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Clean Energy Justice: Clean Energy Access and Vulnerable Communities toward Just Energy Transition

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Abstract

Clean Energy Justice: Clean Energy Access and Vulnerable Communities toward Just Energy Transition

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This dissertation proposes clean energy justice that links energy justice to clean energy access and vulnerable communities in terms of geographic distribution (distributional justice) and community attributes with respect to places, people, and equality (recognition justice). The first study of this dissertation argues that adoption attributes are different by communities and technologies. In particular, I find that rooftop solar adoption is strongly associated with housing variables and communities with lower adoption rates. On the other hand, I find that electric vehicle (EV) charger adoption is additionally and strongly associated with economic variables. Furthermore, communities in Seattle present higher variations in rooftop solar adoption than in EV charger adoption. The second study proposes that energy vulnerability can be characterized by energy resiliency associated with rooftop solar adoption and energy dependency related to energy burden. I find that city-level variations of rooftop solar adoption and energy burden are obvious even after controlling for community attributes. Furthermore, rooftop solar distribution in the Pacific Northwest major cities - Seattle, Bellevue, and Portland, presents significant spatial lag effects while energy burden shows a higher city-level variation. In addition, I identify vulnerable communities in terms of energy resiliency and energy dependency. In the third study, I introduce four energy justice domains in terms of two driving forces - technology development and equitable policies.

Based on inequality and inequity associated with distributional and recognition justice, I quantify clean energy access in terms of four indices in three cities. I find that inequality and inequity of rooftop solar distribution and adoption have increased across communities in the cities over time. In conclusion, I discuss implications for future research and advocate for implementing tailored support to local communities based on the identified attributes.

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DEDICATION

To my mom, wife, and daughter

CONCEPTS AND TERMINOLOGY

Clean Energy: Energy from renewable and zero emission sources such as solar, wind, tidal, hydro power, and geothermal.

Clean Energy Justice: Energy justice specific to clean energy access through the adoption of clean energy technologies or distributed energy resources (DERs).

Climate Justice: A concept focusing on a fair treatment of all communities associated with ethical and political issues of climate change and carbon emission. It developed in the 1990s further from environmental justice (Fuller and McCauley 2016).

Digital Divide: The uneven distribution of telecommunication infrastructure causing a social gap between populations who can access digital technologies versus populations who cannot (Chen and Wellman 2004).

Distributional (spatial) Justice: A concept linking social justice and space associated with resource distribution by identifying locations of disproportionate distribution of benefits, ills, and responsibilities (Jenkins et al. 2016).

Distributed Energy Resources (DERs): Resources providing electricity and power needs to consumers by being installed near consumers and being connected to the distribution system such as rooftop solar, demand response, electric vehicles, wind turbines, batteries, and micro-grids (Akorede et al. 2010; REN21 2019).

Energy Burden: Proportional expenditure of a household income to consume energy (Drehobl et al. 2020).

Energy Divide: Inequalities in access to energy services causing a social gap between populations who can access energy services versus populations who cannot (Bouzarovski and Tirado Herrero 2017).

Energy Equity: A concept recognizing underserved or disadvantaged communities associated with social equity in energy services extended from environmental and climate justice (Jenkins et al. 2016).

Energy Insecurity: Inability to meet energy consumption needs (Drehobl et al. 2020).

Energy Justice: A fair distribution of benefits and burdens associated with the energy system, climate change, and socioeconomic participation by removing the structural barriers to vulnerable communities (Sovacool et al. 2017).

Energy Poverty (Fuel Poverty): Lack of access to energy services in terms of accessibility of physical energy infrastructure, and affordability of energy at an appropriate price (Sovacool et al. 2013).

Environmental Justice: A concept referred to as a fair distribution of environmental benefits and burdens from the early 1980s (Fuller and McCauley 2016).

Fossil Fuel-Based Economy: An economy system based on fossil fuels such as coal, oil, and natural gas entailing carbon emission in the atmosphere by burning them.

GeoAI: A study that extends GIScience with Artificial Intelligence (AI) focusing on spatial attributes by creating intelligent geographic information such as image classification, object detection, scene segmentation, simulation, and interpolation (Janowicz et al. 2020).

Geographic Information System (GIS): A technology that handles geographically referenced data in terms of creating, managing, analyzing and visualizing based on three kinds of representational models (1) a grid of geographic coordinates, (2) map projections affecting shape, angle, and relative positions, and (3) visual representations - vector and raster (Knowles et al. 2015).

GIScience (Geographic information science): A study of science that concerns the understanding of geographic data associated with the use of GIS and relevant technologies such as mapping and spatial analysis (Janowicz et al. 2020).

Phenomenology: A science of phenomena in consciousness of an object who experience the world considering that knowledge comes from the object's point of view (Lea 2020).

Post-phenomenology: A philosophical theory led by limits of positivism after the Second World War and anthropocentrism featuring the analytic centrality of the human experience of life-worlds by taking in the inhuman and the nonhuman against the criticized subjectivism of phenomenology (Lea 2020). Ihde's pragmatic approach to post-phenomenology enables the operative use of philosophy in a social context (Verbeek 2001).

Procedural Justice: A concept associated with fairness in the processes such as remediation, and resource allocations in terms of decision-making, information disclosure, and institutional representation (Jenkins et al. 2016).

Risk: A composition of threat, vulnerability, and consequence (Linkov et al. 2014).

Recognition Justice: A concept focusing on who receive fewer benefits, and is affected, such as underserved communities. The lack of recognition justice entails losing the insights of marginalized social groups (Jenkins et al. 2016).

Regressive Effects: Detrimental effects on low-income households by regulations and policies that benefit the wealthy while imposing costs on all households including the low-income households (Bailey et al. 2019).

Resilience: An ability in preparation, absorption, recovery, and adaptation to stressors in terms of sustainability-related dimensions such as availability, accessibility, affordability, and acceptability (Sharifi and Yamagata 2016).

Spillover Effects: An indirect effect on a subject by neighboring ones (Dharshing 2017).

Vulnerability: Being at risk of having limited capacity to protect one's interests (Mackenzie et al. 2014).

INTRODUCTION

0.1 Background

0.1.1 Transition to distributed energy resources (DERs)

Recent global climate change has triggered a rapid transition to distributed energy resources (DERs) while promoting the development of various clean energy policies aimed at decarbonization and electrification (Nowotny et al. 2018). DERs, such as rooftop solar or photovoltaic systems (PVs), demand response, electric vehicles (EVs), wind turbines, batteries, and micro-grids, provide electricity and power needs by being installed near consumers and being connected to the distribution (Akorede et al. 2010; REN21 2019). The benefits of the transition to such technologies are well studied and documented. For example, the transition from conventional fossil-fuel markets increases grid resilience as a way to mitigate the impacts of climate change (Ajaz 2019; Lin and Bie 2016) in addition to providing economic, health, and environmental benefits by reducing greenhouse gas emissions and air pollutants (Krieger et al. 2016).

0.1.2 Social equity in the transition

Specific to social equity, the fossil fuel-based economy has disproportionately harmed low-income communities, such as power plant facilities located near these communities (Healy and Barry 2017). On the other hand, the transition to DERs has the potential for more equitable distribution of electricity generation by involving a greater number of consumers to participate in energy production compared to a centralized energy supply system (Jenkins et al. 2016). For example, rooftop solar adoption increases energy access for those who have difficulties to connect to the grid, and provides resiliency against the electricity outages (Ajaz 2019; Krieger et al. 2016). In addition, DERs such as rooftop solar can help promote social equity through the reduction of energy poverty (Sovacool et al. 2013). However, the transition to DERs can still lead to social inequity if the benefits and burdens are disproportionately distributed according to socioeconomic status. In addition, energy transition can be a source of geographically uneven social, political, and environmental displacements, increasing vulnerability of particular groups (Bouzarovski and Simcock 2017). This issue can be exacerbated when decision-making processes are not equally accessible or if certain populations are excluded from the benefits of DERs (Carley and Konisky 2020). In that regard, the following concerns have emerged with the current transition of energy systems toward DERs.

0.2 Problems in energy transition

0.2.1 Energy divide

First, societal energy transformation is highly associated with social inequity, as the distribution of benefits from DER adoption is usually localized in higher-income areas (Poruschi and Ambrey 2019). The transition can inadvertently result in uneven access to clean energy, which can disproportionately influence community resilience to adverse conditions. Uneven distribution of DERs can be described as the "energy divide," i.e., inequalities in access to energy services (Bouzarovski and Simcock 2017). The energy divide is a similar concept to the "digital divide" identified in the late 20th century, referring to the disproportionate distribution of telecommunication infrastructure that caused a social gap between populations who can access digital technologies versus populations who do not (Chen and Wellman 2004). Thus, the energy divide results from a failure to provide equal access to energy services including DERs for all communities.

0.2.2 Regressive effects

Second, grid modernization to accommodate DERs may inadvertently result in energy inequity due to financial burdens such as increased electric bills or imposed regressive effects on underserved communities. In general, grid modernization is necessary to improve the reliability of energy systems and their maintenance. However, if the cost of these improvements is passed to electricity customers, increased electricity bills may exacerbate energy inequities (Brown et al. 2020a; Mastropietro 2019). Empirical analyses indicate that some communities are burdened with the costs of accommodating DERs in the grid without receiving commensurate benefits (Jenkins et al. 2016; Poruschi and Ambrey 2019). In addition, rebates and incentives, such as tax credits, production performance credits, and property and sales tax exemptions for installation of DERs, are examples of regressive policies that benefit wealthier households who can already afford to install those technologies, whereas the less wealthy are generally excluded from these benefits (Poruschi and Ambrey 2019). In other words, those who cannot afford to invest in DERs in the first place will not have access to the opportunities offered by such incentives.

0.2.3 Reliability of power supply

Third, the intermittent power generation of PVs and uncertain EV charging schedules can inadvertently impact the reliability of the grid systems. This increases challenges to grid system operators requiring improved forecasting, new operating tools ensuring stability and coordination between systems. This is especially true for regions with higher decentralization trends with the lack of active generation and demand connected as the regions require more diverse and less correlated power sources, energy storage and demand participation (Howell et al. 2017).

0.3 Objectives

In response to these concerns, the present study aims to examine spatio-temporal adoption patterns of DERs and energy burden to identify the energy justice of technology adoption and energy vulnerability in the residential built environment. Energy justice refers to a fair distribution of benefits and burdens associated with the energy system, climate change, and socioeconomic participation by removing the structural barriers to vulnerable communities

(Sovacool et al. 2017). Specifically, distributional justice concerns geographic differences in the distribution of resources (Jenkins et al. 2016), thus it is examined by the geographical distributions of DERs and energy burden. On the other hand, recognition justice deals with sociodemographic differences across populations and communities, potentially leading to social inequities (Jenkins et al. 2016). In this dissertation, I investigate the level of DER adoption and energy burden by grouped communities that share similar characteristics. In particular, the study involves (1) identifying the distribution characteristics of DERs associated with clean energy access, (2) examining energy vulnerability characteristics in terms of energy dependency and energy resiliency to identify vulnerable communities. Moreover, the study is also aimed at (3) quantifying energy justice with suggested indices illustrating spatio-temporal trends of rooftop solar adoption in terms of equality and equity perspectives.

Communities are characterized by "place," "people," and "equality" such that place refers to the characteristics of the built environment and housing, people is associated with the socioeconomic and demographic characteristics, and equality refers to the income equality of communities. The proposed framework to investigate attributes of DER adoption and vulnerable communities with respect to energy justice is summarized in Figure 1.

0.4 Organization of the dissertation

The dissertation is organized in literature review in Chapter 1, research methodologies in Chapter 2, three individual studies in Chapter 3, 4, and 5, and Conclusion. In Chapter 3, I mainly examine distribution characteristics of DERs associated with communities with different adoption rates in Seattle, Washington. Then, I expand the study to other major Pacific Northwest cities - Bellevue and Portland - to identify vulnerability characteristics in terms of energy dependency and energy resiliency in Chapter 4. Furthermore, I identify vulnerable communities using the energy vulnerability attributes. In Chapter 5, I introduce a framework to quantify energy justice by examining the trend of rooftop solar adoption in the Pacific Northwest cities. Finally, I conclude the dissertation with some remarks in Conclusion.

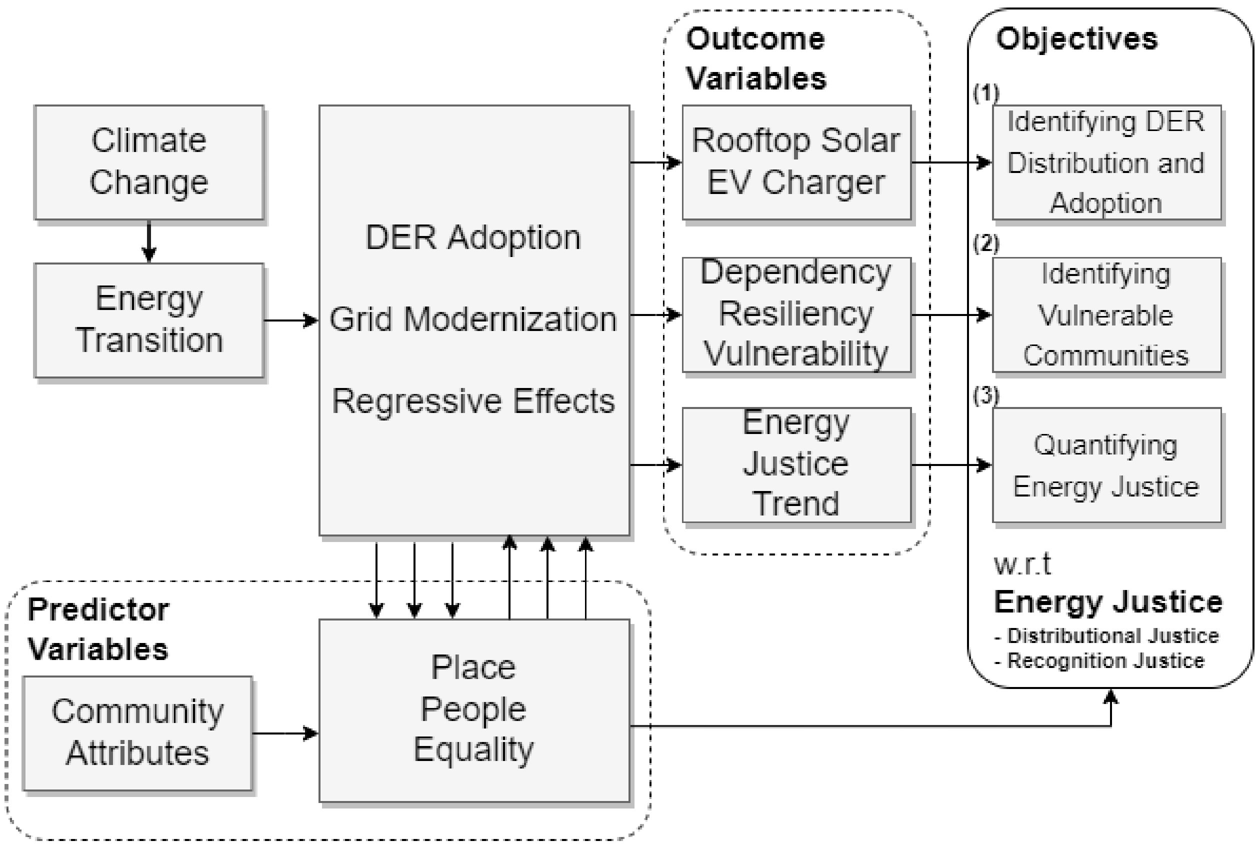

Figure 1: Proposed framework for identifying characteristics of DERs and vulnerable communities and quantifying energy justice to design equitable policies.

0.4.1 Chapter 3: Distribution and adoption characteristics of DERs

Concerns over global climate change have developed various clean energy policies and resources. However, social equity issues have emerged in association with the rapid transition of energy systems toward DERs, evidenced by disparities in clean energy access. While most existing studies have focused on a few significant variables impacting the adoption of DERs, there is a dearth of studies specifically aimed at investigating: (1) which adoption variables of DERs are more significant; and (2) how adoption patterns vary by communities with different adoption rates for different DERs concerning distributional and recognition justice. The objective of the chapter is to characterize the distribution and the adoption of rooftop solar and EV chargers by communities with different attributes in Seattle. The chapter involves identifying latent variables from variables that are highly correlated with each other.

0.4.2 Chapter 4: Identifying vulnerable communities

Climate change has disproportionately affected communities. Government agencies have encouraged clean energy access aimed at developing more resilient communities to address the issue. However, some government programs intended to promote equitable access to clean energy resources have inadvertently caused disproportionate rates of program participants for vulnerable communities in addition to inequitable resource distribution. Better recognition of those vulnerable populations and communities is required for a more equitable distribution of resources and benefits. However, it is difficult to determine vulnerable communities with a single determinant or various measures defining energy vulnerability. The study in this chapter characterizes energy vulnerability to identify vulnerable communities by examining energy justice in terms of energy dependency and energy resiliency. In particular, the study examines vulnerability predictors identified in the literature in three Pacific Northwest cities, Seattle, Bellevue, and Portland. The study further involves introducing a framework to identify vulnerable communities in King County urban area of Washington —which currently does not have energy justice measure data.

0.4.3 Chapter 5: Quantifying energy justice

The objective of this chapter is to answer the three questions. (1) How can clean energy justice be defined as associated with important and uncertain driving forces of the energy transition and plausible scenarios? (2) How can clean energy justice be quantified? (3) What strategies can address clean energy justice? By analyzing spatio-temporal adoption patterns of rooftop solar associated with the built environment, socioeconomic, and demographic characteristics, the chapter examines clean energy justice in terms of two driving forces (technology development and equitable policies) in the Pacific Northwest cities.

0.4.4 Impact of the studies

The impact of the studies is to help policymakers better support communities with limited resources by devising equitable policies for more resilient communities. In particular, the study results show that communities with lower DER adoption rates such as renters and multi-family households are more sensitive to housing variables than income and race variables, so support focused on these populations is likely to be more effective in boosting DER adoption than mere financial assistance. Furthermore, the results reveal that city-level variations exist even after controlling for the other variables with growing inequality and inequity in rooftop solar distribution and adoption. The findings question distributional and recognition justice in the Pacific Northwest cities. The results indicate that policies aimed at increasing DER adoption in vulnerable communities should be tailored to local characteristics concerning the inequality and inequity of the distribution and adoption. The rapid transition to electrification and decarbonization is associated with increasing electricity rates due to grid modernization to accommodate newly installed DERs and financial incentives to encourage DER adoption. By studying DER adoption attributes and adoption strategies associated with community attributes, the studies will encourage DER adoption in vulnerable communities.

Chapter 1

LITERATURE REVIEW

Post-phenomenology relates human experience through technology as a mediation. In particular, people and "place" can be linked through the human experience in different contexts such as city and community. Furthermore, place can be referred to as either geographical location or locale which is a setting of daily activities. In addition, people can be characterized by their built environment, socioeconomic, and demographic characteristics in terms of community and household. Energy justice, particularly distributional and recognition justice are linked to post-phenomenology through the characteristics of place and people. The proposed conceptualization of a relationship between post-phenomenology and energy justice in terms of place, technology, and people is illustrated in Figure 1.1.

1.1 Interconnection among place, technology, and people

1.1.1 Place, technology, and people in post-phenomenology

Resilient and sustainable infrastructure systems are important in an era of climate change with respect to the built environment and local communities, speaking more broadly, technologies, places, and people. Community or neighborhood can be considered as a platform where technologies, places, and people interact. Furthermore, digital technologies and media that have shaped social lives, individual behaviors, and broader cultural understandings have incurred the emergence of post-phenomenology associated with the changing nature of the world (Lea 2020). Don Ihde (2004) conceptualized post-phenomenology with the changing nature of the world with cyberspace and technoscience. Phenomenology is the study of phenomena in consciousness of the subjective who experience the world (Lea 2020). For instance, phenomenology sees that knowledge comes from our own point of view as opposed

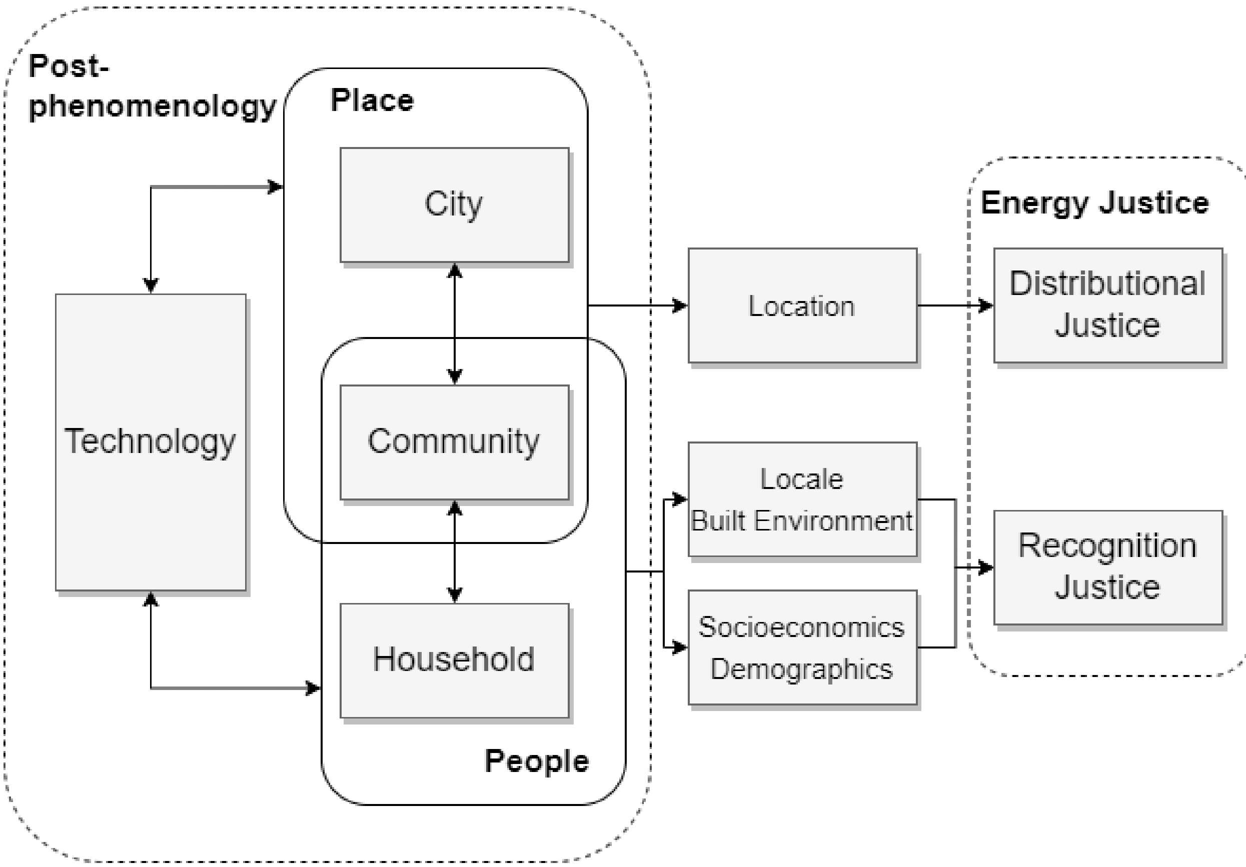

Figure 1.1: Conceptualization of a relationship between post-phenomenology and energy justice in terms of place, technology, and people.

to objective facts. Limits of positivism after the Second World War and anthropocentrism featuring the analytic centrality of the human experience of life-worlds brought about post-phenomenology by taking in the inhuman and the nonhuman against the criticized subjectivism of phenomenology (Lea 2020). Ihde's pragmatic approach to post-phenomenology enables the operative use of philosophy in a social context (Verbeek 2001).

Post-phenomenology relates human experience through technology as a mediator. In particular, with technology, human beings and "place" can be linked through the human experience in different contexts. The relationship between humans and place can be discussed through technologies in terms of embodiment, hermeneutics, autonomy, and background (Verbeek 2001). For example, clean technologies such as distributed energy resources (DERs) are associated with the background relation since the technologies and environment or place become merged such that rooftop solar or EV chargers are parts of place where they are installed. Furthermore, geospatial data is a representation of place on a high level because human beings experience and interpret place through the representation (Zhao 2022).

1.1.2 Place as location and locale

What is "place" in the context of technological innovation and human experience? First, technological innovation has influenced the conceptual definition of place related to the question. GeoAI and GIScience, the new paradigm of joint frameworks of empirical, theoretical, and computational research are examples of the innovation (Janowicz et al. 2020). Place is more than "space" as it is not bounded, rather complex, dynamic, and permeable (Zhou et al. 2018). Place is fundamental to understanding knowledge production and dissemination since it includes the experiences of human beings as agents, while the experience of place varies by different groups from the feminist perspective or pluralism (Agnew and Livingstone 2011).

Place can be described in the concepts of location, locale, and sense of place for empirical purposes (Zhou et al. 2018). Geographic location of a city is an example of place as the location. Place as the locale is associated with settings of daily activities such as home, school, and park. A community is associated with both dimensions of location and locale since a community can be referred to as a geographic location as well as a setting of daily activities of people. In this regard, a community also characterizes people who live there. The sense of place, the other dimension of place, is related to the pluralism associated with feminist, humanist, and performative points of view that interpret places as time-space configurations established by intersections of agents such as people and things. For example, a human agent can physically explore cyberspace through a virtual reality where the agent can perceive the space where it feels to be located with motor control and body ownership or senses of embodiment (Kilteni et al. 2012).

1.1.3 Politics of technology

Technical systems are interwoven with politics in terms of socio-economic context since technology is public power source. For example, clean energy access through DERs enhances resilience of vulnerable communities to climate change events. Furthermore, artifacts that are designed in a certain way or systemic contexts can be tools to present power or establish patterns of power (Winner 1980). In the meantime, social and economic systems where the technical systems are embedded are also significant to the implication of the technical systems. For example, constructivism and hermeneutic approach in regard to social meaning and cultural horizon discovered that public human actors, in fact, could determine the way technology evolves (Feenberg 1992). In other words, once public human actors used to be subordinated to technology, now have advance technology further. This process is referred to as "subversive rationalization" (Feenberg 1992). However, certain technologies are inherently political in that they require specific social structures (Winner 1980). For example, nuclear energy is inherently autocratic requiring a specific social structure (Winner 1980) while rooftop solar is democratic and decentralized in that people can take advantage of resilient and equitable clean energy supply on their own. The equitable energy supply will still depend on the social structure which makes it possible though equitable policies associated with less regressive effects. In short, we cannot ignore the social or economic contexts where the artifacts are embedded.

In the post-phenomenological perspective, technologies shape the interpretive framework and organize political interaction (Feenberg 1992). From a democratic perspective, the post-phenomenological approach to the politics of technology is associated with liberalism and populism (Verbeek 2001). Power relations are technologically mediated with limits and opportunities of liberalism. Also, technologically mediated politics reveal mediated ways to bring people together and provide new forms of political issues and opportunities. For example, clean technologies such as rooftop solar and EV chargers have raised a political issue - energy justice. The disproportionate distribution of technologies has questioned distributional and recognition justice and formed a public consensus of equitable clean energy access regardless of socioeconomic and demographic characteristics such as income, race, and education attainment.

1.2 Energy justice

Energy equity or social equity in energy is referred to as "energy justice," a concept extended from environmental and climate justice (Jenkins et al. 2016). Environmental justice from the early 1980s refers to the fair distribution of environmental benefits and burdens (Fuller and McCauley 2016). Later, climate justice was developed further in the 1990s focusing on fair treatment of all populations and communities from climate change and carbon emission (Jenkins et al. 2016). Energy justice is associated with concepts such as energy accessibility, affordability, availability, poverty, and burden (Sovacool et al. 2013). Energy poverty which can be described as energy insecurity, an inability to meet energy consumption needs entail accessibility of physical energy infrastructure or affordability of energy at an appropriate price (Drehobl et al. 2020; Sovacool et al. 2013). Energy burden is the proportional expenditure of a household income on energy consumption; low- and moderate- income (LMI) and racial minority households disproportionately experience a high energy burden in the U.S.(Drehobl et al. 2020). Energy justice is also associated with energy vulnerability and social equity on distributional unfairness (i.e., geographically disproportionate distribution related to community attributes) (Fuller and McCauley 2016). Energy justice has recently received significant attention for inclusive decision-making on equitable distribution of costs imposed on neighborhoods and benefits from access to modern energy systems (Jenkins et al. 2016; Sovacool et al. 2013).

Energy justice has been further discussed in distributional, recognition, and procedural aspects of energy production and consumption (Jenkins et al. 2016). First, distributional (spatial) justice highlights concerns in resource distribution by identifying locations of disproportionate distribution of benefits, ills, and responsibilities (Healy and Barry 2017). The lack of geographic considerations was emphasized in the understanding of injustice, inequality, and inequity of energy poverty (Bouzarovski and Simcock 2017). Second, recognition justice focuses on who is affected, such as underserved communities which receive fewer benefits (Jenkins et al. 2016). The lack of recognition justice entails losing the insights of marginalized social groups (Jenkins et al. 2016). Also, disregarding the spatial dimension of energy infrastructure can lead to recognition injustice by ignoring certain groups due to spatial segregation (Bouzarovski and Simcock 2017). Therefore, the locale of a place is related to recognition justice. Lastly, procedural justice identifies strategies for remediation in terms of decision-making, information disclosure, and institutional representation (Jenkins et al. 2016).

Sovacool and Dworkin (2015) introduced eight principles of energy justice as a decision-making tool for energy policy: (1) availability for energy security of supply; (2) affordability associated with electricity prices; (3) due process of stakeholder's participation in policy making process; (4) good governance with information, accountability, and transparency; (5) sustainability i.e., meeting the needs of the present without compromising the needs of future generations; (6) intergenerational equity for present and future generation; (7) intragenerational equity for different communities access to energy; and (8) responsibility for environment, climate change, future generation, and non-human species. Moreover, Sovacool et al. (2017) added two more principles: (9) resistance, which is standing up to injustice and (10) intersectionality, which is intertwined with socioeconomic, political and environmental aspects.

Energy justice goes beyond energy equity since it additionally focuses on removing the structural barriers to vulnerable communities. Government agencies can adopt equityoriented policies concentrating on vulnerable communities to address the structural barriers. Such policies include providing customized tools to the specific communities. For example, community solar, by utilizing virtual net energy metering (NEM) in some communities, allows those who cannot afford to install rooftop solar to benefit from the clean energy access (Augustine and McGavisk 2016). Moreover, reducing the soft cost, such as smoothing the electrical permit process of rooftop solar, can lower the barrier to entry for those populations (Seel et al. 2014). Hence, energy justice refers to the equitable distribution of benefits and burdens of the energy system associated with climate change and socioeconomic participation by removing the structural barriers to vulnerable communities.

1.3 Energy resiliency and vulnerability

Energy resilience studies are still at an emerging stage and only a few studies have tried to define energy resilience. The common definition of resilience is discussed in terms of abilities in preparation, absorption, recovery, and adaptation to stressors and sustainability-related dimensions such as availability, accessibility, affordability, and acceptability (Sharifi and Yamagata 2016). "Preparation" in resilience ability and "availability" in sustainable dimensions were the most critical considerations to address energy resilience (Sharifi and Yamagata 2016). Preparation involves early adoption of planning and design measures to avoid potential disruptions and is the most effective method to improve resilience (Sharifi and Yamagata 2016). Furthermore, reserve margins, diverse energy sources, and monitoring systems could improve the "availability" of energy services (Sharifi and Yamagata 2016).

Resilience is different from risk in that risk refers to a composition of threat, vulnerability, and consequence (Linkov et al. 2014). Risk assessment is performed based on known and quantifiable threats. On the other hand, resilience is unknown and uncharacterized that it entails systematic characteristics where four components are sequenced - plan or prepare to absorb, recover, and adapt (Linkov et al. 2014). Typical risk management focuses on planning and avoiding or reducing vulnerabilities while resilience management has additional emphasis on expediting recovery and facilitating adaptation (Roege et al. 2014). Thus, resilience management is an overall process of a recovery in time while risk management is a part of resilience management.

Then, how can we define energy vulnerability? Vulnerability is defined as being at risk of having limited capacity to protect one's interests (Mackenzie et al. 2014). It is mainly interpreted in connection with weakness, dependency, powerlessness, deficiency, and passivity (Gilson 2013). Furthermore, vulnerability can be discussed in two sources - "inherent" and "situational" (Mackenzie et al. 2014). Inherent vulnerability is defined as peoples' neediness and dependence on others. This applies to energy dependency in modern society because energy is essential to the basic human needs to sustain life. Situational vulnerability is context-dependent such that the negative impact of energy poverty on a certain community would be different from the impact on other communities, depending upon social, political, economic, and environmental situations. For example, the effects of winter hurricanes in Texas would be lesser in a community with more resilient or alternative energy systems such as DERs (Public 2021). Thus, characteristics of vulnerability in climate change are associated with energy dependency and social, political, economic, and environmental conditions. The conceptualization of relationships among risk, resilience, and energy justice in terms of energy vulnerability, energy resiliency, and energy dependency is summarized in Figure 1.2.

1.3.1 Social vulnerability

There are indices to represent the social vulnerability of diverse communities for measuring resilience against hazards or risks. For example, the Centers for Disease Control and Prevention (CDC) determines the Social Vulnerability Index (SVI) based on 15 social factors such as poverty, income, and age that are grouped into four major domains – socioeconomic, household composition, minority, and housing type and transportation in response to an emergency or hazardous events (Flanagan et al. 2018). SVI has been used in disaster management such as wildfire, sea-level rise, and youth fitness by government agencies and has been validated that the indices perform better than other indices (Flanagan et al. 2018). For example, SVI are used for the COVID-19 map for decision-making under limited resources such as vaccines. Similarly, another vulnerability index was developed using a factor analytic approach, with 42 socioeconomic and demographic variables at a county level in the U.S.

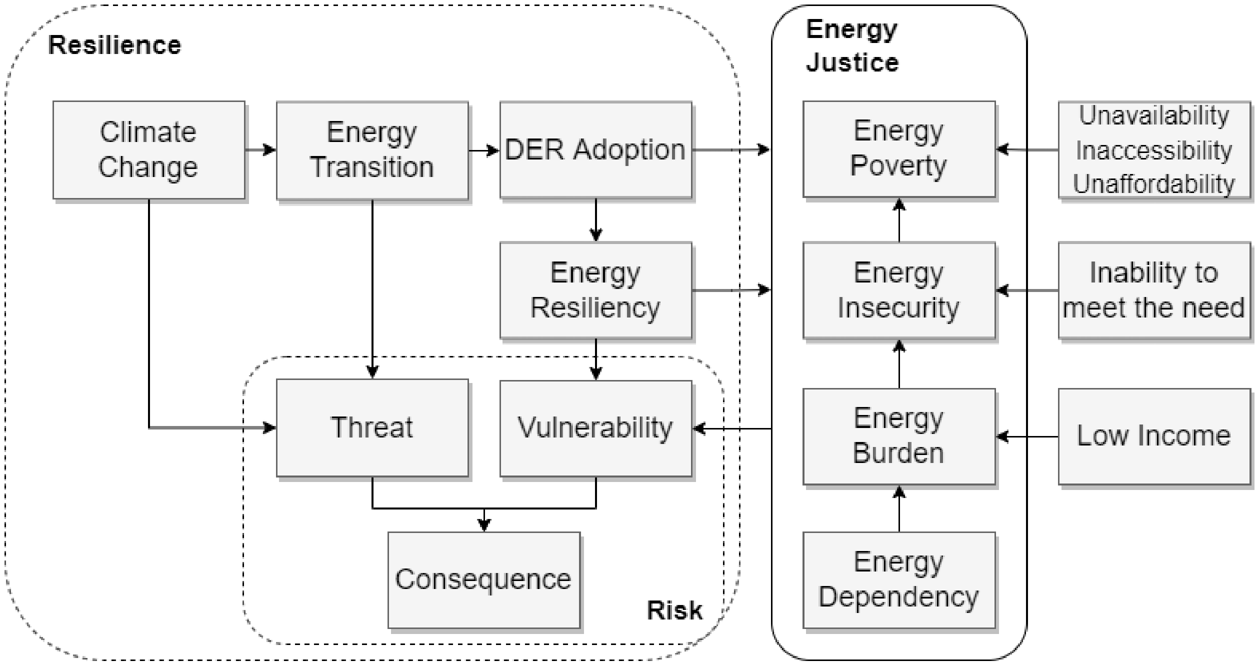

Figure 1.2: Conceptualization of relationships among risk, resilience, and energy justice in terms of energy vulnerability, energy resiliency, and energy dependency.

(Cutter et al. 2003). The 11 independent components led to a summary score, accounting for approximately 76% of the variance using principal components analysis (PCA).

1.3.2 Energy dependency

Energy burden represents energy dependency. A household's energy burden is the percentage of income spent on the housing energy bill for gas and electricity (Drehobl et al. 2020). Above 6% is considered to be a high energy burden and above 10% is regarded as a severe energy burden (Brown et al. 2020a). Studies found that certain groups had disproportionately higher energy burdens than the average household, such as ethnic minorities, renters, low-income, and multi-family residents (Cook and Bird 2018; Drehobl et al. 2020). Almost 38% of all households in the U.S. are energy burdened by paying more than 6% of their income for energy services such as gas and electricity (Drehobl et al. 2020). Grid modernization as a result of the recent transition to DERs has caused higher residential utility costs and can place a disproportionate burden on low-income households (Brown et al. 2020a; Mastropietro 2019). Furthermore, the double effect of energy burden and vulnerability were introduced and analyzed by including energy costs linked to transportation to identify the affected populations and spatial interactions (Mayer et al. 2014; Robinson and Mattioli 2020). Energy burden disparities are important for government agencies to address energy poverty for basic energy needs (Lukanov and Krieger 2019).

1.3.3 Vulnerability variables

Diverse scholars have argued that the integrated approaches addressing energy and vulnerability are better than analyzing a single measure such as energy burden since a single measure cannot account for the complex interdependency of social phenomena (Bouzarovski 2014). Hence, additional measures that reflect broader social and economic characteristics are required for a better understanding of energy vulnerability. How can we identify vulnerable communities? While some studies categorized communities by different variables such as income and race, it is difficult to define vulnerable communities with a single variable because a variety of factors including unobserved latent variables are involved in the social phenomena (Mahoney 2001). Furthermore, unobserved latent variables underlying observed variables may better explain such social phenomena (Cudeck and MacCallum 2007). Hence, it is necessary to identify and characterize vulnerable communities with respect to energy transition with multi-dimensional variables. For example, SVI from CDC comprises 15 social factors for identifying socially vulnerable communities. Community vulnerability caqn be discussed in terms of the two main categories, people and place - socioeconomic and demographic attributes associated with people and the built environment characteristics related to place (Robinson et al. 2019). For example, race (Martiskainen et al. 2021), income (Middlemiss and Gillard 2015; Sánchez-Lozano et al. 2013), and education (Gouveia et al. 2019) are associated with people's abilities to respond to threats. In addition, built environment characteristics such as zoning, urbanization, population density, and housing types, is associated with the vulnerability of places (Cauvain and Bouzarovski 2016; Cutter et al. 2003; Robinson et al. 2019). Socioeconomic attributes associated with housing such as property value and homeownership also affect household vulnerability (Ambrose 2015). The income inequality indicator, the Gini index, predicts energy vulnerability in terms of domestic energy poverty (Galvin 2019).

1.4 Distributed energy resources (DER)

Recent global climate change has led to the development of various clean energy technologies promoting the rapid transition to electrification and decarbonization associated with DERs. DERs such as rooftop solar, concentrated solar power, demand response, electric vehicles (EVs), wind turbine, battery, and micro-grids are proven to increase resiliency in response to the impacts of climate change in addition to providing economic, health, and environmental benefits (Ajaz 2019; Krieger et al. 2016). However, this transition has been disproportionately implemented, creating undesirable burdens to certain populations and communities (Carley and Konisky 2020). Increased electric bills supporting the grid modernization and incentives encouraging the technologies' adoptions are examples (Brown et al. 2020a; Mastropietro 2019). Furthermore, the grid reliability of the power supply can inadvertently be affected by the characteristics of DERs such as intermittent power generation of photovoltaic systems and uncertain charging schedules of EV (ESIG 2019). This increases challenges for system operators to require improved forecasting and new operating tools ensuring stability and coordination between systems (Balta-Ozkan et al. 2015). Hence, equitable distribution and access to DERs is necessary to improve resiliency especially to more vulnerable communities regarding the benefits described above.

1.4.1 Clean energy access

Clean energy access by DER adoption can improve grid resilience as a way to mitigate the impacts of climate change (Ajaz 2019). In addition, access to clean energy provides economic, health, and environmental benefits by reducing greenhouse gas emissions and air pollutants (Krieger et al. 2016). Installing rooftop solar to produce electricity in residential buildings is one example of increasing clean energy access. In addition, utilizing rooftop solar mitigates energy poverty and energy burden by reducing energy bills for households (Sovacool et al. 2013). For example, installing rooftop solar reduces the households' energy burden by producing electricity (Cook and Shah 2018b). Hence, increasing solar adoptions in vulnerable communities such as LMI and communities of color enhances energy justice by creating socioeconomic benefits and a healthier environment through lowering carbon emissions. Several studies have analyzed adoption disparities in rooftop solar by diverse populations and communities. For example, different impacts of policy interventions and business models are presented on rooftop solar adoption by LMI households (O'Shaughnessy et al. 2021). The disparity of distributed solar are illustrated by disadvantaged communities (DACs) defined by CalEnviroScreen (CES) (Lukanov and Krieger 2019). Ethnic differences in rooftop solar adoption across census tracts are grouped by the racial and ethnic majority (Sunter et al. 2019). Those studies found that vulnerable communities related to income and race were left behind in rooftop solar adoption.

1.4.2 Adoption variables

The adoption of DERs may not be explained solely by economic benefits (Islam 2014; Mah et al. 2018; Seel et al. 2014), e.g., reduced electricity bills or provision of financial incentives (Karteris and Papadopoulos 2012). Rather, the adoption of DERs is associated with diverse variables. For example, peer effects through word of mouth and social contagion are among diffusion drivers of rooftop solar (Brudermann et al. 2013; Curtius et al. 2018; Müller and Rode 2013; Rai and Robinson 2013; Scott and Carrington 2011). Spatial neighboring effects and preexisting technologies in the neighborhood are other drivers (Bollinger and Gillingham 2012; Graziano and Gillingham 2015; Hofierka et al. 2014). Financial accessibility (Aklin et al. 2018; Mah et al. 2018; Strupeit and Palm 2016), solar irradiation (Schaffer and Brun 2015; Šúri et al. 2007), and local regulations or policy interventions (Graziano and Gillingham 2015; Mah et al. 2018; O'Shaughnessy et al. 2021) are also associated with the adoption of such technologies. Furthermore, previous studies have found that the distributional disparity of DERs is largely associated with socioeconomic and demographic characteristics. For instance, households with rooftop solar and EV chargers typically had higher income and educational attainment (Davidson et al. 2014; Keirstead 2007; Min and Lee 2020). The significant variables of energy vulnerability and DERs adoption identified through the literature are grouped by the representing domains - demographics, socioeconomics, housing, built environment, and inequality in Table 1.1.

Table 1.1: variables of energy vulnerability and DER adoptions.

Variables	Studies for energy vulnerability	Studies for clean energy adoption
Demographics		
Education	Gouveia et al.(2019)	Balta-Ozkan et al. (2015) Davidson et al. (2014)
Race/ language	Robinson et al. (2019) Martiskainen et al. (2021)	Sunter et al. (2019)
Socioeconomics		
Income	Middlemiss and Gillard (2015) Sanchez-Guevara et al. (2019) Martiskainen et al. (2021)	Guta (2018) Keirstead (2007)
Poverty	Martiskainen et al. (2021)	Aklin et al. (2018) Guta (2018)
Housing		
Property value	Ambrose (2015)	Dastrup et al. (2012)

Table 1.1: variables of energy vulnerability and DER adoptions. *(continued)*

Variables	Studies for energy vulnerability	Studies for clean energy adoption
Homeownership/ rent	Middlemiss and Gillard (2015)	Graziano and Gillingham (2015)
	Ambrose (2015)	Hofierka et al. (2014)
	Martiskainen et al. (2021)	Muller and Rode (2013)
		Drury et al. (2012)
		Keirstead (2007)
Housing type	Cauvain and Bouzarovski (2016)	Graziano and Gillingham (2015)
	Robinson et al. (2019)	Muller and Rode (2013)
Built environment		
Urban density	Cutter et al. (2003)	Graziano and Gillingham (2015)
	Bouzarovski (2014)	Snape (2013)
		Muller and Rode (2013)
		Rode and Weber (2016)
		Zahran et al. (2008)
Inequality		
Gini	Galvin (2019)	Yu et al. (2018)

Chapter 2

METHODOLOGY

In this chapter, I introduce the overall research methodology including study sites, data sources, and brief methods such as Moran's I, dimension reduction, cluster analysis, and spatial regression for each individual study.

2.1 Study sites

Regions with lower adoption rates facilitate investigation of DER adoption patterns since they have a relatively higher proportion of early adopters compared to mature markets. Understanding early adopters' attributes is important for making decisions in policies (Araújo et al. 2019). Seattle, Washington was used as the study area for Chapter 3 because the city features early adoption stage for rooftop solar with a relatively low irradiance of less than 3.5 kWh/m2/day (Sengupta et al. 2018). On the other hand, Washington is one of the pioneering states for clean energy policies due to its active clean energy and renewable portfolio standards (DSIRE 2021). Washington is also known for its innovation, as a home for well-known big tech companies with many employees who are early technology adopters. For example, registrations of all-electric vehicles and plug-in hybrid-electric vehicles in 2018 were 5.83 per 1,000 persons, ranking second in the US, following California (Energy.gov 2021). In addition, Seattle has experienced rapid increases in residential property values and rental fees (Fynn Bruey 2019), which could be associated with the adoption of rooftop solar and EV chargers.

I expanded the study sites to two other Pacific Northwest cities, Bellevue, Washington and Portland, Oregon to examine energy vulnerability and identify vulnerable communities in Chapter 4. Seattle and Portland are geographically close and share high scores in clean energy efforts. For example, Seattle and Portland are the top-tier cities in equity-driven approaches to clean energy planning, implementation, and evaluation scores with two other cities, Minneapolis, Minnesota and Providence, Rhode Island from the 2020 City Clean Energy Scorecard (Ribeiro et al. 2020). The scores represent cities' efforts to address disparities from climate change through climate action, energy efficiency, and renewable energy initiatives, which are measured by procedural, distributional, structural, and transgenerational equity (Ribeiro et al. 2020). Regarding climate, the three cities are listed as the cloudiest cities in the U.S. with a relatively low solar irradiance of less than 3.5 kWh/m2/day (Osborn 2021; Sengupta et al. 2018). Seattle has greater population (0.72 million) than Portland (0.64 million) or Bellevue (0.14 million) in 2019 while Portland area (145 square miles), is a bit larger than Seattle (142 square miles) and Bellevue (38 square miles) (Bureau 2021). I analyzed the spatial distribution of energy burden and rooftop solar adoption associated with energy vulnerability variables identified in the literature.

2.2 Data Sources

2.2.1 Distributed energy resources

The study used rooftop solar and EV charger installation permit records from the open data portals of the Cities of Seattle, Bellevue, and Portland from 2003 to 2019. Permits are required for homeowners to install these DERs on their properties, which assured a complete data set. The data includes geographical coordinates (latitude and longitude), installation dates, and contractor information. The coordinates are used to create a geographic information systems (GIS) point layer, which was aggregated to census tracts, the latter was used as the unit of analysis.

2.2.2 Social vulnerability index

The Agency for Toxic Substances and Disease Registry (ATSDR) provides SVI to CDC to determine vulnerable communities for disease control. SVI helps data users better understand the community demographic characteristics containing 15 individual social factors at the census tract level in area of interest. SVI identifies where critical communities are located and supports resource allocation decisions under resource limits. The 15 social factors are grouped into four themes such as socioeconomic status, household composition, race & language, and housing & transportation and are ranked on a zero to one scale, where a higher ranking value represents higher vulnerability.

2.2.3 Energy burden

The Low-Income Energy Affordability Data (LEAD) Tool, developed by the U.S. Department of Energy (DOE) and the National Renewable Energy Laboratory (NREL), provides annual average energy burdens and energy costs based on counties, cities, and census tracts (Ma et al. 2019). This tool helps characterize low-income households in energy expenditures categorized by household income level and housing unit types such as housing tenure, housing heating fuel type, housing construction year, and the number of units in the housing building. I referred to the annual average energy burden at the census tract level for the measure of energy burden.

2.2.4 Predictor variables

The built environment, socioeconomic and demographic variables from the literature related to adoption of both technologies and vulnerability variables were obtained from the 2014-2018 American Community Survey (ACS), which represents the average characteristics of period estimates over the period of time. I chose the ACS period from the 2014-2018 because it would reflect the community characteristics when the majority of installations occurred. For example, most of installations of both technologies in Seattle has occurred in the past few years. In particular, rooftop solar installations in Seattle peaked in 2015 and have maintained a high level of installation since then. The variables include population density, housing type, income, education, home value, homeownership, poverty, race, and income inequality (Gini index) (Table 2.1). Specifically, I chose ten square meters as the denominator for measuring population density to match the scale with other variables for visualization purpose. For the race variable, I used White population proportion for representing a race characteristic because in most census tracts in Seattle, the race has a greater proportion than other racial groups. I chose the 150 percent poverty level because the population below the 100 percent poverty level was relatively small, resulting in a smaller mean of the variable. Gini index represents the range of income inequality between zero and one; values closed to one indicate higher income inequality in the given administrative unit (Census.gov 2022).

Table 2.1: Descriptions of technology adoption and vulnerability variables.

Variables	Description
PopDensity	Total population/area of tract in ten square meters
HomeOwn	Owner owned units/total housing units
SingleFamily	1-unit structures/total housing units
Edu	Population of bachelor's degree or higher/total population
HomeValue	Median home value in million dollars
Income	Median household income in hundred thousand dollars
White	White population/total population
Poverty	Population above 150% poverty level/total population
Gini	Gini index of income inequality

2.3 Research methods

From the social science point of view, people or more broadly communities interact with each other and affect each other's behavior (Darmofal 2015). This interaction comes primarily from spatial proximity, in that communities that are geographically closer are more likely to interact with each other. Communities often exhibit similar outcomes as a result of shared environmental influences even if there is no physical interaction (Shea and Chesson 2002). To this end, spatial analyses address the spatial proximity and dependent characteristics in a study area. Currently, several spatial methods are available due to the development of computing power such as GIS and data availability with possible collection of multiple spatial data sets at different geographical scales (Janowicz et al. 2020).

There are three data categories representing spatial characteristics: (1) point, (2) area, and (3) geostatistics (Wakefield 2007). Observations are collected in forms of points (i.e., point or geostatistical data) or regions (i.e., area data). Area data features aggregation of observations over a defined boundary such as an administrative unit (e.g., census tract). Point data exhibits the actual configuration of points of an interest subject over a study area. On the other hand, geostatistical data represents the attributes of an interest subject at residential locations in the form of points. In this regard, it is important to design how to collect data because it affects the characteristics of a spatial analysis (Wakefield 2007). Sampling mechanism addresses how data are collected. For example, survey data with a complex design would need weighted analyses if data are not a random sample in space (Pascutto et al. 2000). If data are not a simple random sample, clustering patterns of the data cannot be analyzed in regard to the spatial structure due to the involved bias in the data collection.

Rooftop solar and EV charger installations in this study are represented as point data including geographical coordinates (i.e., latitudes and longitudes). Since the data features complete enumeration, clustering patterns of the points would reveal unbiased distributional characteristics of the clean technologies. Furthermore, by aggregating the point data at the census tract level, spatial regression models could be performed to find a relationship between the distribution of technologies and socioeconomic and demographic characteristics. Aggregation at the census tract level, which is the political boundary, can capture the local characteristics of a community unlike ecological data featuring environmental characteristics, where aggregation at the census tract level does not make sense. This is because the socioeconomic and demographic attributes are human related and census tracts are drawn based on the homogeneous size of the population. However, point data aggregation regardless of its feature, may lead to an ecological fallacy where conclusions based on group-level data are different from those based on individual-level data (Kam et al. 2018). Furthermore, aggregation of point data may also lead to the modifiable areal unit problem (MAUP), where the inconsistency of results exists due to the aggregation under different geographical configurations (Openshaw 1983). MAUP consists of two components depending upon different levels of spatial resolution and regroupings: the scale effect and the zoning effect (Dharshing 2017).

After aggregation, DER adoption counts, energy burden, and the induced vulnerability index become outcome variables at the census tract level. The summary of the research design is illustrated in Figure 2.1. In particular, using Moran's I statistics, I identified spatial autocorrelation or spatial dependency of the distribution of outcome variables to examine distributional justice. On the other hand, predictor variables featuring community attributes were used to investigate recognition justice. Specifically, using factor analysis, predictor variables resulted in a few latent variables characterizing place, people, and the equality of communities. The latent variables were used to identify and characterize vulnerable communities through cluster analysis. Poisson log-linear models and hierarchical mixed-effect models were used to characterize associations between energy vulnerability variables and outcome variables such as rooftop solar adoption and energy burden. Furthermore, classification algorithms were used to identify vulnerable communities. Finally, I investigated the spatio-temporal trends of rooftop solar adoption suggesting indices to quantify energy justice by various communities. Moran's I, dimension reduction, cluster analysis, and spatial regression are explained in more detail below.

2.3.1 Global Moran's I for outcome variables

Spatial clustering patterns present local spatial variations associated with spatial autocorrelation. Spatial autocorrelation exists if observations that are closer to each other in space are correlated (Tobler 2004). In other words, spatial autocorrelation is a dependency in geographical positions. Moran's I statistic (Moran 1948) is the most widely used method to test for the presence of spatial autocorrelation, or spatial dependency. If no spatial dependency exists in an area, the test statistic would be close to zero (it ranges from negative one to positive one). If the value is positive and close to one, the area presents clustering of the interested variable; it presents dispersion if the value of the test statistic is negative and close to negative one. Since the study concerns measuring the similarity of nearby features,

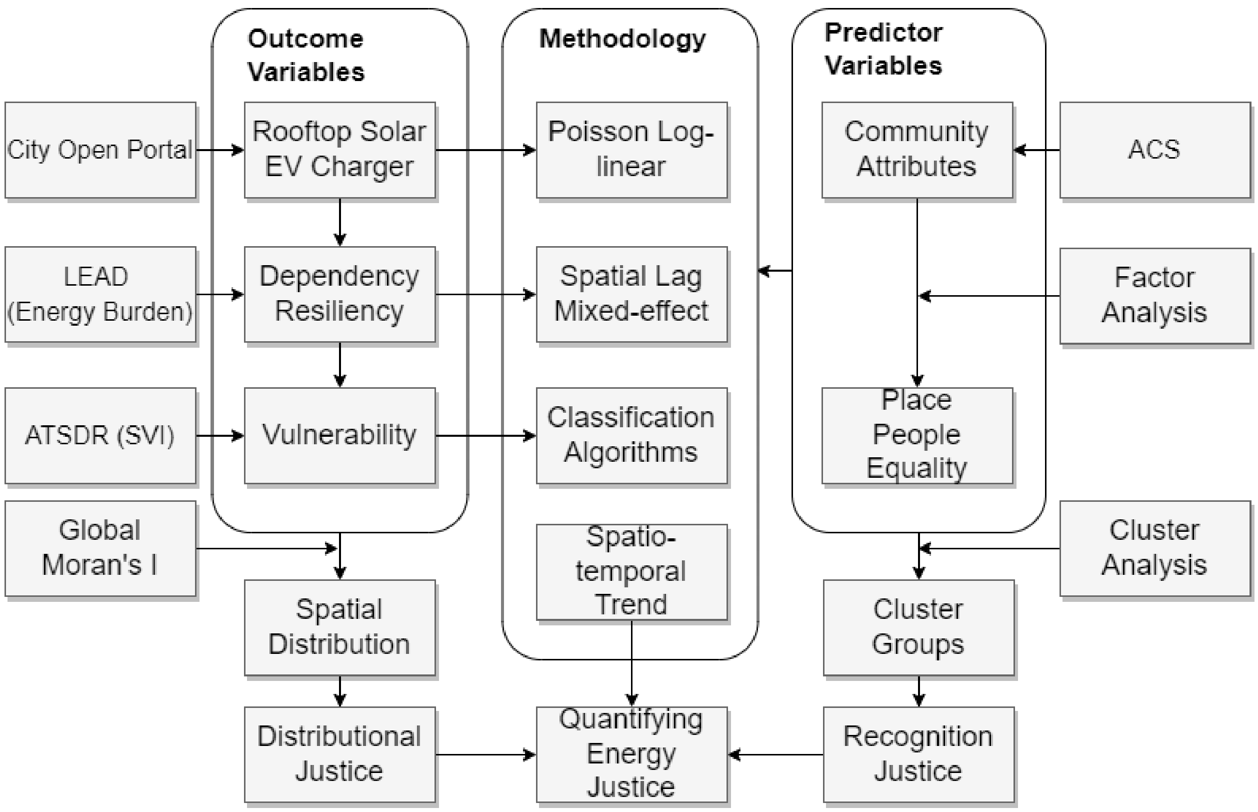

Figure 2.1: Conceptualization of research design including data sources, variables, and methodologies.

Moran's I was used. On the other hand, General G statistic indicates whether any cluster is composed of high or low values (Diggle 2013). In short, Moran's I tells whether data is spatially clustered while General G statistic tells whether there are clusters of high or low values.

Furthermore, there are other statistics to test the local spatial dependencies. For example, Hotspot analysis (Getis - Ord Gi*) compares neighborhood clusters to the global based on z-scores and p-values of the statistic within a study area (Getis 2010). If neighborhoods where a feature is located around are significantly different from an average global area, then the individual feature becomes a hot spot. Since it is by means of neighborhood, a feature with a value close to the global mean value, can be still a hot spot if it is located in a neighborhood with a high score. In addition, local Moran's I (i.e., cluster and outlier analysis) is similar to the hot spot statistic except that it compares a feature with its neighbors (Getis 2010).

2.3.2 Dimension reduction of predictor variables

I developed latent variables from the built environment, socio-economic, and demographic variables identified in the literature using factor analysis to address potential confounding factors or highly correlated variables. Multivariate analysis is appropriate to examine the complexity of human behavior and demographic characteristics (Sheth 1971). Multiple co-variates with high correlation may complicate interpretation of a regression analysis leading to bias results (Tu et al. 2005). For example, having a highly correlated variable in a model can result in significant coefficient changes of other variables. Some techniques such as principal components analysis (PCA), factor analysis, and structural equation modeling (SEM) address the issue related to independent variables highly correlated with each other in ecological multiple regression (Graham 2003). In particular, PCA or factor analysis simplifies redundant information and reduces the complexity of large sets of correlated variables (Tu et al. 2005). For example, Robinson et al. (2019) using PCA, developed three components from 21 vulnerability indicators to energy poverty. Similarly, Cutter et al. (2003) developed vulnerability indices using principal components analysis (PCA), with 42 socioeconomic and demographic variables, which led to 11 independent components. In particular, PCA and factor analysis perform dimension reduction of predictors by summarizing correlations among the predictors. Factor analysis is more suitable than PCA for social science studies as latent variables can be moderately correlated with each other, while PCA does not allow the components to share common effects among orthogonal components (Costello and Osborne 2005). In addition, dimension reduction may help categorize census tracts more effectively by removing redundant attributes among highly correlated variables. Specifically, cluster analysis with highly correlated variables results in distorted grouping because the redundant attributes among correlated variables give more weights in computing distances of cluster formation in multi-dimensional space (Sambandam 2003). Since the social data entails errors and common variances, maximum likelihood was used as a factoring method (Finch 2006). Promax was used as a rotation method for latent variables to be first orthogonal, and then correlated between factors (Russell 2002).

2.3.3 Cluster analysis

Using cluster analysis, census tracts were categorized into groups using the identified latent variables. Specifically, K-means clustering algorithm was used with the number of clusters (K) based on the within-cluster sum of squares to categorize communities (Everitt et al. 2011). Using an elbow method, I picked the number of groups from the elbow of the curve, which is drawn as a function of the within-group sum of squares. When the number of groups increases, the within-group sum of squares gets smaller. The smaller within-group sum of squares is desirable because the variation within groups is small. However, splitting into many groups is not helpful for analysis. Thus, I stopped increasing the number of groups when there was not much improvement in the within-cluster sum of squares. Euclidean distance among attribute points of the latent variables, determines nearest groups for an individual community. In general, categorization of communities leads to more homogeneous characterization within a group while being more heterogeneous across groups. This grouping helped distinguish more vulnerable communities based on the built environment, socioeconomic, and demographic characteristics.

2.3.4 Spatial regression

Spatial dependency of geographic similarities in variables needs to be addressed using spatial regression models that incorporate spatial effects (Darmofal 2015). Ignoring spatial dependency leads to a biased and inconsistent estimate and loss of efficiency (Balta-Ozkan et al. 2015). In general, a linear regression model does not work well if there is a spatial dependency in the error terms or regression residuals. This is because ordinary least squares (OLS) requires the error terms to be uncorrelated with each other while having a constant variance. In other words, observations and regression residuals should be independent with each other. If this assumption is violated, the coefficient estimates can be biased and the residuals can contain spatial dependency, which is distinguishable from random noise (Fotheringham et al. 2003). Since the study involves examining the spatial pattern of DER adoptions and energy burden in terms of distributional justice, I used spatial regression models to address spatial dependencies in variables in order for improved model parameter estimations.

The two common ways to determine neighbor connectivity associated with spatial autocorrelation are Queen and Rook Adjacency depending upon whether communities spatially share either borders or vertices or only borders (Griffith 1996). The common rule is to assign areas as neighbors if they share a common boundary especially in the situation where all regions are similar in size and arranged in a regular pattern. I used Queen Adjacency defining neighbors which share either borders or vertices in the analysis. The other ways to define neighbors are to take a distance such that regions within the distance become neighbors; or to consider cultural similarity. With an n x n spatial weight matrix (n is the number of observations), a vector of the means of the responses of the neighbor observations was created. This weight matrix was used in the estimation of spatial regression and the calculation of Moran's I statistics. The spatial weight matrix, then, became the element of the spatial regression model as a "lag" term, which is a specification at nearby locations in the model.

Mainly two models are considered to address spatial autocorrelation: (1) simultaneous autoregressive (SAR), and (2) conditional autoregressive (CAR) models mostly in econometrics and epidemiology studies (Banerjee et al. 2014). SAR specifies its variance-covariance matrix with more than first order dependencies so that this model is more suitable for a global spatial autocorrelation (Griffith 1996). CAR assumes that only neighbors influence a concerned feature by obeying the spatial Markov property such as Gaussian Markov Random Field (MRF). MRF decides the distribution of S_i given the known values of the neighboring random variables S_j (Rue and Held 2005). The model assumes that spatial random effect follows a normal distribution with the mean of the neighbors' random effects and the variance inversely proportional to the number of neighbors (Besag et al. 1991). SAR has three different forms depending on where the autoregressive process occurs: spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). Several studies used SAR models for rooftop solar adoption. For example, Graziano et al. (2019) addressed spatial spillovers regarding peer effects in solar adoption associated with the built environment and jurisdictional boundaries using a SAR model, a special case of the general SDM. Also, Dharshing (2017) used SAR and SEM to examine rooftop solar adoption regarding economic factors, sociodemographic and attitudinal adopter characteristics, settlement structure, and spillover effects between neighboring counties.

Chapter 3

CLEAN ENERGY JUSTICE: DIFFERENT ADOPTION CHARACTERISTICS OF COMMUNITIES IN ROOFTOP SOLAR AND ELECTRIC VEHICLE CHARGERS IN SEATTLE

3.1 Introduction

Government agencies have acknowledged energy equity and attempted to address energy inequities. For example, the US Department of Energy (DOE) initiated several programs such as SolSmart (NREL 2021a) and Solar Energy Innovation Network (NREL 2021b) to encourage low and moderate income (LMI) households to adopt emerging technologies, such as rooftop solar and energy storage. These programs are designed to encourage more equitable solar deployment by providing technical assistance to local governments, organizations, and related stakeholders. State and local government agencies are also working to remedy this energy inequity issue; for example, the revised Code of Washington (RCW) 19.405.120 (Legislature 2021a) requires utility companies operating in the state to provide energy assistance funding and programs to LMI households starting in July 2021. RCW 19.405 aimed at promoting equitable distribution of benefits to utility customers transitioning to clean energy. The goal of the legislation is to reduce customers' financial burden for weatherization and ownership in distributed energy resources (DERs) (Legislature 2021b). To address any energy inequity issue during the implementation of the legislation, the Washington State Department of Commerce is tasked to investigate household demographics and housing characteristics such as housing type, home vintage, fuel types, energy efficiency potential, and the levels of energy burden and energy assistance needs (DoC 2021).

While federal and local governments have enacted policies to mandate equitable clean energy access and distribution of benefits, little is known about (1) which adoption variables of DERs are more significant among several variables identified in the literature and (2) how adoption characteristics differ by technologies and communities. Several studies have found that various variables are associated with the adoption of DERs (Guta 2018; Min and Lee 2020). However, many of these variables appear to be highly correlated, leading to difficulties in interpretation. Furthermore, when there are high correlations between two or more predictor variables, statistical analyses may suffer due to confounding factors or multi-collinearity, leading to spurious results (Dormann et al. 2012). In addition, social science events such as technology adoption are not explained only by observed variables because unobserved factors may be involved (Mahoney 2001). Unobserved factors may have explanatory power when interpreting complex social phenomena (Cudeck and MacCallum 2007). Furthermore, adoption patterns of various technologies may have both similarities and differences. For example, in New York it was found that the key adopters of rooftop solar and EV often had greater financial means such as higher median income or home value (Araújo et al. 2019). However, spatial diffusion patterns of rooftop solar and EV may differ; in the Netherlands, rooftop solar adopters had lower variation in sociodemographic characteristics than EV adopters (Kam et al. 2018). Moreover, certain characteristics related to adoption may vary by community. For example, White-majority communities were found to adopt more rooftop solar than other racial communities across all 50 US states (Sunter et al. 2019).

The objective of this chapter is to examine energy justice associated with the distribution of DERs, operationalized as distributional and recognition justice. Because energy justice in this study is limited to the spatial distribution and community adoption levels of DERs, I introduce "Clean Energy Justice" to describe the restricted concept. Specifically, distributional justice concerns geographic differences in the distribution of resources, which can be examined by the geographic distributions of DERs (Jenkins et al. 2016). On the other hand, recognition justice deals with sociodemographic differences across populations and communities, potentially leading to social inequities (Jenkins et al. 2016). I investigated the level of DER adoption by grouped communities that share similar characteristics. In particular, rooftop solar and EV chargers were analyzed, since they are the most common DERs adopted in the residential sector. The distribution of rooftop solar and EV chargers is closely associated with clean energy access and justice. For example, rooftop solar reduces households' energy burden by producing local clean energy (Cook and Shah 2018a). Also, EV reduces fuel expenditures in addition to providing benefits including a sustainable and resilient energy supply (Wu et al. 2015).

This chapter is aimed at filling the two gaps in the literature. The first is to tackle problems in variable selection and specification. The study involves identifying latent variables of adoption determinants that are highly correlated with each other. The second is to characterize communities in terms of the adoption levels of different DERs. In this study, I consider communities with relatively lower adoption levels to be the underserved. Specifically, the study is aimed at answering the following questions.

(1) What are the significant variables among the built environment, socioeconomic, and demographic variables with respect to the adoption of rooftop solar and EV chargers?
(2) How do adoption patterns differ by technologies and communities with different attributes?

This study examines distributional justice by analyzing the geographic distribution of rooftop solar and EV chargers. Furthermore, the study aims to investigate recognition justice by identifying adoption patterns across different technologies and communities.

3.2 Research methodology

Per-tract DER installation rates were used because each census tract potentially has a different number of housing units. The census-tract level installation rate is presented in Equation (3.1); the standardized installation ratio (SIR) is defined as the count of rooftop solar or EV charger installations (Y_i) divided by the expected count of rooftop solar or EV chargers (E_i). The expected count (E_i) is the average count of installations per housing unit in Seattle (T_{avg}) multiplied by the total count of housing units (H_i) in a census tract i. A SIR is the maximum likelihood estimator (MLE), which corresponds to a standardized mortality ratio (SMR) of the relative risk for count data in the disease analysis (Pascutto et al. 2000). Tracts with SIR greater than one have more installations than expected, whereas those with

SIR less than one have fewer installations than expected.

$$\begin{aligned} SIR &= Y_i/E_i, \\ E_i &= H_i T_{avg}, \\ T_{avg} &= \sum_{i=1}^{n} Y_i / \sum_{i=1}^{n} H_i \end{aligned} \tag{3.1}$$

Based on the literature, variables related to adoption variables of both technologies were obtained from the 2014-2018 American Community Survey (ACS). The variables include population density, housing type, income, education, home value, homeownership, poverty, race, and income inequality (Gini index) as described in Table 2.1 in Chapter 2.

3.2.1 Research design

The study involved a spatial analysis of the built environment, socioeconomic, and demographic variables related to the distribution of rooftop solar and EV chargers in single- and multi-family residential buildings, using census tract-level data in Seattle, Washington. Other factors such as finance, climate, and policy were not considered. These factors were assumed not to differ across the study area, and although they may have differentially affected households, I lacked household-level sociodemographic data. Neighbor effects at the household level were also not considered since data were aggregated to census tracts. The proposed framework for identifying characteristics of communities associated with rooftop solar and EV chargers regarding clean energy justice is summarized in Figure 3.1.

First, I quantified spatial clustering of the installation using global Moran's I (Moran 1950) to examine distributional justice. For example, a small p-value with a positive test statistic would confirm that the rooftop solar and EV charger rates across census tracts are clustered. I then developed the latent variables (indices) of the built environment, socioeconomic, and demographic variables identified from the literature using factor analysis to address potential confounding factors associated with variables highly correlated with each other. I chose the number of factors satisfying criteria that the eigenvalue of factor analysis is greater than zero and the eigenvalue of the simulated data while omitting factors above

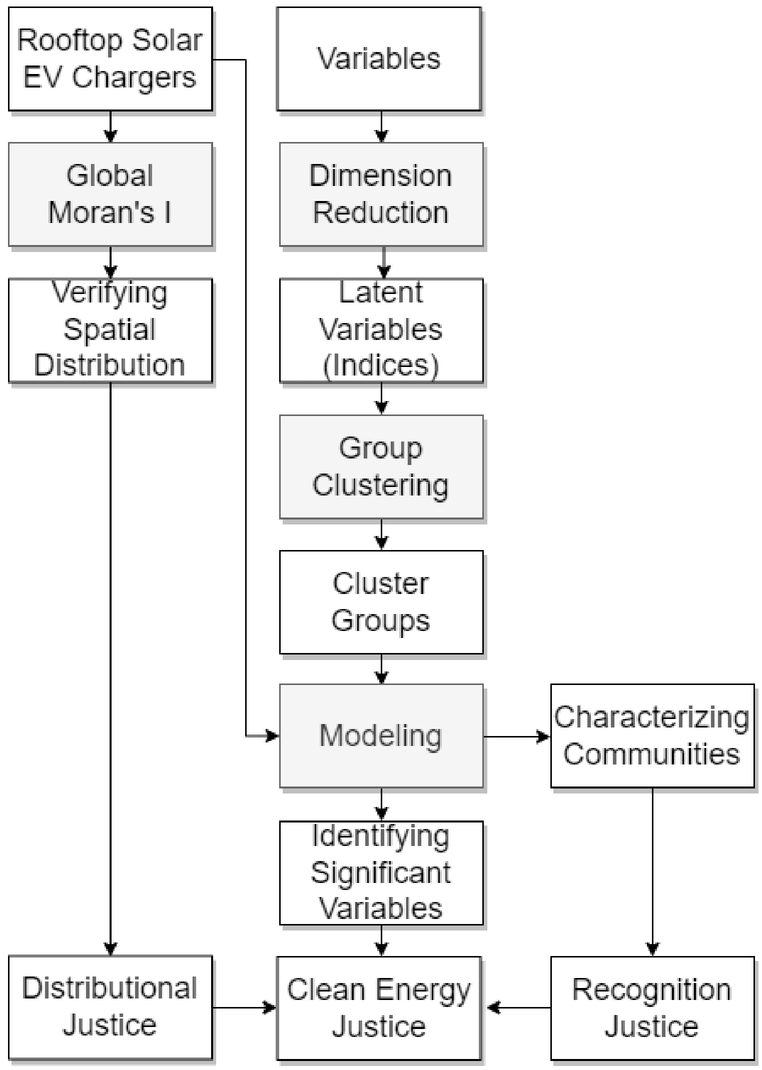

Figure 3.1: Proposed framework for identifying characteristics of underserved communities associated with rooftop solar and EV chargers to design equitable policies.

the elbow of the curve expressed as a function of the number of factors (Howard 2016). I categorized census tracts into separate groups to characterize census tracts with similar attributes and the adoption level of technologies based on the identified latent variables using K-means clustering. Comparing the cluster groups with the rooftop solar and EV charger adoption rates helped identify the different levels of adoption communities.

Then, I used a Poisson log-linear model to investigate recognition justice in communities for technology adoption. In particular, the SIR of rooftop solar and EV chargers was modeled separately across the groups using the latent variables as predictors. Poisson log-linear models were used because the data represented counts and the ratio of installations to total housing units was small. Since each census tract had a different denominator (i.e., housing units), the SIR was used with an offset of the expected count of technology installation as an extra covariate with a fixed coefficient of one. The model uses the logarithmic link function that the logs of SIR is a function of covariates as shown in Equation (3.2), where Y_i is the number of technology installation in a census tract i, E_i is the expected count of technology installation in a census tract i, θ_i is the SIR for a census tract i, β_0 is the intercept, β_k is the coefficient of the kth covariate, X_{ki} is the kth covariate for a census tract i, and ρ is the number of covariates. If rooftop solar and EV charger adoptions show an obvious pattern across the groups, each group can be characterized in terms of the latent variables representing the built environment, socioeconomic, and demographic variables.

$$
\begin{aligned}
Y_i &\sim f_{pois}(E_i\theta_i), \\
log(\theta_i) &= \beta_0 + \sum_{k=1}^{p} \beta_k X_{ki}, \\
log(Y_i) &= \beta_0 + \sum_{k=1}^{p} \beta_k X_{ki} + log(E_i)
\end{aligned}
\tag{3.2}
$$

I then examined the relationship between adoptions of rooftop solar and EV chargers across the groups. Using a random intercept model, the relationship between EV charger adoption and the cluster groups was investigated controlling for rooftop solar adoption:

$$\begin{aligned} \theta_{EV,i} &\sim f_N(\mu_i, \sigma^2), \\ \mu_i &= \alpha_0 + \alpha_j + \beta\theta_{PV,i}, \\ \alpha_j &\sim f_N(0, \alpha_\alpha^2), \end{aligned} \tag{3.3}$$

where $\theta_{EV,i}$ is the SIR of EV chargers, σ^2 is the variance of the SIR of EV chargers, α_0 is an overall intercept, α_j is the random intercept for a cluster group j, β is the coefficient of the SIR of rooftop solar, $\theta_{PV,i}$ is the SIR of rooftop solar, and σ_α^2 is the variance of α_j; all for a census tract i, which is assigned to a cluster group j. I used a random intercept model rather than a fixed effect model because the group-specific effect was present that the between-group variance was greater than the within-group variance. Furthermore, the number of census tracts of each group was not balanced which might lead to biased parameter estimations (Gelman and Hill 2006).

3.3 Results

3.3.1 Spatial distribution patterns

Distributional justice was examined using the Moran's I statistic calculated from the spatial distribution of rooftop solar and EV chargers. The test statistics values were 0.44 and 0.38 for rooftop solar and EV chargers, respectively, with p-values less than 0.001 indicating clustering in both technologies. The adoption rates for rooftop solar and EV chargers were similar but with distinctive differences. For example, while a group of census tracts with higher SIR for both technologies was found in east Seattle, EV chargers were more concentrated in the areas (Figure 3.2). These areas featured higher median income and educational attainment than other areas in Seattle.

Several variables were highly correlated with each other (Figure 3.3). For example, single-family is highly correlated with homeownership, population density, and median income. While most variables are positively correlated with one another, population density and Gini index are mostly negatively correlated with the rest of variables.

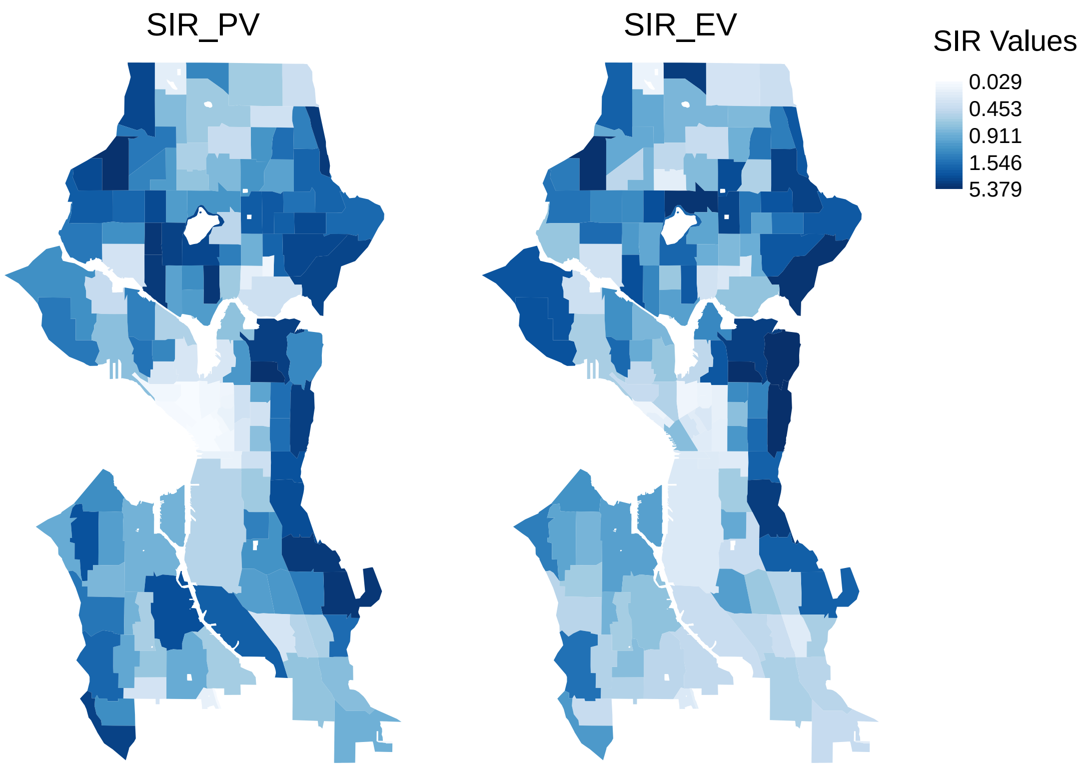

Figure 3.2: SIR distributions for rooftop solar (left) and EV chargers (right) in Seattle. Census tracts with darker blue color represent higher SIR values.

Correlations between the nine predictors and outcome variables (the SIRs of rooftop solar and EV chargers) illustrate that the predictors other than population density and Gini index are positively associated with rooftop solar and EV charger adoptions (Figure 3.4). In particular, census tracts with a higher median income and a higher White population presented greater rooftop solar and EV charger adoptions. This is consistent with previous studies that higher incomes and higher proportions of White are strongly associated with DER adoption.

3.3.2 Dimension reduction

Factor analysis led to four latent variables accounting for correlations among the observed variables. The observed variables based on similar characteristics collectively contribute their loadings to each latent variable (Figure 3.5). The latent variables were named based on the relative loadings of each individual variable. For example, the first latent variable, "Housing," had the strongest relationship with three variables: population density, homeownership, and single-family housing with loadings of above 0.75. The second latent variable, "Demographics" had strongest associations with the proportion of residents 25 years or older with a bachelor's degree or higher (loading of 0.80) and the proportion of population that was White had a loading of 0.86. The third latent variable, "Economics" was most strongly associated with economic variables; median household income had a loading of 0.88, the proportion of population above 150 percent poverty level had a loading of 0.43, and median home value had a loading of 0.42. Home value had considerable loadings for the Demographics (loading of 0.38), Inequality (loading of 0.50), and Economics index (loading of 0.42). The fourth latent variable, "Inequality," mostly included the Gini index, with a loading of 0.72.

Scatter plots of the four indices with respect to DERs for census tracts in Seattle reveal that higher values of the indices except of the Inequality index are positively associated with higher adoption rates (Figure 3.6). The y-axes represent the logs of SIR (considering the

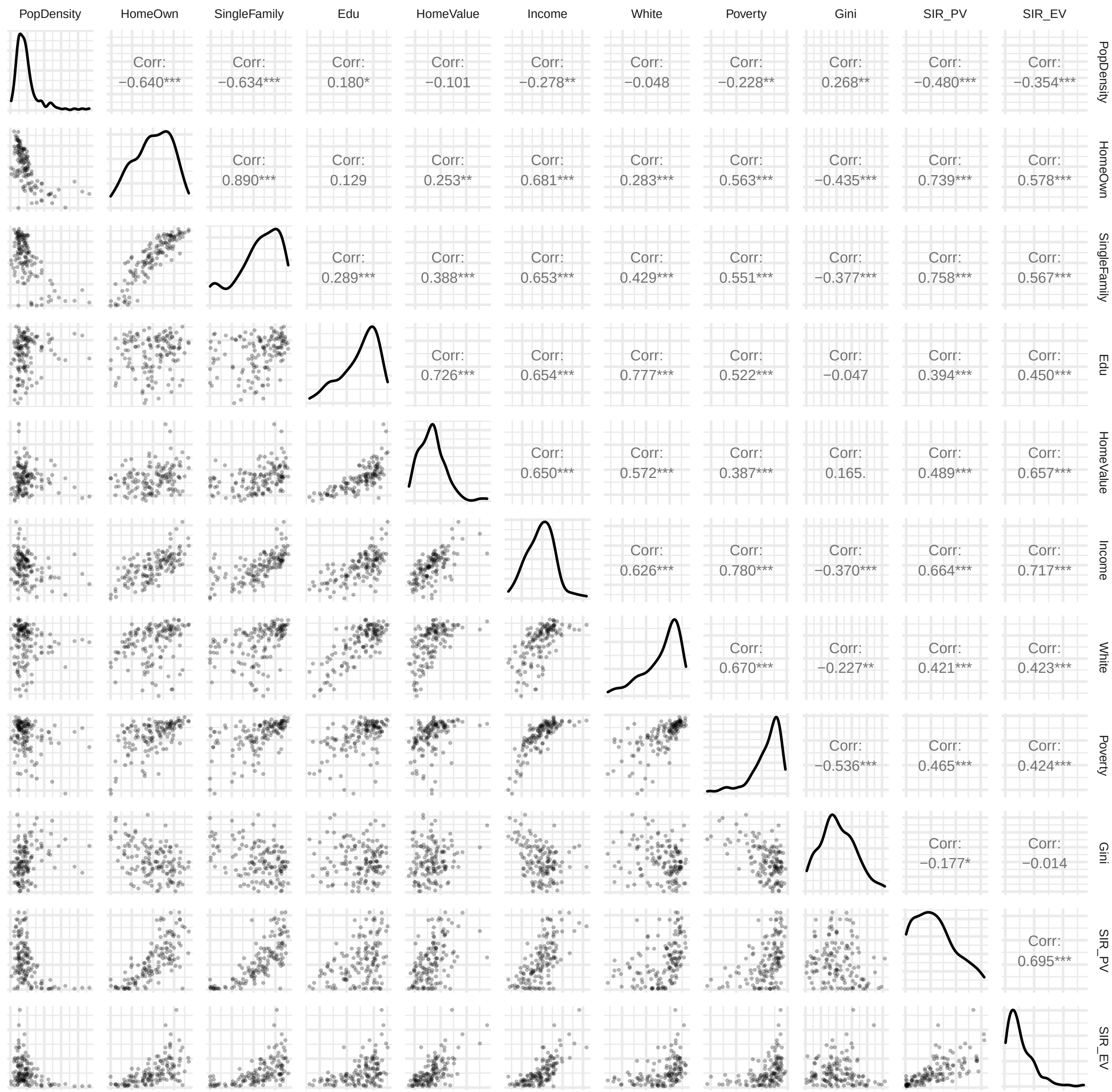

Figure 3.3: Correlations of variables including SIR of rooftop solar (SIR_PV) and EV chargers (SIR_EV). Correlation coefficients are displayed on the right of the diagonal. Distributions of variables are displayed on the diagonal. Bivariate scatter plots are shown on the left of the diagonal. The p-value significance levels are displayed by the number of stars; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

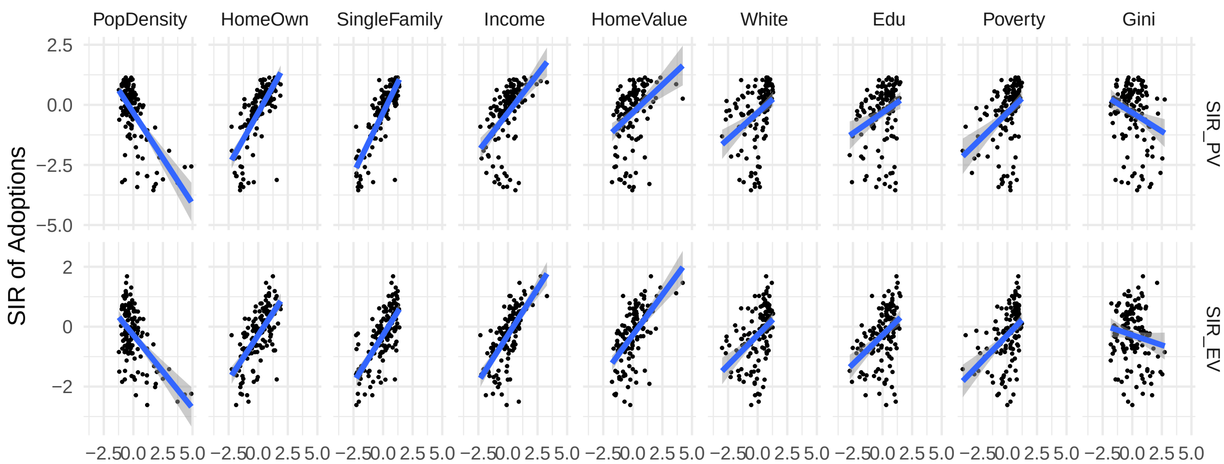

Figure 3.4: Correlations between variables and the logs of SIR of rooftop solar (SIR_PV) and EV chargers (SIR_EV) with linear fitting lines and 95% confidence intervals (unit of analysis: census tract).

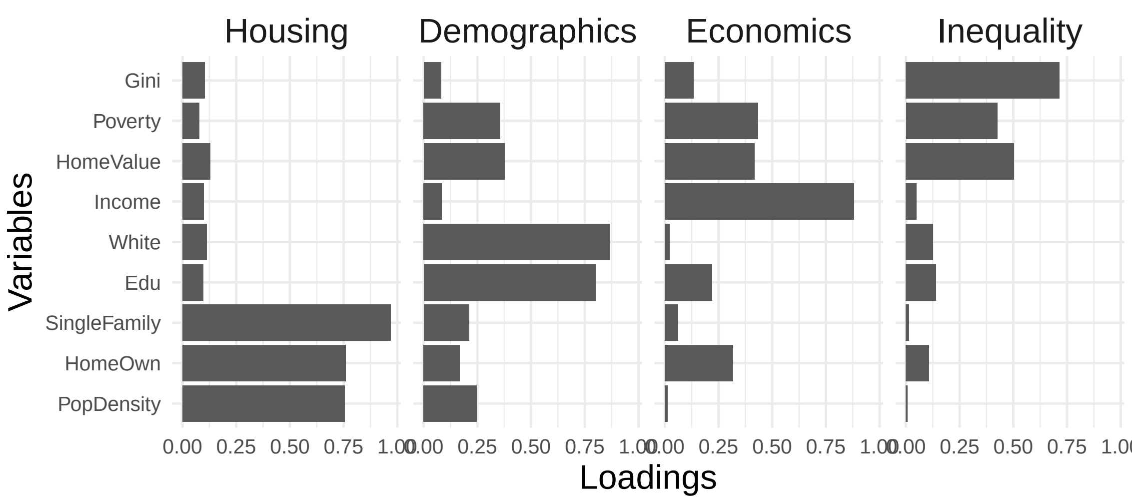

Figure 3.5: Distribution of standardized loadings of variables in the four latent variables of the Housing, Demographics, Economics, and Inequality.

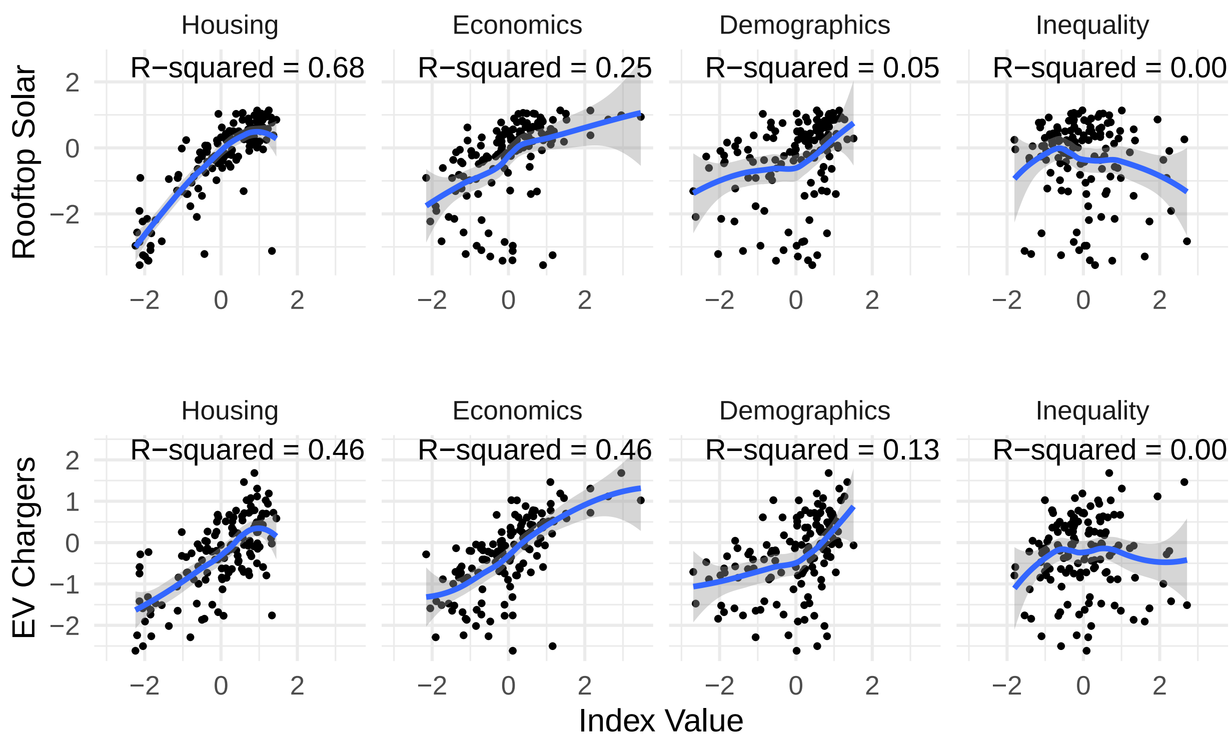

Figure 3.6: The logs of rooftop solar SIR (top four figures) and EV charger SIR (bottom four figures) by the four indices fitted with loess smoothing lines and 95% confidence intervals (unit of analysis: census tract).

Poisson log-linear model) and the x-axes represent the factor scores of each latent variable. Loess smoothing lines with 95% confidence intervals are fitted on each figure. The SIR of rooftop solar is strongly correlated with the Housing index (R-squared = 0.68), while the SIR of EV chargers is mainly correlated with the Housing index (R-squared = 0.46) and Economics index (R-squared = 0.46). On the other hand, the Inequality index shows little association with large variances for both technologies.

3.3.3 Categorizing groups

Categorization of tracts by adoption level helped identify the characteristics of communities associated with each technology. I considered underserved communities to be the communities with lower technology adoptions. Based on the four indices from the factor analysis, K-means clustering was used to identify five groups by minimizing the within-cluster sum of squares so that census tracts within a group were more homogeneous compared to tracts in other groups. Groups were stratified based on the level of adoptions of both technologies from the lowest to highest adoption groups. A gradient of rooftop solar and EV charger installation by cluster groups is illustrated in Figure 3.7. The high and the highest groups were mostly located along the shorelines and in north Seattle, corresponding with many of the single-family zones in the city. On the other hand, the low and lowest groups (underserved communities) were located in commercial districts and downtown. Those groups mostly matched the commercial, low-rise, mid-rise, and high-rise zones in the city. In particular, census tracts around the University of Washington were characterized by student renters and low-income populations and were classified in the lowest group. The medium group's census tracts were mostly located in the northern and southern parts of the city that featured lower values of the Economics and Demographics indices.

Box plots of the five groups in response to the four indices and the two outcome variables show that the patterns of rooftop solar, EV charger, and the Housing index are similar across groups (Figure 3.8). On the other hand, while the Economics and Demographics indices show increasing trends from the lowest to the highest groups, there are some bumps in the middle groups. The highest group had the greatest values for all variables except for the Inequality index. The high group followed a pattern similar to the highest group. The two end groups (the lowest and highest) presented higher values of the Inequality index than the rest of groups. This indicates that the residents in these groups are the most heterogeneous in income.

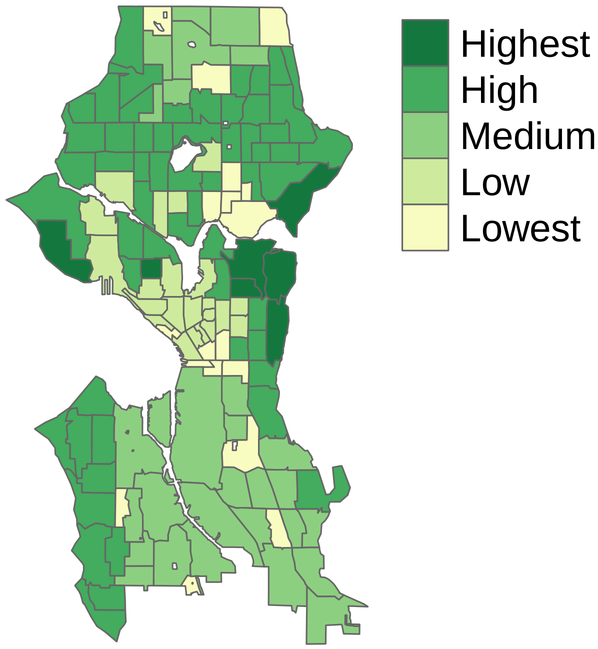

Figure 3.7: Five cluster groups (Lowest, Low, Medium, High, and Highest) by adoption levels of technologies in Seattle.

3.3.4 Characterization of communities

Using a Poisson log-linear model, I characterized cluster groups for rooftop solar and EV charger adoptions. Table 3.1 shows the point estimates with standard errors of each indices for the four regression models based on technology and group. The Housing index had the strongest overall relationships with the technologies, particularly with rooftop solar for the lower groups. On the other hand, the Economics and Inequality indices were more strongly associated with EV charger adoption than rooftop solar adoption. The Demographics index was positively associated only with rooftop solar adoption for the lower groups. To perform a sensitive analysis, I estimated the expected SIR based on counterfactuals with all other variables held constant. For example, Figure 3.9 (left) shows a predicted SIR difference when a predictor increases by two standard deviations with all else being equal. Figure 3.9 (right) shows a predicted SIR for each counterfactual predictor between -1 to 1. The association patterns between indices and technology adoptions were similar between the lower and higher

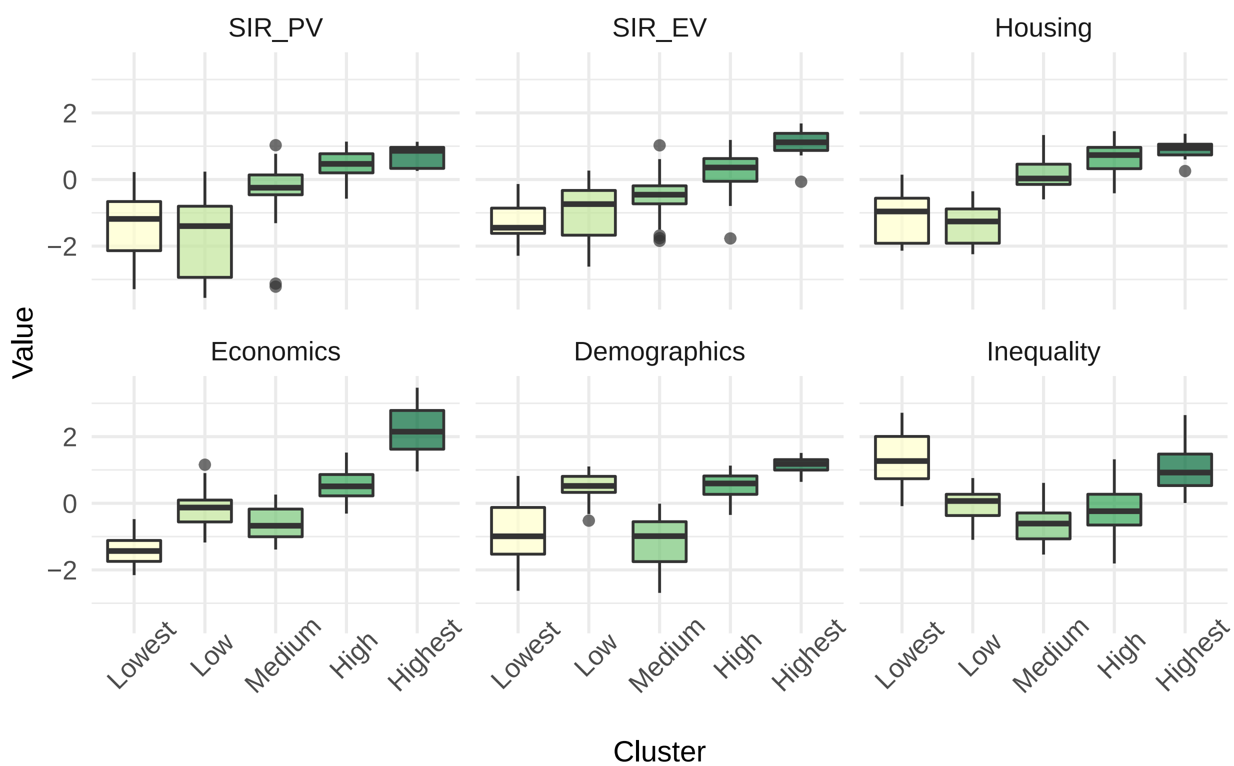

Figure 3.8: Box plots of cluster groups by the four indices (Housing, Economics, Demographics, and Inequality), and the logs of rooftop solar SIR (SIR_PV) and EV charger SIR (SIR_EV).

Table 3.1: Poisson log-linear model results regarding the four indices for lower and higher levels of adoption groups in rooftop solar (PV) and EV chargers (EV). Values indicate model coefficient with t-statistics in parentheses.

	Dependent variable:			
	PV		EV	
	Lower	Higher	Lower	Higher
Housing	1.266***	0.482***	0.656***	0.155
	(0.094)	(0.057)	(0.143)	(0.112)
Economics	−0.159	0.047	0.490***	0.339***
	(0.118)	(0.033)	(0.176)	(0.059)
Demographics	0.285***	0.057	0.072	−0.182
	(0.075)	(0.068)	(0.135)	(0.128)
Inequality	0.016	0.100***	0.256**	0.287***
	(0.072)	(0.030)	(0.128)	(0.056)
Constant	0.021	0.099*	0.027	0.195*
	(0.118)	(0.057)	(0.214)	(0.106)
Observations	40	65	40	65
Log Likelihood	−129.136	−287.594	−75.878	−166.065
Akaike Inf. Crit.	268.272	585.187	161.757	342.131

Note: *p<0.1; **p<0.05; ***p<0.01

groups, but differed between technologies. In particular, the Housing index explained the most variation on rooftop solar adoption, specifically in the lower groups than the rest of indices. On the contrary, the Economics and the Inequality indices were strongly associated with EV charger adoption compared to rooftop solar adoption.

To verify the model results, I estimated technology adoptions using the original variables. The model results show that housing variables such as housing type and housing tenure are as significant as the Housing index to rooftop solar and EV charger adoptions except for the higher group for EV charger adoption (Figure 3.9). For the income variable, rooftop solar adoption was weakly or negatively associated with the variable while EV charger adoption was positively associated with it, which corresponded to the associations between the Economics index and the technology adoptions. The racial variable, White was negatively associated with the technologies for the higher groups. The model results based on the original variables were mostly consistent with those based on the indices.

Furthermore, controlling for the rest of variables, I found that the associations between outcome variables and income and race variables were different. For example, rooftop solar and EV charger adoptions, which are positively correlated with the income and race variables (Figure 3.4) are negatively correlated with the same variables in the model (Figure 3.10). In summary, housing variables such as housing tenure and housing type were found to be important predictors of rooftop solar adoption, particularly in communities with lower adoption rates in Seattle. In addition, depending on technology and group, income and racial variables were differently associated with rooftop solar and EV charger adoptions when other variables are controlled.

The random effect model identified that adoptions of rooftop solar and EV chargers were positively correlated with each other in Seattle for every group. However, the random intercept differs across groups with an intraclass correlation coefficient (ICC) of 0.87 showing a high between-group variation (Table 3.2). The highest group presents a greater SIR of EV charger than that of rooftop solar (Figure 3.11). Furthermore, the model shows higher increases in rooftop solar adoption per the same interval increase in EV charger adoption for every group. This indicates that the distribution of rooftop solar is more clustered with a

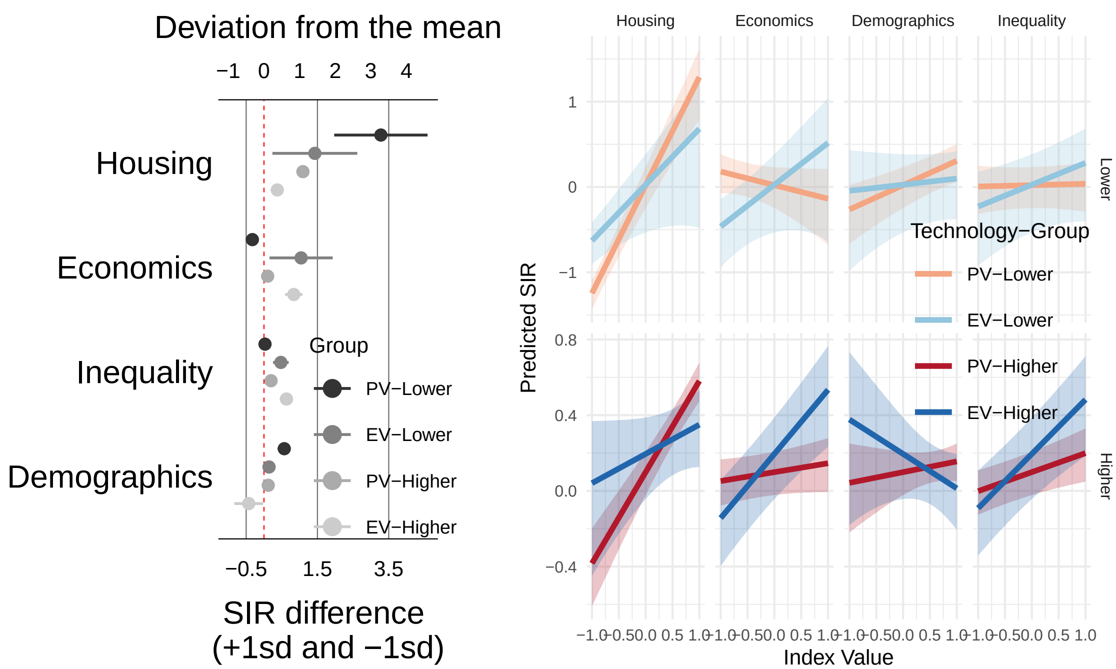

Figure 3.9: Model prediction of the SIR differences between +1 and -1 standard deviation of each index (left) and the logs of SIR prediction (right) with all else being equal to the mean values in terms of the four indices for higher and lower level of adoption groups in rooftop solar and EV chargers (PV: rooftop solar, EV: EV chargers, Higher: the high and highest groups, Lower: the lowest and low groups). Index Value indicates counterfactuals from -1 to 1 for each index with 95% confidence intervals.

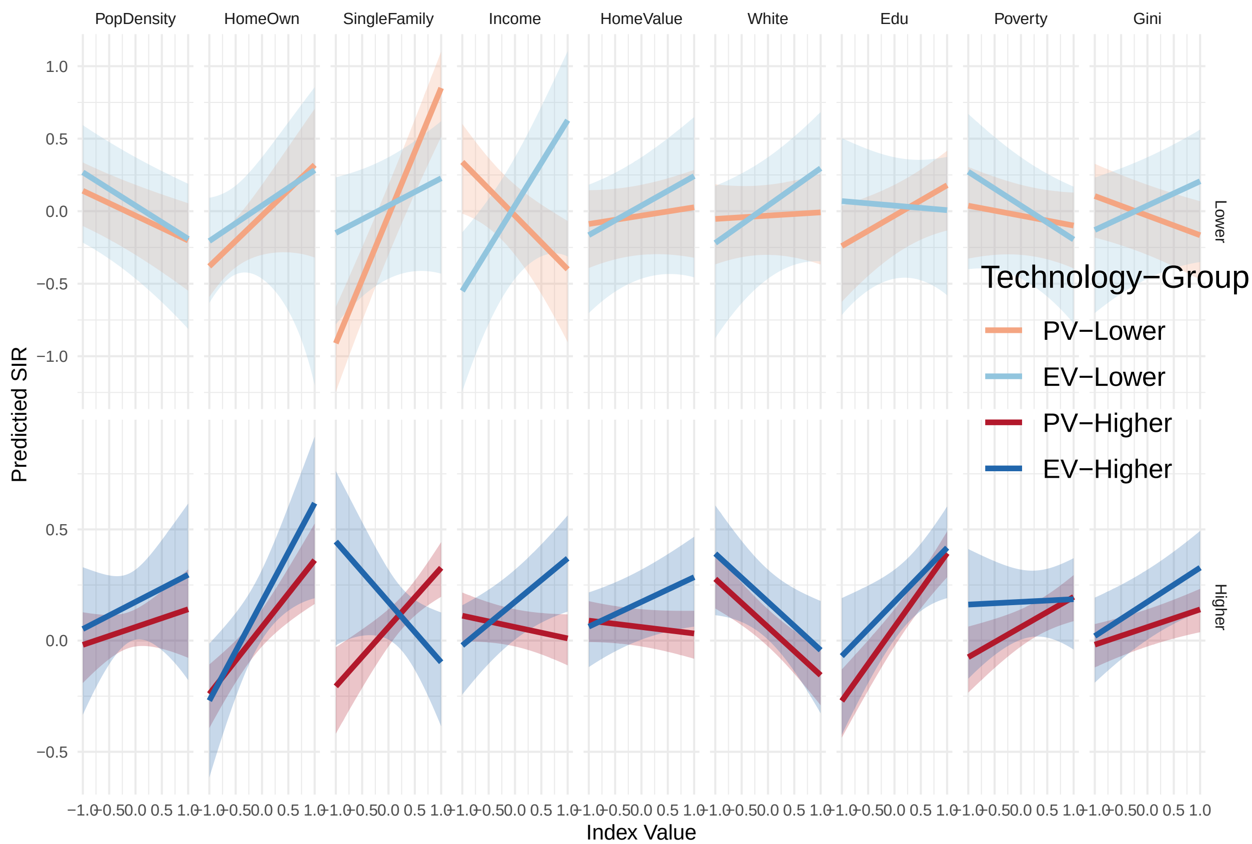

Figure 3.10: The logs of SIR prediction of the Poisson log-linear regression in terms of each predictor of the original variables with all else being equal to the mean values for higher and lower level of adoption groups in rooftop solar and EV chargers (PV: rooftop solar, EV: EV chargers, Higher: the High and Highest groups, Lower: the Lowest and Low groups). Index Value indicates counterfactuals from -1 to 1 for each index.

Table 3.2: Random intercept model results of EV charger SIR (SIR EV) controlling for rooftop solar SIR (SIR PV) in terms of cluster groups. Values indicate model coefficient with t-statistics in parentheses.

	Dependent variable:
	SIR_EV
SIR_PV	0.522***
	(0.083)
Constant	0.660*
	(0.359)
ICC	0.87
Variance	0.27
Group Variance	0.87
Group Number	5
Observations	135
Bayesian Inf. Crit.	259.351
Note:	*p<0.1; **p<0.05; ***p<0.01

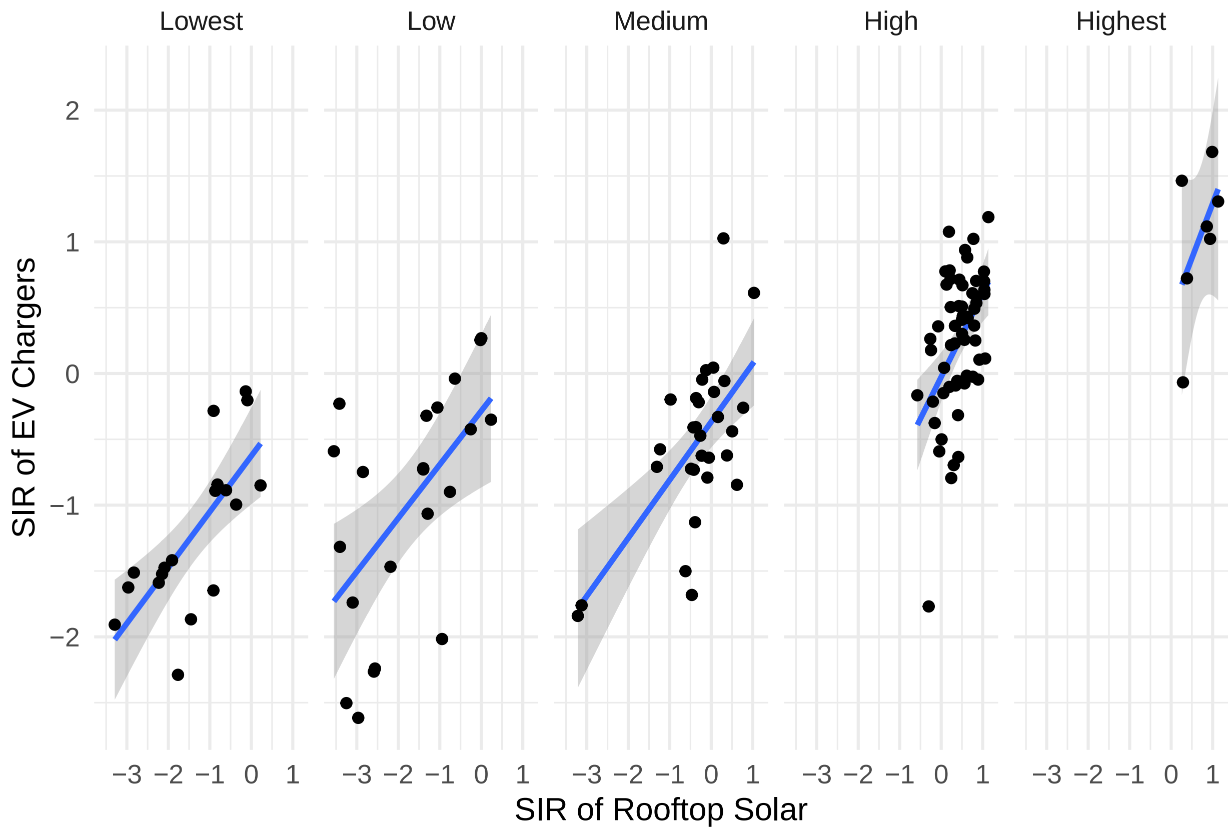

Figure 3.11: Model prediction of the logs of EV charger SIR in terms of the logs of rooftop solar SIR and cluster groups. Linear lines were fitted with 95% confidence intervals.

higher variation within groups than EV chargers.

Controlling for rooftop solar SIR, the estimation of EV charger SIR illustrates an adoption disparity across groups (Figure 3.12). In particular, the high and the highest groups were expected to install more EV chargers than the rest of groups given the same condition of rooftop solar adoption. Furthermore, the low group was expected to have slightly greater EV charger adoption than the medium group. The result indicates that a greater value of the Economics index in the low group can be related to the greater estimation of EV charger adoption than in the medium group. However, in reality, the medium group presented greater adoption in both technologies than the low group because EV charger adoption was also strongly associated with rooftop solar adoption.

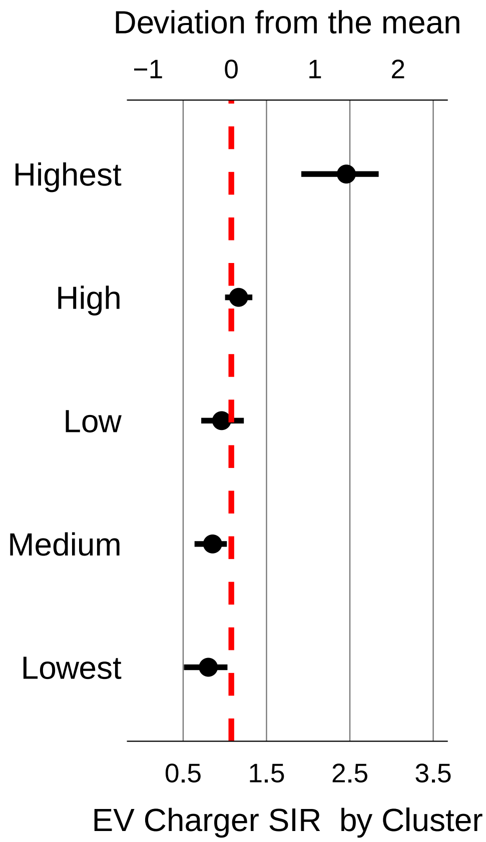

Figure 3.12: Estimations of EV charger SIR controlling for rooftop solar SIR in terms of the cluster groups with 95% confidence intervals. The cluster groups are listed in order of SIR. A red dotted line indicates the mean of EV charger SIR in Seattle for reference.

3.4 Discussion

This empirical study investigated distributional justice in terms of spatial clustering in the distribution of rooftop solar and EV chargers. It was found that rooftop solar and EV charger adoptions presented spatial disparities in Seattle. Furthermore, recognition justice was examined considering different adoption patterns of these technologies at different levels of the adoption communities. Four latent variables, Housing, Economics, Demographics, and Inequality, were developed to explain variations in the adoptions of both technologies. Cluster analysis was then used to categorize census tracts into five groups that shared similar characteristics. Cluster results showed that census tracts in commercial districts and downtown had fewer installations of rooftop solar and EV chargers. The log-linear model results revealed that housing variables were the most important predictors to rooftop solar adoption and even stronger in communities with low adoption rates. On the other hand, economic variables were found to be strong indicators of EV charger adoption. In addition, a higher variation of rooftop solar adoption implied that the spatial inequality of rooftop solar distribution in Seattle was higher than that of EV charger distribution.

While a previous study (Sunter et al. 2019) revealed that racial disparity was present after controlling for household income and housing tenure, the results of the current study show that the disparity due to race is different depending on communities. In particular, communities in higher adoption groups present fewer adoptions with greater White population. The results show that the significance of racial factors is dependent on community attributes. Although most previous studies have focused on racial and income disparities for rooftop solar adoption, this study's findings show that housing variables such as housing tenure and housing type are more important to adoption than race and income variables. Therefore, the study findings can contribute to the body of knowledge on DER adoption by providing important adoption variables by different technologies and community attributes.

The study results indicate that financial incentives may not be effective for DER deployment to those who cannot afford to install DERs due to housing barriers. In particular, the study found that groups that ranked higher on economic variables demonstrated lower rooftop solar and EV charger adoption if their Housing indices were lower. The lower Housing index, which mainly consists of housing tenure, housing type, and population density, features relatively higher proportions of renters and multi-family residences. For example, renters are not capable of installing rooftop solar and EV chargers on their rented properties. Households in multi-family residences may not be able to install rooftop solar on their shared rooftop (Augustine and McGavisk 2016). Also, homeowners who plan to move out may be dissuaded from installing rooftop solar due to the time required to recoup the initial investment. For example, the average payback period of a rooftop solar was about 15 years in Seattle (EnergySage 2022) and 6 to 9 years in California (Maharana and Nsoesie 2018). Thus, financial incentives may not be sufficient for communities with low adoption rates to accommodate DERs if their housing-related conditions are not satisfactory.

Housing-related support can include policies or assistance enabling renters or multi-family residents to access DERs through clean energy programs such as community solar. Community solar can be an option for those who lack homeownership, available roof or spaces to install the technologies (Chan et al. 2017). Furthermore, financial assistance such as the Low Income Home Energy Assistance Program (LIHEAP) (DoC n.d.a) and the Weatherization Assistance Program (WAP) (DoC n.d.b) aimed at reducing financial burden can increase DER development if they are designed to increase clean energy access. For instance, electric utilities in Washington are mandated to provide energy assistance to low-income households through energy assistance programs including direct customer ownership in rooftop solar (Legislature 2021b). Furthermore, solar leasing may promote rooftop solar adoption in cooperation with such housing support (Drury et al. 2012). Also, having DERs more accessible to renters and multi-family residents through a variety of programs is important, especially in densely populated cities like Seattle, as barriers to access to DERs are more challenging. To this end, increasing adoption of DERs through a comprehensive and strategic approach was suggested including a less regressive means than carbon taxes or flat levies on energy bills (Bouzarovski and Simcock 2017). In summary, the study findings suggest that housing-related support will be more beneficial than direct financial incentives for communities with low adoption rates.

The results of this study about different adoption characteristics between rooftop solar and EV chargers can support creating synergies of dual adoption of the technologies benefiting the local grid because rooftop solar and EV charger integration increases self-consumption of electricity and the local grid stability (Kam and Sark 2015). Moreover, by identifying and categorizing communities in terms of community attributes associated with DER adoptions, the results may help policymakers better support communities with limited resources by devising equitable clean energy policies.

The study has some limitations that future studies may address. First, the adoption variables of DERs in this study are limited to available built environment, socioeconomic, and demographic variables. I did not include other factors, such as peer effects and pre-existing technologies in neighborhoods because of a lack of data at the household level, yet these have previously been found to be important drivers of diffusion of rooftop solar in the early adoption stage (Curtius et al. 2018). There are other drivers such as policy interventions affecting the adoption of such technologies (Graziano and Gillingham 2015; Hofierka et al. 2014; O'Shaughnessy et al. 2021). Future research should include those drivers in the analyses of adoption through collecting sociodemographic data at the household level.

Second, aggregating individual observations to the census tract level can lead to an ecological fallacy; conclusions based on group-level data may be different from those from individual-level data. However, the study result of the relationship between the outcome and predictor variables are consistent with those of previous studies. For example, the current study revealed that communities with a higher adoption of rooftop solar and EV chargers featured higher proportions of single-family housing units, homeowners, White populations, and populations with more education, and higher median incomes and home values. These characteristics are consistent with previous studies on individual adopters' attributes (Barbose et al. 2021; Dastrup et al. 2012; Hofierka et al. 2014). Furthermore, several studies have analyzed DER adoptions based on geographic areas such as census tracts and their socioeconomic and demographic characteristics (Drury et al. 2012; Graziano and Gillingham 2015; Sunter et al. 2019).

Finally, the study is limited to a single city, Seattle, so the findings cannot be generalized to other locations. Expanding the research framework introduced in the study to other regions with diverse political, demographic, and geographic characteristics would help determine whether the observed adoption patterns are generalizable. I also limited the analyses to two DERs (rooftop solar and EV); other patterns may have been observed for other DERs (e.g., batteries).

Chapter 4

CHARACTERIZATION OF ENERGY VULNERABILITY IN TERMS OF URBAN ADMINISTRATIVE AND COMMUNITY ATTRIBUTES IN THE PACIFIC NORTHWEST CITIES

4.1 Introduction

Climate change has presented threats to societies, especially associated with electricity supply. For example, the state of Texas experienced extremely cold weather which led to electricity outages in February 2021 (Public 2021). The state of California also went through a power shut-off associated with its main utility company, Pacific Gas & Electric (PG&E), in response to the risk of wildfire in October 2019 (Fuller 2019). In addition, climate change has disproportionately affected communities, particularly in rural area or along the coast (Reckien et al. 2017). Government agencies have tried to address the disproportionate impact of the climate change on vulnerable communities by recognizing the importance of resilient energy systems. In particular, some government agencies have focused on resolving disproportionate clean energy access while developing more resilient communities. For example, SolSmart, and Solar Energy Innovation Network from the US Department of Energy (DOE) target low- and moderate- income (LMI) households to encourage rooftop solar adoption. However, some of those programs intended to encourage equitable access to distributed energy resources (DERs) have inadvertently caused disproportionate rates of program participants of certain communities (Scavo et al. 2016). Therefore, better recognition of those underserved or vulnerable communities is necessary to develop more equitable policies (Martiskainen et al. 2021). To this end, there have been efforts to develop ways to identify those vulnerable communities. For example, the US federal government is working on how to identify disadvantaged communities to support through various programs such as the Justice40 Initiative of the Biden-Harris Administration (Young et al. 2021). Also, various studies have attempted to analyze adoption disparities in DERs based on diverse communities such as LMI, disadvantaged communities, and racial and ethnic majority communities (Lukanov and Krieger 2019; O'Shaughnessy et al. 2021; Sunter et al. 2019). In particular, race (Martiskainen et al. 2021), income (Middlemiss and Gillard 2015; Sanchez-Guevara et al. 2019), and education attainment (Gouveia et al. 2019) are associated with households' vulnerability in terms of their abilities to respond to threats.

However, it is difficult to identify vulnerable communities with a single variable, or to verify which variables are more significant when determining vulnerable communities. There are also different measures associated with energy vulnerability such as energy burden, energy poverty, social vulnerability, energy affordability, and energy accessibility (Drehobl et al. 2020; Flanagan et al. 2018; Galvin 2019). Furthermore, ways to identify vulnerable communities vary depending on institutional purposes. The previous study on Seattle in Chapter 4 showed that adoption rates of rooftop solar are significantly associated with the built environment and housing characteristics of the communities. Specifically, rooftop solar installations are strongly correlated with single-family housings, homeownership, and population density. However, the findings may not be consistently applicable to other cities due to geographical heterogeneity including diverse political and geographic characteristics.

Considering those concerns, this chapter is aimed at answering the question: "how to identify and characterize vulnerable communities in terms of energy justice in the Pacific Northwest cities for equitable policies?" To answer the question, this chapter involves (1) investigating energy vulnerability in the Pacific Northwest cities (Seattle, Bellevue, and Portland) associated with community characteristics in terms of places, people, and Equality, (2) performing a comparative analysis of the three cities for inferring and characterizing energy vulnerability, and (3) identifying their vulnerable communities for policy recommendations to mitigate observed energy justice.

In particular, this chapter involves investigating energy vulnerability characterized by energy dependency and energy resiliency considering different urban administrative and community characteristics. Energy dependency reveals the level of energy vulnerability in connection with weakness, powerlessness, deficiency, and passivity (Gilson 2013). On the other hand, energy resiliency is more relevant to preparation against threats and availability of resources to recover (Sharifi and Yamagata 2016). Energy dependency and energy resiliency are operationalized by energy burden and rooftop solar distribution respectively, since energy burden reveals consumers' energy dependency and rooftop solar adoption increases resiliency against the electricity outages (Ajaz 2019; Krieger et al. 2016). This chapter's objective is further to identify the relationship between energy burden and rooftop solar adoption in addition to their associations with the built environment and residents' characteristics in Seattle, Bellevue, and Portland. The identified relationship between energy burden and rooftop solar adoption can verify arguments that grid modernization as a result of the recent transition to DERs has caused higher residential utility costs and disproportionate financial burdens on LMI households (Brown et al. 2020a; Mastropietro 2019). For example, energy burden can be higher for LMI households than other income groups because LMI households have little access to financial resources to upgrade their energy efficiency measures and to install DERs (Brown et al. 2020b). On the other hand, rooftop solar reduces households' energy burden by producing clean energy (Cook and Shah 2018a).

In this chapter, I focus on geographical heterogeneity and community characteristics to characterize energy vulnerability in the three cities. This study investigates distributional justice in terms of spatial dependencies of energy dependency and energy resiliency. Furthermore, the study examines recognition justice by identifying vulnerable communities associated with energy dependency and energy resiliency.

4.2 Research methodology

The Low-Income Energy Affordability Data (LEAD) Tool developed by the U.S. Department of Energy (DOE) and National Renewable Energy Laboratory (NREL) provides annual average energy burden and energy cost based on counties, cities, and census tracts (Ma et al. 2019). This tool helps characterize LMI households in energy expenditures categorized by household income level and housing unit types such as housing tenure, housing heating fuel type, housing construction year, and the number of units in each building. For the analysis presented in this chapter, I used the annual average energy burden at the census tract level as a measure of energy burden.

The analysis is based on rooftop solar and EV charger installation permit records from the open data portals of the Cities of Seattle, Bellevue, and Portland from 2003 to 2019. According to the code, a permit is required for homeowners to install rooftop solar on their property, so the permit data set from the portals are deemed complete. The data includes geographical coordinates (latitudes and longitudes), installation dates, and contractor information. The coordinates are used to create a geographic information systems (GIS) point layer, which was aggregated to census tracts, the latter was used as the unit of analysis. Standardized rooftop solar adoption was measured by the number of rooftop solar installations divided by the number of households in a census tract. The built environment, socioeconomic and demographic variables related to rooftop solar adoption and vulnerability predictors were obtained from the 2014-2018 American Community Survey (ACS). The variables include population density, housing type, income, education, home value, homeownership, poverty, race, and income Equality (Gini index).

4.2.1 Research design

The objective of this chapter is to identify and characterize vulnerable communities in energy justice for equitable policy implementation. In particular, this study is aimed at characterizing energy vulnerability in the urban areas of the Pacific Northwest region to understand its association with social equity. The study involves performing a spatial analysis of energy burden and rooftop solar adoption in terms of the built environment, socioeconomic, and demographic characteristics, using census tract-level data in Seattle, Bellevue, and Portland. The proposed framework for identifying and characterizing vulnerable communities associated with energy justice is conceptualized in three phases, namely exploration, characterization, and prediction (Figure 4.1). First, in the exploration phase, distributional justice was examined by Moran's I statistics for the distribution of energy burden and rooftop solar adoption. Ignoring spatial dependency leads to biased and inconsistent estimates and loss of efficiency of a regression model (Balta-Ozkan et al. 2015). Depending on whether spatial dependencies existed in energy burden and rooftop solar distribution, I determined to apply

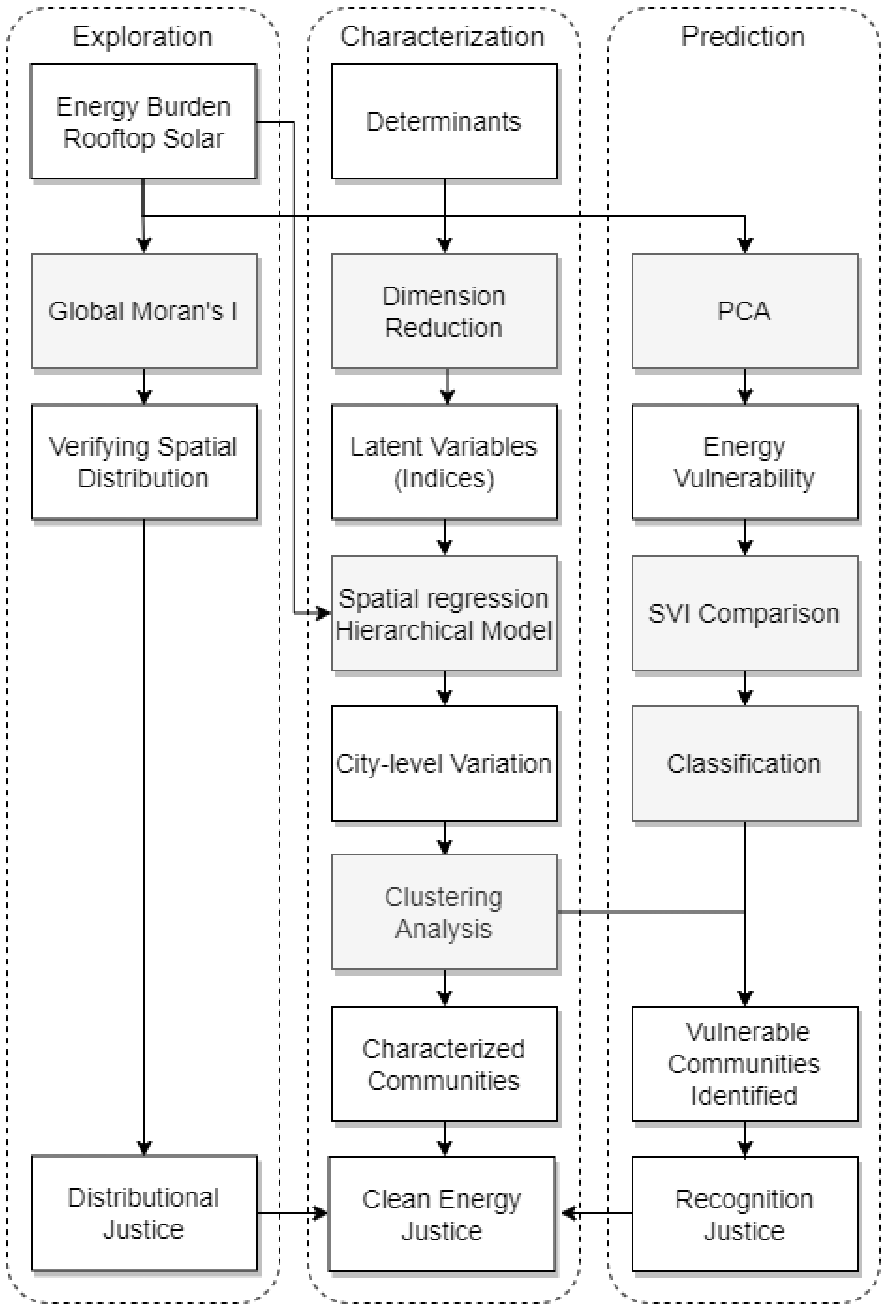

Figure 4.1: Proposed framework for identifying and characterizing vulnerable communities associated with energy justice in three phases. Grey rectangles present analysis processes while white rectangles are interim outcomes used as inputs for the next steps.

spatial regression models for characterizing energy vulnerability.

Second, in the characterization phase, I used the nine vulnerability predictors identified from the literature to develop latent variables featuring community attributes in terms of place, people, and equality. Here, place refer to the built environment and housing characteristics while people are associated with socioeconomic and demographic characteristics of a community. Equality is represented by Gini index, the equality of income distribution within a community. I combined all census tracts of the cities for the dimension reduction so that cities could be comparable with each other. With respect to the three latent variables of community characteristics, I characterized rooftop solar adoption and energy burden using several regression models. These models were compared using model performance approximations such as Akaike information criterion (AIC) and Bayesian information criterion (BIC). I first applied Ordinary Least Squares (OLS) regression to identify presence of spatial autocorrelation in regression residuals. If rooftop solar and energy burden distributions presented clustering in their Moran's I values, and if the OLS residuals revealed spatial autocorrelation, spatial linear regression models would be suggested (Balta-Ozkan et al. 2015). Graziano et al. (2019) addressed spatial spillovers of solar energy technologies regarding the built environment and jurisdictional boundaries using a simultaneous autoregressive (SAR) model. Dharshing (2017) examined rooftop solar adoptions between neighboring counties using SAR and spatial error model (SEM). In contrary, I used a spatial lag model (SLM), a special form of spatial Durbin model (SDM) for the characterization of energy burden and rooftop solar distribution since the study focuses on the spatial distribution of the outcome variables. SDM becomes simplified into SLM when θ is zero, while it becomes SEM when θ becomes $-\rho\beta$ (Balta-Ozkan et al. 2015):

$$Y = \rho WY + X\beta + WX\theta + \epsilon, \tag{4.1}$$

where Y(N x 1) is a vector of observations, ρ is a spatial autoregressive parameter, θ is a spatial lag parameter for the covariates X, W(N x N) is a spatial weights matrix, β(K x 1) is a vector of coefficients of covariates, X(N x K) including an intercept, ϵ is a vector of error terms, N is the number of observations, and K is the number of covariates and an intercept.

Multilevel or hierarchical models were added to the analysis to account for variability between group-specific effects (i.e., city-level variation). If observations are clustered with group-specific effects while sharing within-group variance, observations would be neither independent nor identically distributed (Gelman and Hill 2006). All observations belonging to the same group would have a non-zero intraclass correlation coefficient (ICC). In this case, group-specific effects should be taken into account in the model specification (Gelman and Hill 2006). ICC is defined by the between-group variance divided by the summation of the between-group variance and within-group variance (Gelman and Hill 2006). If ICC is close to one, there would be strong evidence of between-group variance; thus group-specific effects should be considered.

Hierarchical models are statistical models with measures at multiple levels. Ecological studies normally have an observational unit in a group rather than in the individual level. Group observations may lead to the ecological fallacy assuming patterns of variability at the group level applied to the individual level. Fully pooled approaches disregard group level differences while fully stratified approaches disregard characterizing patterns of variability between groups and group-specific effects (Gelman and Hill 2006). On the other hand, partially pooled models such as mixed effect models allow partial variability between groups while others vary by group. To this end, the census tracts of the three cities, Seattle, Bellevue, and Portland were aggregated resulting in a pooled dataset to construct a hierarchical model. In particular, the model would identify the city-level variation of energy burden and rooftop solar adoption using a mixed effect model. For example, census tracts in the three cities could be associated with two non-nested group levels such as city-level (j) and cluster-level (m). Specifically, random effects instead of fixed effects were applied to the analysis since the number of census tracts in Bellevue was comparatively smaller than in the other two cities. Because the unbalanced group sample sizes and the small group number would cause biased parameter estimations, random effect models would lead to more precise estimation of groups by mutually borrowing information from each other, especially in favor of groups with smaller sample sizes (Gelman and Hill 2006). A mixed effect model including spatial autocorrelation and two group effects:

$$
\begin{aligned}
Y_i &\sim Gamma(k_i, \theta_i), \\
k_i\theta_i &= \mu_i, \\
log(\mu_i) &= \rho_j W Y_i + \eta + \alpha_j + \gamma_m + \sum_{l=1}^{p} (\beta_l + \beta_{lj}) X_{li}, \\
\begin{bmatrix} \beta_{lj} \\ \alpha_j \\ \gamma_m \end{bmatrix} &\sim Normal_{MV} \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\beta^2 & \sigma_{\beta\alpha} & \sigma_{\beta\gamma} \\ \sigma_{\beta\alpha} & \sigma_\alpha^2 & \sigma_{\alpha\gamma} \\ \sigma_{\beta\gamma} & \sigma_{\alpha\gamma} & \sigma_\gamma^2 \end{bmatrix} \right),
\end{aligned}
\tag{4.2}
$$

where, Y_i is a outcome variable for an observation i following a Gamma distribution with a shape parameter k_i and a scale parameter θ_i. The mean function consists of a spatial lag term, ρWY which has a spatial dependence parameter ρ and a weight matrix W defining neighbors. The η is an overall intercept that any nonzero mean for the γ and α distributions could be folded into it. The parameters α_j and γ_m represent the random intercepts for the respective group variables j and m, while β_l is a covariate coefficient, and β_{lj} is a random slope for a specific group j. The $\sigma_\beta^2, \sigma_\alpha^2, \sigma_\gamma^2, \sigma_{\beta\alpha}, \sigma_{\beta\gamma}$, and $\sigma_{\alpha\gamma}$ are variance and covariance of estimations for β_{lj}, α_j, and γ_m. In particular, I used a Gamma distribution in the model specification because the outcome variables were rates presenting more variance as the value of predictors increased and the relationship between the outcome variables and predictors was non-linear.

Upon verification of city-level variances, I performed a cluster analysis as described in Chapter 2 to identify groups of similar communities based on community attributes. In particular, communities in Seattle, Bellevue, and Portland were grouped by community characteristics in terms of places, people, and Equality. I included the cluster group variable into the hierarchical model specification to examine the model improvement associated with parameter estimation, assuming that cluster groups would reflect the variability of the outcome variables. If so, cluster grouping would help to characterize vulnerable communities.

Finally, in the application phase, I used principal components analysis (PCA) to develop an energy vulnerability index by consolidating all the variables, including energy burden and rooftop solar adoption. Compared to factor analysis, PCA is more effective to extract an important composite index by reducing correlated variables (Costello and Osborne 2005). I compared the vulnerability index with social vulnerability index (SVI) to verify which index represents energy vulnerability better.

Furthermore, based on community characteristics, multinomial logistic regression was used to predict energy vulnerability of urban areas in King County. The reason I used the prediction model is because some outcome variables, such as energy burden and rooftop solar adoption, were not available. In addition, cluster grouping varies depending on the characteristics of regions and the size of observations. Different cluster grouping leads to difficulty in comparison across regions. For example, a specific community clustered within Seattle may be differently grouped within King County. Hence, I trained the model for energy vulnerability index based on available data from the three cities, and estimated energy vulnerability for the areas where data was not available. In general, machine learning algorithms feature a gradient descent which is a generic optimization algorithm. For example, to minimize a cost function $f(\theta^{(k)})$, the algorithm starts with an arbitrary point θ_0 and repeats the algorithm until it is near the optimal point. The cost function could be different depending upon the models. The goal is to find the weight (θ), which minimizes the cost function:

$$\theta^{(k+1)} = \theta^{(k)} - \eta k \nabla f(\theta^{(k)}), \tag{4.3}$$

where, $\eta k \nabla f(\theta^{(k)})$ is the direction of steepest descent of the function at a point θ; ηk is the "step size" or "learning rate." $\theta^{(k+1)}$ has a less cost function value than θ^k. With each step of gradient descent, the cost function value gets lower. Eventually, the algorithm converges to a local minimum.

4.3 Results

Figure 4.2 shows the distributions of standardized values of the nine predictors and the two outcome variables. City-level variations are obvious across cities of Seattle, Bellevue, and Portland.

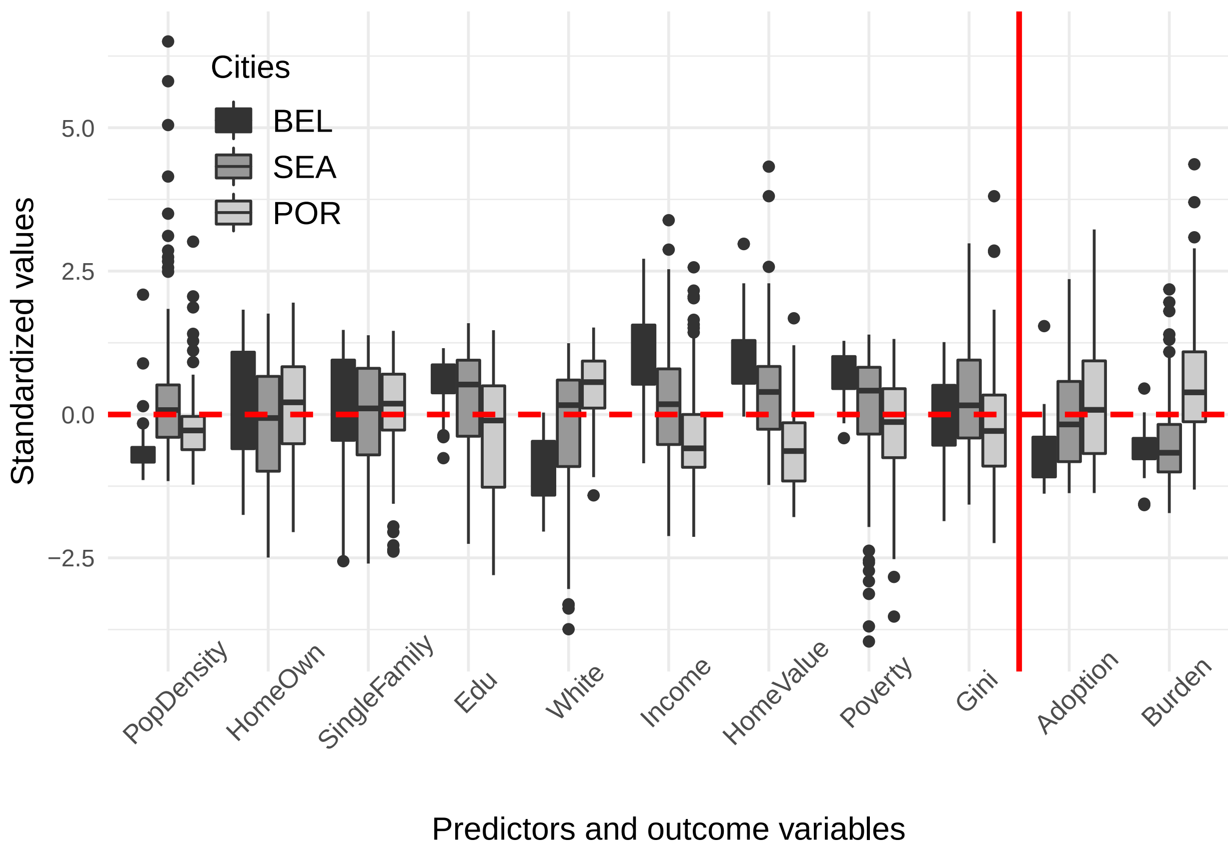

Figure 4.2: Descriptive statistics of the standardized values of predictors (left from the red solid line) and outcome (right from the red solid line) variables at the census tract level for the City of Bellevue (BEL), Seattle (SEA), and Portland (POR).

Table 4.1: Global Moran's I (p-values) for the distributions of rooftop solar adoption and energy burden in Seattle, Bellevue, and Portland.

Cities	Adoption	Burden
Bellevue	-0.121 (0.78)	0.281 * (<0.005)
Seattle	0.424 ** (<0.001)	0.616 ** (<0.001)
Portland	0.470 ** (<0.001)	0.569 ** (<0.001)

Note:

** <0.001; * <0.005

4.3.1 Spatial distribution patterns

Table 4.1 shows spatial dependencies based on the global Moran's I values of rooftop solar adoption and energy burden in Seattle, Bellevue, and Portland. All values are significantly positive indicating spatial clustering except for rooftop solar adoption in Bellevue. In particular, energy burden in Seattle (0.62) and Portland (0.57) indicate stronger spatial clustering than rooftop solar adoption. The results reveal geographically disproportionate distribution of rooftop solar adoption and energy burden in Seattle, Bellevue, and Portland. As seen in Table 4.1, Figure 4.3 reveals spatial autocorrelation with clustering patterns in the cities, so spatial regression models are needed to address spatial autocorrelation for characterizing energy dependency and resiliency.

4.3.2 Dimension reduction

In order to characterize communities, I used factor analysis to identify latent variables accounting for correlations among the variables of each city. The nine vulnerable predictors led to three latent variables. The standardized loadings based on the variables' correlation matrix of each city reveal similar patterns across the cities (Figure 4.4 top). Then, I combined all the census tracts of the cities to investigate city-level variations. Likewise, using factor analysis based on the combined census tracts of the three cities, I identified the similar

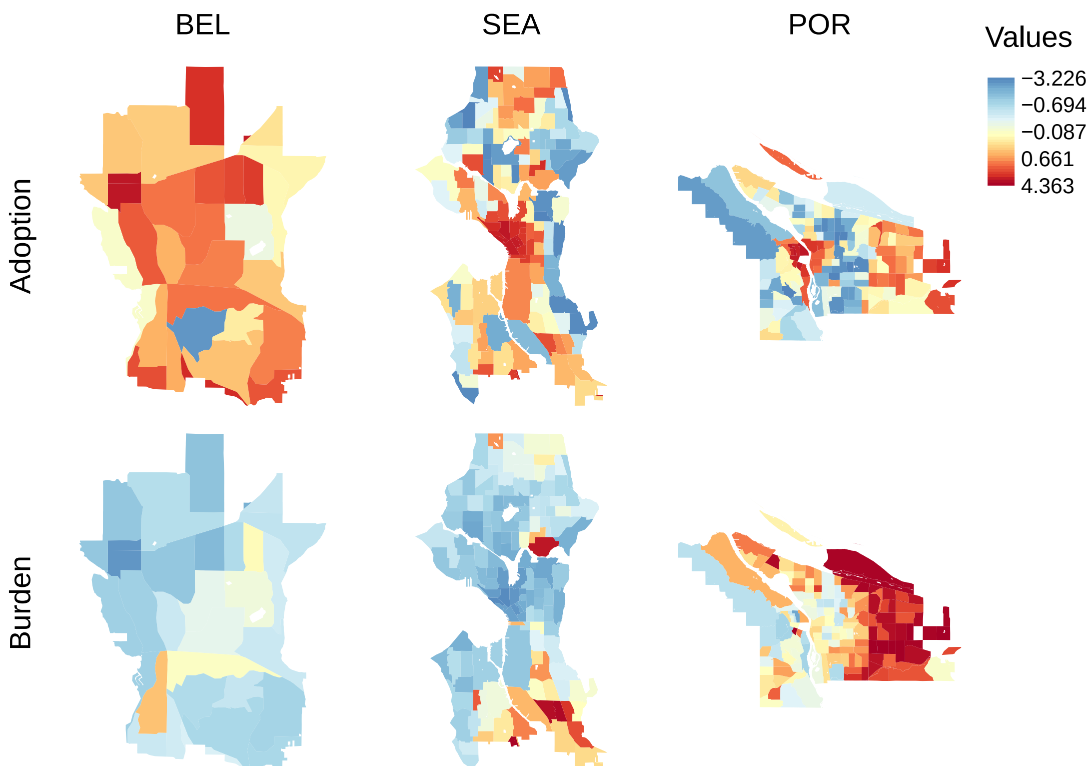

Figure 4.3: Rooftop solar adoption and energy burden distributions in Seattle, Bellevue, and Portland (to avoid confusion with the vulnerable intensity of energy burden, adoption values are inversed that higher values mean lower adoption, overall, darker red represents more vulnerability; all values are standardized).

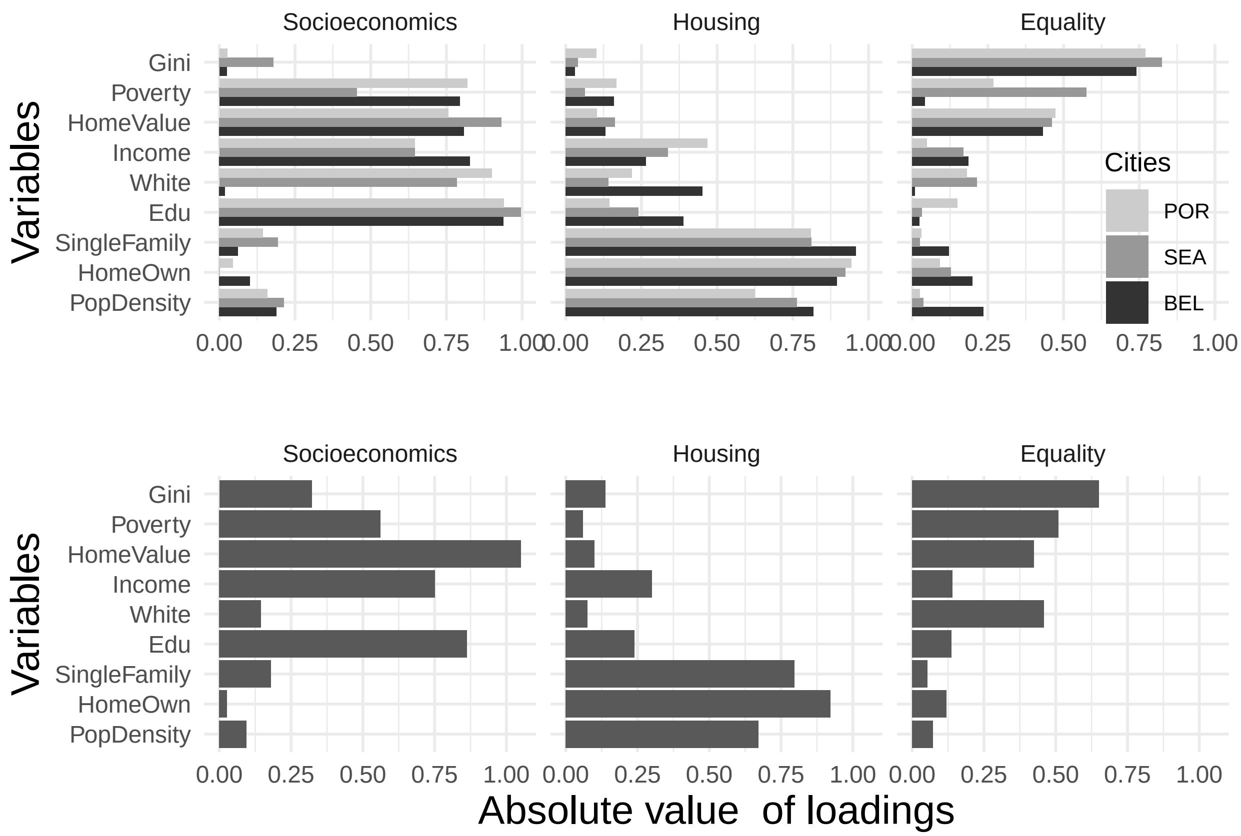

Figure 4.4: Standardized loadings of the nine vulnerability predictors for the three latent variables (Socioeconomics, Housing, and Equality) for each city (top) of Seattle (SEA), Bellevue (BEL), and Portland (POR) and the combined (bottom). All the loadings are in absolute value.

patterns of the distribution of loadings (Figure 4.4 bottom).

The latent variables were named based on the characteristics of the highly governing individual variables with higher loadings. For example, the first latent variable, "Socioeconomics" are mostly associated with the "people" characteristics such as the proportion of population above 150% poverty level, median home value, median income, and the proportion of residents that are 25 years or older with a bachelor's degree or higher. The second latent variable, "Housing" features the "places" characteristics, mainly consisting of the built environment and housing types such as single-family housing, homeownership, and popula-

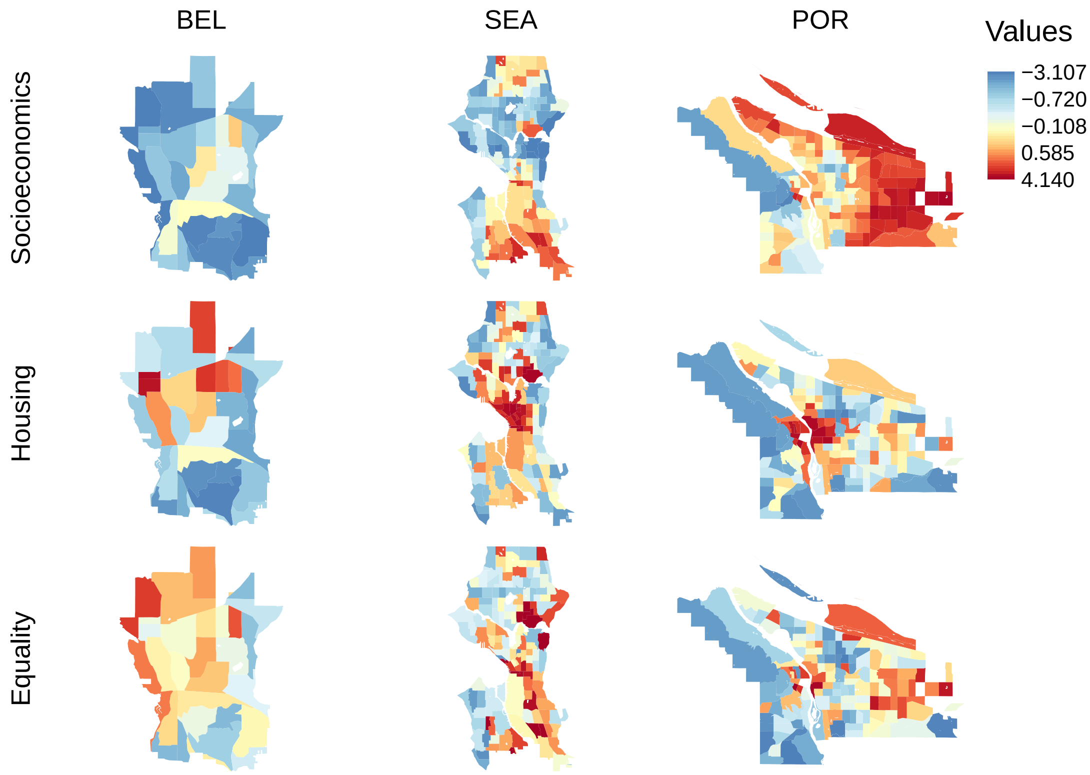

Figure 4.5: Distributions of the three latent variables (Socioeconomics, Housing, and Equality) in Seattle, Bellevue, and Portland (to avoid confusion, values of the Socioeconomics, Housing, and Equality are inversed that higher values mean lower Socioeconomics, Housing, and Equality; overall, darker red represents more vulnerability; all values are standardized).

tion density. Finally, the last latent variable, "Equality" mainly comprises one predictor, Gini and the proportion of population that are white. While the proportion of population above 150% poverty level highly contribute to the latent variable, the predictor has more associations with the Socioeconomics. The Equality index represents income equality within a census tract. The three indices are illustrated in the maps of Seattle, Bellevue, and Portland in Figure 4.5.

Exploratory data analysis reveals the city-level variations of the variables, specifically, the Socioeconomics index, rooftop solar adoption, and energy burden as shown in Figure 4.6

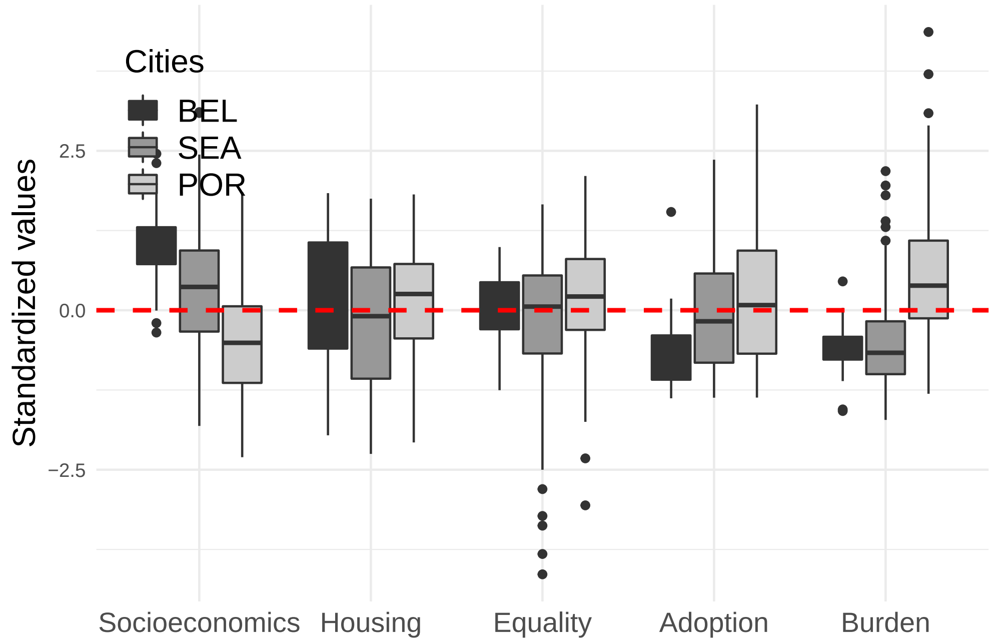

Figure 4.6: Box plots of standardized values of the three latent variables (Socioeconomics, Housing, and Equality) and two outcome variables (rooftop solar adoption and energy burden) in Seattle, Bellevue, and Portland (the red line represents zero, the standardized mean values of all variables).

illustrating the city-level variations of standardized values of the three latent variables and the two outcome variables in the three cities. In particular, higher energy burden is mostly observed in Portland while Bellevue features higher values of the Socioeconomics index.

4.3.3 Spatial lag

In order to examine city-level variations and spatial dependencies, three models of OLS, fixed-effect OLS, and fixed-effect SLM were compared for modeling rooftop solar adoption and energy burden with respect to the three latent variables. In addition, rooftop solar adoption as a covariate was included in the model specification for modeling energy burden, and energy burden was also included in the model for estimating rooftop solar adoption to examine the association between the two variables. Furthermore, city-level between-group effects (i.e., fixed effects) were included in the model specifications to verify city-level variations. The performances of each model based on AIC including covariate coefficients and fixed effects are illustrated in Table 4.2. The Socioeconomics index is positively associated with adoption but negative for burden. The fixed-effect OLS residuals of rooftop solar adoption and energy burden presented spatial clustering with significant Moran's I values (0.34 for rooftop solar, and 0.2 for energy burden). The SLM outperforms the OLS for both rooftop solar adoption and energy burden estimations, given that the AIC values are lower. In addition, the high values of spatial autoregressive parametersthere indicates spatial clustering in both outcome variables. Specifically, the lag term in SLM explains the additional variations in the outcome variables. Considering Moran's I statistics of the residuals, OLS cannot address spatial autocorrelations in the outcome variables. Since the values of the spatial autoregressive parameter (rho = 0.48 for rooftop solar adoption, and 0.22 for energy burden) are significant, it provides justification to include lagged terms. The model results confirm that SLM is better than OLS by addressing spatial autocorrelation in the outcome variables.

In addition, the model results indicate significant city-level variations. The SLM estimations of rooftop solar adoption and energy burden controlling for the rest of the variables, reveal that Portland has the highest rooftop solar adoption rate followed by Seattle and Bellevue (Figure 4.7). Regarding energy burden, Portland also indicates the highest energy burden rate followed by Bellevue and Seattle. This confirms that there are significant city-level variations in both rooftop solar adoption and energy burden in the three cities even after controlling for community characteristics of the Socioeconomics, Housing, and Equality indices.

4.3.4 Mixed effect

Rooftop solar adoption and energy burden were further estimated using Gamma log-link function with random-intercept (RI) and random-slope (RS) models. The Moran's I statistics on the residuals reveal little spatial clustering since the spatial lag terms addressed spatial autocorrelation. For rooftop solar adoption, the RS model did not improve the model perfor-

Table 4.2: Model summaries of OLS and SLM (A-lag for Adoption and B-lag for Burden) with city-level fixed effects (Seattle, Bellevue, and Portland) for rooftop solar adoption and energy burden.

	Dependent variable:					
	Adoption			Burden		
	OLS	OLS FE	SLM FE	OLS	OLS FE	SLM FE
A_lag			0.634***			
			(0.060)			
B_lag						0.198***
						(0.041)
Socioeconomics	0.226***	0.321***	0.192***	−0.689***	−0.542***	−0.460***
	(0.083)	(0.078)	(0.067)	(0.023)	(0.025)	(0.029)
Housing	0.398***	0.473***	0.363***	0.382***	0.381***	0.318***
	(0.063)	(0.060)	(0.053)	(0.030)	(0.025)	(0.027)
Equality	0.147**	−0.008	−0.014	−0.330***	−0.413***	−0.385***
	(0.062)	(0.068)	(0.058)	(0.029)	(0.024)	(0.024)
Burden	0.119	−0.040	−0.051			
	(0.105)	(0.115)	(0.098)			
Adoption				0.036	−0.010	−0.003
				(0.031)	(0.029)	(0.028)
Akaike Inf. Crit.	641.8	570.4	474.9	271.9	148.6	127

Note: *p<0.1; **p<0.05; ***p<0.01

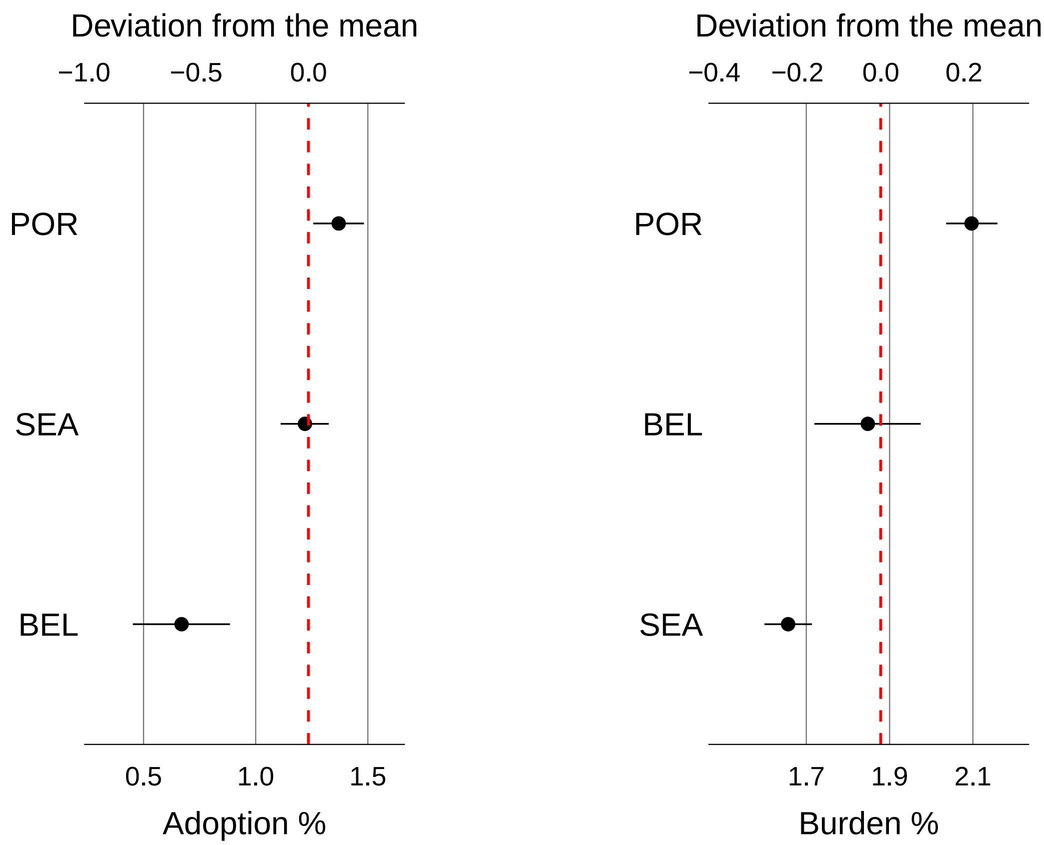

Figure 4.7: SLM estimations of rooftop solar adoption (left) and energy burden (right) in Seattle, Bellevue, and Portland with 95% confidence intervals (the red line represents mean values of rooftop solar adoption, and energy burden in the three cities).

mance as both AIC and BIC increased. On the other hand, both AIC and BIC indicate that the RS model improved the energy burden estimation (Table 4.3). The mixed effect model

Table 4.3: Linear and Gamma model summaries with the city-level random-intercept and random-slope for rooftop solar adoption and energy burden.

	Dependent variable:					
	Adoption			Burden		
	Linear RI	Gamma RI	Gamma RS	Linear RI	Gamma RI	Gamma RS
A_lag	0.643***	0.873***	0.854***			
	(0.060)	(0.075)	(0.075)			
B_lag				0.202***	0.057***	0.052***
				(0.040)	(0.019)	(0.018)
Socioeconomics	0.187***	0.199**	0.142	−0.461***	−0.266***	−0.275***
	(0.067)	(0.081)	(0.105)	(0.029)	(0.014)	(0.017)
Housing	0.359***	0.480***	0.578***	0.316***	0.197***	0.211***
	(0.053)	(0.062)	(0.120)	(0.027)	(0.013)	(0.043)
Equality	−0.010	0.003	−0.024	−0.383***	−0.207***	−0.200***
	(0.058)	(0.067)	(0.074)	(0.024)	(0.012)	(0.011)
Burden	−0.047	0.204*	0.144			
	(0.098)	(0.121)	(0.137)			
Adoption				−0.001	0.037***	0.033***
				(0.028)	(0.013)	(0.013)
Log Likelihood	−246.263	−219.058	−217.425	−76.405	2.170	29.134
Akaike Inf. Crit.	508.527	454.117	460.850	168.810	11.659	−32.269
Bayesian Inf. Crit.	538.341	483.932	509.299	198.625	41.474	16.180

Note: *p<0.1; **p<0.05; ***p<0.01

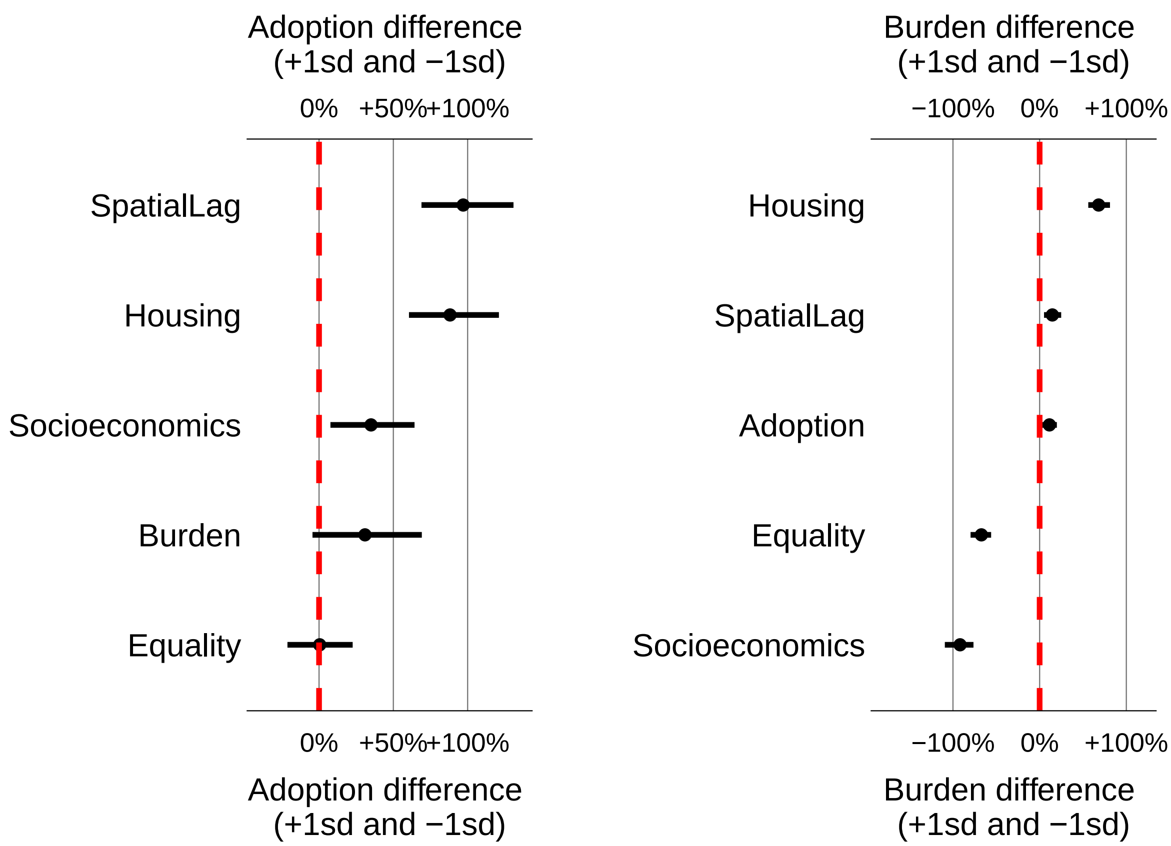

Figure 4.8: Mixed effect model estimations of the relative likelihood of the variables between higher values (+1sd), and lower values (-1sd) of the community characteristics with 95% confidence intervals for rooftop solar adoption (left), and energy burden (right) in the three cities (the red line represents the same likelihood).

reveals that rooftop solar adoption is highly correlated with the Housing for the three cities (Figure 4.8). On the other hand, energy burden is more associated with the Socioeconomics, followed by the Housing than the other variables. Furthermore, interestingly, the spatial lag term of rooftop solar adoption is as significant as the Housing index compared to that of energy burden. This indicates a higher clustering pattern in rooftop solar distribution.

In particular, the Housing index is the strongest predictor of rooftop solar adoption, and stronger for Portland than Seattle or Bellevue (Figure 4.9). The ICC of the model for the rooftop solar adoption is 0.35, indicating a significant between-group variation among the

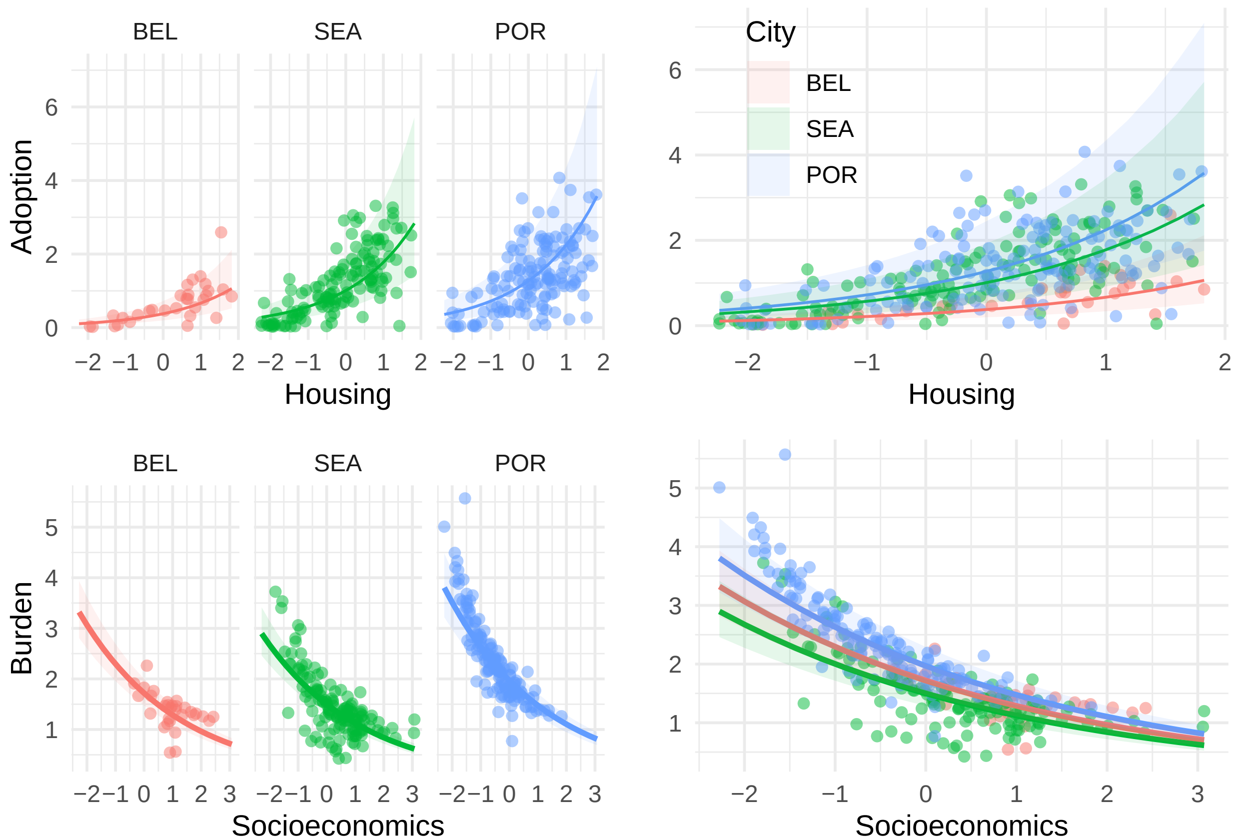

Figure 4.9: Mixed effect model estimations of (i) rooftop solar adoption and (ii) energy burden with 95% confidence intervals (lines and shades) with respect to the latent variable, Housing and Socioeconomics (left: separate per city and right: all together); the points are original data.

three cities. For energy burden, Portland has a comparatively higher intercept. The model also estimated a higher intercept for energy burden in Bellevue even though the empirical data of Bellevue are limited to higher Socioeconomics index and lower energy burden. The ICC of the model of energy burden is 0.42 indicating that energy burden across cities has a higher between-group variation than rooftop solar adoption.

4.3.5 Categorizing groups

In order to characterize communities within each city for rooftop solar adoption and energy burden, K-means clustering algorithm was used to cluster census tracts into five groups in the three cities based on the latent variables. Then, the model improvement and parameter changes were examined by incorporating cluster group variances into the hierarchical model specification. If cluster groups reflected the variability of the outcome variables, cluster grouping would help to characterize vulnerable communities.

The five groups, Lowest, Low, High-BE, High-SE, and Highest are named based on the level of vulnerability and their characteristics associated with the three latent variables. For example, the Lowest and Low groups have lower vulnerability while the High-BE, High-SE, and Highest groups feature higher vulnerabilities. Particularly, the High-BE group is more vulnerable in terms of the built environment characteristics while the High-SE group is more vulnerable in terms of socioeconomics features. The Highest group is vulnerable in both characteristics of the built environment and socioeconomics. In particular, the High-BE group presents lower Housing and higher Socioeconomics values while the High-SE group shows the opposite (Figure 4.10). The Highest group represents the most vulnerable group with respect to the Socioeconomics, Housing, and Equality indices. In addition, the Highest group features higher variations while the other groups are more homogeneous within groups.

The group distribution reveals obvious patterns in the cities. For example, the Lowest and Low groups in Portland are mostly located to the west of the city (Figure 4.11). On the contrary, most communities in the High-SE group are located in either the north or the south of Seattle, and the north or the east of Portland. These areas are associated with lower Socioeconomics index and higher energy burden. The High-BE and Highest groups are mostly located near the city center in all cities. In addition, the Highest group is not present in Bellevue. The results reveal that the communities with geographically similar characteristics tend to cluster each other associated with disproportionate distribution of rooftop solar adoption and energy burden in the cities of the Pacific Northwest.

After sorting cluster groups by each city, the analysis reveals that there are unbalanced

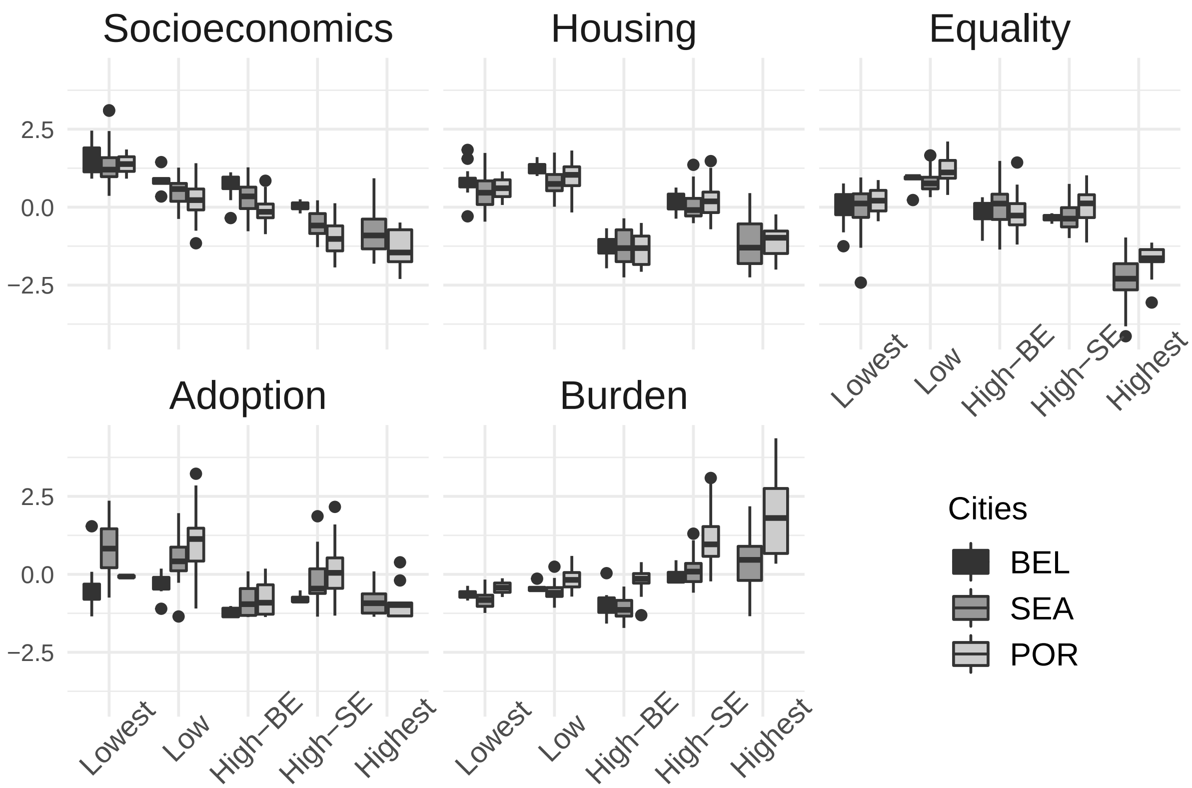

Figure 4.10: Box plots of cluster groups (Lowest, Low, medium, High-BE, High-SE, and Highest) with respect to the three latent variables in Bellevue (left), Seattle (center), and Portland (right). The y-axes present the standardized values of the variables.

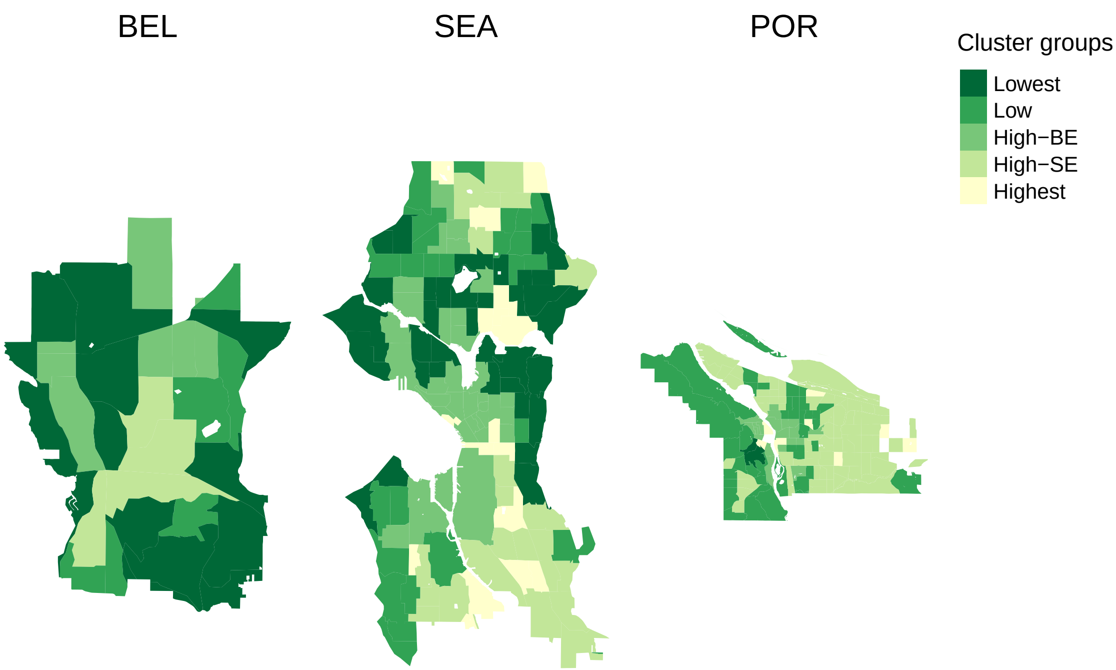

Figure 4.11: Five cluster groups (Lowest, Low, medium, High-BE, High-SE, and Highest) determined by K-means clustering algorithm in Bellevue (left), Seattle (center), and Portland (right).

distributions of the five groups in the cities (Figure 4.12). In particular, Seattle presents more balanced distribution of the cluster groups compared to Bellevue or Portland. For example, Portland has a higher proportion of the Low and High-SE groups while Bellevue relatively has a higher proportion of the Lowest and High-BE groups. The results are consistent with the city-level variations of rooftop solar adoption and energy burden. For example, Portland has the highest rooftop solar adoption and energy burden among the cities and the majority of cluster groups in Portland consist of the Low and High-SE groups. As shown in Figure 5.10, the Low group features higher rooftop solar adoption, while the High-SE group characterizes higher energy burden and lower Socioeconomics index.

4.3.6 Random effect model including cluster groups

Since spatial clustering is reflected in group clustering, I modeled the original outcome variables rather than the residuals with the lag terms removed. Furthermore, Gamma distribution was applied to both outcome variables to address a non-linear relationship between the outcome variables and predictors. Including the cluster group variable in the model specification improved the model performance with lower AIC and BIC (Table 4.4). For example, the AIC and BIC of the mixed effect models decreased as they were developed from city-level random-intercept model (one between-group effect) to city- and cluster-level random-intercept model (two between-group effects). However, the two-group RI model of rooftop solar adoption shows lower BIC than the two-group RS model. This indicates that adding a random slope effect does not improve the rooftop solar adoption estimation while the two-group effect model still outperforms the one-group effect model. On the other hand, the AIC and BIC of energy burden models decreased as the model was developed from city-level random-intercept model (one between-group effect) to city- and cluster-level random-slope model (two between-group effects). This shows that adding the cluster group improves the model only when a random-slope effect is applied for energy burden estimation.

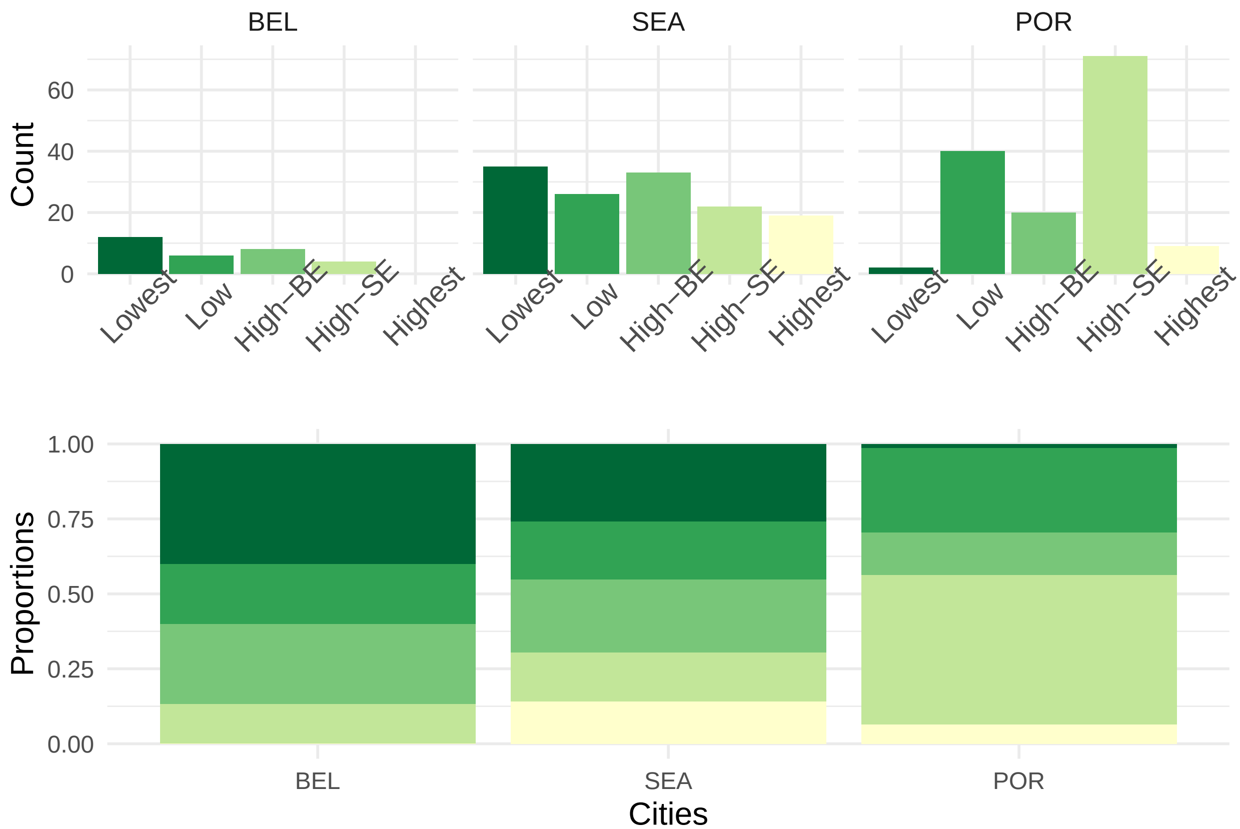

Figure 4.12: Distribution of cluster groups (Lowest, Low, medium, High-BE, High-SE, and Highest) in Bellevue (left), Seattle (center), and Portland (right). The y-axes present (i) the counts, and (ii) the proportions of the census tracts in each cluster group.

Table 4.4: Model summaries of the city-level random-intercept (1G) and city- and cluster-level random-intercept (2G) in terms of random-intercept (RI) and random-slope (RS) for rooftop solar adoption and energy burden.

	Dependent variable:					
	Adoption			Burden		
	1G RI	2G RI	2G RS	1G RI	2G RI	2G RS
Socioeconomics	0.199^{**}	0.189^{**}	0.140	-0.266^{***}	-0.258^{***}	-0.243^{***}
	(0.081)	(0.091)	(0.103)	(0.014)	(0.016)	(0.024)
Housing	0.480^{***}	0.413^{***}	0.511^{**}	0.197^{***}	0.178^{***}	0.192^{**}
	(0.062)	(0.078)	(0.202)	(0.013)	(0.019)	(0.084)
Equality	0.003	-0.031	-0.082	-0.207^{***}	-0.199^{***}	-0.177^{***}
	(0.067)	(0.080)	(0.075)	(0.012)	(0.014)	(0.013)
Burden	0.204^{*}	0.123	-0.015			
	(0.121)	(0.122)	(0.107)			
A_lag	0.873^{***}	0.870^{***}	0.793^{***}			
	(0.075)	(0.074)	(0.074)			
Adoption				0.037^{***}	0.031^{**}	0.022^{*}
				(0.013)	(0.014)	(0.012)
B_lag				0.057^{***}	0.054^{***}	0.046^{***}
				(0.019)	(0.019)	(0.017)
Akaike Inf. Crit.	454.117	450.095	447.228	11.659	11.623	-59.156
Bayesian Inf. Crit.	483.932	483.637	518.038	41.474	45.165	11.654

Note: *p<0.1; **p<0.05; ***p<0.01

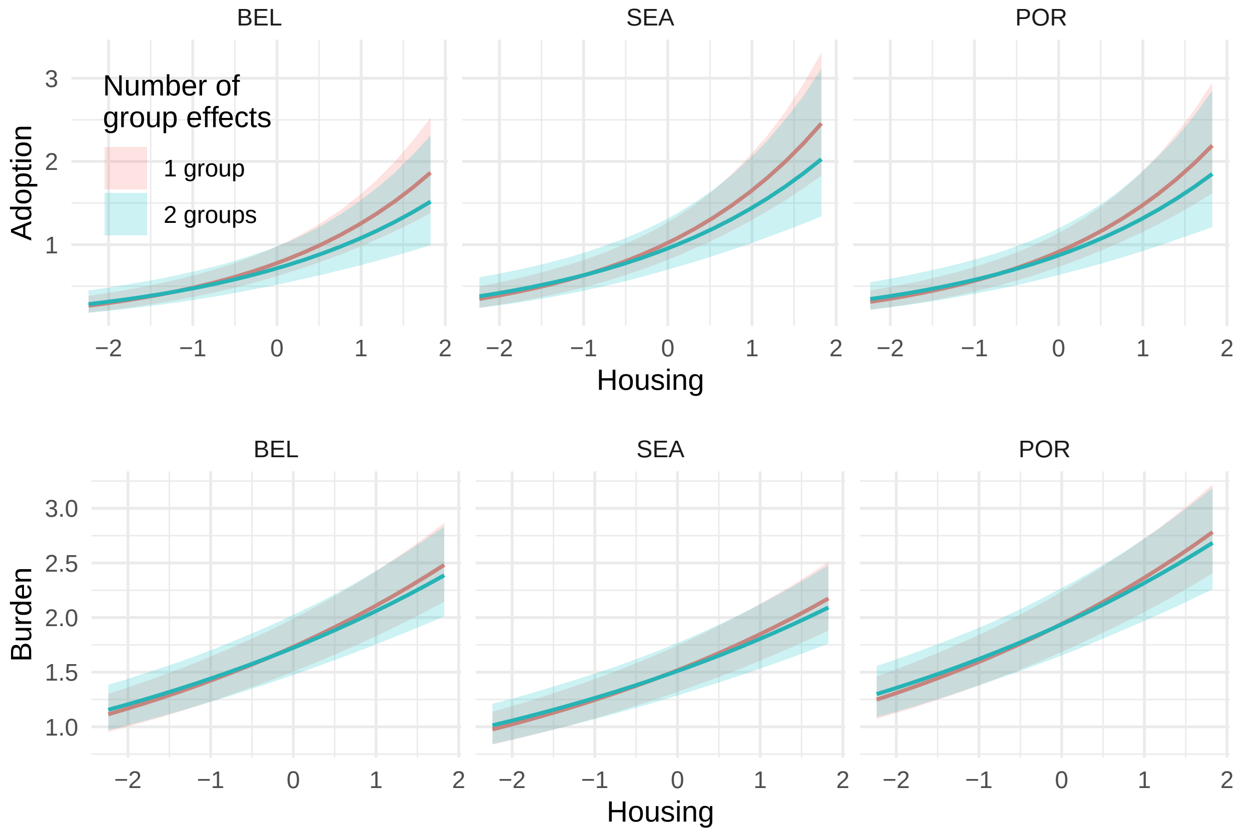

Figure 4.13: Estimations between models of one group RI and two group RI with 95% confidence intervals of (i) rooftop solar adoption and (ii) energy burden with respect to the latent variable, Housing (lines and shades) in Bellevue (left), Seattle (center), and Portland (right).

Adding the cluster group variable to the models reduced the Housing effect on both rooftop solar adoption and energy burden. For example, the point estimate of the Housing coefficient changes from 0.60 to 0.51 for rooftop solar adoption, and from 0.21 to 0.19 for energy burden. The declining pattern of the Housing coefficient is observed in all three cities (Figure 4.13). This shows that cluster groups reflect the variabilities of rooftop solar adoption and energy burden while reducing the Housing effect and improving the model performance. Furthermore, cluster groups would help to characterize vulnerable communities by identifying group characteristics. In addition, among the three vulnerable groups, the two group mixed

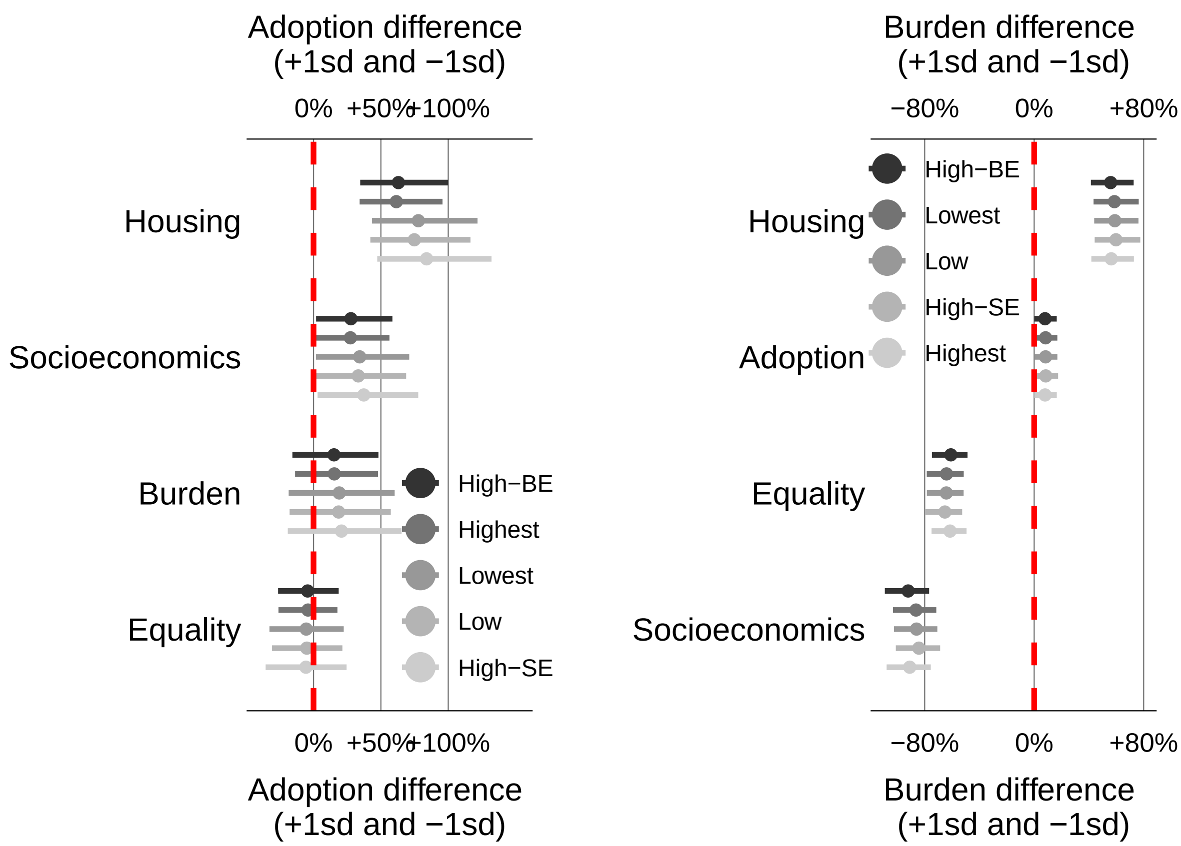

Figure 4.14: Two group mixed effect model estimations of predictor sensitivities with 95% confidence intervals for rooftop solar adoption (left) and energy burden (right) with respect to the five cluster groups in Bellevue, Seattle, and Portland; red lines indicate the no difference of outcome variables.

effect model reveals that the High-SE group presents more sensitivity to the Socioeconomics index while the High-BE group is more sensitive to the Housing index for both rooftop solar adoption and energy burden (Figure 4.14). In particular, the High-SE group indicates the highest rooftop solar adoption and energy burden. For example, the predicted values of the High-SE group is higher than those of the High-BE and Highest groups for both rooftop solar adoption and energy burden (Figure 4.15). This analysis shows that for both rooftop solar adoption and energy burden, the High-BE and Highest groups, which lag the most in rooftop solar adoption, are more sensitive to the Housing index. On the other hand, the High-SE

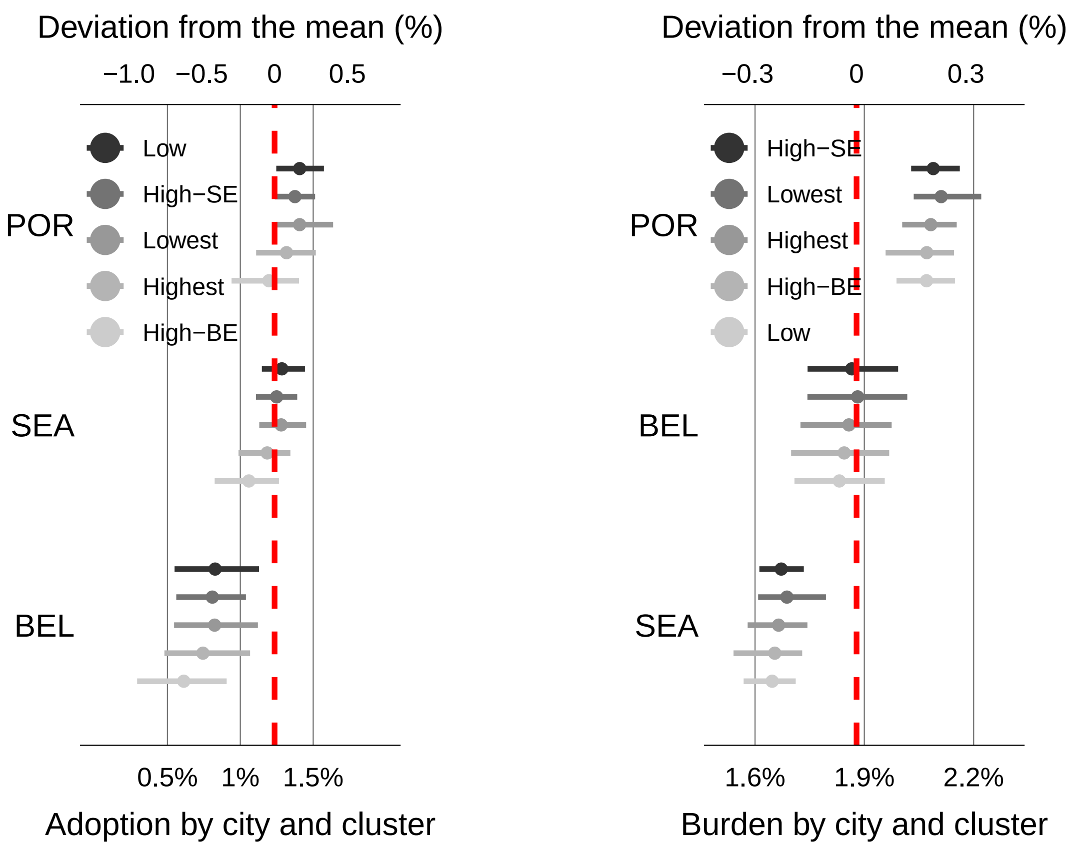

Figure 4.15: Two group mixed effect model estimations with 95% confidence intervals for rooftop solar adoption (left) and energy burden (right) with respect to the five cluster groups in Bellevue, Seattle, and Portland; red lines indicate the mean of outcome variables.

group, which has the highest energy burden, is more sensitive to the Socioeconomics index.

4.3.7 Energy vulnerability estimation

In order to identify vulnerable communities in terms of energy dependency and resiliency, I used PCA to develop an energy vulnerability index by consolidating all the predictor variables including the outcome variables, energy burden and rooftop solar adoption. The Vulnerability index was compared with the SVI to verify which index is more suitable to reflect energy dependency and resiliency in terms of rooftop solar adoption and energy burden. The comparison was done by modeling outcome variables using the indices. If the coefficient

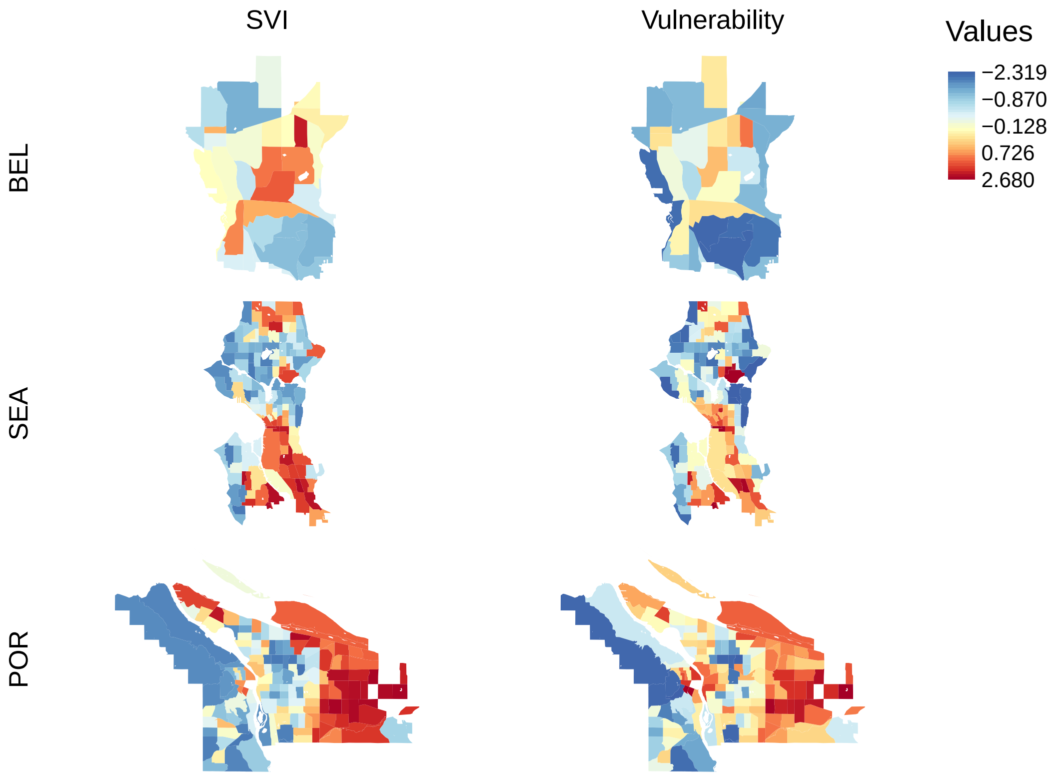

Figure 4.16: Distributions of the SVI and Vulnerability index in the cities (Bellevue, Seattle, and Portland).

of an index is more significant, the index would be more suitable to represent energy vulnerability. After standardization, the SVI shows more extreme values and variance across the cities than the Vulnerability index (Figure 4.16).

Furthermore, cluster groups illustrate more within-group variability for the SVI than the Vulnerability (Figure 4.17). Estimations of rooftop solar and energy burden are better explained by the Vulnerability index than the SVI. For example, both fixed effect and random effect models, including city and cluster between-group variations, reveal that the Vulnerability index is the more significant predictor to the model estimations of rooftop solar adoption and energy burden than the SVI. For example, the Vulnerability index is more significant than SVI for the four models (Table 4.5). Finally, the Vulnerability index and cluster groups

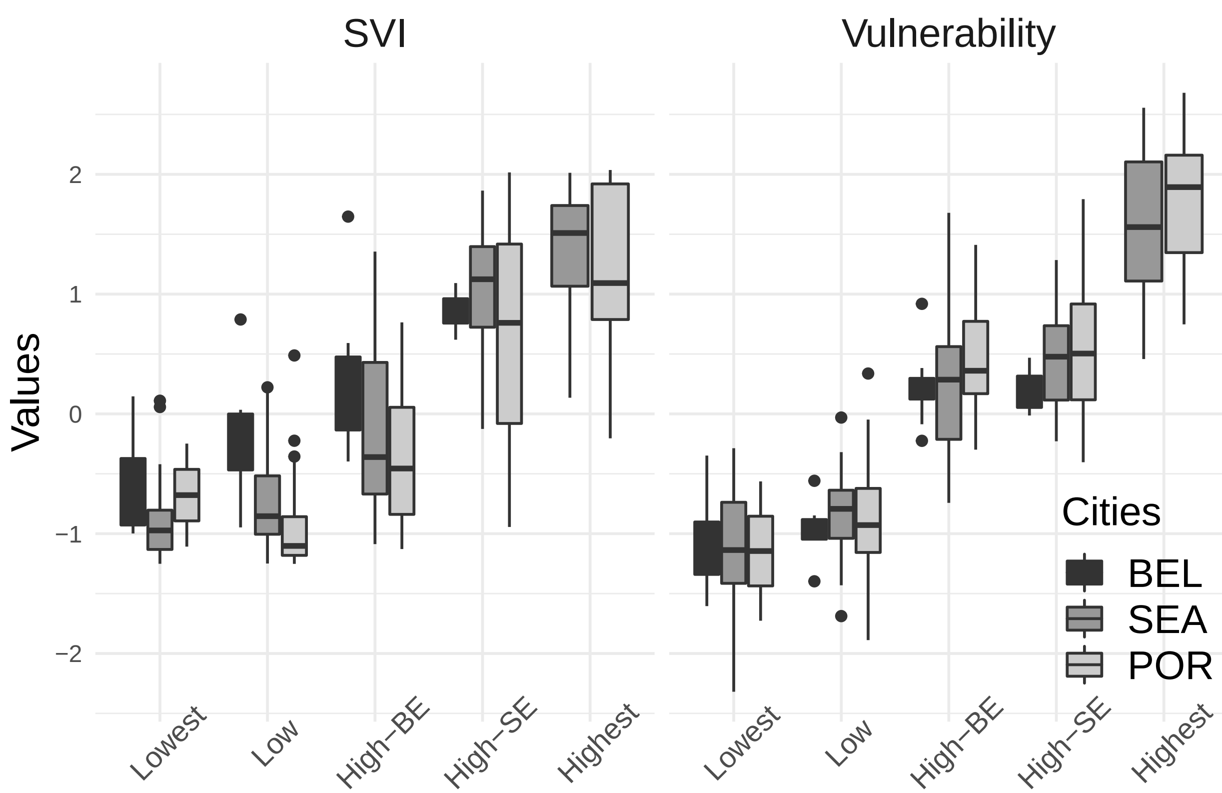

Figure 4.17: Box plots of cluster groups (Lowest, Low, High-BE, High-SE, and Highest), and cities (Bellevue, Seattle, and Portland) with respect to the SVI and Vulnerability index. The y-axes present the standardized values of the variables.

Table 4.5: Index comparison of SVI and Vulnerability index for the estimation of rooftop solar adoption and energy burden including city- and cluster-level fixed effects.

	Dependent variable:			
	Adoption	Burden	Adoption	Burden
	OLS	*OLS*	*linear mixed-effects*	*linear mixed-effects*
scale(SVI)	0.128^{**} (0.065)	0.232^{***} (0.048)	0.138^{**} (0.064)	0.235^{***} (0.047)
Vulnerability	-0.833^{***} (0.079)	0.393^{***} (0.058)	-0.815^{***} (0.074)	0.382^{***} (0.057)
cityBEL	0.255^{*} (0.131)	1.874^{***} (0.096)		
cityPOR	1.366^{***} (0.119)	2.540^{***} (0.087)		
citySEA	1.074^{***} (0.103)	1.808^{***} (0.075)		
clusterLow	0.083 (0.104)	-0.068 (0.076)		
clusterHigh-BE	-0.282^{**} (0.135)	-0.919^{***} (0.099)		
clusterHigh-SE	0.309^{**} (0.144)	-0.142 (0.106)		
clusterHighest	0.493^{**} (0.206)	-0.339^{**} (0.151)		
Adjusted R^2	0.881	0.965		
Akaike Inf. Crit.			513.887	329.781
Bayesian Inf. Crit.			536.248	352.142
Note:				*p<0.1; **p<0.05; ***p<0.01

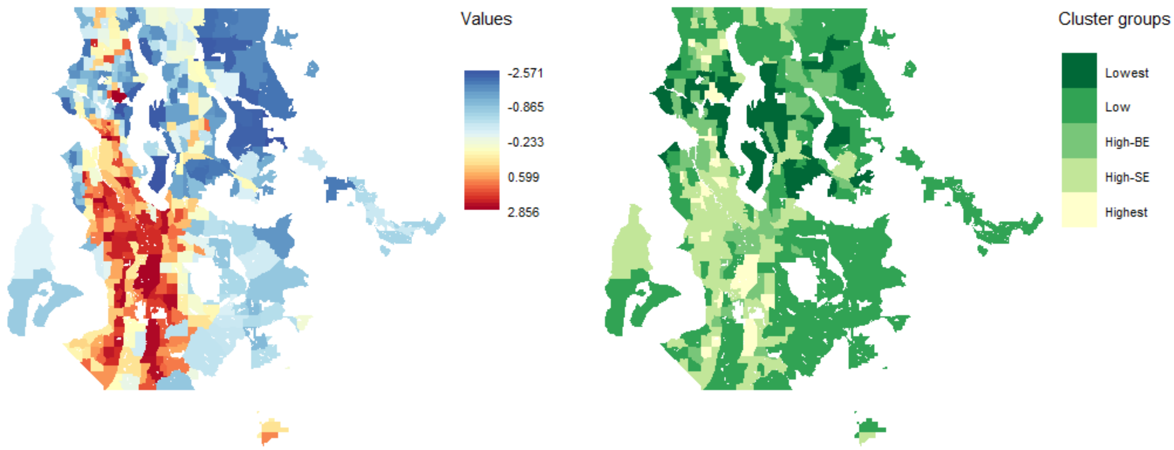

Figure 4.18: The predicted distributions of the Vulnerability index (left), and cluster groups (right) in the urban areas of King County including Seattle, and Bellevue based on the prediction models.

in King County urban areas were estimated using prediction models. In particular, based on the nine predictors, an OLS was used to predict the Vulnerability index while a multinomial logistic model was selected to predict cluster groups in the areas. The multinomial logistic model among other classification models was chosen because its prediction performance of cross-validation was higher than other algorithm models such as random forest and stochastic gradient descent (SGD). The pattern of the distribution of higher Vulnerability index is similar to that of the cluster groups, mainly the High-SE and Highest groups (Figure 4.18).

4.4 Discussion

The results presented in this chapter revealed that the cities in the Pacific Northwest had a disproportionate geographic distribution of rooftop solar adoption and energy burden. In addition, spatial lag models addressed the spatial dependencies in the distributions of rooftop solar adoption and energy burden. However, city-level variations were still observed for which, mixed effect models were used to address the group variations. As a result, the mixed effect models led to more precise estimation of city-level estimations by mutually borrowing statistical information across cities, especially for Bellevue with a smaller size of census tract. Furthermore, the five cluster groups categorized by the three latent variables partially explained the city-level variation by illustrating an unbalanced distribution of the groups across the three cities. The groups feature different attributes in the built environment, housing, socioeconomic, demographic, and income equality characteristics. By incorporating cluster groups to the model specification, the two group mixed-effect model could improve the model performance of estimating city- and cluster-level variations in addition to within-group variations of community characteristics. Finally, the Vulnerability index was developed using PCA integrating all the predictors including the two outcome variables to identify vulnerable communities in the urban areas of King County. In addition, a multinomial logistic model was used to predict cluster groups in the same areas to complement the identification of the communities.

Surprisingly, the proportions of cluster groups varied by each city. In particular, Portland has more vulnerable communities than Bellevue. This explains the different distribution of the variables including rooftop solar adoption and energy burden. For example, Portland mostly comprises the Low and High-SE groups which feature higher Housing values associated with higher rooftop solar adoption and higher energy burden. On the other hand, Bellevue mainly consists of the Lowest, and High-BE groups. Especially, the High-BE group is characterized by lower Housing values, higher Socioeconomics, and Equality values associated with lower rooftop solar adoption and lower energy burden. The findings indicate that state-level policies should account for the city-level variations when identifying vulnerable communities. For example, any programs to support vulnerable communities may consider the city-level variations to distribute resources.

Furthermore, three types of vulnerable groups can be characterized in terms of the group attributes: a group of communities more vulnerable to socioeconomic predictors while having advantageous housing characteristics (the High-SE group), a group more vulnerable to the built environment and housing predictors while having advantageous socioeconomic characteristics (the High-BE group), and a group vulnerable to both socioeconomic and housing predictors (the Highest group). Furthermore, rooftop solar adoption is highly associated with the built environment and housing predictors while energy burden has a strong correlation with socioeconomic predictors for the three cities. Therefore, the High-SE group features higher rooftop solar and energy burden associated with the higher Housing index but lower Socioeconomics index. On the other hand, the High-BE group is characterized by lower rooftop solar adoption and energy burden related to the higher Socioeconomics index, but lower Housing index. The Highest group is characterized by lower rooftop solar and higher energy burden. In addition, the Highest group has the highest within-group variation and its Equality index is the lowest among groups. This means that the group consists of more heterogeneous communities within the group. Most of the communities in the Highest group are located in the downtown or commercial areas which have greater heterogeneity compared to residential areas. Most of the High-SE group's communities are located north and south of Seattle, in the center of Bellevue, and north and east of Portland. The results revealed that the vulnerable communities tend to cluster each other in the cities geographically.

Energy justice in terms of distributional and recognition justice were further examined by identifying and characterizing energy resiliency and dependency associated with community attributes. In particular, between-group variations using the mixed-effect model investigated distributional justice through city and cluster group level variations. Moreover, within-group variations revealed recognition justice by characterizing communities, particularly the High-SE, High-BE, and Highest groups. For example, with respect to the spatial distribution of rooftop solar adoption and energy burden, the model identified between-group variations, specifically city- and cluster-level differences. The between-group variations were even more obvious after controlling for within-group variations of community characteristics. The study results question distributional justice associated with energy resiliency and energy dependency in urban areas of the Pacific Northwest. Furthermore, within a city or a cluster group, the patterns of associations between outcome and predictor variables were similar. For example, rooftop solar adoption is mostly associated with the built environment and housing predictors while energy burden is strongly correlated with socioeconomic predictors of a community. The relationships of community characteristics with energy resiliency and energy dependency helped characterize energy vulnerability, and identify vulnerable communities associated with recognition justice through a model prediction.

Some limitations are acknowledged for the study in this chapter, which future studies may address. First, the vulnerability variables associated with energy justice are limited to built environment, housing, socioeconomic, and demographic characteristics. The study does not include other factors such as local regulation or policy interventions affecting city-level variations of rooftop solar and energy burden associated with energy vulnerability. In addition, the study is limited to the two energy justice measures: rooftop solar adoption and energy burden, while other measures can affect energy justice. For example, transport energy poverty can be considered as the energy justice measure since double energy vulnerability is a result of the intersection of domestic energy poverty and transport energy poverty (Robinson and Mattioli 2020). Future research is suggested to investigate other measures indicating temporal trends of those measures. Furthermore, identifying vulnerable communities in different regions other than the Pacific Northwest with other statistical models including other predictors such as peer effects may expand the research framework introduced in the chapter. This may help determine if the patterns of relationships between energy vulnerability and associated predictors found in this study are generalizable to other regions. Regarding future research, The methods presented here could be applied to classify other characteristics of communities (e.g., health outcomes).

Chapter 5

QUANTIFYING CLEAN ENERGY JUSTICE IN TERMS OF INEQUALITY AND INEQUITY OF THE DEPLOYMENT OF ROOFTOP SOLAR IN THE PACIFIC NORTHWEST CITIES

5.1 Introduction

Climate change associated with carbon emission, and resiliency have led to energy transition to clean energy systems (Nowotny et al. 2018). In particular, sustainable energy systems mitigate climate change by reducing greenhouse gas emissions, while resilient energy systems are more robust in response to climate change (Brown 2014). However, clean energy access has been limited for those who cannot afford it due to high installation costs or unavailability of technologies (Carley and Konisky 2020). Furthermore, the energy divide, which might be a direct result of the rapid transition of energy systems, can affect local resilience by disproportionate distribution of energy services (Bouzarovski and Simcock 2017). In other words, adoption disparities in distributed energy resources (DERs) are obvious for disadvantaged and racial minority communities. For example, rooftop solar has been disproportionately deployed in communities depending on race (Martiskainen et al. 2021) and income (Middlemiss and Gillard 2015; Sanchez-Guevara et al. 2019) such that low income and minority communities are associated with low adoption. On the other hand, technology development and equitable policies to encourage clean energy access, especially for those disadvantaged communities, have helped increase DER adoption. For example, increased affordability of technologies such as rooftop solar have enabled the technologies to be more deployed and allowed people to access clean energy more economically (Augustine and McGavisk 2016). Moreover, equitable policies focusing on low-moderate income (LMI) households have provided communities with customized support to adopt rooftop solar (NREL 2021a). In particular, federal and local government agencies have attempted to address energy inequity. For example, the Clean Energy and Pollution Reduction Act (Senate Bill 350) requires California to identify barriers and opportunities for rooftop solar adoption and clean energy access by LMI communities (SB-350 2015).

However, some programs intended to encourage equitable access to DERs are inadvertently associated with disproportionate rates of program participants of tenants and multi-family households (Scavo et al. 2016). To this end, several agencies have tried to create energy equity metrics to quantify performance and progress of energy assistance programs. For example, the California Energy Commission (CEC) provided indicators to identify opportunities to increase clean energy technologies for LMI communities, and improve community resilience (CEC 2018). The Los Angeles Department of Water and Power (LADWP) established the Equity Metrics Data Initiative to track how its programs are performing with 15 equity metrics (LADWP 2022). In regard to the general community equity, National Equity Atlas (2022) presented indicators to track key community equity measures based on socioeconomics and demographics across geographies. Those suggested indicators are helpful to understand equity trends although they lack integration perspectives to compare equity trends across communities. The goal of this chapter is to answer the following three questions:

(1) How can clean energy justice be defined as associated with important and uncertain driving forces of the energy transition and plausible domains?
(2) How can clean energy justice be measured?
(3) What strategies can address clean energy justice?

Based on the spatial distribution and community adoption levels of DERs, I have defined the concept of energy justice related to DER adoption and distribution as "clean energy justice." This study operationalizes clean energy access in terms of the adoption of rooftop solar. Rooftop solar is chosen because it provides access to clean energy produced and used at the household or building level (Cook and Shah 2018a). By analyzing adoption patterns of rooftop solar associated with the built environment, socioeconomic, and demographic characteristics, the study examines clean energy justice in terms of two driving forces in

Pacific Northwest cities, namely (1) technology development and (2) equitable policies. Using dimension reduction technique and cluster analysis, the study involves identifying temporal adoption patterns of diverse communities.

In particular, two driving forces to the energy transition from the human and technology perspectives are investigated in terms of four domains of Inequality, Inequity, Equity, and Justice. Th Inequality domain refers to unequal access to opportunity, while the Inequity domain refers to a situation where providing evenly distributed resources is not enough to access opportunities. The Equity domain features addressing the issue of the inequity domain by considering individual's conditions and providing customized tools that address underlying inequality. Finally, the Justice domain refers to a situation where inequity in a social system is improved by removing the structural barriers that prevent disadvantaged individuals from accessing opportunities. The study involves investigating distributional justice in terms of spatial dependencies of rooftop solar adoption. Furthermore, the study examines recognition justice by identifying equity gaps across communities. The study aims to help policymakers quantify clean energy justice with respect to DER adoption for better support local communities.

5.2 Research methodology

The study in this chapter involves quantifying energy justice associated with the distribution of rooftop solar adoption by communities with different attributes in the Pacific Northwest cities, Seattle, Bellevue, and Portland. I used rooftop solar permit records from the cities' open portal to count the number of installations from 2003 to 2019. As in Chapter 3, I used the standardized installation ratio (SIR), the count of rooftop solar installations divided by the expected count of rooftop solar proportional to the count of annual installations, to track the longitudinal trend of installation in the three cities. Specifically, the framework for quantifying energy justice in terms of inequality and inequity associated with rooftop solar adoption is summarized in Figure 5.1. First, I developed domains depending on the level of energy justice in terms of the two driving forces, technology development and equitable policy. According to the degree of the intensity of the two driving forces, four domains were created

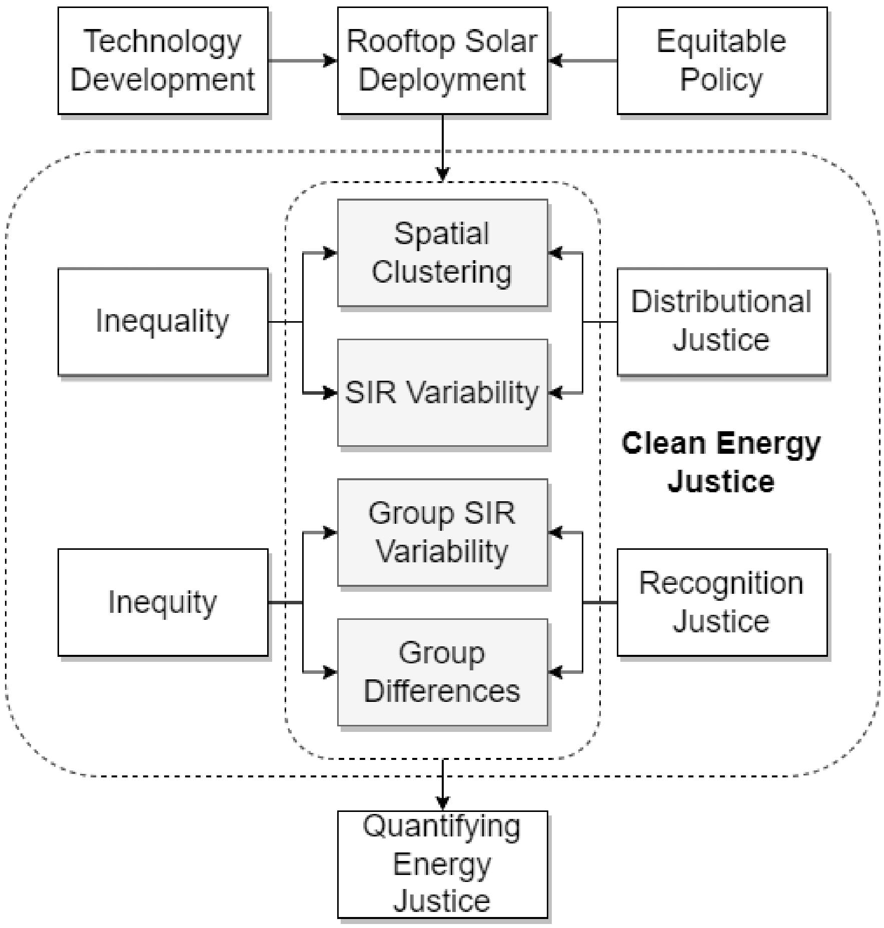

Figure 5.1: The framework of quantifying energy justice associated with rooftop solar in terms of the spatial distribution and community adoption.

– the Inequality, Inequity, Equity, and Justice domains. Once each domain was analyzed, I developed four indices to quantify energy justice associated with rooftop solar adoption. In particular, two indices were used to quantify the inequality of rooftop solar adoption in terms of the spatial distribution and the adoption variability by communities. Distributional justice is related to these indices because they concern geographical distribution and its variability of rooftop solar across communities. The other two indices were used to quantify the inequity by comparing the adoption variability by each group and the adoption difference between groups. The indices concern recognition justice by addressing group differences in rooftop solar adoption.

Then, I conducted analyses based on the developed four indices for the three cities. To quantify the inequity across groups of communities that share similarities, the cluster analysis performed in Chapter 4 was applied to classify communities in the three cities to the five groups, the Lowest, Low, High-BE, High-SE, and Highest. Since the groups characterize communities based on built environment, socioeconomic, and demographic characteristics, temporal adoption trends of the groups were compared with each other in terms of the developed indices. Based on the study results, implications of the methodology and strategies to enhance the more equitable adoption and to promote clean energy justice were analyzed.

5.2.1 Four domains in the energy transition

Four domains were identified through the two driving forces of energy transition – technology development and equitable policies. In a situation with a lack of equitable policies, technology development can help transform the Inequality domain into the Inequity domain. Furthermore, higher equitable policies can lead the Inequity domain to the Equity domain and further technology development leads to the Justice domain (Figure 5.2). The two driving forces, technology development and equitable policies, are characterized by technology and human respectively associated with post-phenomenology.

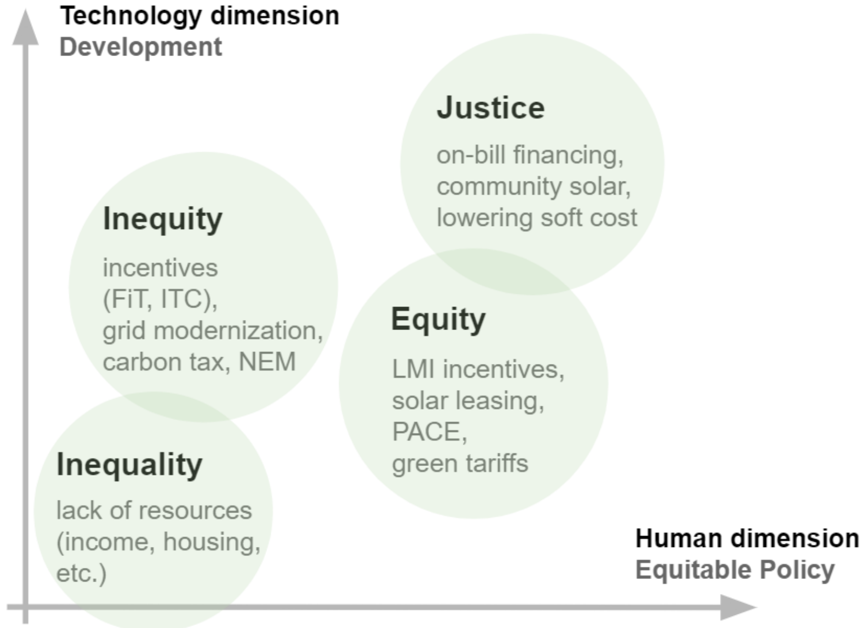

Figure 5.2: Four domains depending on the two driving forces, technology development, and equitable policies. Each domain features inequality, inequity, equity, and justice respectively.

Inequality domain

The Inequality domain features lack of resources such as housing, income, and technological availability to clean energy access. The transition to a new energy system has inadvertently resulted in disproportionate distribution of clean energy access such that disadvantaged communities have been left behind (Schaffer and Brun 2015). Accordingly, clean energy access can disproportionately influence how communities respond to climate change events because DERs such as rooftop solar can lead to better mitigation to extreme weather (Lin and Bie 2016). Such disproportionate distribution of DERs can be described as an inequality in clean energy access. In general, failing to provide equal opportunities to people regardless of where they live is an example of spatial inequality. For example, disproportionate distribution of telecommunication infrastructure caused spatial inequality associated with local communities (Chen and Wellman 2004). Energy and societal transformation are highly associated with inequality, as the distribution of benefits are localized in higher-income areas (Poruschi and Ambrey 2019). Therefore, addressing energy inequality is desirable through equitable policies and technology development.

Inequity domain

Clean energy access can be improved to the Inequity domain through incentive mechanisms to encourage DER adoptions. For example, investment tax credit (ITC) and Fit-in tariff (FiT) through technology development such as net energy metering (NEM) allow customers to get credits for generation of electricity from their own DERs (Augustine and McGavisk 2016). While those policies have promoted clean energy access, the policies can benefit wealthier households more, resulting in regressive effects on LMI households and leading to energy inequity. For example, FiT has transferred the operating cost of decentralized electricity to electricity consumers, resulting in distributional injustice for LMI communities (Poruschi and Ambrey 2019). Opportunities to take part in incentives are difficult for those who cannot afford to invest in installing DERs. Furthermore, the Inequity domain features technology development associated with cost decreases of DERs. However, accommodating DERs requires grid modernization for reliability of new energy systems in addition to maintenance. If the cost of such improvements is passed to electricity customers, increased electricity bills may exacerbate inequities because benefits are not shared. For example, LMI communities were burdened due to the cost of accommodating DERs in the grid without receiving commensurate benefits (Jenkins et al. 2016). Thus, equitable policies are necessary to provide customized assistance such as LMI focused support to disadvantaged communities.

Equity domain

The Equity domain involves providing customized supports such as LMI focused incentives, leasing programs, Property Assessed Clean Energy (PACE), and green tariffs to disadvantaged communities. In particular, government agencies such as CEC and LADWP have adopted policies focusing on LMI communities to increase clean energy access (CEC 2018; LADWP 2022; NREL 2021a). Those policies are more equitable and actively support disadvantaged communities by providing customized assistance rather than simple incentives and policies aimed at encouraging DER adoptions in the Inequity domain.

However, technology development is required due to the intermittent power generation of DERs affecting the reliability of power supply at the community level. While decentralized energy systems such as DERs improve resilience, higher penetration and disproportionate distribution of rooftop solar and electric vehicle (EV) charging lead to uncertain supply and demand schedules to the local electrical grid, and challenges to grid system operators (Khatibi and Ahmed 2019). In other words, communities with higher decentralization trends need to address uncertain power generation schedules due to the lack of active generation and demand connectivity (Rangu et al. 2020). As a result, communities need more diverse and independent power sources, energy storage, and demand participation. Furthermore, an electric network with higher decentralization trends requires improved forecasting technologies and new operating tools to ensure stability and coordination among transmission systems (Ourahou et al. 2020). In addition, efforts to reduce the soft cost of installation can be another opportunity to increase clean energy access for disadvantaged communities. Those technology developments based on equitable policies aimed at removing structural barriers for disadvantaged communities lead to the Justice domain.

Justice domain

The Justice domain goes beyond the Equity domain by focusing on removing structural barriers to achieve the goal of equity. Community or shared solar by utilizing virtual NEM through technology development can be an example of the Justice domain. Shared solar is a purchasing arrangement in which multiple customers share the electricity or the economic benefits of solar power from a single array (Feldman and Margolis 2015). An array is typically built in a single location, and individual customers sign up to own or lease parts of the array, or to purchase (or be credited for) some portion of the electricity generated by the array (Energy.gov 2022). Shared solar is designed to increase access to solar energy and to reduce upfront costs for participants. Thus, it allows a group of communities to invest in solar that is not affixed to their own residence so shared solar avails clean energy access to a wider range of populations (Augustine and McGavisk 2016). In addition, reducing the soft cost of rooftop solar installations such as smoothing the electrical permit process, and on-bill financing program for LMI communities characterize the Justice domain promoting clean energy access.

5.2.2 Quantifying energy justice in clean energy access

Based on geographical distribution and community adoption of rooftop solar adoption in terms of inequality and inequity, four indices were developed to quantify energy justice in clean energy access. Table 5.1 summarizes the four indices quantifying clean energy justice.

Table 5.1: Descriptions of the four indices quantifying clean energy justice.

Index	Measure	Relevance to focal issue	Relevant justice domain
Spatial Inequality	Moran's I statistics of the logs of SIR	Identifying the clustering pattern of spatial distribution	Distributional Justice Inequality
Adoption Inequality	Standard deviation of the logs of SIR	Identifying the variability across census tracts	Distributional Justice Inequality
Adoption Inequity	Standard deviation of the group Adoption Inequality	Identifying the variability across groups	Recognition Justice Inequity
Inequity Gap	The difference of the logs of SIR between the Low and the High-BE groups	Identifying the group difference	Recognition Justice Inequity

5.2.3 Spatial Inequality index

Global Moran's I or G estimate can quantify spatial clustering of rooftop solar adoption. Moran's I statistic (Moran 1948) is the most widely used method of testing for spatial autocorrelation or spatial dependencies:

$$Spatial\ Inequality = N(\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})/W(\sum_i (x_i - \bar{x})^2), \tag{5.1}$$

where, N is the number of observations indexed by i and j, x is the log of SIR, w_{ij} is a matrix of spatial weights, and W is the sum of all w_{ij}. If no spatial dependencies in the area exist, the test statistic would be close to zero. Moran's I will tell whether data is clustered or autocorrelated. Similarly, a semivariogram can identify a spatial dependence in unequally-spaced point data (Getis 2010). Points close together tend to be similar; thus the variance of the pairwise difference will be small while the difference tends to increase as the distance increases. At some distance, the points will be independent of each other. Furthermore, empirical distribution functions (EDF) such as the G function can also identify point patterns with respect to complete spatial random (Diggle 2013). It is simulated with several realizations under the null by resampling from n points while forming the G estimate for each set and producing Monte Carlo envelopes. The estimates being off the envelopes indicates that the distribution is far from randomness. Since this study involved counting rooftop solar installations by census tracts, Moran's I statistics were used for the study on the three Pacific Northwest cities. A series of temporal Moran's I values may indicate trend of clustering patterns of rooftop solar distribution along with the spatial equality trend of the technology. Furthermore, annual distribution of rooftop solar was mapped using a generalized additive model (GAM) based on latitude and longitude coordinates to examine the spatial distribution trends of rooftop solar.

5.2.4 Adoption Inequality index

Distributional justice concerns the spatial distribution of resources. Geographical aspects are important in the distribution of energy resources. For example, Bouzarovski and Simcock

(2017) addressed the lack of geography considering energy poverty. Distributional justice refers to spatial justice related to the geographical dimension of inequality and inequity. Because spaces of misrecognition can result in ignoring certain groups, distributional justice can be associated with recognition justice. In this context, the Adoption Inequality index is associated with distributional or spatial justice and is the standard deviation of the logs of SIR given the rooftop solar adoption of each census tract:

$$Adoption\ Inequality = \sqrt{\sum (x_i - \bar{X})^2 / N}, \tag{5.2}$$

where, N is the number of observations, and x is the log of SIR indexed by i. If the standard deviation of SIR in a city increases over time, this provides some evidence of increasing inequality of rooftop solar adoptions.

5.2.5 Adoption Inequity index

The other two indices concern recognition justice in terms of the built environment, socioeconomic, and demographic aspects. Community characteristics are important for these indices because transition to a clean energy system is associated with social, political, and environmental displacements that may lead to vulnerability of particular groups (Bouzarovski and Simcock 2017). For example, solar adopters tend to have higher income and home value and to be more educated than non-adopters (Davidson et al. 2014; Keirstead 2007; Min and Lee 2020). The Adoption Inequity index is the standard deviation of the adoption Inequality index of each cluster group:

$$Adoption\ Inequity = \sqrt{\sum (\sigma_k - \bar{\sigma})^2 / K}, \tag{5.3}$$

where, K is the number of groups, and σ is the standard deviation of the log of SIR by a group indexed by k.The index illustrates the variability of the logs of SIR across groups. A higher value of the index indicates more variation across groups in a city.

5.2.6 Inequity Gap index

The Inequity Gap index measures the difference of the group mean logs of SIR between the Low and High-BE groups as shown in Equation (5.4), where μ_L is the mean of the logs of SIR for the Low group, and μ_H is the mean of the logs of SIR for the High-BE group.

$$Inequity\ Gap = \mu_L - \mu_H, \tag{5.4}$$

The two groups are characterized by different housing, socioeconomic, and demographic characteristics. For example, the Low group features higher advantages of housing, and socioeconomic factors while the High-BE group lacks those characteristics, particularly homeownership and single family housing. The index identifies the differences between groups in terms of recognition justice.

5.3 Results

The four indices were applied to the three cities in the Pacific Northwest. The study refers to census tracts grouped to five clusters from Chapter 4 (Figure 4.11). Most notably, the adoption pattern of rooftop solar by cities and cluster groups illustrates that the majority communities of the Lowest, Low, and High-SE groups maintain their SIR rates over time while the most of communities in High-BE and Highest groups display a decreasing pattern (Figure 5.3).

The spatial distribution of rooftop solar each year also highlights not only hotspots where higher concentrations of the installation are located, but also temporal patterns over the years (Figure 5.4). In particular, all the three cities show increasing intensity of concentrations of rooftop solar over time; the yellow and blue colors get stronger, illustrating a more clustering pattern. The SIR changes from the previous year reveal that the SIR changes each year in Bellevue are more dynamic than the other two cities (Figure 5.5). On the other hand, Portland has been mostly stable with rooftop solar adoption following a constant pattern.

Following the stronger clustering and divergent patterns of the SIR distribution over time, the Spatial Inequality index reveals that the clustering of rooftop solar adoption in

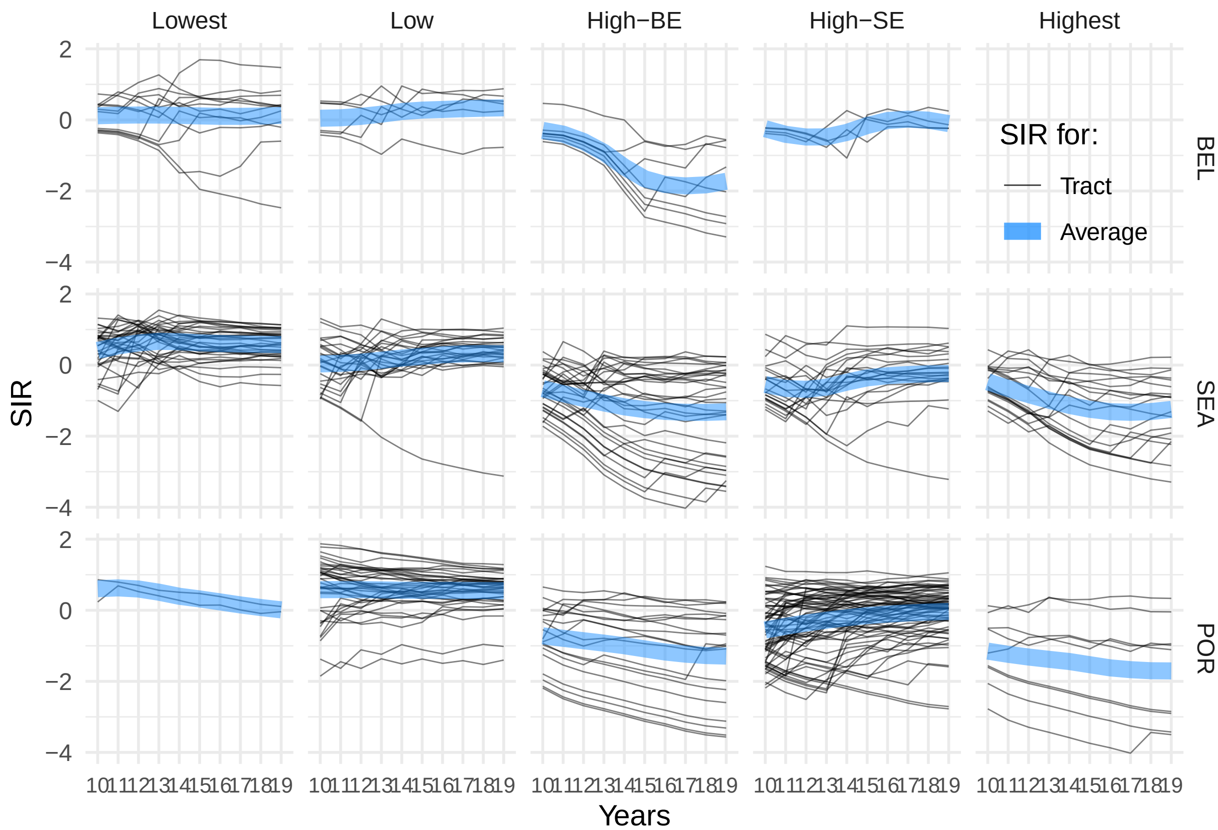

Figure 5.3: The logs of rooftop solar SIR by the five cluster groups (Lowest, Low, High-BE, High-SE, and Highest), and the three cities (BEL: Bellevue, SEA: Seattle, and POR: Portland) from 2010 to 2019. Each census tract is in a solid line while the group mean is presented in loess smoothing line (the thick light blue line).

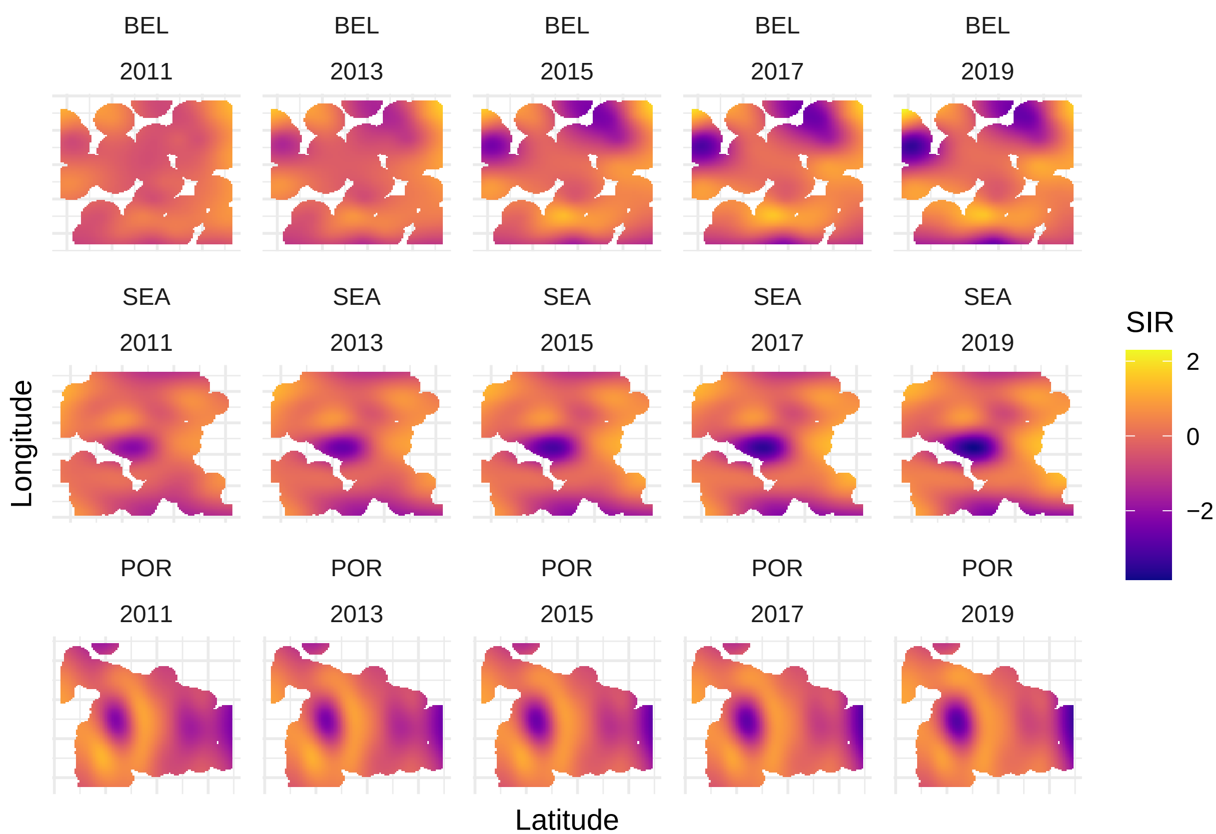

Figure 5.4: The temporal distribution of the logs of rooftop solar SIR in the three cities: (i) Bellevue, (ii) Seattle, and (iii) Portland in order of top to bottom every two years from 2011 to 2019.

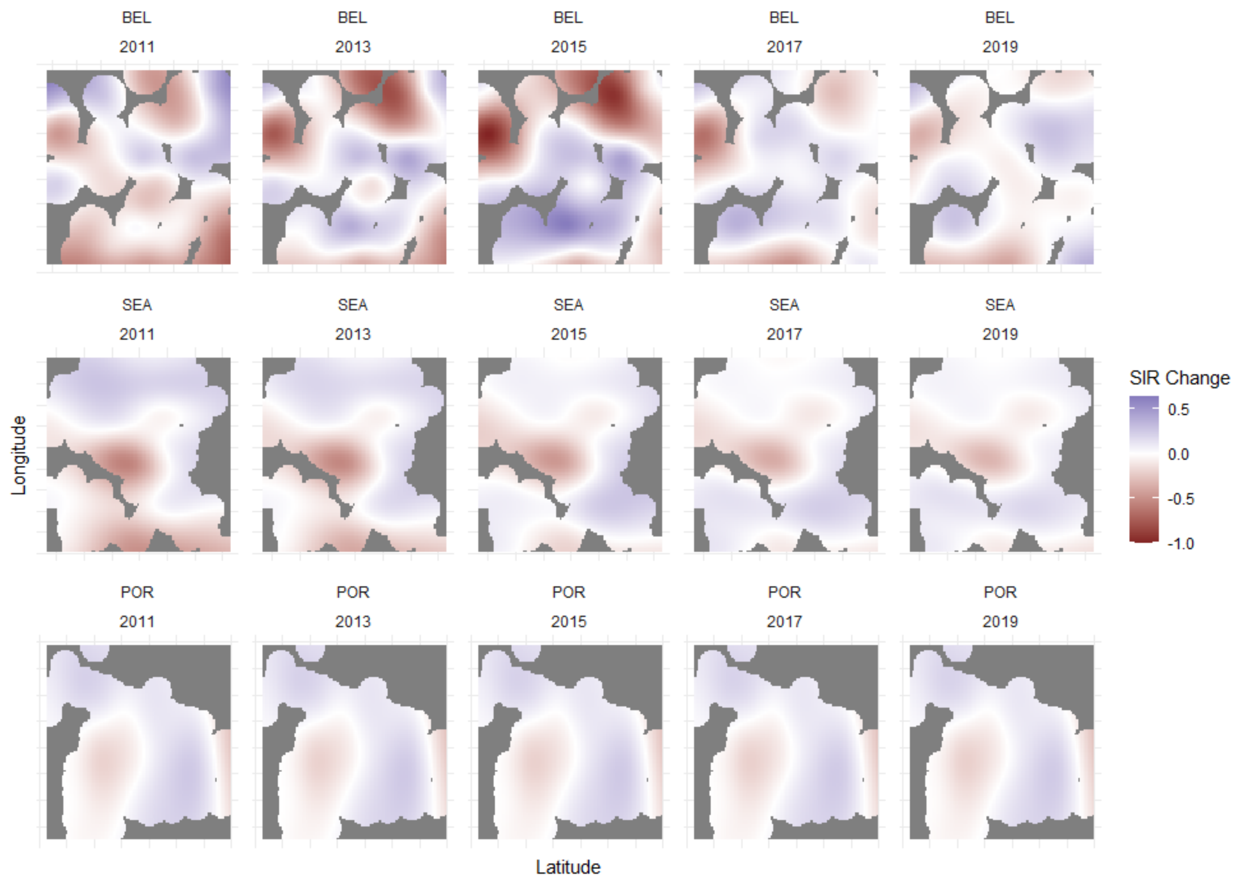

Figure 5.5: The temporal distribution changes of the logs of rooftop solar SIR in the three cities: (i) Bellevue, (ii) Seattle, and (iii) Portland in order of top to bottom every two years from 2011 to 2019.

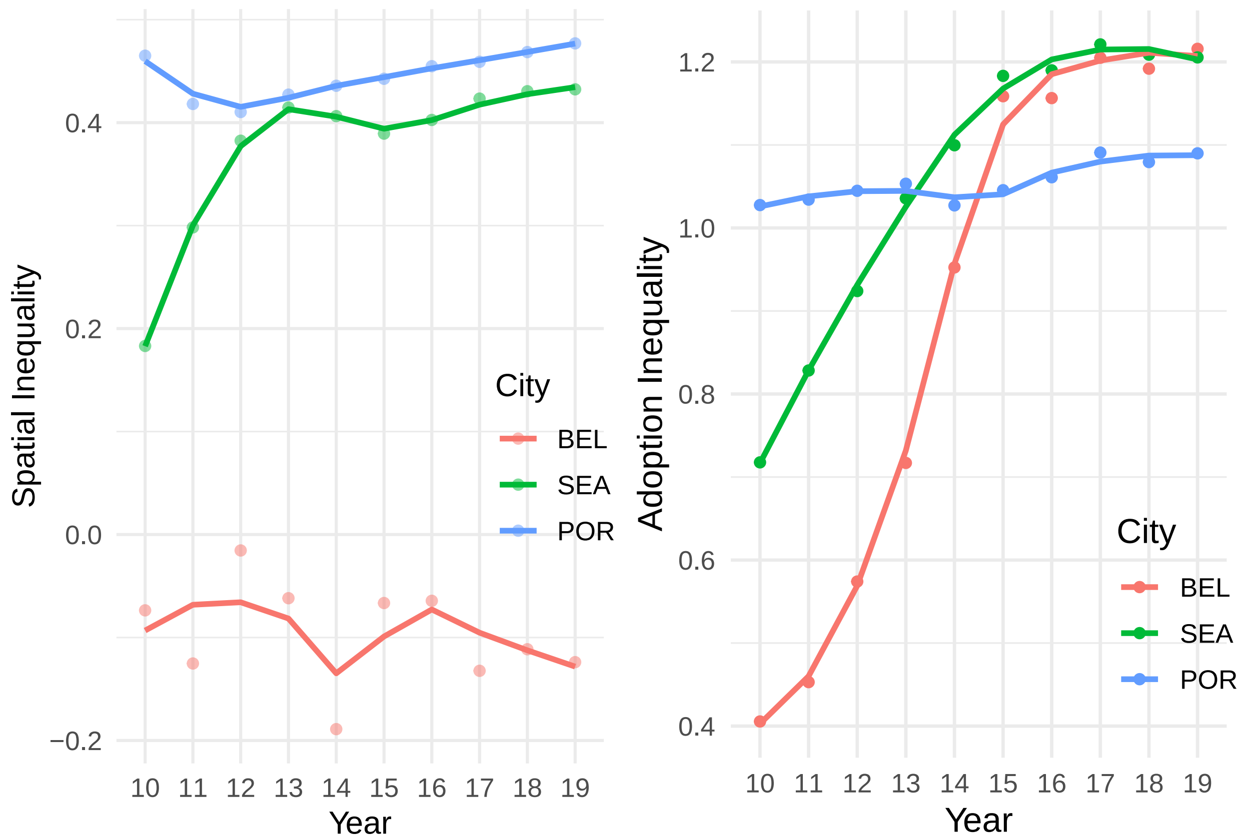

Figure 5.6: (i) The Moran's I of the logs of rooftop solar SIR (Spatial Inequality) and (ii) the standard deviation of the logs of rooftop solar SIR (Adoption Inequality) in the three cities (BEL: Bellevue, SEA: Seattle, and POR: Portland) from 2010 to 2019.

Seattle and Portland has increased (Figure 5.6). Since Bellevue has a comparatively smaller number of census tracts, the Moran's I statistic of Bellevue may involve uncertainty. The Adoption Inequality index illustrates the distribution of rooftop solar in Seattle and Bellevue has drastically changed compared to Portland (Figure 5.6). In addition, the Adoption Inequality index was decomposed by groups to identify the variability of within-group variance across groups in a city. There are similar patterns across the cities. For example, the Lowest, Low, and High-SE groups show either a decreasing or monotonous pattern over the years while the High-BE and Highest groups illustrate an increasing pattern (Figure 5.7). On the other hand, the average rooftop solar adoption of the High-BE and Highest groups shows a

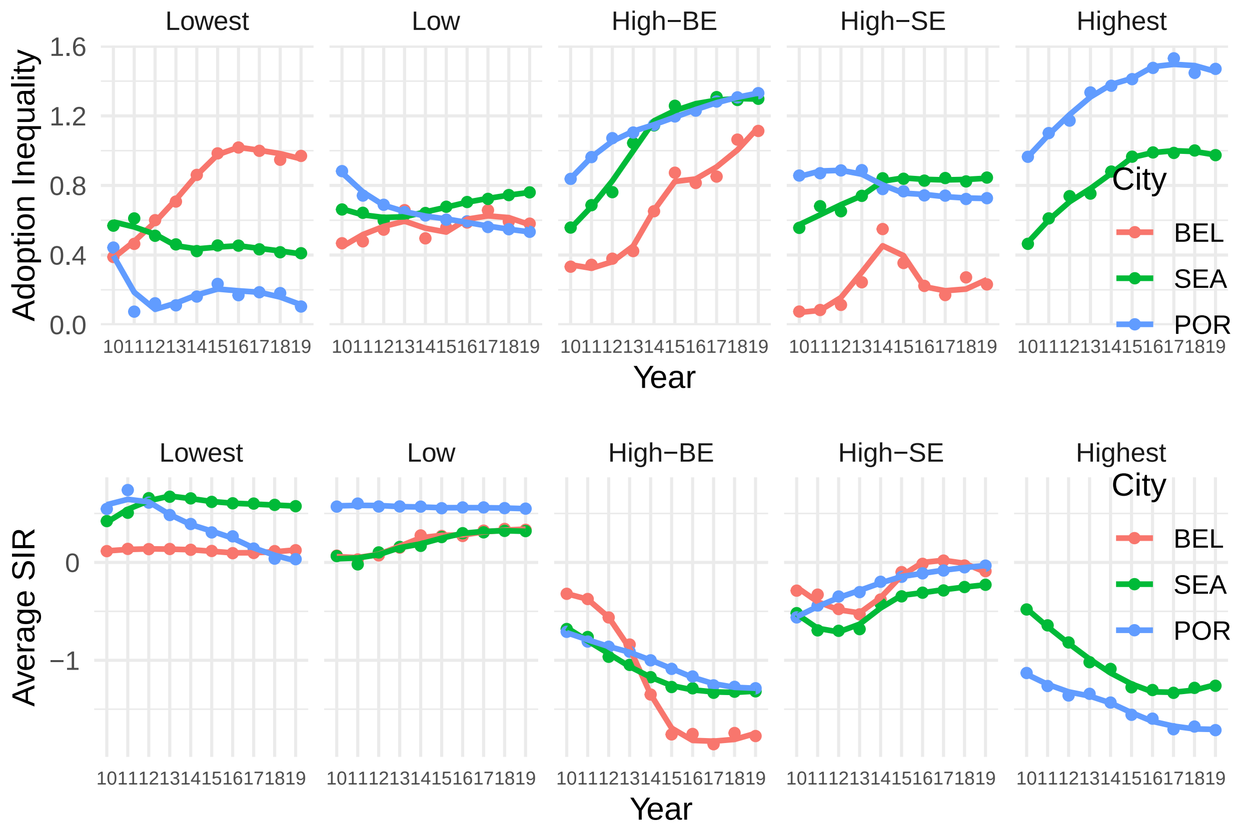

Figure 5.7: (i) The standard deviation of the logs of SIR (Adoption Inequality) and (ii) the mean of the logs of SIR (Average SIR) by groups (Lowest, Low, High-BE, High-SE, and Highest) in the three cities (BEL: Bellevue, SEA: Seattle, and POR: Portland) from 2010 to 2019.

decreasing pattern while that of the High-SE group increases (Figure 5.7).

The inequity of rooftop solar adoption across groups accompanies an increasing pattern. For example, the Adoption Inequity index, which is the standard deviation of the group Adoption Inequality index has increased over time in the three cities (Figure 5.8). This means the adoption gap across groups increases. Similarly, the Inequity Gap index (i.e., group difference) reveals an increasing pattern of the difference of the logs of SIR between the Low and High-BE groups over time (Figure 5.8).

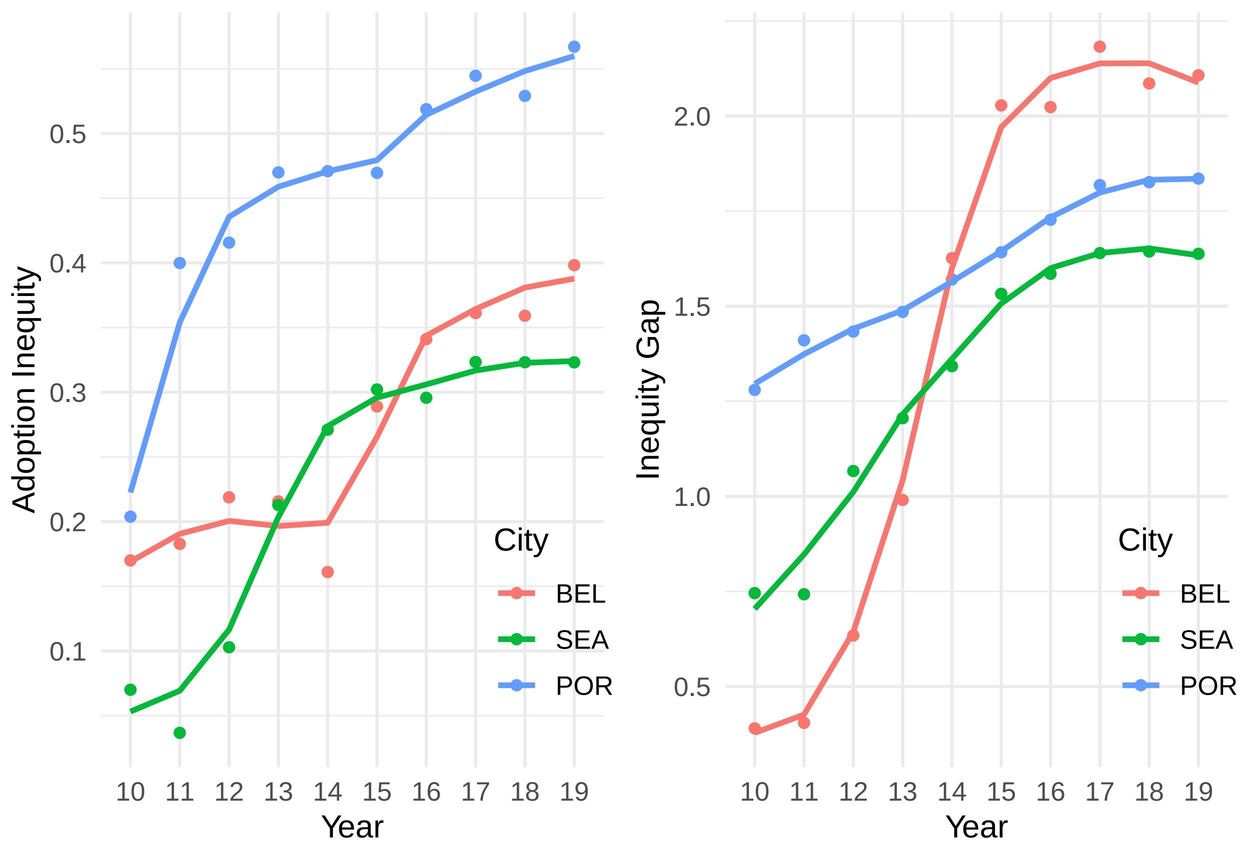

Figure 5.8: (i) The standard deviation of the group Adoption Inequality (Adoption Inequity) and (ii) the difference of the average logs of SIR between the Low and the High-BE (Inequity Gap) in the three cities (BEL: Bellevue, SEA: Seattle, and POR: Portland) from 2010 to 2019.

5.4 Discussion

The study involved investigating the four indices on the three Pacific Northwest cities to quantify the inequality and inequity of the spatial distribution and the group adoption of rooftop solar. Those four indices are associated with distributional and recognition justice in light of the geographical distribution and the different adoption patterns at different communities. The Spatial Inequality index indicated that the clustering of rooftop solar distribution increased in Portland followed by Seattle over the period of 2010 to 2019. The Adoption Inequality index revealed that the variation of rooftop solar adoption across communities increased in all three cities while Seattle and Bellevue showed more marked changes. Furthermore, the inequity of rooftop solar adoption across groups also increased in all three cities. For example, the Adoption Inequity index showed an increase in the group differences of rooftop solar adoption, indicating more heterogeneity in rooftop solar adoption between groups. The Inequity Gap index also illustrated that between-group variations of rooftop solar adoption increased in all three cities. The study revealed that rooftop solar adoption was becoming more disproportionate, particularly in High-BE and Highest groups over the years. Moreover, although Portland's disproportionate rooftop solar adoption remained high, Seattle and Bellevue narrowed the gap, presenting an increasing disproportionate rooftop solar adoption over time. Overall the three cities revealed increasing gaps in rooftop solar adoption across communities and cluster groups.

Given the results, it is important to discuss how to address the inequality and inequity of rooftop solar adoption in the cities. Government policies including regulations and financial support such as grants and incentives may increase rooftop solar adoption. However, these policies can inadvertently serve as barriers if not well designed, because the integration of rooftop solar to the grid is associated with electricity rate designs including modifying credit rates for the surplus electricity to the grid, revising fixed charges, and demand charges (Darghouth et al. 2017). Strategies such as community solar, policy mandates, and community connection through off-grids are proposed to increase access to clean energy that leads to more equal and equitable communities achieving energy justice.

5.4.1 Community solar

About 50% of consumers and businesses are unable to host solar systems for not owning a house, not enough finance, or not enough area to install (Heeter et al. 2018). Other reasons are: roof is too shaded or requiring re-roofing; the size, orientation, or type of roof are not proper; some equipment is obstructing a solar installation; it is difficulty for renters to control their rooftop; and homeowners plan to move out in the near future (Cook and Shah 2018b). To that end, encouraging multi-family households to collaborate with solar cooperatives and community organizations can help to increase solar adoption (Noll et al. 2014). Furthermore, share-ownership initiatives are necessary to include densely populated areas and lower-income areas to promote solar adoption (Graziano et al. 2019). For example, community solar models can work for those who can't afford to install rooftop solar. Community solar is a purchasing arrangement in which multiple customers share the electricity or the economic benefits of solar power from a single array through virtual net metering (Augustine and McGavisk 2016). An array is typically built in a single location, and individual customers sign up to own or lease parts of the array, or to purchase (or be credited for) some portion of the electricity generated by the array. Community solar may be located on public or jointly-owned property. Participating in community solar can be an easier way for customers to benefit from a local solar energy project because they can participate with lower initial or overall investment (Chan et al. 2017).

5.4.2 Policy mandates

Many states have enabled community solar programs aiming at increasing LMI households to access solar and reducing their energy burdens (Aznar and Gagne 2018). Policies mandating community solar investment can be a strategy in favor of energy justice related to LMI households. For example, state policies for promoting community solar are mainly related to carve-out and providing incentives. Carve-out mandates solar developers to have a certain percentage of electricity output from clean energy sources (Heeter et al. 2018). Another mandate example is the community reinvestment act (CRA) obligation that encourages banks to invest in community solar projects associated with a tax deduction. For example, Clean Energy Collective (CEC) was required to allocate 5% of its output to LMI households. Alpine Bank according to CRA, bought 5% of the output from CEC and donated it to Family& Intercultural Resource Center, which distributed net metering credits to the LMI households (Heeter et al. 2018). By doing that, Alpine Bank was eligible to get a tax deduction and CEC satisfied the 5% output allocation. At the end, Alpine Bank paid nothing but donated panels through a discount from CEC and the tax deduction. This example shows how different business entities under mandates can collaborate to reach their own benefits. With mandates, communities with lower adoption rates can experience an expansion of community solar deployment, hence can see the reduction of the inequity in clean energy access.

5.4.3 Off-grid by aggregation

Aggregation of community connections through off-grid energy systems can increase clean energy access for those who cannot afford to install rooftop solar, hence can increase energy justice. Yamagata et al. (2016) analyzed several algorithms to find the optimal clustering of communities in terms of self-sufficiency, sharing cost, and stability of energy supply. Off-grid energy systems can achieve spatial diversity because of their tendency to decentralize energy networks. Also, off-grid energy systems are more resilient in response to disruptions, because a disruption to a part of a network will not affect other parts of the network, as they are separate from each other (Malhotra et al. 2017). Thus, spatial diversity lessens the effect of a disruption. Furthermore, independent energy systems are more robust. For example, a portfolio of less correlated energy sources can increase resilience according to portfolio theory (Shakouri et al. 2015, 2017). Aggregation of community connection with diverse energy sources will increase not only the local access to clean energy, but also community resiliency against disruptions caused by climate change.

5.4.4 Adaptive and transformative strategies

Government mandates to invest in LMI focused energy programs can be an adaptive strategy associated with adjusting to surrounding environments or situations rather than changing environments. Taking advantage of available structures or policies, such as incentive programs and technologies, LMI communities may expand community-oriented energy systems which enable benefits from the systems to stay in communities (SEIA 2019). On the other hand, aggregation of community connections that encourages spatial diversity is a transformative strategy. This is because such strategy typically requires technology development and equitable policies to be executed while it involves uncertainty associated with how to design the systems.

The mandate strategy may work well in the Inequality and Inequity domains, where governments can urge increasing rooftop solar adoption in disadvantaged communities through regulation and policies. All four indices may decrease in this strategy. On the contrary, community aggregation with the spatial diversity strategy may benefit all domains, in particular, the Equity domain, by providing technical solutions to disadvantaged communities for clean energy access that leads to the Justice domain. All those strategies benefit the four domains in terms of increasing the adoption of technologies. The mandate strategy will expedite community-oriented energy systems mostly for disadvantaged communities as a temporal and quick adoption solution addressing the issue of equity. However, transformative strategies such as community aggregation will be necessary to address the equity issue in the long run by providing technical solutions.

CONCLUSION

Global climate change has led to the development of clean energies and related policies, which have encouraged the deployment of DERs. DERs contribute to mitigating climate change by reducing greenhouse gas emissions through local energy production and consumption. However, the energy divide, stemming from the rapid transition to DERs, could adversely affect disadvantaged communities due to potentially disproportionate distribution of benefits derived from DERs. While government agencies have enacted policies to mandate equitable clean energy access and distribution of benefits, little is known about:

(1) Which adoption variables related to DERs are most salient and how adoption attributes differ by technologies and communities.
(2) How energy vulnerability is characterized and accordingly, who vulnerable communities are.
(3) How clean energy justice is defined and quantified.

To this end, this dissertation is aimed at examining energy justice in terms of DER adoptions and energy vulnerability (namely clean energy justice) associated with community characteristics. The community characteristics are based on place (built environment and housing), people (residents' socioeconomic and demographics), and equality (community income equality) attributes. Energy vulnerability was examined in terms of energy resiliency and energy dependency. Energy resiliency and energy dependency were operationalized by rooftop solar adoption associated with clean energy access and energy burden, respectively. Furthermore, spatio-temporal characteristics of energy vulnerability were compared by cluster groups in the three cities in the Pacific Northwest over the period of 2010 to 2019. As a result, the dissertation led to (1) the identification of the DER distribution attributes by communities and technology, (2) the recognition of vulnerable communities in terms of energy resiliency

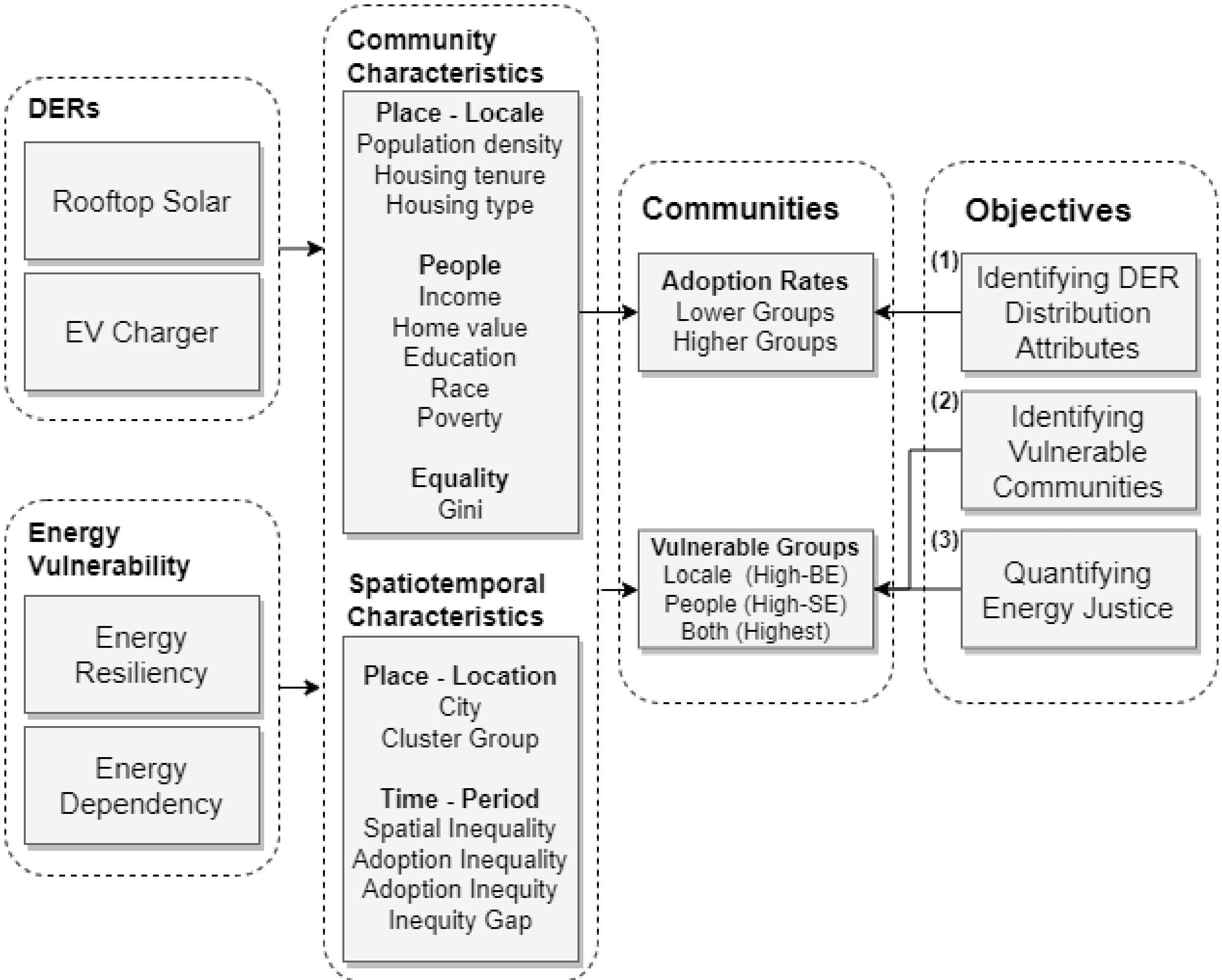

Figure 5.9: The study summary of clean energy justice associated with clean energy access and vulnerable communities in terms of DER adoptions and energy vulnerability.

and energy dependency, and (3) the quantification of energy justice in terms of inequality and inequity of rooftop solar adoption in the three cities in the Pacific Northwest. Figure 5.9 illustrates the summary of this dissertation examining clean energy justice in terms of DER adoptions and energy vulnerability.

Clean energy justice: different adoption characteristics of communities in rooftop solar and electric vehicle chargers in Seattle

Chapter 3 identified the geographic distribution of rooftop solar and EV chargers in Seattle, specifically highlighting energy justice issues related to clean energy access associated with DER adoptions in the city. In particular, distributional justice was examined in relation to the geographic distribution of the technologies and recognition justice was discussed in terms of community attributes and adoption patterns. The study found that rooftop solar and EV charger adoptions in Seattle presented spatial and community disparities. In summary, Chapter 3 produced important findings, as follows:

(1) Rooftop solar adoption is more strongly associated with housing variables (housing type, housing tenure, and population density) than other variables such as income and race, while EV charger adoption involves strong association with economic variables. This implies that economic factors play a more important role in EV charger adoption than rooftop solar while housing factors are important to the adoption of both technologies.
(2) For communities with lower adoption rates, both DER adoptions are more sensitive to housing variables than for communities with higher adoption rates.
(3) For communities with higher EV adoption rates, economic variables are more important than housing variables.
(4) Spatial inequality of rooftop solar adoption in Seattle is higher than spatial inequality of EV charger adoption. Specifically, communities present higher variations in rooftop solar adoption than to EV charger adoption.

Communities with low adoption rates were found to be sensitive to housing variables for the adoption of both technologies. Therefore, housing-related support, particularly targeted at renters and residents of multi-family housing units, is likely to be more effective for communities with low adoption rates to increase the adoption of technologies than financial assistance alone. Considering that the installations of rooftop solar and EV chargers were concentrated in particular communities, the study results imply that policies aiming to increase the adoption of DERs should be tailored to local communities having specific characteristics.

Characterization of energy vulnerability in terms of urban administrative and community characteristics in the Pacific Northwest cities

Climate change has recently revealed more threats to our society, such as electricity supply disruption. Such threats have disproportionately affected communities, particularly in rural or coastal areas. Better recognition of those vulnerable communities is important in achieving a more equitable distribution of resources and benefits. The objective of Chapter 4 is to characterize energy vulnerability to identify vulnerable communities by examining energy justice associated with energy vulnerability, energy dependency, and energy resiliency. In particular, Chapter 4 examined vulnerability predictors identified from the literature to characterize community attributes in terms of places, people, and equality in Seattle, Bellevue, and Portland. City- and cluster-level variations were identified for rooftop solar adoption and energy burden even after controlling for local community attributes. Rooftop solar adoption was found to be more sensitive to housing variables while energy burden was more sensitive to socioeconomic variables. Finally, Chapter 4 involved developing a framework to identify vulnerable communities by suggesting the energy vulnerability index for policy makers to identify those communities. In particular, the energy vulnerability index was used to identify vulnerable communities in regions without energy justice measure data. The study was aimed at addressing an issue where different regions are not directly comparable due to the different cluster patterns involved with observation size and data normalization within regional data sets. Hence, the framework can help compare other regions with a reference region in energy justice measures. Vulnerable communities in King County urban regions were identified while featuring different patterns of demands in terms of socioeconomic and housing resources. Chapter 4 suggests that the identified High-SE group lack social and financial resources to address their higher energy burden. On the other hand, the High-BE group identified in the study may need more equitable policies associated with housing conditions such as housing tenure and multi-family living conditions to increase rooftop solar adoption.

Quantifying clean energy justice in terms of inequality and inequity of the deployment of rooftop solar in the Pacific Northwest cities

Using longitudinal data of rooftop solar adoption, Chapter 5 aimed to address energy justice in terms of the four domains of equality and equity associated with technology development and equitable policies. According to the scenario attributes, four indices were proposed to quantify energy justice, particularly associated with rooftop solar adoption (i.e., clean energy access). The study based on the four indices to quantify clean energy justice in the Pacific Northwest cities, Seattle, Bellevue, and Portland revealed the following findings:

(1) Rooftop solar distribution in Seattle and Portland showed increasing spatial inequality (spatial clustering) across communities between 2010 and 2019.
(2) The inequality of rooftop solar adoption across communities (community adoption variability) increased with an increasing clustering pattern.
(3) Social inequity of rooftop solar adoption was also present across cluster groups (group adoption variability) that were characterized by different built environment, socioeconomic, and demographic attributes.

In particular, two specific groups (i.e., the High-BE and Highest) presented a sharp decline in rooftop solar adoption over time. The results showed growing inequality and inequity in rooftop solar distribution and adoption in the Pacific Northwest cities in terms of distributional and recognition justice. In response, three strategies were proposed to enhance clean energy access. Chapter 5 provided answers to the main questions about clean energy justice associated with plausible scenarios, quantifying clean energy justice, and strategies to address inequality and inequity in the energy transition.

Climate change has led to the development of clean energy policies, which have encouraged sustainable and resilient energy systems characterized by decarbonization and electrification associated with DERs. However, inequitable access to DERs can affect local resilience in addition to socioeconomic benefits aimed at improving conditions for local communities.

The empirical analyses of the study provided the trend of rooftop solar adoption for diverse groups of communities associated with clean energy access. The suggested three strategies—community solar, policy mandates, and community aggregation of electricity networks by off-grids—can help address the inequality and inequity of clean energy access. The framework of quantifying clean energy justice can support policymakers to identify communities to focus in terms of the spatio-temporal trend of technology adoption for better support.

Future research

Considering the geographical concentration of those characteristics, the study results in dissertation imply that policies aimed at increasing DER adoption and supporting vulnerable communities associated with energy justice should be tailored to local characteristics concerning the inequality and inequity of the distribution and adoption. However, the results have some limitations that future studies may address. First, the study is limited to specific area-based built environment, socioeconomic, and demographic variables that were used to explain the variability of the spatio-temporal distribution of DER adoption and energy vulnerability. Other contextual and individual-level variables such as policy interventions, spillover effects, peer effects, and household-level data may explain the variability of those outcome variables. For example, pre-existing rooftop solar in neighbors increases rooftop solar adoption (Graziano and Gillingham 2015). Furthermore, energy vulnerability can be discussed beyond energy resiliency and energy dependency that the study operationalized in terms of rooftop solar adoption and energy burden, respectively. In addition, including other type of DERs such as batteries can expand the study in terms of association with rooftop solar and EV chargers. Finally, expanding the study sites from the three cities in the Pacific Northwest to other regions with diverse political and geographic attributes would increase the generalizability of results.

To this end, the long term vision of my research is to address social inequity in energy transition by suggesting adoption strategies of DERs such as rooftop solar, EV chargers, energy storage, and community solar in vulnerable communities through research findings. In particular, the future study is aimed at:

(1) investigating spillover effects of DER adoption and spatio-temporal diffusion characteristics of the technologies and,

(2) examining diversification effects of consumer behavior associated with portfolio theory to optimize the distribution of limited resources while improving social equity of communities in terms of people and places.

Future study can involve interdisciplinary research approaches including population studies, social sciences, urban design, public policies, spatial statistics, and machine learning, which require the collaboration of multiple academic disciplines. Investigating social justice and technology adoption by interdisciplinary research approaches will create innovative solutions in consideration of the attributes of vulnerable communities and DER adoption and the diversity of consumer behavior.

COLOPHON

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 ui       RTerm
 language (EN)
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sp              * 1.4-6     2021-11-14 [1] CRAN (R 4.1.2)
SpatialEpi      * 1.2.7     2021-11-15 [1] CRAN (R 4.1.2)
spatialreg      * 1.2-1     2021-11-11 [1] CRAN (R 4.1.2)
spatstat        * 2.3-3     2022-02-21 [1] CRAN (R 4.1.2)
spatstat.core   * 2.4-0     2022-02-15 [1] CRAN (R 4.1.2)
spatstat.data   * 2.1-2     2021-12-17 [1] CRAN (R 4.1.2)
spatstat.geom   * 2.3-2     2022-02-12 [1] CRAN (R 4.1.2)
spatstat.linnet * 2.3-2     2022-02-16 [1] CRAN (R 4.1.2)
spatstat.random * 2.1-0     2022-02-12 [1] CRAN (R 4.1.2)
spatstat.sparse   2.1-0     2021-12-17 [1] CRAN (R 4.1.2)
spatstat.utils    2.3-0     2021-12-12 [1] CRAN (R 4.1.2)
spData          * 2.0.1     2021-10-14 [1] CRAN (R 4.1.2)
spdep           * 1.2-2     2022-01-28 [1] CRAN (R 4.1.2)
splancs         * 2.01-42   2021-04-20 [1] CRAN (R 4.1.0)
stargazer       * 5.2.2     2018-05-30 [1] CRAN (R 4.1.1)
stars             0.5-5     2021-12-19 [1] CRAN (R 4.1.2)
stringi           1.7.6     2021-11-29 [1] CRAN (R 4.1.2)
stringr         * 1.4.0     2019-02-10 [1] CRAN (R 4.1.0)
svglite           2.1.0     2022-02-03 [1] CRAN (R 4.1.2)
systemfonts       1.0.4     2022-02-11 [1] CRAN (R 4.1.2)
tables            0.9.6     2020-09-22 [1] CRAN (R 4.1.3)
tensor            1.5       2012-05-05 [1] CRAN (R 4.1.0)
terra             1.5-21    2022-02-17 [1] CRAN (R 4.1.2)
testthat          3.1.2     2022-01-20 [1] CRAN (R 4.1.2)
tibble          * 3.1.6     2021-11-07 [1] CRAN (R 4.1.2)
tidycensus      * 1.1       2021-09-23 [1] CRAN (R 4.1.2)
tidyr           * 1.2.0     2022-02-01 [1] CRAN (R 4.1.2)
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tidyselect       1.1.2    2022-02-21 [1] CRAN (R 4.1.2)
tidyverse      * 1.3.1    2021-04-15 [1] CRAN (R 4.1.2)
tigris         * 1.6      2022-02-22 [1] CRAN (R 4.1.0)
tmap           * 3.3-2    2021-06-16 [1] CRAN (R 4.1.2)
tmaptools        3.1-1    2021-01-19 [1] CRAN (R 4.1.0)
tmvnsim          1.0-2    2016-12-15 [1] CRAN (R 4.1.0)
TTR            * 0.24.3   2021-12-12 [1] CRAN (R 4.1.2)
tzdb             0.2.0    2021-10-27 [1] CRAN (R 4.1.2)
units            0.8-0    2022-02-05 [1] CRAN (R 4.1.2)
usethis        * 2.1.5    2021-12-09 [1] CRAN (R 4.1.2)
utf8             1.2.2    2021-07-24 [1] CRAN (R 4.1.2)
uuid             1.0-3    2021-11-01 [1] CRAN (R 4.1.2)
V8               4.1.0    2022-02-06 [1] CRAN (R 4.1.2)
vctrs            0.4.1    2022-04-13 [1] CRAN (R 4.1.3)
viridisLite      0.4.0    2021-04-13 [1] CRAN (R 4.1.0)
vroom            1.5.7    2021-11-30 [1] CRAN (R 4.1.2)
webshot          0.5.3    2022-04-14 [1] CRAN (R 4.1.3)
withr            2.5.0    2022-03-03 [1] CRAN (R 4.1.3)
wk               0.6.0    2022-01-03 [1] CRAN (R 4.1.2)
xfun             0.29     2021-12-14 [1] CRAN (R 4.1.2)
XML              3.99-0.8 2021-09-17 [1] CRAN (R 4.1.2)
xml2             1.3.3    2021-11-30 [1] CRAN (R 4.1.2)
xtable           1.8-4    2019-04-21 [1] CRAN (R 4.1.0)
xts            * 0.12.1   2020-09-09 [1] CRAN (R 4.1.0)
yaml             2.3.5    2022-02-21 [1] CRAN (R 4.1.2)
zoo            * 1.8-9    2021-03-09 [1] CRAN (R 4.1.0)

[1] C:/Users/yohan/Documents/R/win-library/4.1
[2] C:/Program Files/R/R-4.1.0/library
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