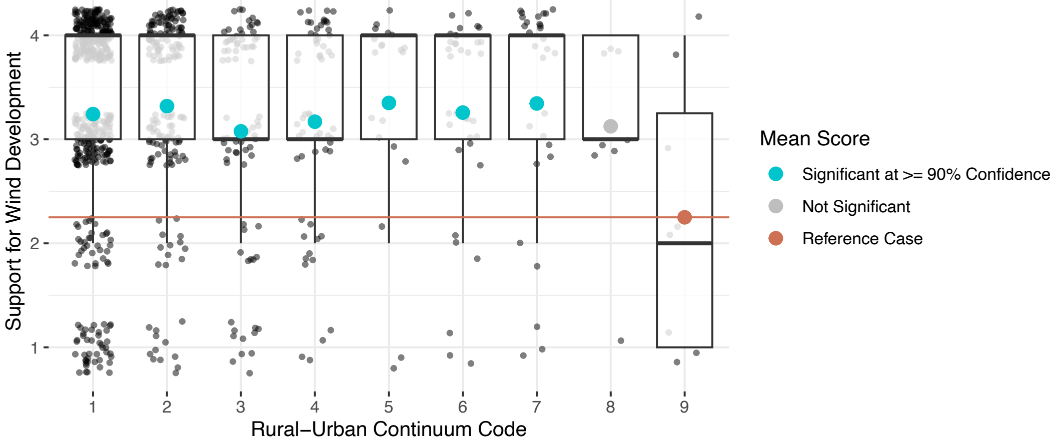

Figure 17. **Rural-Urban Continuum and Support for Wind**

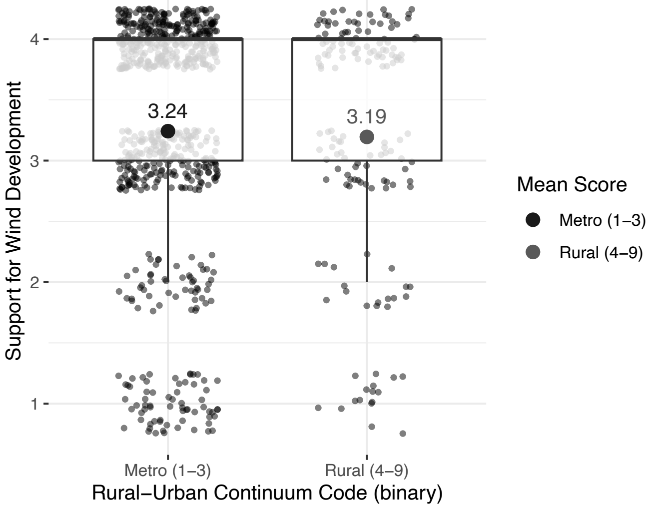

Figure 18. **Binary Rural-Urban Designation and Support for Wind**
Note. The grey scale indicates non-significance.

Proximity Interaction

As described in the ‘Building the Models’ section, I was not able to appropriately include the three-way interaction between proximity (operationalized as county-level wind capacity), political views, and state of residence because the model could not support a random slope for political views across counties, either using completes cases or multiply imputed data, and thus, the random-effects parameters could not be identified. Bolstered by the fact that the three-way interaction was not significant in Model 4, even without inclusion of the random slope, I conducted assumptions testing, multiple imputation, and results interpretation using Model 3, which excluded the three-way interaction. However, using the final model with imputed data, I explored a two-way interaction between wind capacity and political views, without the state component. The interaction was not significant in the final model ($b = 0.027$, $t = 0.170$, $df = 1{,}900.5$, $p = .87$), meaning that the relationship between county-level wind capacity and support for wind development did not vary by an individual's political views (see Figure 19).

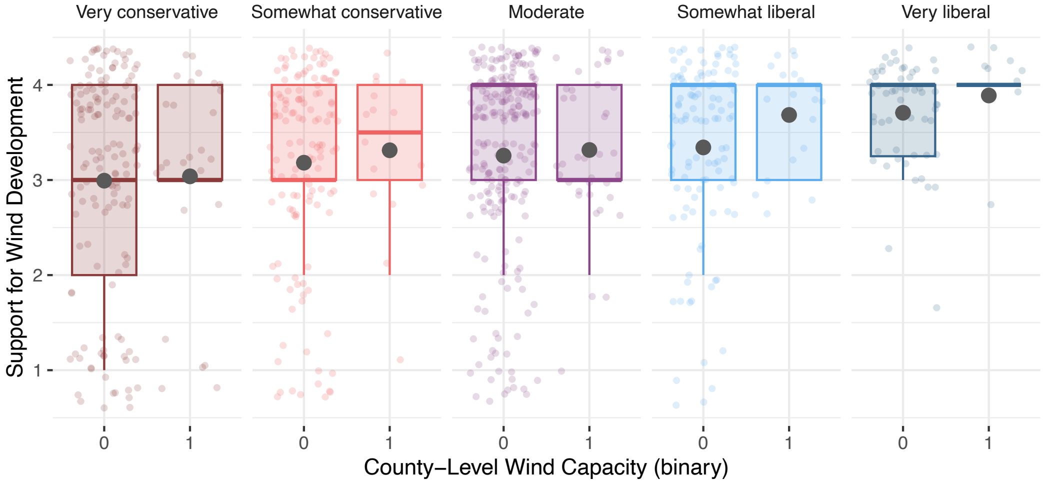

Figure 19. **Wind Capacity by Political Views**
Note. A majority of participants' counties of residence had no wind capacity, so for ease of viewing, this figure uses binary wind capacity (0 = no wind capacity; 1 = wind capacity > 0). This interaction was non-significant.

Conclusion

In total, eight terms from the full model were significant at the 95% confidence level or greater (see Figure 2). All five technology variables were significant, climate change acceptance was significant, the rural-urban continuum code was significant, and, at certain levels of climate change acceptance, the variable significantly moderated the relationship between wind support and the belief that turbines create jobs. Additionally, educational attainment was significant at the 90% confidence level. None of the state-level variables were significant.

Among the technology variables, the belief that turbines create jobs was the most predictive of support for wind development, whereas the belief that turbines create noise pollution was the least predictive, though still significant.

Among the people variables, higher educational attainment was associated with a small increase in wind support with marginal significance. Contrary to my expectations, political views did not significantly predict support for wind development. Accepting that climate change is occurring and, further, is caused by human activities is associated with higher support for wind development than asserting that climate change is not happening. In addition, the belief that turbines create jobs is less predictive of wind support among those who accept that climate change is caused by human activities than among those who assert that climate change is not happening.

Most place variables were not significant, with the exception of county-level rural designation. However, these results should be interpreted with caution. The number of participants included in the current research who were from highly rural areas was small. After dichotomizing the 9-point rural designation into rural counties and metropolitan counties, I found that the difference in wind support between those two groups was non-significant. Therefore, it is unclear whether and how the relationship between rural designation and support for wind development might change with additional sampling among individuals from highly rural counties.

CHAPTER IV: EXPLORATORY ANALYSES

Using visualizations and building upon the final model developed in the previous chapter, I assessed several exploratory interactions:

- Proximity to wind development with:
    - The technology variables
    - The people variables
    - Binary rural designation
- Binary rural designation with:
    - The technology variables
    - The people variables

I also tested a main effect—the impact of age of energy infrastructure installation on support for wind development.

Results and Discussion

Additional Proximity Interactions

Proximity was operationalized as wind capacity in the current research. None of the exploratory proximity interactions were significant—the technology variables, the people variables, and the binary rural-urban designation did not moderate the association of wind capacity with support for wind development (see Table 17). This means that the relationship between wind capacity and support for wind development does not vary based on a participants' beliefs about wind turbines, their demographic characteristics, climate change acceptance, nor the rural designation of the county in which they live. For example, Figure 20 displays the non-significant interaction between binary wind capacity and the belief that turbines help limit climate change. The slopes of the lines are similar, and any differences seen are non-significant.

Table 17. **Exploratory Results from the Proximity Interactions**

	Final Model (with Exploratory Interactions Added Individually)					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Technology						
Turbine noise x Wind capacity	-0.160	0.198	-0.810	1,298.5	-0.549	0.228
Visual problems x Wind capacity	-0.053	0.239	-0.223	103.4	-0.527	0.420
Jobs x Wind capacity	-0.145	0.292	-0.495	2,436.5	-0.717	0.428
Property values x Wind capacity	0.076	0.242	0.314	279.7	-0.400	0.551
Climate impacts x Wind capacity	-0.162	0.230	-0.702	145.9	-0.617	0.294
People						
Political views x Wind capacity	0.027	0.162	0.170	1,900.5	-0.289	0.344
Gender (Female) x Wind capacity	-0.081	0.394	-0.204	5,314.6	-0.853	0.692
Age x Wind capacity	0.242	0.161	1.504	11,275.1	-0.073	0.557
Education x Wind capacity	-0.006	0.165	-0.037	2,126.0	-0.329	0.317
Income x Wind capacity	0.037	0.130	0.289	710.2	-0.218	0.293
CC accept (Human activity) x Wind capacity	-0.198	0.642	-0.309	613.3	-1.458	1.062
CC accept (A combination) x Wind capacity	0.115	0.810	0.141	2,558.2	-1.474	1.703
CC accept (Natural patterns) x Wind capacity	0.674	0.768	0.877	2,143.1	-0.833	2.181
CC accept (Not sure of cause) x Wind capacity	-0.116	1.036	-0.112	2,789.9	-2.147	1.914
CC accept (Not sure if happening) x Wind capacity	0.642	0.898	0.715	1,466.5	-1.120	2.404
Place						
RUCC (4-9) x Wind capacity	0.254	0.493	0.514	7,035.0	-0.714	1.221

Note. CC accept = climate change acceptance; RUCC = rural-urban code. All interactions were added individually to the final model; therefore, each estimate does not take into account the other interactions included in the table. The reference cases are as follows: CC accept is "not happening," gender is "male," and RUCC is scores of 1-3. The square root of wind capacity was used in each interaction.

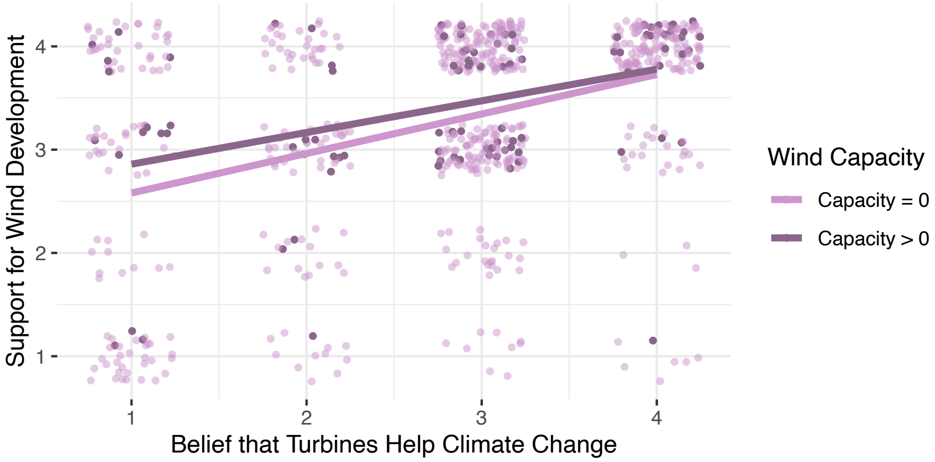

Figure 20. **Wind Capacity by Belief that Turbines Help Climate Change**
Note. This interaction was non-significant. A majority of participants' counties of residence had no wind capacity, so for ease of viewing, this figure uses binary wind capacity (0 = no wind capacity; 1 = wind capacity > 0).

Rural Interactions

I also tested interactions between the rural-urban designation and each of the technology variables: turbine noise, visual problems, job creation, property value impacts, and climate impacts. When individually added to the final model, the interaction between the belief that wind turbines create jobs and the binary rural designation trended toward significant but did not meet a 90% threshold ($b = 0.166$, $t = 1.595$, $df = 372.3$, $p = .11$). The trend indicates that the belief that wind turbines create jobs might predict support for wind development more strongly among those living in rural counties than among those living in metropolitan counties (see Figure 21). Future research should investigate this interaction further—with oversampling among individuals who live in highly rural areas, the effect could become more pronounced.

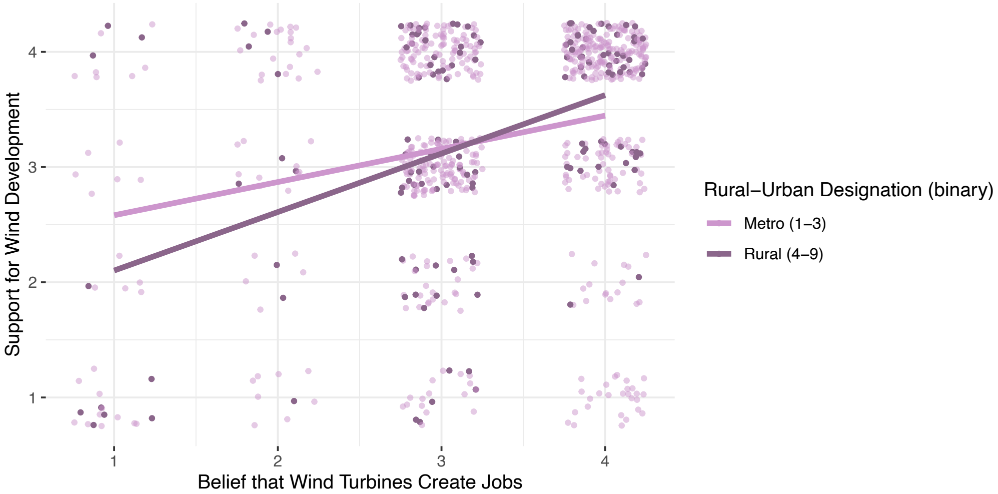

Figure 21. **Job Impacts by Rural-Urban Designation**
Note. This interaction was non-significant.

I also tested interactions between the rural-urban designation and each of the people variables: political views, gender, age, education, income, and climate change acceptance. When individually added to the final model, the interaction between political views and the binary rural designation trended toward significant but did not meet a 90% threshold ($b = -0.106$, $t = -1.507$, $df = 800.7$, $p = .13$; see Figure 22). Future research should also investigate this interaction further. The trend shows that political views might predict support for wind development more strongly among those living in metropolitan counties than among those living in rural counties, and with oversampling among individuals who live in highly rural areas, the effect could become more pronounced.

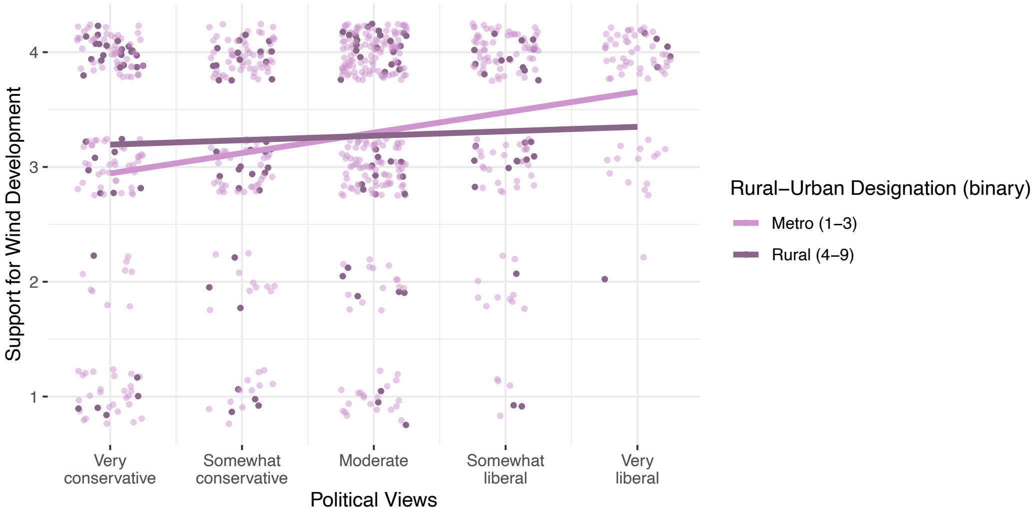

Figure 22. **Political Views by Rural-Urban Designation**
Note. This interaction was non-significant.

Additionally, future research could investigate a potential interaction between rural-urban designation and educational attainment. Although not significant in the final model developed in the current research ($b = 0.06$, $t = 0.87$, $df = 3{,}871.4$, $p = .39$), the visualization appears to trend toward an effect (see Figure 23). I explored the interaction further and found that it was marginally significant when modeled using a simpler multilevel model with educational attainment, rural-urban designation, and their interaction as the only predictors of support for wind development ($b = 0.13$, $t = 1.67$, $df = 23{,}916.8$, $p < .10$). The trend shows that educational attainment might predict support for wind development more strongly among those living in rural counties than among those living in metropolitan counties—again, with oversampling among individuals with less than high school education and individuals who live in highly rural areas, the effect could become more pronounced. None of the other technology and people variables displayed these trends, with rural and metropolitan participants scoring similarly on wind support across each of the other technology and people variables (see Table 18).

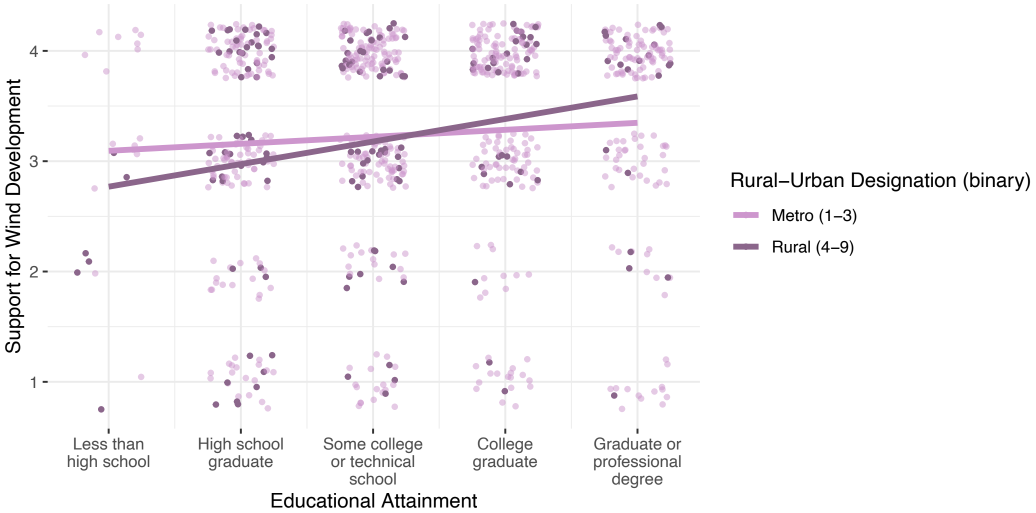

Figure 23. **Educational Attainment by Rural-Urban Designation**
Note. This interaction was non-significant.

Table 18. **Exploratory Results from the Rural-Urban Interactions**

	Final Model (with Exploratory Interactions Added Individually)					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Technology						
Turbine noise x RUCC (4-9)	0.054	0.090	0.598	379.5	-0.123	0.230
Visual problems x RUCC (4-9)	-0.002	0.084	-0.025	866.9	-0.166	0.162
Jobs x RUCC (binary)	0.166	0.104	1.595	372.4	-0.039	0.372
Property values x RUCC (4-9)	0.077	0.086	0.894	755.8	-0.092	0.246
Climate impacts x RUCC (4-9)	0.076	0.093	0.817	198.4	-0.107	0.259
People						
Political views x RUCC (4-9)	-0.106	0.070	-1.507	800.7	-0.244	0.032
Gender (female) x RUCC (4-9)	-0.123	0.156	-0.785	6,879.6	-0.430	0.184
Age x RUCC (4-9)	-0.078	0.073	-1.072	3,701.7	-0.220	0.0644
Education x RUCC (4-9)	0.063	0.073	0.865	3,871.5	-0.080	0.207
Income x RUCC (4-9)	-0.027	0.052	-0.523	315.7	-0.128	0.074
CC accept (Human activity) x RUCC (4-9)	0.152	0.227	0.668	3,760.4	-0.293	0.596
CC accept (A combination) x RUCC (4-9)	-0.063	0.261	-0.240	1,904.0	-0.573	0.448
CC accept (Natural patterns) x RUCC (4-9)	-0.157	0.256	-0.611	4,654.7	-0.659	0.346
CC accept (Not sure of cause) x RUCC (4-9)	-0.079	0.519	-0.152	354.6	-1.100	0.942
CC accept (Not sure if happening) x RUCC (4-9)	0.096	0.276	0.349	859.1	-0.446	0.638

Note. CC accept = climate change acceptance; RUCC = rural-urban code. All interactions were added individually to the final model; therefore, each estimate does not take into account the other interactions included in the table. The reference cases are as follows: CC accept is “not happening,” gender is “male,” and RUCC is scores of 1-3.

Age of Installation

Fossil technologies and certain renewable technologies, including hydroelectric dams, were more widespread earlier in the 20th century than wind and solar technologies (EIA, 2023); thus, the age in years of the oldest and newest installations of fossils and renewables in each county ranged more widely than for wind and solar installations (see Table 19). The county-level age of the oldest and newest solar, renewable, and fossil installations did not significantly predict support for wind development when each variable was added to the final model individually (see Table 20). When the county-level age of the oldest and newest wind installations were added to the final model individually, the model was rank deficient with an insufficient number of data points to fit the complexity of the model. Therefore, I tested the variables individually using a simple multilevel regression, with each variable as the only predictor of wind support and a random intercept for county. Although neither of the wind installation age variables were significant, the visualization for both variables displays a trend which suggests more recent installations tend to be associated with lower support for wind development (see Table 21, Figure 24, and Figure 25), with a greater potential effect for the age of the newest wind installation. Because the analysis could only leverage participants from counties with wind development, the sample size used in the analysis was relatively small (*n* = 117). Future research can explore this relationship further by obtaining a larger sample of individuals from counties with wind infrastructure, which could make the effect more pronounced.

Table 19. **Descriptive Statistics for Age of Installation**

Variable	**Multiply Imputed Data**		
	m	***SD***	***min, max***
Wind			
Age of oldest installation	10.12	10.27	0, 41
Age of newest installation	4.13	3.54	0, 28
Solar			
Age of oldest installation	6.39	5.33	0, 30
Age of newest installation	1.50	2.24	0, 8
Renewables			
Age of oldest installation	65.98	37.30	0, 125
Age of newest installation	28.90	29.17	0, 113
Fossils			
Age of oldest installation	46.80	19.57	1, 91
Age of newest installation	11.78	12.58	0, 63

Table 20. **Exploratory Results for Age of Solar, Renewable, and Fossil Installations**

	Final Model (with Exploratory Main Effects Added Individually)					
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Oldest solar installation	-0.005	0.018	-0.259	4,957.1	-0.040	0.030
Newest solar installation	0.016	0.032	0.505	7,639.2	-0.046	0.078
Oldest renewable installation	0.000	0.002	0.265	1,110.3	-0.003	0.004
Newest renewable installation	0.001	0.002	0.627	1,161.8	-0.003	0.006
Oldest fossil installation	0.003	0.002	1.409	1,149.3	-0.001	0.008
Newest fossil installation	0.004	0.003	1.291	1,698.7	-0.002	0.011

Note. All variables were added individually to the final model; therefore, each estimate does not take into account the other variables included in the table.

Table 21. **Exploratory Results for Age of Wind Installations**

	Simple Multilevel Regressions					
Oldest Wind Installation Regression						
Fixed Effects	***b***	***SE***	***t***	***df***	***CI: Lower***	***CI: Upper***
Intercept	3.271	0.109	29.928	7,264.8	3.056	3.484
Oldest wind installation	0.007	0.008	0.854	1,477.4	-0.009	0.022
Newest Wind Installation Regression						
Fixed Effects						
Intercept	3.244	0.119	27.276	10,482.7	3.011	3.477
Newest wind installation	0.023	0.022	1.055	55,007.2	-0.020	0.065

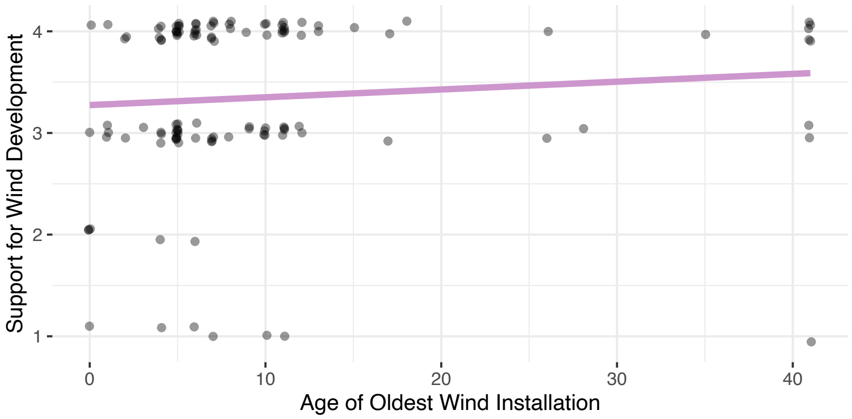

Figure 24. **Age of Oldest Wind Installation and Support for Wind**

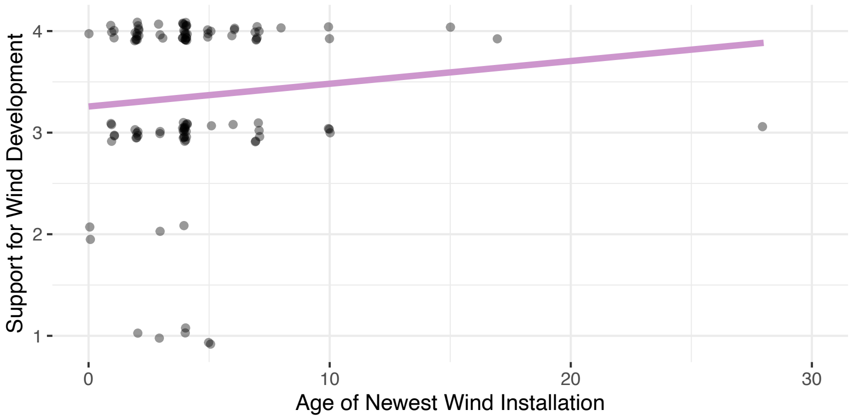

Figure 25. **Age of Newest Wind Installation and Support for Wind**

Conclusion

The exploratory analyses produced no significant results. However, trends suggest that several of the predictors are worth further investigation. The extent to which one's county is rural could impact the effect of several variables. Support for wind development among individuals from rural counties could be more heavily influenced by their beliefs that wind turbines create jobs than among individuals from metropolitan counties. Similarly, support for wind development among individuals from rural counties could be more heavily influenced by their educational attainment than among individuals from metropolitan counties. In contrast, support for wind development among individuals from rural counties could be less influenced by their political views than among individuals from metropolitan counties. The recency of wind installations could also predict support for wind development—though non-significant, trends demonstrate that individuals from counties with older installations might support wind development more than those from counties with newer installations. Additional research, with a particular focus on collecting data from individuals who live in rural counties, individuals with less-than-high-school educational attainment, and individuals who live in counties with wind installations, could yield the trends identified in the current research more pronounced.

CHAPTER V: GENERAL DISCUSSION

Geographies of Support for Wind Energy

Overview

The goal of the current research was to investigate geographies of support for wind energy development to better align development interests with community interests. The specific research objectives were to: 1) test Boudet's (2019) framework in the context of utility-scale wind development, 2) investigate the relationship between DAC status and support for wind development, and 3) investigate the existence of interactions between the variables included in the model to help establish geographies of support and to explain inconclusive past research. To achieve these objectives, I developed a multilevel linear regression model to examine support for wind development using operationalized technology, people, and place variables (Boudet, 2019). Overall, the model explained 25% of the variance in wind support and yielded several significant main effects, including all the technology variables, climate acceptance, educational attainment, and rural designation. I found that wind support is likely to be highest in communities where residents hold positive perceptions of the economic impacts of wind turbines, including job creation and increased property values. Wind support is also likely to be strongest in areas where the occurrence of climate change is accepted and where community members believe that wind turbines help address climate change. Finally, in areas where residents do not accept that climate change is happening, perceptions of the job impacts of wind turbines will be particularly important for wind development support. The study also identified trends suggestive of the potential existence of additional geographies of support. Specifically, the relationship between the perceptions of the economic impacts of wind turbines, educational attainment, and political views with support for wind energy could be affected by rurality. These results, taken together with the fact that wind farms are typically installed in rural areas, indicate that future research should oversample residents of rural communities.

The current research contributes to the literature on wind support in several ways. The study is the first test of Boudet's (2019) framework in the context of utility-scale energy development. In doing so, the study integrates psychological and sociological variables to generate a more wholistic explanation for wind support. This research also explored interactions between variables across geospatial levels and variable categories—namely, the moderating effect of several variables on proximity to development and rural designation. The study is also the first to explore the relationship between DAC status and support for wind development. Stakeholders interested in developing wind energy will be able to use this work to help prioritize community interests in discussions about wind energy siting.

To support the analyses in this study, I also assembled a large dataset comprised of variables in Boudet's technology, people, and place categories at varying geospatial levels that originated from many disparate sources. The dataset will be shared publicly so that the data can be leveraged by future wind development and research efforts and to promote transparency in research and replication of findings.

Boudet's Framework

This work tested three of the variable categories in Boudet's (2019) framework: technology, people, and place. Using a multilevel linear regression model, I found that the technology category predicts support for wind development consistent with findings from previous research (Rand & Hoen, 2017). Thus, perceived environmental and economic impacts of wind turbines, such as perceived noise pollution, visual obstruction, job creation, property value impacts, and climate impacts, are important aspects of Boudet's framework in the context of wind development. Given the category's importance, future research should include additional technology variables. One potentially important variable not included in the current research is perceived and actual impact of wind turbines on household energy costs.

I found little evidence that the people category is impactful on attitudes about wind energy development, which is also consistent with previous research (Rand & Hoen, 2017). People variables, which largely comprised sociodemographic characteristics in the current research, have been shown to be unrelated to wind energy attitudes (Carlisle et al., 2014, 2015; Nilson & Stedman, 2023; Rand & Hoen, 2017; Roddis et al., 2018; Walker & Baxter, 2017). Therefore, at least in the context of wind energy research, most sociodemographic characteristics are likely unnecessary to include as explanatory variables in the people category of Boudet's framework. However, sociodemographic variables can be used as controls and to assess the extent to which diverse perspectives have been included in the research. Additionally, the current work found that rurality could be related to support for wind development; therefore, rurality should be included in future research. Lastly, Boudet includes values, norms, and trust in relevant institutions, such as government and industry, in the people category. Those variables were not available in the NSEE dataset from which I obtained the people variables, with one exception—acceptance of climate change, which the current research did find to be a significant predictor of attitudes about wind development.

Climate change acceptance moderated the effect of the belief that turbines create jobs on support for wind development. This finding confirms qualitative research that revealed that perceived economic impacts of wind development are especially important in forming opinions about wind development among individuals with low concern about climate change (Jepson et al., 2012). Therefore, future research should include attitudes about climate change and predictors of those attitudes when leveraging Boudet's framework and conduct further investigation into the people category to determine whether additional non-demographic people variables, such as trust in institutions, relate to support for wind development when included with a full model that contains the other variable categories, similar to the model tested in the current research.

The current study failed to establish evidence that the place category is impactful on attitudes about wind energy development. This indicates that contextual, sociological variables could matter less in the development of wind energy attitudes than individual-level variables that more closely match the specificity of wind energy attitudes. Future research should nevertheless include place variables, consider operationalizing them differently than the current study, and re-examine them in the full context of Boudet's framework to gather additional evidence about the importance of place variables in the framework. For instance, several of the place variables pertained to fossil-based and renewable (non-wind) energy development at the county and state levels, none of which were significant predictors of wind support. One possible explanation could be that the current research assessed these variables using county- and state-level fossil and renewable capacity, but many of these technologies are not salient to individuals living in the county or state where the infrastructure exists. If an individual does not know that energy infrastructure exists in their county, their opinions about future energy development are unlikely to be impacted by the existing infrastructure. Future research should instead examine these variables differently—for example, by using self-reported experience with local energy development and infrastructure or by using participants' distance from infrastructure.

To the author's knowledge, this study is the first test of whether DAC status predicts support for wind development. In the final model, DAC status, which was another place variable, was non-significant. Future research should explore this connection further to confirm or refute these findings. DAC status could in fact not relate to support for wind energy development. The non-significant finding could also be due to the way in which DAC status was transformed in the current study. Because the current study's dataset was resolved at the county level, DAC status, which is resolved at the census tract level in the source file, had to be aggregated to a lower resolution. To this end, DAC status in the current study represented the proportion of census tracts designated as disadvantaged within a county. Individuals not from DACs might nevertheless live in counties with disadvantaged census tracts and might have responded to the survey in greater numbers than those who live in DACs. Future research should be structured to allow for a DAC designation at the individual level, which would also allow an investigation into potential moderators of the relationship between DAC status and support for wind development, such as rurality. Future research could also include components of DAC status as individual variables, such as energy insecurity or energy burden, which could uncover relationships not evident when DAC status is examined as a community variable. Regardless, if future research finds that DAC status is indeed not related to support for wind energy, development efforts should nevertheless leverage distributive and procedural justice, and communities' historical experiences with inequitable energy systems should be understood and addressed.

However, as described in the next section, I did identify one exception in the place category that significantly predicted support for wind development in the final model—county-level rural designation.

Rural Designation and Support for Wind Development

In the final model, individuals from highly rural counties with scores of 9 on the rural-urban continuum had significantly lower wind support than those from less rural counties. This could indicate that cultural norms in rural areas are pervasive and impactful enough to yield wind energy attitudes distinct from metropolitan attitudes. However, these results should be interpreted with caution. The number of participants included in the current research who were from highly rural areas was small, and once I dichotomized the 9-point rural designation into rural counties and metropolitan counties, I found a non-significant difference in wind support between those groups. Therefore, it is unclear whether and how the relationship between rural designation and support for wind development in the context of Boudet's framework might change with additional sampling of individuals from highly rural counties. Indeed, previous research has been mixed, with some studies finding that individuals from rural areas often have high levels of support and positive attitudes about wind energy (Fergen & B. Jacquet, 2016; K. Mulvaney et al., 2013), whereas a qualitative study of individuals living in rural areas of New York state found that rural participants felt they were bearing the heaviest burden of utility-scale solar development while largely sending the benefits to urban areas (Nilson & Stedman, 2023), indicating that distributive justice, and likely procedural justice, will be particularly important in the development of wind energy in rural areas. For instance, research has shown that community-owned wind projects tend to face less opposition (Jami & Walsh, 2017; Rand & Hoen, 2017; Stokes et al., 2023).

The current research also identified potential geographies of support relevant to rurality. Though not quite a significant effect in the current research, individuals from rural counties tended to rely more on perceived economic impacts of wind energy in the formation of opinions about development than did individuals from metropolitan counties, which is also evidenced in previous research that found that wind farms are perceived as mechanisms to reverse economic decline in rural areas of Texas and Iowa (Slattery et al., 2012). Additionally, the educational attainment of individuals from rural areas tended to predict their opinions about wind development more than those from metropolitan counties, and conversely, political views tended to be less important in the formation of opinions about wind energy among rural individuals than among metropolitan individuals.

These potential effects warrant further investigation in future research with larger samples of rural residents who are most often affected by wind development. Representative sampling of liberal or progressive individuals and oversampling of individuals from highly rural areas and those with less than high school educational attainment will provide more precise estimates of these trends. Future research can also focus data collection in areas with wind turbines to obtain more precise estimates of the impact of the age of historical energy installations on wind support. Finally, participants' ratings of support for wind development in the current work were quite high (m = 3.23, SD = 0.97). Although high ratings of support are common in research on support for renewable energy, the limited variability could have weakened the findings in the current study.

Proximity and Support for Wind Development

Another question the current research sought to address was the impact of proximity to development on support for development. Previous research has produced mixed results on the relationship between proximity and support (Devine-Wright, 2005; Hoen et al., 2019; Larson & Krannich, 2016), which not only refutes the NIMBY hypothesis but also signals the need for additional research and the possible existence of moderation effects. The current research did not find any evidence of moderating variables—proximity does not seem to be moderated by the technology variables (perceived noise, visual, job, property value, and climate impacts of turbines), nor is it moderated by rural designation or the people variables (demographic characteristics and climate change acceptance).

One possible explanation for the lack of significant moderators on proximity in the current study's final model could be the way in which proximity was operationalized. Because this work was not able to identify actual proximity to energy development as previous studies have (e.g., Zanocco et al., 2020), I used county-level wind capacity to estimate proximity. This, however, posed a problem—most counties in the U.S. have no wind capacity, and therefore, the data were highly skewed with only some counties having values greater than 0. If higher gradience were captured by estimating distance from participants' homes to the nearest wind installation, future research might be able to identify significant interactions.

Another avenue that future research can explore to identify proximity interactions is the process category in Boudet's framework, which captures the extent to which development projects are perceived as distributionally and procedurally just. The current research did not include process variables because opinions about hypothetical wind development were assessed instead of opinions about actual or proposed development. However, proximity could very well be moderated by justice-related characteristics of energy development projects—contentious development processes could potentially impact the effect of proximity on support for development. For instance, among individuals living near wind projects that had poor distributive and procedural characteristics, proximity might be impactful on support for the projects because the associated injustices could be more salient for those living closer to the installations. In contrast, among individuals living near wind projects that successfully distributed benefits across community members and included them meaningfully in decision-making processes, proximity might be less impactful on support for the projects. Future research should therefore assess the process category of Boudet's framework using data collected from actual development projects and explore the moderating effects of justice-related variables on proximity to development.

Strengths and Limitations

Public Opinion Research

Public opinion surveys on support for renewable energy development have been criticized for 1) focusing exclusively on questions of support without examining possible explanations for respondents' opinions and 2) focusing on general support as opposed to local support (Rand & Hoen, 2017; Sütterlin & Siegrist, 2017). The NSEE, which was the dataset used to assess support for wind development in the current study, does include explanatory variables, which were leveraged by the current work's models. Additionally, the NSEE assessed local support by asking participants their opinion about wind development in their community, which was used as the outcome variable in the current work. Assessing participants' support for local development is likely more accurate than asking about broad support;

however, the question is still hypothetical and self-reported and thus might not capture participants' true reactions to real-world wind projects proposed near their homes. This underscores the need for governments, practitioners, and developers to work directly with communities before making siting decisions rather than relying solely on results from this work or any other work based on public opinion research. Future work can determine the relationship between real-world occurrences of opposition to wind development and the NSEE's item about support for community development to determine the extent to which the item predicts actual opposition.

Racial Representation

Participants who identified as a race or ethnicity other than white were underrepresented in the NSEE wave used in the current research (i.e., Fall 2016), especially those who identified as Hispanic or Latinx (U.S. Census Bureau, 2016). The Census Bureau reported that, in 2016, 17% of Americans were Hispanic or Latinx, whereas only 6% of participants in the NSEE identified as such. Assessing the extent to which Hispanic or Latinx participants are underrepresented is challenging, however, because the NSEE assessed race and ethnicity in the same question, whereas the Census Bureau asked about race and ethnicity in separate questions because the bureau considers Hispanic and Latinx to be ethnic and not racial identities. By asking about race and ethnicity separately, those surveyed by the Census Bureau might have had a better opportunity to identify as both white and Hispanic or Latinx than those surveyed by the NSEE. Regardless, other races or ethnicities were also underrepresented among NSEE participants, including Black or African American, Asian, and those identifying with two or more races or ethnicities. Because demographic characteristics tend not to predict support for wind development, it is unclear whether representative sampling will impact model results. However, future research should nevertheless strive to obtain more representative samples.

Data Vintage and Political Representation

The vintage of the data used in the current research should also be considered when interpreting findings. Most data used in the current research were collected in 2016, and contextual and psychological circumstances might be different in the current year. Indeed, the percent of Americans supportive of wind energy decreased from 2016 to 2023 (83% to 75%; Funk & Kennedy, 2016; Kennedy et al., 2023a). This change can be attributed to a change in support among Republicans—although support for wind energy among Democrats increased slightly from 2016 to 2023 (87% to 91%), support for wind energy among Republicans decreased more substantially during that time (80% to 60%). Because the data vintage matched across variables in the current research, the analysis provides evidence about the relationships between the variables examined; however, further research will be needed to determine how changing opinions might impact results, especially among opinions that are changing according to political views. The current work found no significant effect for political views on support for wind energy in the full model. Because liberal individuals tend to be more supportive of wind energy (Funk & Kennedy, 2016; Kennedy et al., 2023a), the current research might have failed to find a significant effect for political views because liberal individuals are underrepresented in the data. Additionally, because the gap between wind energy opinions among Democrats and Republicans is widening, political views might be more strongly related to support for wind development currently than they were in 2016. Future research should conduct this re-assessment and obtain a sample that is more representative of political views in the U.S.

Conclusion

In the current research, I developed a multilevel linear regression model to test Boudet's (2019) framework on attitudes about wind development and to explore geographies of support that can help practitioners identify communities in which development efforts might be more successful. I found that Boudet's technology category predicts support for wind development, that demographic components of the people category do not predict support for wind development but climate change acceptance does, and that the place category is not predictive of support for wind development when modeled in tandem with individual-level variables. In addition to performing the first test of Boudet's framework in the context of utility-scale wind development, the current work examined geographies of support for wind development, which contextualize conditions conducive to community-supported development, in the form of interactions across variable categories, which have not previously been explored in the context of wind development. The belief that turbines create jobs is more impactful on support for development among those who assert that climate change is not happening than among those who assert that climate change is caused by a combination of human activities and natural patterns. I also uncovered trends that indicate the potential existence of additional geographies and warrant further investigation. Representative sampling of liberal or progressive individuals and oversampling of individuals from highly rural areas and those with less than high school educational attainment will provide more precise estimates of the potential moderating effect of rural designation on three variables—the belief that turbines create jobs, political views, and educational attainment. Exploration into the impact of the age of historical energy installations on wind support also revealed no significant results but an interesting trend—more recent installations tended to be associated with lower support for wind development, which can be explored further in future research that focuses data collection in areas with wind installations.

This work can inform first steps in the wind energy siting process by highlighting when and why certain geographies tend to be supportive of wind development. However, meaningful and inclusive engagement and community-led siting decisions must follow for the well-being of local community members and for the success of development projects. Suggestions and guidance abound for just renewable energy development. For examples, see Baker et al. (2019), Bidwell (2016c), Jami and Walsh (2017), Ottinger et al. (2014), Ross and Day (2022), and Sovacool and Dworkin (2015). Not only does meaningful community engagement in renewable energy siting processes increase buy-in, but engagement can also yield more successful development projects because resident stakeholders have deep expertise of their communities and can provide invaluable insights that improve project outcomes. By identifying geographies of support, the current work can help practitioners better align development interests with community interests. Although research shows that those supportive of wind development outnumber those in opposition, working with communities to address the concerns of those opposed to development is an important component of energy justice, and predicting where this opposition is likely to occur will aid in the pursuit of successful, equitable energy transitions.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
CO_2	Carbon dioxide
DAC	Disadvantaged community
FIPS	Federal Information Processing Series
GHG	Greenhouse gas
NIMBY	Not-in-my-backyard
NSEE	National Surveys on Energy and Environment
$PM_{2.5}$	Particulate matter
RPS	Renewable portfolio standard

APPENDIX A

Table A.1. **Descriptive Statistics by State Using Imputed Data: Continuous Variables**

State (*n*)	Wind support	Turbine noise	Visual problems	Jobs	Property values	Climate impacts
			m (SD)			
AL (16)	2.9 (1.1)	2.9 (1.0)	2.8 (1.1)	3.2 (0.9)	2.3 (1.1)	2.5 (1.2)
AR (5)	3.6 (0.8)	2.7 (1.1)	3.2 (0.8)	3.2 (0.8)	3.0 (1.2)	2.9 (1.2)
AZ (23)	3.4 (1.0)	3.0 (1.1)	2.8 (1.0)	3.3 (0.6)	2.8 (1.0)	3.2 (0.7)
CA (104)	3.4 (0.8)	3.1 (1.0)	2.9 (1.0)	3.4 (0.8)	2.5 (0.9)	2.9 (1.0)
CO (9)	3.1 (0.6)	2.6 (0.9)	1.9 (0.9)	3.3 (0.5)	2.3 (0.7)	2.9 (0.9)
CT (5)	3.2 (0.8)	3.2 (1.0)	3.2 (0.4)	3.4 (0.5)	2.4 (0.8)	3.2 (0.4)
DE (3)	3.7 (0.5)	2.6 (1.4)	2.3 (0.7)	3.3 (0.5)	2.0 (0.0)	2.6 (0.7)
FL (57)	3.3 (0.9)	2.9 (1.0)	2.9 (1.0)	3.3 (0.9)	2.6 (0.9)	2.8 (1.0)
GA (26)	3.0 (1.0)	3.2 (1.0)	3.0 (0.9)	2.7 (1.1)	2.5 (1.0)	2.6 (1.1)
IA (18)	3.4 (0.8)	2.8 (1.0)	3.2 (0.8)	3.7 (0.5)	2.8 (1.1)	3.0 (0.9)
ID (5)	3.7 (0.7)	3.4 (0.9)	3.5 (0.7)	3.3 (0.5)	3.2 (0.9)	2.3 (1.0)
IL (50)	3.3 (1.0)	3.3 (0.7)	3.1 (1.0)	3.3 (0.6)	2.7 (0.9)	2.7 (1.0)
IN (13)	2.8 (0.9)	2.6 (1.0)	2.7 (1.1)	3.3 (0.6)	2.4 (0.9)	2.2 (1.1)
KS (11)	2.9 (1.2)	3.0 (1.2)	2.8 (0.9)	3.5 (0.6)	2.8 (0.9)	2.4 (1.1)
KY (8)	2.9 (0.9)	3.2 (1.0)	3.0 (0.7)	3.2 (0.7)	2.4 (0.6)	2.8 (1.1)
LA (10)	3.0 (0.9)	2.6 (1.1)	3.0 (1.0)	3.0 (1.0)	3.1 (0.8)	3.1 (1.0)
MA (19)	2.9 (1.0)	2.1 (1.1)	2.5 (1.1)	3.4 (0.7)	2.0 (0.9)	2.4 (1.0)
MD (24)	3.4 (0.7)	3.2 (0.6)	2.9 (1.0)	3.3 (0.6)	2.6 (0.9)	3.2 (0.8)
ME (2)	3.5 (0.5)	3.6 (0.8)	3.5 (0.5)	3.1 (0.5)	1.6 (0.9)	2.0 (1.0)
MI (24)	3.4 (0.7)	3.1 (0.8)	3.0 (1.0)	3.5 (0.5)	2.5 (0.9)	2.9 (1.0)
MN (21)	3.4 (0.8)	3.1 (1.1)	2.8 (1.0)	3.3 (0.6)	3.0 (1.1)	2.5 (0.9)
MO (21)	3.2 (1.1)	3.3 (1.0)	3.2 (0.9)	3.4 (0.7)	3.0 (1.0)	3.1 (1.0)
MS (7)	3.0 (0.8)	3.1 (1.0)	3.1 (0.9)	3.2 (0.6)	2.3 (0.7)	2.6 (1.1)
MT (4)	2.7 (1.2)	3.1 (0.7)	3.2 (0.9)	3.0 (0.6)	2.2 (0.9)	2.2 (1.0)
NC (24)	3.0 (1.1)	2.7 (1.0)	2.7 (1.0)	3.2 (0.9)	2.4 (1.0)	2.9 (1.0)
ND (5)	2.9 (1.1)	2.2 (1.1)	1.6 (0.5)	3.0 (0.4)	1.8 (0.6)	2.3 (1.0)
NE (8)	2.8 (1.2)	2.2 (0.7)	1.8 (0.7)	2.5 (1.0)	2.1 (0.9)	2.6 (1.0)
NH (5)	3.4 (0.8)	3.2 (1.0)	2.4 (1.2)	2.7 (1.0)	2.9 (1.0)	2.6 (1.0)
NJ (31)	3.2 (1.1)	2.9 (1.0)	2.8 (1.0)	3.4 (0.6)	2.8 (0.8)	2.8 (1.0)
NM (6)	3.5 (0.8)	3.4 (0.8)	3.1 (1.0)	3.2 (0.7)	2.6 (0.8)	2.3 (1.2)
NV (7)	3.1 (1.0)	3.1 (1.1)	2.9 (1.0)	2.9 (0.8)	2.9 (1.0)	2.3 (0.9)
NY (41)	3.4 (0.9)	3.0 (0.9)	3.0 (0.9)	3.4 (0.8)	2.8 (0.9)	2.9 (0.9)
OH (37)	3.1 (1.0)	3.0 (1.0)	2.8 (0.9)	3.1 (0.8)	2.4 (1.0)	2.4 (1.0)
OK (17)	3.2 (1.1)	2.9 (1.0)	2.6 (1.1)	3.1 (0.6)	2.4 (1.0)	2.3 (1.1)
OR (14)	2.9 (1.1)	2.8 (0.9)	3.0 (1.0)	3.4 (0.7)	2.4 (0.9)	2.8 (0.9)

State (*n*)	Wind support	Turbine noise	Visual problems	Jobs	Property values	Climate impacts
	m (SD)					
PA (35)	3.3 (1.0)	3.2 (0.9)	3.2 (0.9)	3.3 (0.9)	2.9 (1.1)	2.7 (1.0)
RI (3)	3.0 (0.8)	3.3 (0.5)	3.3 (0.5)	3.3 (0.5)	3.0 (0.8)	3.1 (1.0)
SC (10)	3.3 (0.7)	3.0 (0.9)	2.5 (1.1)	3.6 (0.6)	2.5 (0.9)	3.0 (1.1)
SD (1)	4.0 (0.0)	4.0 (0.0)	1.0 (0.0)	4.0 (0.0)	2.0 (0.0)	4.0 (0.0)
TN (16)	2.9 (1.2)	2.8 (1.0)	3.2 (0.7)	3.4 (0.9)	2.3 (1.0)	3.1 (1.0)
TX (64)	3.3 (0.9)	3.2 (0.9)	3.0 (0.9)	3.2 (1.0)	2.8 (1.0)	2.9 (1.0)
UT (12)	2.9 (1.3)	3.1 (0.8)	2.9 (1.0)	2.8 (0.8)	2.5 (0.9)	2.3 (0.9)
VA (17)	3.0 (0.9)	2.9 (1.0)	2.5 (1.0)	3.1 (1.0)	2.4 (0.8)	2.9 (0.9)
VT (1)	4.0 (0.0)	4.0 (0.0)	4.0 (0.0)	4.0 (0.0)	3.0 (0.0)	3.0 (0.0)
WA (17)	3.4 (0.9)	3.4 (0.8)	3.2 (0.9)	3.2 (0.7)	2.3 (0.7)	2.9 (0.8)
WI (27)	3.3 (0.9)	3.2 (0.9)	3.0 (1.0)	3.3 (0.7)	2.7 (1.0)	2.5 (1.1)
WV (7)	2.4 (1.2)	3.1 (1.2)	2.3 (1.3)	2.7 (1.3)	2.0 (0.9)	2.6 (1.1)
WY (2)	1.9 (1.3)	2.4 (1.2)	2.0 (1.2)	1.7 (1.1)	1.8 (1.2)	3.0 (0.8)

Table A.2. **Descriptive Statistics by State Using Imputed Data: Ordinal and Nominal Variables**

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
AL (16)	18-29 years: 27% 30-44 years: 13% 45-64 years: 26% 65 and older: 34%	Less than high school: 0% High school graduate: 21% Some college: 21% College graduate: 39% Graduate degree: 19%	Less than $20,000: 18% $20,000 to $40,000: 19% $40,000 to $60,000: 12% $60,000 to $80,000: 10% $80,000 to $100,000: 21% Over $100,000: 20%	Very conservative: 35% Somewhat conservative: 27% Moderate: 36% Somewhat liberal: 2% Very liberal: 0.3%	Male: 47% Female: 53%	White: 60% African American: 26% Hispanic or Latinx: 0.3% Mixed race and other: 13%	Protestant: 59% Catholic: 16% Jewish: 0.3% Hindu: 0.3% Other: 23% Atheist: 1%
AR (5)	18-29 years: 0% 30-44 years: 40% 45-64 years: 40% 65 and older: 20%	Less than high school: 0% High school graduate: 40% Some college: 60% College graduate: 0% Graduate degree: 0%	Less than $20,000: 23% $20,000 to $40,000: 46% $40,000 to $60,000: 24% $60,000 to $80,000: 4% $80,000 to $100,000: 2% Over $100,000: 1%	Very conservative: 20% Somewhat conservative: 20% Moderate: 60% Somewhat liberal: 0% Very liberal: 0%	Male: 80% Female: 20%	White: 100%	Protestant: 40% Catholic: 40% Other: 20%
AZ (23)	18-29 years: 40% 30-44 years: 14% 45-64 years: 10% 65 and older: 35%	Less than high school: 0% High school graduate: 22% Some college: 35% College graduate: 30% Graduate degree: 13%	Less than $20,000: 9% $20,000 to $40,000: 19% $40,000 to $60,000: 32% $60,000 to $80,000: 16% $80,000 to $100,000: 18% Over $100,000: 6%	Very conservative: 22% Somewhat conservative: 23% Moderate: 28% Somewhat liberal: 22% Very liberal: 5%	Male: 61% Female: 39%	White: 91% African American: 9%	Protestant: 23% Catholic: 32% Other: 40% Atheist: 5%
CA (104)	18-29 years: 25% 30-44 years: 23% 45-64 years: 34% 65 and older: 18%	Less than high school: 2% High school graduate: 22% Some college: 26% College graduate: 32% Graduate degree: 17%	Less than $20,000: 11% $20,000 to $40,000: 19% $40,000 to $60,000: 16% $60,000 to $80,000: 15% $80,000 to $100,000: 12% Over $100,000: 26%	Very conservative: 21% Somewhat conservative: 18% Moderate: 34% Somewhat liberal: 16% Very liberal: 11%	Male: 62% Female: 38%	White: 66% African American: 5% Hispanic or Latinx: 14% Asian: 4% Mixed race and other: 12%	Protestant: 33% Catholic: 32% Jewish: 2% Hindu: 0% Other: 27% Atheist: 5%
CO (9)	18-29 years: 44% 30-44 years: 11% 45-64 years: 33% 65 and older: 11%	Less than high school: 0% High school graduate: 37% Some college: 36% College graduate: 2% Graduate degree: 26%	Less than $20,000: 6% $20,000 to $40,000: 16% $40,000 to $60,000: 5% $60,000 to $80,000: 17% $80,000 to $100,000: 28% Over $100,000: 28%	Very conservative: 16% Somewhat conservative: 26% Moderate: 46% Somewhat liberal: 13% Very liberal: 1%	Male: 89% Female: 11%	White: 87% African American: 1% Hispanic or Latinx: 11% Asian: 1% Mixed race and other: 1%	Protestant: 57% Catholic: 11% Other: 31% Atheist: 1%
CT (5)	18-29 years: 20% 30-44 years: 20% 45-64 years: 40% 65 and older: 20%	Less than high school: 0% High school graduate: 20% Some college: 20% College graduate: 40% Graduate degree: 20%	Less than $20,000: 2% $20,000 to $40,000: 26% $40,000 to $60,000: 22% $60,000 to $80,000: 5% $80,000 to $100,000: 21% Over $100,000: 24%	Very conservative: 0% Somewhat conservative: 40% Moderate: 20% Somewhat liberal: 20% Very liberal: 20%	Male: 40% Female: 60%	White: 100%	Protestant: 40% Catholic: 40% Other: 20%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
DE (3)	18-29 years: 33% 30-44 years: 0% 45-65 years: 0% 65 and older: 67%	Less than high school: 0% High school graduate: 0% Some college: 33% College graduate: 33% Graduate degree: 33%	Less than $20,000: 0% $20,000 to $40,000: $40,000 to $60,000: 33% $60,000 to $80,000: 33% $80,000 to $100,000: 0% Over $100,000: 33%	Very conservative: 33% Somewhat conservative: 0% Moderate: 0% Somewhat liberal: 33% Very liberal: 33%	Male: 100% Female: 0%	White: 100%	Protestant: 33% Catholic: 33% Other: 33%
FL (57)	18-29 years: 20% 30-44 years: 22% 45-64 years: 29% 65 and older: 29%	Less than high school: 4% High school graduate: 24% Some college: 26% College graduate: 28% Graduate degree: 19%	Less than $20,000: 18% $20,000 to $40,000: 17% $40,000 to $60,000: 19% $60,000 to $80,000: 16% $80,000 to $100,000: 11% Over $100,000: 20%	Very conservative: 14% Somewhat conservative: 26% Moderate: 39% Somewhat liberal: 15% Very liberal: 7%	Male: 58% Female: 42%	White: 78% African American: 6% Hispanic or Latinx: 14% Asian: 0% Mixed race and other: 2%	Protestant: 39% Catholic: 30% Jewish: 4% Muslim: 0% Hindu: 0% Other: 25% Atheist: 3%
GA (26)	18-29 years: 27% 30-44 years: 35% 45-64 years: 19% 65 and older: 19%	Less than high school: 0% High school graduate: 31% Some college: 42% College graduate: 8% Graduate degree: 19%	Less than $20,000: 7% $20,000 to $40,000: 34% $40,000 to $60,000: 16% $60,000 to $80,000: 19% $80,000 to $100,000: 18% Over $100,000: 7%	Very conservative: 27% Somewhat conservative: 9% Moderate: 20% Somewhat liberal: 35% Very liberal: 9%	Male: 58% Female: 42%	White: 50% African American: 35% Hispanic or Latinx: 4% Asian: 4% Mixed race and other: 8%	Protestant: 42% Catholic: 35% Other: 19% Atheist: 4%
IA (18)	18-29 years: 22% 30-44 years: 11% 45-64 years: 33% 65 and older: 33%	Less than high school: 0% High school graduate: 22% Some college: 22% College graduate: 39% Graduate degree: 17%	Less than $20,000: 12% $20,000 to $40,000: 25% $40,000 to $60,000: 27% $60,000 to $80,000: 12% $80,000 to $100,000: 2% Over $100,000: 22%	Very conservative: 19% Somewhat conservative: 15% Moderate: 38% Somewhat liberal: 27% Very liberal: 1%	Male: 67% Female: 33%	White: 89% Hispanic or Latinx: 6% Asian: 6%	Protestant: 30% Catholic: 42% Jewish: 0% Hindu: 6% Other: 22% Atheist: 1%
ID (5)	18-29 years: 25% 30-44 years: 26% 45-64 years: 22% 65 and older: 27%	Less than high school: 0% High school graduate: 37% Some college: 50% College graduate: 10% Graduate degree: 3%	Less than $20,000: 5% $20,000 to $40,000: 32% $40,000 to $60,000: 29% $60,000 to $80,000: 14% $80,000 to $100,000: 7% Over $100,000: 13%	Very conservative: 26% Somewhat conservative: 29% Moderate: 35% Somewhat liberal: 7% Very liberal: 3%	Male: 73% Female: 27%	White: 71% African American: 2% Hispanic or Latinx: 1% Asian: 1% Mixed race and other: 25%	Protestant: 41% Catholic: 15% Jewish: 1% Other: 41% Atheist: 2%
IL (50)	18-29 years: 34% 30-44 years: 16% 45-64: years 32% 65 and older: 18%	Less than high school: 0% High school graduate: 38% Some college: 20% College graduate: 28% Graduate degree: 14%	Less than $20,000: 16% $20,000 to $40,000: 23% $40,000 to $60,000: 13% $60,000 to $80,000: 18% $80,000 to $100,000: 20% Over $100,000: 10%	Very conservative: 22% Somewhat conservative: 18% Moderate: 32% Somewhat liberal: 23% Very liberal: 5%	Male: 64% Female: 36%	White: 72% African American: 10% Hispanic or Latinx: 6% Asian: 6% Mixed race and other: 6%	Protestant: 48% Catholic: 23% Jewish: 2% Hindu: 2% Other: 20% Atheist: 5%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
IN (13)	18-29 years: 8% 30-44 years: 0% 45-64 years: 31% 65 and older: 62%	Less than high school: 8% High school graduate: 31% Some college: 38% College graduate: 15% Graduate degree: 8%	Less than $20,000: 29% $20,000 to $40,000: 13% $40,000 to $60,000: 14% $60,000 to $80,000: 13% $80,000 to $100,000: 18% Over $100,000: 13%	Very conservative: 11% Somewhat conservative: 33% Moderate: 45% Somewhat liberal: 10% Very liberal: 1%	Male: 62% Female: 38%	White: 92% African American: 8%	Protestant: 88% Catholic: 2% Muslim: 0% Other: 9% Atheist: 0%
KS (11)	18-29 years: 0% 30-44: years 18% 45-64 years: 36% 65 and older: 45%	Less than high school: 0% High school graduate: 9% Some college: 55% College graduate: 18% Graduate degree: 18%	Less than $20,000: 3% $20,000 to $40,000: 25% $40,000 to $60,000: 25% $60,000 to $80,000: 11% $80,000 to $100,000: 13% Over $100,000: 24%	Very conservative: 18% Somewhat conservative: 27% Moderate: 27% Somewhat liberal: 9% Very liberal: 18%	Male: 36% Female: 64%	White: 91% Mixed race and other: 9%	Protestant: 82% Catholic: 9% Other: 9%
KY (8)	18-29 years: 12% 30-44 years: 38% 45-65 years: 0% 65 and older: 50%	Less than high school: 0% High school graduate: 25% Some college: 12% College graduate: 38% Graduate degree: 25%	Less than $20,000: 2% $20,000 to $40,000: 28% $40,000 to $60,000: 28% $60,000 to $80,000: 27% $80,000 to $100,000: 1% Over $100,000: 15%	Very conservative: 12% Somewhat conservative: 38% Moderate: 38% Somewhat liberal: 0% Very liberal: 12%	Male: 38% Female: 62%	White: 100%	Protestant: 75% Catholic: 16% Jewish: 1% Muslim: 1% Other: 6% Atheist: 1%
LA (10)	18-29 years: 40% 30-44 years: 10% 45-64 years: 10% 65 and older: 40%	Less than high school: 10% High school graduate: 20% Some college: 40% College graduate: 30% Graduate degree: 0%	Less than $20,000: 34% $20,000 to $40,000: 12% $40,000 to $60,000: 10% $60,000 to $80,000: 22% $80,000 to $100,000: 11% Over $100,000: 12%	Very conservative: 14% Somewhat conservative: 15% Moderate: 36% Somewhat liberal: 34% Very liberal: 2%	Male: 70% Female: 30%	White: 50% African American: 30% Mixed race and other: 20%	Protestant: 30% Catholic: 20% Other: 40% Atheist: 10%
MA (19)	18-29 years: 5% 30-44 years: 5% 45-64 years: 47% 65 and older: 42%	Less than high school: 5% High school graduate: 5% Some college: 16% College graduate: 37% Graduate degree: 37%	Less than $20,000: 11% $20,000 to $40,000: 18% $40,000 to $60,000: 23% $60,000 to $80,000: 15% $80,000 to $100,000: 9% Over $100,000: 24%	Very conservative: 29% Somewhat conservative: 13% Moderate: 29% Somewhat liberal: 18% Very liberal: 11%	Male: 53% Female: 47%	White: 89% Hispanic or Latinx: 5% Asian: 5% Mixed race and other: 1%	Protestant: 37% Catholic: 30% Hindu: 0% Other: 21% Atheist: 11%
MD (24)	18-29 years: 40% 30-44 years: 23% 45-64 years: 27% 65 and older: 10%	Less than high school: 0% High school graduate: 14% Some college: 36% College graduate: 23% Graduate degree: 26%	Less than $20,000: 2% $20,000 to $40,000: 4% $40,000 to $60,000: 34% $60,000 to $80,000: 25% $80,000 to $100,000: 3% Over $100,000: 32%	Very conservative: 10% Somewhat conservative: 19% Moderate: 46% Somewhat liberal: 16% Very liberal: 10%	Male: 60% Female: 40%	White: 70% African American: 13% Hispanic or Latinx: 4% Asian: 9% Mixed race and other: 5%	Protestant: 42% Catholic: 23% Jewish: 1% Muslim: 0% Hindu: 4% Other: 20% Atheist: 10%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
ME (2)	18-29 years: 50% 30-44 years: 0% 45-65 years: 50% 65 and older: 0%	Less than high school: 0% High school graduate: 50% Some college: 0% College graduate: 0% Graduate degree: 50%	Less than $20,000: 0% $20,000 to $40,000: 50% $40,000 to $60,000: 50% $60,000 to $80,000: 0% $80,000 to $100,000: 0% Over $100,000: 0%	Very conservative: 50% Somewhat conservative: 0% Moderate: 50% Somewhat liberal: 0% Very liberal: 0%	Male: 50% Female: 50%	White: 100%	Protestant: 50% Catholic: 50%
MI (24)	18-29 years: 22% 30-44 years: 18% 45-64 years: 47% 65 and older: 14%	Less than high school: 21% High school graduate: 22% Some college: 19% College graduate: 25% Graduate degree: 13%	Less than $20,000: 15% $20,000 to $40,000: 16% $40,000 to $60,000: 17% $60,000 to $80,000: 15% $80,000 to $100,000: 8% Over $100,000: 29%	Very conservative: 33% Somewhat conservative: 6% Moderate: 40% Somewhat liberal: 20% Very liberal: 1%	Male: 61% Female: 39%	White: 85% African American: 5% Hispanic or Latinx: 0% Asian: 1% Mixed race and other: 9%	Protestant: 24% Catholic: 38% Jewish: 0% Hindu: 0% Other: 33% Atheist: 4%
MN (21)	18-29 years: 10% 30-44 years: 20% 45-64 years: 26% 65 and older: 44%	Less than high school: 0% High school graduate: 25% Some college: 29% College graduate: 30% Graduate degree: 15%	Less than $20,000: 17% $20,000 to $40,000: 27% $40,000 to $60,000: 7% $60,000 to $80,000: 9% $80,000 to $100,000: 10% Over $100,000: 31%	Very conservative: 25% Somewhat conservative: 39% Moderate: 25% Somewhat liberal: 10% Very liberal: 1%	Male: 64% Female: 36%	White: 85% African American: 5% Hispanic or Latinx: 5% Mixed race and other: 5%	Protestant: 36% Catholic: 20% Muslim: 5% Other: 39% Atheist: 0%
MO (21)	18-29 years: 15% 30-44 years: 34% 45-64 years: 15% 65 and older: 35%	Less than high school: 0% High school graduate: 25% Some college: 40% College graduate: 16% Graduate degree: 19%	Less than $20,000: 13% $20,000 to $40,000: 25% $40,000 to $60,000: 27% $60,000 to $80,000: 17% $80,000 to $100,000: 7% Over $100,000: 11%	Very conservative: 11% Somewhat conservative: 30% Moderate: 32% Somewhat liberal: 16% Very liberal: 10%	Male: 50% Female: 50%	White: 94% African American: 0.5% Asian: 0.2% Mixed race and other: 5%	Protestant: 49% Catholic: 14% Jewish: 0% Other: 31% Atheist: 5%
MS (7)	18-29 years: 0% 30-44 years: 29% 45-65 years: 0% 65 and older: 71%	Less than high school: 14% High school graduate: 14% Some college: 29% College graduate: 29% Graduate degree: 14%	Less than $20,000: 20% $20,000 to $40,000: 9% $40,000 to $60,000: 6% $60,000 to $80,000: 37% $80,000 to $100,000: 21% Over $100,000: 7%	Very conservative: 19% Somewhat conservative: 1% Moderate: 46% Somewhat liberal: 32% Very liberal: 1%	Male: 43% Female: 57%	White: 43% African American: 57%	Protestant: 43% Catholic: 14% Other: 29% Atheist: 14%
MT (4)	18-29 years: 6% 30-44 years: 31% 45-64 years: 28% 65 and older: 35%	Less than high school: 1% High school graduate: 2% Some college: 9% College graduate: 54% Graduate degree: 34%	Less than $20,000: 5% $20,000 to $40,000: 10% $40,000 to $60,000: 32% $60,000 to $80,000: 12% $80,000 to $100,000: 5% Over $100,000: 35%	Very conservative: 56% Somewhat conservative: 2% Moderate: 34% Somewhat liberal: 6% Very liberal: 1%	Male: 36% Female: 64%	White: 94% African American: 1% Hispanic or Latinx: 2% Mixed race and other: 2%	Protestant: 35% Catholic: 31% Hindu: 1% Other: 30% Atheist: 3%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
NC (24)	18-29 years: 26% 30-44 years: 9% 45-64 years: 39% 65 and older: 26%	Less than high school: 0% High school graduate: 40% Some college: 31% College graduate: 15% Graduate degree: 14%	Less than $20,000: 10% $20,000 to $40,000: 35% $40,000 to $60,000: 37% $60,000 to $80,000: 4% $80,000 to $100,000: 6% Over $100,000: 9%	Very conservative: 41% Somewhat conservative: 23% Moderate: 16% Somewhat liberal: 14% Very liberal: 5%	Male: 53% Female: 47%	White: 74% African American: 9% Hispanic or Latinx: 4% Asian: 5% Mixed race and other: 9%	Protestant: 36% Catholic: 24% Other: 32% Atheist: 8%
ND (5)	18-29 years: 40% 30-44 years: 0% 45-65 years: 60% 65 and older: 0%	Less than high school: 0% High school graduate: 20% Some college: 40% College graduate: 20% Graduate degree: 20%	$20,000 to $40,000: 1% $40,000 to $60,000: 26% $60,000 to $80,000: 24% $80,000 to $100,000: 44% Over $100,000: 5%	Very conservative: 40% Somewhat conservative: 40% Moderate: 20% Somewhat liberal: 0% Very liberal: 0%	Male: 60% Female: 40%	White: 80% Asian: 20%	Protestant: 80% Catholic: 20%
NE (8)	18-29 years: 12% 30-44 years: 25% 45-64 years: 50% 65 and older: 12%	Less than high school: 0% High school graduate: 25% Some college: 38% College graduate: 12% Graduate degree: 25%	Less than $20,000: 2% $20,000 to $40,000: 16% $40,000 to $60,000: 6% $60,000 to $80,000: 16% $80,000 to $100,000: 15% Over $100,000: 44%	Very conservative: 42% Somewhat conservative: 41% Moderate: 2% Somewhat liberal: 15% Very liberal: 0%	Male: 62% Female: 38%	White: 100%	Protestant: 54% Catholic: 42% Jewish: 1% Hindu: 1% Other: 2% Atheist: 1%
NH (5)	18-29 years: 20% 30-44 years: 40% 45-64 years: 20% 65 and older: 20%	Less than high school: 0% High school graduate: 0% Some college: 20% College graduate: 60% Graduate degree: 20%	Less than $20,000: 20% $20,000 to $40,000: 20% $40,000 to $60,000: 0% $60,000 to $80,000: 0% $80,000 to $100,000: 20% Over $100,000: 40%	Very conservative: 47% Somewhat conservative: 5% Moderate: 5% Somewhat liberal: 22% Very liberal: 21%	Male: 40% Female: 60%	White: 100%	Protestant: 20% Catholic: 40% Jewish: 20% Other: 20%
NJ (31)	18-29 years: 24% 30-44 years: 26% 45-64 years: 26% 65 and older: 23%	Less than high school: 3% High school graduate: 21% Some college: 30% College graduate: 30% Graduate degree: 16%	Less than $20,000: 6% $20,000 to $40,000: 17% $40,000 to $60,000: 16% $60,000 to $80,000: 16% $80,000 to $100,000: 15% Over $100,000: 30%	Very conservative: 25% Somewhat conservative: 15% Moderate: 24% Somewhat liberal: 30% Very liberal: 6%	Male: 58% Female: 42%	White: 77% African American: 4% Hispanic or Latinx: 10% Mixed race and other: 10%	Protestant: 22% Catholic: 49% Jewish: 6% Muslim: 0.2% Hindu: 0.2% Other: 20% Atheist: 3%
NM (6)	18-29 years: 0% 30-44 years: 50% 45-65 years: 0% 65 and older: 50%	Less than high school: 17% High school graduate: 17% Some college: 17% College graduate: 17% Graduate degree: 33%	Less than $20,000: 17% $20,000 to $40,000: 33% $40,000 to $60,000: 17% $60,000 to $80,000: 17% $80,000 to $100,000: 17% Over $100,000: 0%	Very conservative: 50% Somewhat conservative: 0% Moderate: 17% Somewhat liberal: 0% Very liberal: 33%	Male: 83% Female: 17%	White: 83% Hispanic or Latinx: 17%	Protestant: 23% Catholic: 21% Hindu: 1% Other: 38% Atheist: 17%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
NV (7)	18-29 years: 14% 30-44 years: 29% 45-64 years: 14% 65 and older: 43%	Less than high school: 0% High school graduate: 14% Some college: 29% College graduate: 57% Graduate degree: 0%	Less than $20,000: 0% $20,000 to $40,000: 29% $40,000 to $60,000: 14% $60,000 to $80,000: 14% $80,000 to $100,000: 14% Over $100,000: 29%	Very conservative: 29% Somewhat conservative: 0% Moderate: 43% Somewhat liberal: 14% Very liberal: 14%	Male: 71% Female: 29%	White: 86% Mixed race and other: 14%	Protestant: 45% Catholic: 35% Other: 19% Atheist: 1%
NY (41)	18-29 years: 27% 30-44 years: 15% 45-64 years: 32% 65 and older: 27%	Less than high school: 5% High school graduate: 29% Some college: 20% College graduate: 27% Graduate degree: 20%	Less than $20,000: 16% $20,000 to $40,000: 18% $40,000 to $60,000: 13% $60,000 to $80,000: 22% $80,000 to $100,000: 13% Over $100,000: 18%	Very conservative: 18% Somewhat conservative: 16% Moderate: 25% Somewhat liberal: 18% Very liberal: 23%	Male: 49% Female: 51%	White: 63% African American: 20% Hispanic or Latinx: 10% Asian: 2% Mixed race and other: 5%	Protestant: 39% Catholic: 31% Jewish: 5% Muslim: 0.1% Hindu: 3% Other: 22% Atheist: 0.5%
OH (37)	18-29 years: 11% 30-44 years: 24% 45-64 years: 35% 65 and older: 30%	Less than high school: 5% High school graduate: 32% Some college: 32% College graduate: 16% Graduate degree: 14%	Less than $20,000: 13% $20,000 to $40,000: 19% $40,000 to $60,000: 17% $60,000 to $80,000: 17% $80,000 to $100,000: 9% Over $100,000: 26%	Very conservative: 37% Somewhat conservative: 18% Moderate: 31% Somewhat liberal: 9% Very liberal: 6%	Male: 57% Female: 43%	White: 92% African American: 5% Mixed race and other: 3%	Protestant: 49% Catholic: 23% Muslim: 3% Other: 26%
OK (17)	18-29 years: 12% 30-44 years: 24% 45-64 years: 47% 65 and older: 18%	Less than high school: 0% High school graduate: 25% Some college: 31% College graduate: 8% Graduate degree: 36%	Less than $20,000: 15% $20,000 to $40,000: 11% $40,000 to $60,000: 11% $60,000 to $80,000: 18% $80,000 to $100,000: 16% Over $100,000: 29%	Very conservative: 21% Somewhat conservative: 16% Moderate: 54% Somewhat liberal: 8% Very liberal: 1%	Male: 71% Female: 29%	White: 68% African American: 1% Hispanic or Latinx: 7% Asian: 6% Mixed race and other: 18%	Protestant: 59% Catholic: 24% Jewish: 1% Muslim: 0.3% Hindu: 12% Other: 3% Atheist: 1%
OR (14)	18-29 years: 43% 30-44 years: 1% 45-64 years: 32% 65 and older: 24%	Less than high school: 7% High school graduate: 31% Some college: 37% College graduate: 9% Graduate degree: 16%	Less than $20,000: 23% $20,000 to $40,000: 26% $40,000 to $60,000: 9% $60,000 to $80,000: 12% $80,000 to $100,000: 4% Over $100,000: 26%	Very conservative: 14% Somewhat conservative: 19% Moderate: 41% Somewhat liberal: 10% Very liberal: 16%	Male: 60% Female: 40%	White: 99% Asian: 0.4% Mixed race and other: 0.4%	Protestant: 38% Catholic: 23% Other: 25% Atheist: 15%
PA (35)	18-29 years: 29% 30-44 years: 17% 45-64 years: 26% 65 and older: 29%	Less than high school: 0% High school graduate: 37% Some college: 26% College graduate: 31% Graduate degree: 6%	Less than $20,000: 23% $20,000 to $40,000: 17% $40,000 to $60,000: 24% $60,000 to $80,000: 21% $80,000 to $100,000: 5% Over $100,000: 10%	Very conservative: 10% Somewhat conservative: 27% Moderate: 39% Somewhat liberal: 15% Very liberal: 10%	Male: 57% Female: 43%	White: 88% African American: 3% Hispanic or Latinx: 3% Mixed race and other: 6%	Protestant: 34% Catholic: 26% Jewish: 3% Muslim: 3% Other: 31% Atheist: 3%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
RI (3)	18-29 years: 0% 30-44 years: 0% 45-65 years: 33% 65 and older: 67%	Less than high school: 0% High school graduate: 0% Some college: 33% College graduate: 0% Graduate degree: 67%	Less than $20,000: 7% $20,000 to $40,000: 10% $40,000 to $60,000: 38% $60,000 to $80,000: 3% $80,000 to $100,000: 3% Over $100,000: 38%	Very conservative: 0% Somewhat conservative: 0% Moderate: 67% Somewhat liberal: 0% Very liberal: 33%	Male: 33% Female: 67%	White: 93% African American: 2% Hispanic or Latinx: 5%	Protestant: 13% Catholic: 77% Other: 8% Atheist: 2%
SC (10)	18-29 years: 10% 30-44 years: 20% 45-64 years: 30% 65 and older: 40%	Less than high school: 0% High school graduate: 30% Some college: 40% College graduate: 10% Graduate degree: 20%	Less than $20,000: 6% $20,000 to $40,000: 18% $40,000 to $60,000: 7% $60,000 to $80,000: 55% $80,000 to $100,000: 6% Over $100,000: 6%	Very conservative: 2% Somewhat conservative: 32% Moderate: 54% Somewhat liberal: 11% Very liberal: 1%	Male: 40% Female: 60%	White: 100%	Protestant: 60% Catholic: 10% Other: 30%
SD (1)	18-29 years: 0% 30-44 years: 100% 45-65 years: 0% 65 and older: 0%	Less than high school: 0% High school graduate: 0% Some college: 0% College graduate: 0% Graduate degree: 100%	Less than $20,000: 0% $20,000 to $40,000: 0% $40,000 to $60,000: 0% $60,000 to $80,000: 100% $80,000 to $100,000: 0% Over $100,000: 0%	Very conservative: 0% Somewhat conservative: 0% Moderate: 100% Somewhat liberal: 0% Very liberal: 0%	Male: 0% Female: 100%	White: 100%	Catholic: 100%
TN (16)	18-29 years: 25% 30-44 years: 31% 45-64 years: 31% 65 and older: 12%	Less than high school: 6% High school graduate: 19% Some college: 50% College graduate: 19% Graduate degree: 6%	Less than $20,000: 4% $20,000 to $40,000: 24% $40,000 to $60,000: 17% $60,000 to $80,000: 10% $80,000 to $100,000: 14% Over $100,000: 31%	Very conservative: 19% Somewhat conservative: 26% Moderate: 47% Somewhat liberal: 1% Very liberal: 7%	Male: 38% Female: 62%	White: 94% Hispanic or Latinx: 6%	Protestant: 42% Catholic: 28% Jewish: 6% Hindu: 0.3% Other: 22% Atheist: 1%
TX (64)	18-29 years: 29% 30-44 years: 14% 45-64 years: 35% 65 and older: 22%	Less than high school: 2% High school graduate: 31% Some college: 22% College graduate: 23% Graduate degree: 22%	Less than $20,000: 17% $20,000 to $40,000: 24% $40,000 to $60,000: 16% $60,000 to $80,000: 13% $80,000 to $100,000: 11% Over $100,000: 20%	Very conservative: 16% Somewhat conservative: 16% Moderate: 41% Somewhat liberal: 16% Very liberal: 11%	Male: 56% Female: 44%	White: 64% African American: 6% Hispanic or Latinx: 13% Asian: 8% Mixed race and other: 9%	Protestant: 41% Catholic: 23% Hindu: 3% Other: 20% Atheist: 13%
UT (12)	18-29 years: 50% 30-44 years: 17% 45-64 years: 25% 65 and older: 8%	Less than high school: 0% High school graduate: 17% Some college: 33% College graduate: 50% Graduate degree: 0%	Less than $20,000: 30% $20,000 to $40,000: 22% $40,000 to $60,000: 25% $60,000 to $80,000: 5% $80,000 to $100,000: 10% Over $100,000: 8%	Very conservative: 27% Somewhat conservative: 35% Moderate: 18% Somewhat liberal: 18% Very liberal: 1%	Male: 67% Female: 33%	White: 100%	Protestant: 22% Catholic: 13% Hindu: 1% Other: 54% Atheist: 9%

State (*n*)	**Variable**						
	Age	**Education**	**Income**	**Political Views**	**Gender**	**Race**	**Religion**
VA (17)	18-29 years: 24% 30-44 years: 24% 45-64 years: 29% 65 and older: 24%	Less than high school: 0% High school graduate: 29% Some college: 53% College graduate: 12% Graduate degree: 6%	Less than $20,000: 19% $20,000 to $40,000: 3% $40,000 to $60,000: 8% $60,000 to $80,000: 13% $80,000 to $100,000: 12% Over $100,000: 45%	Very conservative: 14% Somewhat conservative: 14% Moderate: 38% Somewhat liberal: 21% Very liberal: 13%	Male: 59% Female: 41%	White: 59% African American: 35% Mixed race and other: 6%	Protestant: 41% Catholic: 12% Jewish: 6% Other: 35% Atheist: 6%
VT (1)	18-29 years: 100% 30-44 years: 0% 45-65 years: 0% 65 and older: 0%	Less than high school: 0% High school graduate: 0% Some college: 0% College graduate: 100% Graduate degree: 0%	Less than $20,000: 100% $20,000 to $40,000: 0% $40,000 to $60,000: 0% $60,000 to $80,000: 0% $80,000 to $100,000: 0% Over $100,000: 0%	Very conservative: 0% Somewhat conservative: 0% Moderate: 0% Somewhat liberal: 0% Very liberal: 100%	Male: 100% Female: 0%	White: 100%	Atheist: 100%
WA (17)	18-29 years: 24% 30-44 years: 24% 45-64 years: 18% 65 and older: 35%	Less than high school: 0% High school graduate: 20% Some college: 43% College graduate: 13% Graduate degree: 24%	Less than $20,000: 9% $20,000 to $40,000: 35% $40,000 to $60,000: 4% $60,000 to $80,000: 17% $80,000 to $100,000: 4% Over $100,000: 31%	Very conservative: 23% Somewhat conservative: 16% Moderate: 35% Somewhat liberal: 14% Very liberal: 13%	Male: 59% Female: 41%	White: 71% African American: 3% Hispanic or Latinx: 0% Asian: 18% Mixed race and other: 7%	Protestant: 29% Catholic: 11% Muslim: 0.3% Hindu: 7% Other: 46% Atheist: 7%
WI (27)	18-29 years: 16% 30-44 years: 34% 45-64 years: 24% 65 and older: 27%	Less than high school: 0% High school graduate: 15% Some college: 27% College graduate: 27% Graduate degree: 31%	Less than $20,000: 12% $20,000 to $40,000: 20% $40,000 to $60,000: 14% $60,000 to $80,000: 13% $80,000 to $100,000: 21% Over $100,000: 21%	Very conservative: 27% Somewhat conservative: 13% Moderate: 33% Somewhat liberal: 18% Very liberal: 8%	Male: 54% Female: 46%	White: 85% African American: 4% Hispanic or Latinx: 0% Asian: 7% Mixed race and other: 4%	Protestant: 27% Catholic: 38% Hindu: 4% Other: 31% Atheist: 0.2%
WV (7)	18-29 years: 0% 30-44 years: 43% 45-65 years: 0% 65 and older: 57%	Less than high school: 14% High school graduate: 29% Some college: 29% College graduate: 14% Graduate degree: 14%	Less than $20,000: 21% $20,000 to $40,000: 34% $40,000 to $60,000: 9% $60,000 to $80,000: 22% $80,000 to $100,000: 6% Over $100,000: 7%	Very conservative: 22% Somewhat conservative: 17% Moderate: 25% Somewhat liberal: 35% Very liberal: 1%	Male: 71% Female: 29%	White: 100%	Protestant: 66% Catholic: 16% Jewish: 1% Other: 18%
WY (2)	18-29 years: 10% 30-44 years: 15% 45-64 years: 15% 65 and older: 60%	Less than high school: 5% High school graduate: 65% Some college: 18% College graduate: 8% Graduate degree: 5%	Less than $20,000: 0% $20,000 to $40,000: 5% $40,000 to $60,000: 5% $60,000 to $80,000: 58% $80,000 to $100,000: 8% Over $100,000: 25%	Very conservative: 65% Somewhat conservative: 8% Moderate: 18% Somewhat liberal: 8% Very liberal: 3%	Male: 82% Female: 18%	White: 95% Hispanic or Latinx: 2% Mixed race and other: 2%	Protestant: 68% Catholic: 12% Jewish: 2% Other: 15% Atheist: 2%